UNIVERSIDAD POLITÉCNICA DE MADRID

ESCUELA TÉCNICA SUPERIOR DE INGENIEROS DE
TELECOMUNICACIÓN

On the Theoretical Economic Study of the
Industrial Organization of Digital Platforms

TESIS DOCTORAL

Juan Manuel Sánchez Cartas

B.S., University of Extremadura (2013)

M.S., University of Alcala (2015)

DEPARTAMENTO DE INGENIERÍA DE
SISTEMAS TELEMÁTICOS

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supervised by

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2018

To my dad and my mom.

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Submitted to the Departamento de Ingeniería de Sistemas Telemáticos
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Abstract

Internet-of-Things (IoT) technologies are the new digital revolution. A revolution that is based on digital multi-sided platforms. An interesting and representative IoT market is the wearable market, or more specifically, the fitness-tracker market. In that sense, the study of this market and its properties can be helpful in the launching of other IoT technologies based on multi-sided platforms. We address the state-of-the-art of the literature on multi-sided platforms, and we highlight the most relevant open questions in the literature with regard to the fitness tracker market. In that sense, we highlight that there are two main areas: compatibility or data sharing among databases, and the launching phase of the platforms. The contribution of this Thesis is twofold. On the one hand, we develop a theory on the role of compatibility in multi-sided business models. On the other hand, we develop a price competition algorithm for multi-agent systems that allows us to implement theoretical frameworks in agent-based models. In that way, we can simulate the optimal pricing of platforms during the launching phase of their products. This Thesis highlights several interesting insights for managers and public authorities with regard to the pricing of digital platforms. On the one hand, we show that users' expectations matter. The optimal pricing depends on how users perceive the value of the platform. It is easier to launch a platform if there is a device that users value than when all the value relies on attracting other groups of users. On the other hand, we show that compatibility is profitable for the companies, and they are interested in compatibility agreements because they reduce competition. Platforms increase their market power and their profits. Nonetheless, this feature lead to the creation of barriers to entry. Therefore, public authorities have to mitigate those agreements if they want to promote competition and foster new ecosystems. Platforms tend to avoid the entrance of new competitors by launching new brands, and we show that platforms have incentives to do so. We also point out that public authorities have to be cautious with platforms that sell data because there are incentives to create monopolies by splitting the market. One company that provides the data, and another one that provides the devices. However, public authorities may have another bigger problem. We prove

that platforms tend to subsidize one side to attract another group of users but also, they can even make temporal cross-subsidies to attract future consumers. In that sense, prices of digital platforms can be even lower than what one-shot theoretical models predict. The last contribution of the Thesis is with regard to the simulation of digital multi-sided platforms. We prove that addressing the launching of multi-sided platforms with the available theoretical models can be intractable, and we propose an algorithm for the simulation of those models that allows us to keep the tractability of theoretical models when we relax their simplifying assumptions. We prove that the algorithm resembles the best response map, but without assuming any particular theoretical model or function. We apply it in three launching cases, and we obtain three relevant conclusions. First, how users get aware of the existence of products is as important as other theoretical features, such as the differentiation. Optimal pricing must track how is the diffusion of information among consumers. The faster, the better. Second, not all users are equal. Some users are more important than others in transmitting information. The presence of those users increases the profits of platforms, without them, failures in launching are more likely. Third, when launching platforms with the idea of disrupting a previous market, platforms' owners have to provide significant value to users. It is not enough with providing a similar solution than the existing one. It has to be significantly better if not, the platform will fail. Our simulation maps some theoretical thresholds to determine how much value is necessary to avoid the failure in launching.

Resumen

Las tecnologías del Internet-de-las-Cosas (IoT) son la nueva revolución digital. Una revolución que está basada en plataformas multilaterales. Un mercado interesante y representativo de estas tecnologías es el mercado de “wearables” (ponibles), o más específicamente, el mercado de “fitness-trackers” (dispositivos de seguimiento de la actividad física). En este sentido, el estudio de este mercado y sus propiedades puede ser útil en el lanzamiento de otras tecnologías IoT basadas en plataformas multilaterales. En este trabajo, abordamos el estado del arte sobre las plataformas multilaterales y señalamos las cuestiones abiertas más relevantes de la literatura en lo referente al mercado de fitness-trackers. En este sentido, destacamos dos áreas: compatibilidad o compartición de datos entre bases de datos y la fase de lanzamiento de las plataformas. La contribución de la tesis es doble. Por un lado, desarrollamos una teoría sobre el rol de la compatibilidad en los modelos de negocio multilaterales. Por otro lado, desarrollamos un algoritmo de competencia en precios para sistemas multi-agente que nos permite implementar marcos teóricos en modelos basados en agentes. De esta forma podemos simular la fijación óptima de precios de las plataformas durante la fase de lanzamiento de sus productos. Esta Tesis destaca varias interesantes intuiciones para gestores y autoridades que emergen de los hallazgos sobre la fijación óptima de precios en plataformas digitales. Por un lado, mostramos que las expectativas de los usuarios importan. El precio óptimo depende de cómo los usuarios perciben el valor de la plataforma. Es más fácil lanzar una plataforma si ésta lleva aparejada un dispositivo

que los usuarios valoran que cuando el valor reside en atraer a otro grupo de usuarios. Por otro lado, mostramos que la compatibilidad es beneficiosa para las compañías, y éstas están interesadas en dicha compatibilidad porque reduce la competencia en el mercado. Las plataformas incrementan su poder de mercado y sus beneficios cuando existe compatibilidad. Sin embargo, esta característica lleva a la creación de barreras de entrada. Por lo tanto, las autoridades deben reducir dichos acuerdos de compatibilidad si desean promover la competencia y nuevos ecosistemas basados en los ya existentes. Las plataformas tienden a evitar la entrada de nuevos competidores lanzando nuevas marcas, en esta Tesis probamos que las plataformas tienen incentivos para ello. Adicionalmente, destacamos que las autoridades tienen que ser muy cautas con las plataformas que venden datos porque existen incentivos a crear monopolios partiendo el mercado. Una plataforma que provee los datos, y otra plataforma que provee los dispositivos. Sin embargo, las autoridades tienen un problema mayor. Las plataformas tienden a subsidiar un lado atrayendo a otros consumidores, pero es que este subsidio puede ser intertemporal, en este sentido, los precios óptimos de las plataformas digitales pueden ser incluso menores de lo que los modelos teóricos de un solo periodo predicen. La última contribución de la tesis es con respecto a la simulación de las plataformas digitales multilaterales. Demostramos que abordar el lanzamiento de plataformas multilaterales con los modelos teóricos disponibles puede ser muy complejo de resolver, por ello, proponemos un algoritmo para simular esos modelos que nos permite mantener la sencillez de los modelos teóricos cuando relajamos sus supuestos simplificadores sin aumentar la complejidad. Demostramos que dicho algoritmo reproduce el mapa de mejor respuestas pero sin asumir ningún modelo o forma funcional concreta. Aplicamos dicho algoritmo a tres casos y obtenemos tres interesantes resultados. Primero, la forma en la que los usuarios llegan a conocer los productos es tan importante como otras características teóricas, como la diferenciación. El precio óptimo debe tener en cuenta como es la difusión de información entre los consumidores. A más rapidez, mejor. Segundo, no todos los usuarios son iguales. Algunos usuarios son más importantes que otros en transmitir información. La presencia de estos usuarios incrementa los beneficios de las plataformas, sin ellos, el fracaso de los lanzamientos es más probable. Tercero, al lanzar una plataforma con la idea de cambiar radicalmente un mercado previo, ésta debe proveer a los potenciales usuarios con un valor añadido significativamente grande. No es suficiente con proveer una solución similar o levemente mejor. En caso contrario, el fracaso del lanzamiento está casi asegurado. Nuestra simulación mapea algunos umbrales teóricos para determinar el nivel concreto de valor añadido necesario.

Thesis Supervisor: Gonzalo León Serrano
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Chapter 1

Introduction

1.1 The Digital Economy and the Platforms

The digital economy is at the gate of a new revolution based on existing and evolving Information and Communication Technologies (ICT). During the last years, we have been watching an astonishing growth in the digital economy, 114% between 2004 and 2014 around the globe, and 427% growth in Internet companies alone, see ALTRAN (2015).

The use of ICT has also become a major topic in the digital agenda of the European Union (EU), as we observe in the steady increase of EU-funded projects (through H2020 or structural funds) that are focused on smart solutions, such as District of the Future (DoF)¹, ENVIronmental Services Infrastructure with Ontologies (ENVISION)², or the Network of Excellence: Advanced Road Cooperative Traffic management in the Information Society (NEARCTIS)³.

However, the real impact of many of these technologies is largely unknown because they are not reaching the mainstream markets yet. In some cases, we observe that these technologies reach the market in the US only⁴. Nonetheless, there is a tech-

¹http://cordis.europa.eu/project/rcn/111353_en.html

²http://cordis.europa.eu/project/rcn/93797_en.html

³http://cordis.europa.eu/project/rcn/87274_en.html

⁴https://www.cbinsights.com/blog/iot-smart-cities-market-map-company-list/?utm_source=CB+Insights+Newsletter&utm_campaign=d6de1daf99-Top_Research_Briefs_04_02_2016&utm_medium=email&utm_term=0_9dc0513989-d6de1daf99-86652009

nology that has reached the mainstream markets. The wearables. **These devices are one of the most interesting Internet-of-Things (IoT) technologies, and they can be used as a representative domain.**

The first fitness tracker was launched in 2009⁵, three years later, the market worths \$2 billion, and by 2019, it is estimated to reach \$5.4 billion, and the same pattern is expected in other wearable markets like smartwatches⁶. Although wearables are economically significant, wearable markets are smaller than other ICT markets, such as broadband internet access, search engines, OS software, etc. but they are no longer irrelevant. Wearables are attracting the attention of bigger agents⁷. In that sense, Insights (2015) shows that in the wearable market has been invested \$1.4 billion since 2009. IDC states that this market has reached a shipment volume of 18.1 million, and it grew 223.2% from 2014 to 2015⁸. **Therefore, the economic relevance of wearables in the short run is unquestionable.**

These devices are also relevant because **they illustrate the main features of the new digital revolution: devices, platforms, and data.** Users buy a *device* to know more about their fitness, their health, or their daily activities. These devices are based on *platforms* that coordinate users with developers, advertisers, or other stakeholders that are interested in the *users' data*. This market structure based on multi-sided platforms is not new in Economic Science, and it also exists in “traditional markets”, such as supermarkets, credit cards, newspapers, TV-channels. It is also common in other digital markets, such as video-consoles, smart cars, smartphones, etc. **Therefore, some of the conclusions of studying the wearable markets apply to other digital markets.** However, despite these similarities, the wearable market and the IoT markets have not been addressed in the multi-sided platforms literature. There is a lack of works that study these markets, their characteristics, and their behaviors. In that sense, many questions are open. Why did some digital

⁵<http://www.businessinsider.com/the-smartwatch-and-fitness-band-market-2015-1?IR=T>

⁶<http://www.wareable.com/fitness-trackers/fitness-tracker-market-to-top-dollar-5-billion-by-2019-995>

⁷<http://www.zdnet.com/article/time-to-pay-attention-the-internet-of-things-is-about-to-go-mainstream/>

⁸IDC Worldwide Quarterly Wearable Device Tracker, August 27, 2015.

platforms succeed and others fail? Why do wearable platforms cooperate by sharing data with each other? Should competition authorities address this case? This is only a small subset of all the questions that are unanswered nowadays.

Digital platforms create a value *by reducing transactions costs faced by multiple distinct economic agents that would benefit from coming together*, Evans (2011). **Nowadays, it is becoming more and more important the analysis based on multi-sided platforms.** The interest in these models is justified, as it is pointed out by Nielsen (2014). Nonetheless, its importance is going to be superior because of the Internet of Things (IoT) revolution⁹. But first, we need to know to what extent we can rely on the multi-sided platform literature to address new digital markets, such as the wearables one, or to what extent the existing models can answer our questions about these markets. We specifically address which questions remain unanswered, and which features of these markets need to draw our attention.

Digital platform markets are exciting to study but also, it quite complex to describe them and their characteristics because they are so unique that, in most of the cases, no data is available to analyze their impact, performance, or behavior. Many companies have enough data to address this issue. However, they are reluctant to share that data with third-party institutions because they fear that it will allow competitors to overtake the market by studying the strategies of the incumbent. In this situation, **the only possible approach is to consider a theoretical perspective.**

As a summary, there is a steady increase of the economic relevance of digital markets. The market opportunities and the growing capabilities of IoT markets are astonishing. These markets are based on digital platforms that coordinate users, advertisers, developers, and other stakeholders. In that sense, there are companies that have adopted a multi-sided platform business model. These new and exciting ICT markets are disrupting businesses, and it is time to address these markets and to study their characteristics. However, given the lack of data, the only way to address this issue is a theoretical approach.

⁹In this sense, CISCO (2013) observes business opportunities worth \$4.6 trillion, and they point out that only in the US IoT technologies have generated \$253 billion in 2013.

1.2 Sections of this Work. Topics and Results

We start by presenting the wearables market and by describing its characteristics. It is a very illustrative example of the role played by platforms in the new generation of ICT markets. Afterward, we address the current state of the literature on multi-sided platforms, we discuss the current caveats and gaps in the literature, and we lay out the open questions. Then, we address those questions, such as the role of compatibility (data sharing) and differentiation among companies, how to properly price these platforms to foster the adoption. These questions are addressed from a theoretical point of view, but not all of them can be answered with the same tools, for example, those regarding the launching of platforms. Therefore, we present the state-of-the-art techniques regarding the launching of products. In other words, we address the multi-agent (or agent-based) modeling approach with its pros and cons. After reviewing the caveats, we propose an algorithm that solves some of the pricing problems highlighted in the literature. Afterward, we use that algorithm to study the launching of digital services as well as other interesting questions regarding those launching processes. Each section of this Thesis focuses on a specific topic that is studied in-deep. Although each one can be read independently, it is highly recommended to read them in order.

In Chapter 2, we describe the current state of the fitness tracker market from an economic point of view. We first define this market holistically, then we highlight the main operators and their market shares in the last years. These market shares are the result of the competition in the previous years, and that competition allows us to trace back the successful market strategies. In that sense, we analyze the market features, and we derive some stylized facts. We conclude the chapter by pointing out the relationship between this market and the multi-sided market literature, and how these stylized facts may apply to other IoT markets. These stylized facts help us in deriving the research questions that are addressed in the following chapters.

In Chapter 3, we describe the current state of the literature of multi-sided

platforms or markets. We start by defining multi-sided platforms and their origins. Then, we pay attention to those features that make this business strategy different from others, and we present the most relevant taxonomies in the literature. Once that we know the relevance of platforms and how to identify and classify them, we address which areas have been studied in this literature and their findings. First, we address the research on pricing on those platforms, and then we address the different organization schemes that have been studied. We continue by pointing out the role of singlehoming and multihoming on the platforms' strategies, and the role of exclusive content on different platforms. Then, we address the study of digital platforms, anti-trust issues, the empirical evidence about those platforms, and those areas in which there is research going on. We conclude by highlighting some of the current limitations of the literature. Lastly, we wrap-up, and we point out the research questions that cannot be answered with the current evidence, and that will be addressed in the rest of this work.

In Chapter 4, we develop several theoretical economic models to address some of the open questions in the literature, and at the same time, to explain some of the stylized facts that we observe in Chapter 2. We start by laying out a monopolistic model to illustrate the most simple case that may reproduce the first stages of the launching of an IoT platform (when competitors are not in the market yet). Then, we develop a more realistic model with competitors, and we observe how the competition in prices brings new behaviors. In this framework, we test several degrees of heterogeneity, and we address the incentives of platforms to establish compatibility networks with competitors as well as the incentives to try to deter the entry of new competitors. We lay out a dynamic model with two stages to illustrate how the dynamics of these multi-sided markets may lead to price structures much more extreme than those highlighted by static models. We also highlight how the complexity is increasing with each stage, and we propose a simple model of coordination to illustrate that platforms face a great problem when launching their platforms because there are multiple equilibria, and it is uncertain where the market will go. In that sense, we have a new problem. We need a way to include dynamics in these static

models but, at the same time, we need to increase the complexity and heterogeneity of the models without losing tractability. In that sense, we propose multi-agent systems to deal with this issue.

In Chapter 5, we introduce the reader to the multi-agent systems or agent-based modeling. We discuss the problems of this literature, and we illustrate its utility by pointing out the extensive use of this tool in the marketing literature, especially, in the literature about the diffusion of technology or innovations. We pay attention to the open issues in this literature, especially, those issues regarding competition and companies' behavior. Then, we discuss the risks of this tool, and we conclude by highlighting the opportunities and flaws of multi-agent systems with special attention to its potential use as a tool to simulate the launching of multi-sided platforms.

In Chapter 6, we start by proposing an algorithm for agent-based models that tackle the best-answer functions of players in a game of price competition. This algorithm solves two problems. On the one hand, **it solves the problem of how to simulate price competition** or optimal behaviors of companies in multi-agent systems. On the other hand, it helps in building a bridge between multi-agent systems, and the Industrial Organization literature. To prove these points, we test the algorithm in five theoretical models from the Industrial Organization literature, and we observe how the algorithm always converges to the theoretical equilibrium. Then, we test the same algorithm in cases in which the tractability of theoretical models is compromised, and we observe how it is able to provide us with rational equilibria. Then, **we address the launching of a digital platform.** We extend a previous theoretical model, and we observe the adoption of users and developers in several scenarios. After that, we address the role of networks and the flow of information in the adoption of platforms, and we simulate such adoption assuming that users are linked by a random network, a preferential attachment network or a small-world network. In these scenarios, we also test the role of influencers in the spreading of information and how platforms may react to mitigate or amplify their impact. Then, we extend the previous models, and we test the role of one-sided companies (third

options). In this framework, platforms have to compete with them but also, they have to be careful with users that abandon the platforms and choose the third option. We test how platforms can mitigate the impact of the third option, and we conclude by pointing out the main findings.

In Chapter 7, we lay out the main insights of this work as well as potential new lines of research that other researchers may follow. On the one hand, we have shown the relevance of multi-sided platforms as business models, especially, in the case of digital platforms. We have contributed to the literature by extending the previous research on compatibility and data sharing. We have observed that **companies that share data in a multi-sided market increase their market power** and prices. We have highlighted that this is not a collusive behavior, but a consequence of the multi-sided nature of the market. Nonetheless, **sharing data may increase the incentives of companies to try to deter entry**. We have also proved that how people perceive the platform is essential. If the consumers perceive that the added value is on the device, the price strategy must be different than if they perceive that the value is on connecting with others. Lastly, we find evidence that **vertically differentiated markets are more prone to monopolies than horizontal ones**. In that sense, the commoditization of data may lead to vertically differentiated markets in which only the sharing of data and the specialization on one of the sides of the market may allow platforms to earn profits.

On the other hand, we have shown that some of these models cannot be extended to deal with other questions such as the launching of platforms. In that sense, we developed an algorithm to allow us to compute the Nash equilibria in those cases in which equation-based modeling is not tractable enough to derive intuitive conclusions. We prove that **the algorithm is capable of simulating price competition and extending the existing models**. Based on this result, we extended some classical models to address the launching of digital platforms. We consider three cases.

1. A simple launching of a platform following an infection process in a random network of interconnected consumers. We have observed that prices are essential to promote the launching. S-Shape adoptions arise endogenously using the

extended theoretical frameworks from the Industrial Organization literature. We also show that **the speed of the word-of-mouth process and the differentiation are the main drivers of prices and failures.**

2. We extend the previous case to different kind of networks, and we address the node relevance. We test which kind of networks are more resilient to the removal of influencers. Platforms adapt their prices to balance the presence of influencers. Profits are lower without them, but prices may vary depending on which users are on the network and how influence is measured. Platforms face a trade-off between incentivizing adoption with low prices and earning profits with higher prices. **This case also reveals that the network topology may influence the failure in the launching.**
3. Lastly, we consider the role of the third options or one-sided companies in the previous frameworks. We show that, if platforms are not able to create enough value in the launching, third-options may increase the competition, and may reduce the adoption and the profits of platforms. We show that, in those cases, omitting the third option may overestimate the adoption of platforms. Nonetheless, this effect is non-linear. This section concludes by highlighting that, unless platforms are launched in a totally new market, one-sided incumbents influence the adoption of platforms in a negative way. **Therefore, a potentially profitable strategy is to launch the platform as a one-sided platform.**

We conclude by discussing these results and their implications from a policy point of view, as well as pointing out limitations of the current work, and highlighting futures lines of research.

Chapter 2

Wearables: The case of Fitness Trackers

2.1 Wearables and Fitness Trackers. Introduction

One of the most iconic technologies in the Internet of Things (IoT) landscape are the “wearables”. Currently, this is a global market worth six billion U.S. dollars approximately, and it is growing each year¹.

However, it is not the growth what makes it interesting. There are two features that make this market relevant. On the one hand, it combines a physical device with an integrated digital platform. This digital platform is used not only by customers who wear the wearables but also, by developers who are interested in the digital ecosystem around that device. On the other hand, in contrast with pure digital platforms such as Airbnb, Facebook, LinkedIn, etc. that tend to be *de facto* monopolies in comparison with their competitors. In the wearables market, we find many different players. In fact, there are companies who offer devices plus a digital platform, others who offer only devices, or even those that only offer a digital platform. Several business models coexist. In contrast, in other markets, the market configuration and the pricing policies are clearly established, and there is no such heterogeneity.

We expect that many other IoT markets will follow the path adopted by wearables,

¹<https://www.statista.com/statistics/302482/wearable-device-market-value/>

and especially, by fitness trackers. So, many of the questions addressed here can be useful in other markets yet to come. In this sense, we need to understand this market, its features, and especially, those features that are exclusive of digital markets.

In this chapter, we define fitness trackers, and we introduce the reader to their main features, such as companies, products, business models, etc. We provide a top-level vision of the current state of the market and the most important changes in the last years. We conclude with some stylized facts that help us in defining the research questions of this Thesis.

2.1.1 Concepts and Definitions

Not every device that is “wearable” is part of this set of technologies. We only consider as “wearables” those devices that are part of a network of physical objects that exchange data with several agents (manufacturers, operators and/or other connected devices), without requiring human intervention². For example, a pair of trendy headphones is not a “wearable” unless it is connected to a network. There are several definitions of “wearable technologies”, but every definition shares a feature: The devices have to be part of a larger network. Let’s see some of those definitions:

- *[Wearables] refer to electronic technologies or computers that are incorporated into items of clothing and accessories which can comfortably be worn on the body. These wearable devices can perform many of the same computing tasks as mobile phones and laptop computers. [...] wearable technology will have some form of communications capability and will allow the wearer access to information in real time, see Wearablesdevices.com*
- *Wearable computers are basically small and compact electronic devices designed to be worn by a user, see Androidauthority.com*

The relevant point in those definitions is the connectivity. Wearables are not only devices that can be put on and taken off with ease. There are more invasive versions

²See International Telecommunication Union (2012)

Table 2.1: Worldwide Wearable Device Market Share by Product

Product Category	2015 Market Share	2016 Market Share	2017 Market Share
<i>Watch</i>	40.4%	41.0%	55.4%
<i>Wrist Band</i>	50.2%	50.5%	39.1%
<i>Eyewear</i>	0.2%	0.2%	1.5%
<i>Clothing</i>	0.6%	2.2%	2.3%
<i>Others</i>	8.7%	6.1%	1.6%
Source: IDC Worldwide Quarterly Wearable Device Tracker			

of wearables, such as “smart tattoos”, or implanted devices. As we observe, in this definition may fit a lot of heterogeneous devices that compete in very different markets (e.g. Oculus Rift and Fitbit). However, we focus on the most iconic wearable device, the fitness tracker. This market is a very specific segment of the wearables market (“Wrist Band” and “Watch” in Table 2.1), and it is the most prominent device in the wearable landscape. In fact, it is not clear whether or not other wearable devices have reached the “early adoption” stage. Therefore, we have to define what a fitness tracker is, but it is not easy. In many cases, it is not clear if we are in front of a fitness tracker or a smartwatch. Sometimes, the only difference between them is in how they display time/metrics, or how many apps you can install on them. In this case, it is clear that smartwatches and fitness tracker share a part of the market, and they can be studied together.

On the other hand, other wearable devices are the “head-mounted displays” (like Oculus Rift, Google Glass or Steam VR), and the smart clothing. In those cases, it is clear they are aimed to fulfill different necessities, and they should not be considered together. The key point here is that, although there are devices with the same technology (e.g. heart rate monitor), they may play different roles when considering different devices, so the market definition of fitness trackers have to be carefully handled.

2.2 Fitness Trackers. A short story of their History

Fitness trackers are the most iconic device in the wearable world. They are the best-selling device. Nine out of ten wearable devices sold are fitness trackers³. Historically, fitness trackers have their roots in the “Manpo-kei” pedometer, a device invented by Dr. Yoshiro Hatano to fight obesity in Japan but also, in Polar devices which were oriented towards measuring heart-rate. But a fitness tracker is more than a device to measure the heart rate or to count steps, although the first ones were only devices to measure those metrics⁴.

The first fitness tracker was launched by Fitbit in 2009, but in this case, this device was attached to the user’s belt, and it only measured steps. In the case of smartwatches, it was in 2012 when the market kicked off with Pebble. From these starting points until now, we have seen an explosion in the number of devices. As it has happened with wearables, there is not a close definition of what a fitness tracker is, in fact, the difference between fitness trackers and smartwatches is either given by the company (They sell the devices, and they choose to identify them as fitness trackers or smartwatches even when the difference between the two is not appreciable), or by the experts (They contribute with their opinion with respect to what they consider as a fitness tracker or as a smartwatch).

The problem with both visions is the same. It depends on the set of knowledge, experiences, or beliefs that each one has. For example, some experts consider that the difference relies on whether your device *is designed to help you communicate [...], or [it] keeps track of exercise and health*, Walsh (2017). Other experts consider there is a trade-off between fashion (smartwatch) and utility (fitness tracker), and also between budget (fitness tracker) and luxury (smartwatch), see Taylor (2015).

Recently, the line between those features has become thinner as consequence of the “convergence”. The functionalities of both, smartwatches and fitness trackers, are beginning to converge. For example, some smartwatches like the Apple Watch tracks your steps, calories burned, etc. On the other hand, some fitness trackers like Fitbit

³See Table 2.1. Watch and Wrist Band categories.

⁴<http://www.wearable.com/fitness-trackers/the-origins-of-the-fitness-tracker-1234>

Surge sends you notifications of incoming calls or messages. In this environment, it is needed to redraw the borders of the market from time to time because the way we define fitness trackers today may not be useful tomorrow.

In that sense, and for simplicity's sake, we make no distinction between fitness tracker or smartwatches. In fact, our conclusions will apply to both of them and many other devices. In this Thesis, we do not only address the common features of fitness trackers or smartwatches but also, common features of other IoT devices.

2.2.1 Main Operators and Market Share

For simplicity's sake and illustrative purposes, we adopt the wearable definition of International Data Corporation (IDC). This definition includes fitness trackers and smartwatches but also, other devices that can be worn on other parts of the body. This definition relies on a broader concept of wearable⁵. As it is depicted in Fig. 2-1,

Figure 2-1: Wearables. Companies Market Shares 2014-2017. Source: IDC

⁵From a formal point of view, the correct approach would be to define the “relevant market”. In other words, to determine all the producers with similar technical capabilities and all the products with a large cross-elasticity. However, this approach has some flaws: it is dynamic, and it requires a lot of data. Data that we do not have yet.

the main operator in the wearable market is Fitbit followed by Apple and Xiaomi. However, the vast majority of the market depends on a heterogeneous set of firms that accounts for less than the 5% of the market individually. From 2014 until now, we observe an interesting pattern: an increase in the relevance of big companies such as Apple or Xiaomi. This trend can be explained by the growth of this market that has started to attract the attention of big players.

Fitbit is the leader in the fitness tracker market because it is the leader in selling devices. Nonetheless, it is losing ground. Newcomers (e.g. Xiaomi or Apple) are eroding the previous large market share. On the other hand, there are companies (e.g. Garmin) that have been able to retain their market shares by focusing on specific market niches. At the same beginning of 2017, Fitbit, Apple, and Xiaomi are the ones who fight for the mainstream market. If we take a broader picture of the market, and we consider the data collected by different platforms using fitness trackers, we will get a different picture of the market. Under Armour has less than a 5% of the market share in the fitness tracker market, however, it controls Endomondo and MyfitnessPal platforms, which are central hubs in the market⁶, see Fig. 2-2.

If we only consider the data market, Under Armour is the big player, and its influence is not limited to this side of the market, it also expands to the users' side. Therefore, we need an approach that considers both markets, users' and developers' market.

Proposition 1. *The fitness tracker/wearable market is composed of two markets, the users and the developers (data) ones. Both markets are intermediated by several platforms that compete with each other. In this sense, they are platform markets in which a device is sold to users, and access to users' data is sold to developers.*

2.2.2 Market Features. Stylized facts

We are aware that given the limited amount of public data, this set of stylized facts may not be exhaustive, and maybe there are other stylized facts that we miss.

⁶Adidas has tried to stay competitive in the fitness tracker market with the acquisition of Runtastic in 2015, a platform with 70 million users, <http://www.wearables.com/under-armour-adidas-runtastic/>

Nonetheless, this Subsection does not pretend to describe in detail the market, but to provide a top-level vision of the market features.

Quality races or Races to the Bottom

Since the launch of the first Fitbit in 2009, companies have tried to overcome competitor's functionalities. If a device tracks calories burned, the next generation will track calories but also, sleep quality. This behavior is known as "quality races", companies engage in a long-term fighting for consumers. The competition is based on being superior in qualities/functionalities. This behavior is clearly observed when we look at the same company devices (e.g. from Fitbit Flex to Fitbit Charge HR; or from Misfit Shine to Misfit Shine 2), or between companies (Fitbit Ionic was launched to compete with Garmin Vivofit HR, they even share the same basic design). This is one of the main features of the fitness tracker market, and it is an essential part of the long-term strategy of companies in other markets.

PwC (2016) has pointed out that consumers in this market are very sensitive to changes in prices. To them, this is the most important part of the fitness tracker. Recently, fitness tracker companies have started a "race to the bottom", cheap trackers are getting as good as the flagship devices of Fitbit, Garmin, etc. one clear example is the Xiaomi Mi Band 2, and some experts are considering that this will become the trend in the industry, see Ciklum (2016). However, incumbents like Fitbit are replying to this challenge with new metrics, larger customization options, but maintaining high prices. For example, the recently launched Fitbit Changer HR 2 includes new functionalities like breathing control and new customization options⁷.

Proposition 2. *We observe an increasing trend in the number of functionalities that basic fitness trackers have. This strategy can be considered a quality race. Therefore, quality and functionalities are important dimensions in the fitness tracker market as well as customization. Companies engage in differentiation process too to isolate the influence of competitors.*

⁷<http://www.wareable.com/fitbit/fitbit-charge-2-review>

Compatibility

An interesting feature that we observe throughout the wearable ecosystem is a network of compatibilities among the fitness tracker platforms. From the technical point of view, the vast majority of platforms have chosen to use open API's. The reasons behind why companies create compatibility network may be several. It depends on the objectives of each company. In some cases, companies may try to comply with European laws⁸. But in other cases, companies may want to create a larger user base to sell to developers. Figure 2-2 considers the definition of activity trackers used

Figure 2-2: Compatibility Networks among Wearables Companies. Source: own

by Wearable.com to classify these devices⁹. Following its definition, we look for the companies that produce fitness trackers and, by consulting their web pages, we have established the compatibility relationships among them. However, it worth pointing out that compatibility relationships in some cases are asymmetric, in the sense that one device may send information to others, but the others cannot send information

⁸https://europa.eu/youreurope/citizens/consumers/internet-telecoms/telecommunication-services/index_en.htm

⁹Solid lines are fitness tracker companies. Dotted lines are digital platforms that do not sell fitness trackers.

back. In this network, some nodes are isolated. This does not imply they are isolated in a strict sense, there are other ways that allow users to transfer data from those devices to other platforms. However, those intermediary platforms are beyond the scope of this work, and the offer is so extense that we cannot address them properly. For simplicity's sake, we have only included two of them in Fig. 2-2.

Proposition 3. *Fitness tracker companies seem to have incentives to create compatibility networks among them to allow users and developers to exchange users' data.*

Brand Expansion

Another interesting strategy in this market is the “brand expansion”. It consists in the introduction of new products to capture other market niches¹⁰.

The Fitbit case is probably the most iconic one, they started selling in 2009 the Fitbit One. Several years later, Fitbit sells four types of devices for “everyday activities”, two devices for “active people”, and one device for “sportsmen/women”, and Fitbit is considering selling “fashionable devices” to reach other niches. These actions of customization are aimed to deal with many customers as possible in adjacent markets. On the other hand, other players like Moov and Garmin have several devices oriented towards particular sports like swimming, golf, cycling, etc. Each one of those devices is oriented towards a particular market niche. Apart from expanding the market, this strategy may try to avoid new companies entering the market. In that way, incumbents can retain market power and increase their profits. Recognizing these strategies is essential to avoid entering into a fight in which the incumbent has advantages.

Proposition 4. *Fitness tracker companies are periodically launching new brands or devices. These new devices tend to aim smaller market niches of people with more homogeneous tastes.*

¹⁰The term “brand expansion” should not be confused with “brand extension”. The last one is a concept in marketing related to the use of the brand in other markets, e.g. Ralph Lauren shirts and fragrance.

Data and Privacy

By collecting, transmitting, and storing users' data, IoT companies posed themselves in a tricky position¹¹. Privacy is one of the biggest concerns in digital markets, especially, after the Facebook data leak¹². However, as it is pointed out by Motti and Caine (2015) and by PwC (2016), privacy is a concern but, it is not the biggest one. Motti and Caine (2015) analyze more than 2000 comments in 59 web pages, and they show that the vast majority of concerns are common to other devices and services. These concerns are related to the “right to forget”, or the implications of “location disclosure”. Nonetheless, the authors show that there are concerns and fears related to the continuous surveillance, but these concerns do not translate into “privacy strategies by companies”. In our analysis of the web pages of the biggest players in this market, we can confirm this point. We have found no statement related to this issue. To have information about privacy issues, we need to directly go to their Privacy Policy or Terms and Conditions of Use sections, and the information is rather vague¹³.

However, the problem with the data collected by those devices is not only in how the data can be used or collected by third parties. Another problem is when data is combined with other complementary data, see Motti and Caine (2015). In other words, combining data may lead to sensitive users' data being disclosed but also, given the heterogeneous set of companies involved, it is difficult to remove that data from the Internet. As it is pointed out by Josh Lifton¹⁴: *the complexity of infrastructure means that deleting data is often very difficult to do because of the interconnected nature of databases*.

On the other hand, Hilts et al. (2016) analyze security and privacy issues related to

¹¹In the fitness tracker case, this issue is relevant because the data collected can be considered medical data.

¹²<https://www.reuters.com/article/us-facebook-privacy/facebook-says-data-leak-hits-87-million-users-widening-privacy-scandal-idUSKCN1HB2CM>

¹³The vast majority of fitness tracker companies are clear with the definition of personal and non-personal data, but they are opaque in the use of non-personal data. The companies keep the right to use that data for multiple purposes. However, this would change on May 25th 2018 with the new data protection law in Europe. It will be mandatory to acknowledge the use of data explicitly.

¹⁴<http://www.techrepublic.com/article/the-dark-side-of-wearables-how-theyre-secretly-jeopardizing-your-security-and-privacy/>

the data collected by fitness trackers, and they found that: *In some notable cases, we discovered severe security vulnerabilities [...] and unclear policies leaving the door open for the sale of users' fitness data to third parties without express consent of users.* This last point is probably the most interesting one from Europe's point of view, given that the European Data Protection Supervisor (EDPS) has stated that fitness data cannot be treated as non-personal information in Europe, so the potential commercial use is limited. That contrasts with the definition of non-personal data given by many fitness tracker companies. However, US-based companies can collect that data because under US laws that data is not classified as "health data", see Hilts et al. (2016).

The European legal framework limits the data that can be sold, and it limits the multi-sidedness of the market, but it does not remove this possibility¹⁵. Digital platforms can keep attracting developers only with the number of potential users for their apps. Nonetheless, this implies a commoditization of users. From companies' point of view, the picture is the following: the higher the number of users, the larger the value of the platform for developers, advertisers, and other stakeholders. This fact would justify why some companies have made their APIs pay-to-use. For example, Garmin has a one-time license fee of \$5000, although in 2014 was completely free. But a common pattern in all the cases is that all fitness tracker companies with a digital platform want to foster their ecosystem by promoting the development of apps on top of their platforms¹⁶. As a conclusion, even if the use of data is limited in Europe, fitness tracker companies are operating two-sided platforms by offering fitness trackers to users, and a closed market (users of fitness trackers) to developers.

Proposition 5. *Privacy is not an essential dimension for companies in their competition with other companies. The use of data may be restricted in the near future in the European Union, which may imply mitigating of the two-sidedness of the market. Nonetheless, currently, the vast majority of fitness tracker companies are operating two-sided platforms.*

¹⁵In the following Chapter, we introduce the concept of multi-sidedness.

¹⁶This conclusion is easy to obtain by visiting the Developers Section on all the websites of the major companies in this market.

The Users' Profile

Although several surveys have been launched in the past months, the public analysis of this market is still in its infancy. We can only “guess” who is buying them and why. IDC (2016) finds that *consumers who plan on purchasing a wearable product in the next six months are tech savvy, highly social, and extremely style conscious*. Wearable intenders' preferred brands differ by category, with the most preferred brands being Apple (52%) for smartwatches, Fitbit (37%) for fitness trackers, Google (36%) for eyewear, and Nike (40%) for clothing. Those depicted as *tech savvy, highly social, and extremely style conscious* are those who are entering the market.

On the other hand, PwC (2016) finds that the main barrier to purchasing wearables is the price followed by the fear of not using it. However, PwC also found that only 14% of customer would take into account how cool or fashionable is the product when buying them. Nonetheless, both, IDC and PwC, agree with the idea of wearables becoming more and more a trending topic. Among the motivations to buy a wearable, they have found that health benefits and connectivity (not only with their smartphones but also, with other people) may boost the adoption¹⁷.

Proposition 6. *The profile of current users of fitness tracker is a social person (network effects, they value the presence of others, or at least, the presence of valuable content) who cares about price, style (subjective feature), and the technology (objective feature).*

2.2.3 Wrap-up and Research Questions

Wearables are one of the most iconic devices of this new age of ICT, and especially, fitness trackers. In this sense, it is essential to study them because other IoT markets will presumably behave in a similar way. In this section, we have made a small description of the market and its characteristic that can be common to other IoT markets in the future.

¹⁷The increase in functionalities can be considered as indirect evidence of the presence of technology lovers. See the Annex for a depiction of the technologies in fitness trackers.

As a summary, we have observed that the mainstream fitness tracker market encompasses two sub-markets, one in which devices are sold to users, and another one in which users' data attract developers. Both markets are intermediated by several platforms that compete with each other. In this sense, there are platform markets in which a device is sold to users, and access to users (or users' data) is sold to developers. We also find that companies tend to launch new devices to keep the users base but also, to attract other users with more specific needs. We find that price is the most important variable for users when making the purchase, but they also take into account their tastes and the technical features of the devices. Lastly, we find that privacy is not an essential concern for users a priori, but it is a posteriori.

In this scenario, it is clear that the majority of the companies are multi-sided platforms that coordinate users and developers so, to understand their behaviors and their strategies, we need to address the literature of multi-sided platforms to ask ourselves to what extent the current state of this literature can explain the stylized facts that we have observed. But also, we need to know to what extent this literature can explain the rise of these platforms. In this spirit, this work sets out the following questions:

What is a multi-sided platform? Is their pricing different to other markets? Are the traditional economic insights valid? Which one is better, multi-sided platforms or one-sided markets? How is the content of those platforms affecting the consumption? What if users adopt several platforms? What is the role of users expectations? Is it matter if users care about the device but not about the connecting with other people? Why do platforms become compatible with each other? When will that happen? Under which conditions? What are the implications of commoditization of users' data? Why do fitness trackers try to differentiate themselves? Why do they launch new products if that increases competition? Is there a risk of monopolization in this market? Under which circumstances monopolies (such as Google or Facebook) may appear? What is the optimal pricing policy of a platform for a successful launching? Is it difficult

to launch a platform? What does foster their adoption? Is it a matter of how users transmit the information? What is easier, to create a new market, or to disrupt an existing one?

This is a big set of questions, and we do not pretend to answer all of them. In the following Chapter, we depict the current state of the literature, and we highlight which of those questions are already answered, and which ones remain open. We focus our attention on those open questions, which will be highlighted at the end of the next Chapter.

Chapter 3

Literature Review

3.1 Introduction

We live surrounded by platforms. They are everywhere, and they are disrupting businesses, behaviors and even governments. This revolution is based on allowing interchanges, transactions, and connecting people who need each other in some way. But thanks to the information and communication technologies (ICTs), the consequences of these interchanges are global, and they are changing how we buy, communicate, and even run. The fitness tracker market is only one more example in the huge set of platform markets. And this set will keep growing with the development of Internet-of-Things (IoT) technologies. In this sense, the basic features of these markets are worth knowing.

The idea of putting in touch two or more groups of people who need each other is not new. Newspapers, academic journals and even fairs work in this way. They “connect” readers and advertisers, researchers and readers, and buyer and sellers. However, ICTs have allowed us to scale up this idea to the whole world. Traditional newspapers or fairs have two clear shortcomings that digital platforms avoid: the physical copy and the physical presence. To benefit from a fair, you have to be there. To read a paper, you need a copy. In both cases, it is costly to print a newspaper or to set a stand at a fair. However, digital platforms allow us to overcome these two issues: you do not need to be physically in some place, and copies can be made for

free. These two features have allowed platforms to reach global significance. The larger the number of users, the more relevant they become. All platforms are made by their users. Amazon is made by sellers and buyers, Facebook is made by users and advertisers, Youtube is made by watchers and broadcasters (youtubers), Fitbit is made by users and developers, etc.

In this section, we introduce the concept of multi-sided platforms, and how this concept has evolved in the literature. We explain the different multi-sided platforms that can be found in real markets, and we address the specific features that make multi-sided platforms interesting, such as prices, coordination problems, organization schemes, exclusivity and multihoming decisions, the role of content, the adoption of platforms and the barriers to entry, the role of digital platforms, or the anti-trust literature on platforms. We pay special attention to digital platforms and how they have been addressed in the literature. Lastly, we conclude with the open questions in the literature.

3.2 Definitions and Concepts

What is a platform?¹ Unfortunately, multi-sided markets do not have a clear and widely accepted definition as is pointed out by van Damme et al. (2010), Evans (2011) or OECD (2009). In fact, *you know a [multi-sided] market when you see it*, see Rochet and Tirole (2006).

Its identification present several problems. On the one hand, we have to define what we mean by “platforms” because there is no “industry of platforms” in official statistics. In fact, platforms are technologies that can be used by a great number of industries, see Evans et al. (2008). In this case, we can consider that a platform is a technology that minimizes transactions costs, or a technology that creates a value allowing transactions that otherwise would not occur, see Evans and Schmalensee (2005).

¹In this work, we refer to two-sided platforms, two-sided markets, multi-sided markets and multi-sided platforms as synonyms. We know that this is not true. However, for simplicity’s sake, and for keeping the same language than the original authors, we refer to them interchangeably.

Nevertheless, this definition is very broad and, virtually, every market could be studied as a particular case of multi-sided markets (or two-sided markets). The term “two-sided markets” was first used in Rochet and Tirole (2003). However, these markets had been studied before by Parker and Van Alstyne (2000), Caillaud and Jullien (2001) and Caillaud and Jullien (2003). In the last two works, they refer to the platforms as “cibermediaries”². Initially, Rochet and Tirole proposed a definition that considered markets and platforms as the same item: *A market with network externalities is a two-sided market if platforms can effectively cross-subsidize between different categories of end users that are parties to a transaction. That is, the volume of transactions and the profit of a platform depend not only on the total price charged to the parties to the transaction, but also on its decomposition.*

For example, in the credit card market, buyers normally do not pay for the transaction, but sellers do. If we evenly share the price paid by sellers among sellers and buyers, the number of transactions will not remain equal. Fewer buyers will be willing to pay with credit card, and fewer sellers will accept credit card too. The main shortcoming of this definition is that it only relies on the price structure and on considering markets in which platforms can control the transactions like credit card markets. However, they do not take into account markets like newspapers, where the platform (newspaper) cannot control if the reader is interested in the advertising.

One of the first works in proposing a broader definition was Evans (2003): *Multi-sided platforms coordinate the demand of distinct groups of customers who need each other in some way.* In contrast with the Rochet and Tirole’s definition, Evans’ considers the possibility of platforms that do not control transactions. The main shortcoming of this definition is that it is too broad. Almost every relationship may fit the Evans’ condition of “who need each other in some way”.

On the other hand, the great contribution of Rochet and Tirole is to highlight the difference between one-sided and two-sided markets. **In other words, what really**

²The birth of this literature is a conflictive issue because, for some authors, the birth is when the term “two-sided market” is coined. To others, it is when the first paper with inter-dependent demands between two markets was published. In this regard, the birth is attributed to Parker and Van Alstyne

matters is who pay for the service. Their definition emphasizes the essential role of indirect network effects, and if we consider a broader definition of prices, we can use their definition to identify other two-sided markets where “transactions” are not easy to notice. For example, let’s consider a nightclub in which men’s ticket is \$10 and women’s ticket is \$5. The total price paid by both sides is \$15 but, if we evenly share the price (\$7.5 each), will there be the same number of customers in the nightclub? If the answer is no, that is a hint that we are facing a two-sided platform. Rochet and Tirole recognize that under their definition almost every company would be a two-sided platform. However, they argue that, at least in competitive environments, companies are often *de facto* one-sided platforms because if the number of companies tends to infinity, the networks effects tend to zero, i.e. without network effects, there is no multi-sided platform. **The larger the number of platforms, the less likely we will deal with a multi-sided platform**³.

Nonetheless, Rochet and Tirole highlight there are some factors that generate multi-sidedness such as membership fees because they could modify the volume of transactions⁴.

However, the vast majority of the literature has opted for using a simpler and straightforward definition (also highlighted by Rochet and Tirole), the presence of indirect network effects: *the net utility on side “i” increases with the number of members on side “j”*. Although this definition is very broad, other authors consider the presence of cross externalities a fundamental element in the definition of multi-sided markets. In

³What is even more interesting is the link between their definition and the Coase Theorem. The Coase Theorem states that if property rights are clearly established and tradeable, and if there are no transaction costs nor asymmetric information, the outcome of the negotiation between two or more parties will be Pareto efficient, even in the presence of externalities. The idea is that if outcomes are inefficient and nothing hinders bargaining, people will negotiate their way to efficiency. In the previous example, couples can reallocate their tickets. A nightclub in which only couples go would be a one-sided platform. In the credit card example, sellers and buyers cannot coordinate themselves to reallocate their prices, so the Coase Theorem fails. Therefore, this market is more likely to be a two-sided one.

⁴This was noticed by Caillaud and Jullien (2003). In their model, consumers follow an efficient bargaining process to determine the transaction price, which yields an efficient share of trade surplus. In other words, their price structure is neutral. Nevertheless, membership fees are different, and every agent value the cost of entering the platform differently, so there is room for multi-sidedness. The multisidedness is obvious when a platform adopts a “Divide and Conquer (DC)” strategy (platform subsidizes one group, and recovers the loss on the other side). By definition, this strategy implies a non-neutral price.

general, a lot of definitions are based on the existence of these externalities, such as those in Evans (2003), Schiff (2003), Wright (2004), Ambrus and Argenziano (2004), Hagiu (2004), Jullien (2005), Anderson and Coate (2005), Armstrong and Wright (2007), Parker and Van Alstyne (2005), Evans et al. (2008), Weyl (2010), Weisman and Kulick (2010), Ivaldi et al. (2011), but this idea is not shared by all authors. Hagiu and Wright (2015) criticize Rochet and Tirole’s approach and the cross externalities approach used by Evans (2003) and others. They propose a definition of multi-sided businesses based on two characteristics:

- Multi-sided businesses enable direct interactions between two or more sides
- Each side is affiliated with the platform

By “direct interaction”, they mean that two or more sides retain control over the essential terms of the interaction. For example, on the Uber platform there are two sides, users and drivers. Drivers retain control rights over the car (it is the drivers’ car) as opposed to the one-sided intermediaries (taxi companies) that have total control over their fleet. Therefore, this is the main difference between the one-sided and the multi-sided worlds. By “affiliation”, they mean that users on each side consciously make platform-specific investments that are necessary in order for them to be able to interact with each other directly, for example, paying membership fees or registering. In the Uber example, both users and drivers have to invest time in registering in the App. The affiliation helps to distinguish multi-sided platforms from inputs suppliers. This distinction is better illustrated by the authors:

Microsoft’s Windows acts as a multi-sided platform enabling interactions between application developers and PC users, but Intel’s microprocessors are mere inputs to PC manufacturers. The direct interaction that consists of users installing and using PC applications is enabled by the microprocessor just as much as it is enabled by the operating system. The key difference, however, is that application developers affiliate with Windows by investing significant resources in using its Application Programming Interfaces (APIs), but they typically make few if any investments or design choices specific to the microprocessor

The most remarkable contribution of Hagiu and Wright is that their definition does not require any reference to indirect or cross-network effects. **Hagiu and Wright consider that indirect network effects are not sufficient to define a multi-sided platform.** However, indirect network effects could be consequence of “affiliation” or “direct interaction”. The authors consider that the hypothesis that every market with indirect network effects is a two-sided market is not correct, and they explain it in this way: *note that indirect network effects are not limited to multi-sided platforms [...]. [In] traditional consulting firms clients will be attracted to a consulting firm that has many other clients since this means it will have access to a greater number of qualified consultants.*

Given the complexity of defining a two-sided market, it is normal to find works that consider different definitions. Some authors such as Filistrucchi and Klein (2013) or Evans et al. (2008) have shown that reality is very ambiguous. In fact, Filistrucchi and Klein (2013) and Rysman (2009) claim that, theoretically, Rochet and Tirole’s definition can include one-sided cases. That is why it is usual to find works in which the Evans’ definition is used, such as Affeldt (2011), Song (2013), Evans (2011), Affeldt et al. (2013), Filistrucchi and Klein (2013), Filistrucchi et al. (2012a), or a mix between Evans’ and Rochet and Tirole’s Kaiser and Wright (2006), Weisman and Kulick (2010), Weyl (2010), Filistrucchi and Klein (2013)⁵.

Another point of criticism related to the Rochet and Tirole’s and Evans’ definitions is that they refer to “markets”, not to businesses or platforms like the Hagiu and Halaburda’s. Rysman and Evans share this criticism. They point out that the definition of multi-sided markets is not totally correct because it is hard to find “pure multi-sided markets”. On the other hand, it is easier to find “multi-sided businesses/platforms”. We can find markets where there are companies using multi-sided strategies and companies using one-sided strategies. Following this criticism, Rysman proposes another definition: *two-sided market is one in which 1) two sets of agents interact through an intermediary or platform, and 2) the decisions of each set of agents affects the*

⁵In van Damme et al. (2010), we find an example of ambiguity between Evans’ and Rochet and Tirole’s definitions.

*outcomes of the other set of agents, typically through an externality*⁶. No one will be interested in the platform if the other party is not on the platform.

He uses as an example Amazon that was a one-sided platform in the market of books and a multi-sided platform in other markets. That is why it is important to Rysman to focus on the strategies adopted by firms because multisidedness is an endogenous decision of firms. **The main question is not to know if a market is a multi-sided one, virtually all markets might be multi-sided to some extent. What is relevant is to know how important multi-sided issues are.** Evans argues in a similar way, he points out that, in the US newspaper industry, there are examples with high consumer fees and low level of advertising (The Economist), with a high level of advertising and low consumer fees (Vogue), or free for consumers but with the highest level of advertising (online newspapers), see Evans and Noel (2008), Evans et al. (2008) and Evans (2011). Those features are also common in social networks in which there are users who pay and have low levels of advertising (LinkedIn premium), or free users with advertising (Facebook). The same features are shared by Netflix (paid access without advertising) and by Youtube (free access but with advertising). There are others authors whose definitions highlight the link between groups and platforms, such as Kumar et al. (2010): *Two different types of users may realize gains by interacting with one another through one or more platforms or mediators*, or Amelio and Jullien (2012): *The concept of two-sided market refers to a specific instance of networks where the services are used by two distinct groups of customers interacting*. With this approach, we have other definitions proposed by Anderson and Coate (2005), Evans et al. (2008), Cabral (2011) or Ivaldi et al. (2011).

Lastly, there are works whose definitions are worth analyzing because they show different characteristics but also because they are in conflict with other works. For example, Ambrus and Argenziano (2004) argue that two-sidedness implies that there are indirect network effects, and both sides are consuming the same product. On the other hand, Ivaldi et al. (2011) argues that two-sided platforms are multi-product

⁶This definition seems that there is no difference between “market and platform”. However, Rysman refers to the interior market of the platforms.

firms which serve different products to each side, and there are indirect network effects among sides. In other words, this definition does not imply the consumption of the same product like in Ambrus and Argenziano's approach.

In general, the vast majority of authors and international organisms recognize that there is not a universally accepted definition of multi-sided markets or platforms yet.

There is a consensus on the idea of two or more groups of agents who need each other in some way and who rely on platforms to intermediate transactions between them. There is also consensus on the idea that it is more important to determine the linkages between the two sides of the market than the market itself, see OECD (2009), Filistrucchi et al. (2012a) or Weyl (2010). Weyl highlights that definitions have their flaws but, in general, multi-sided markets have three features:

- There is a multi-product firm. A platform provides distinct services to two sides (or more) of the market
- There are cross network effects. Users' benefits from participation depend on the extent of user participation on the other side of the market
- Bilateral market power. Platforms are price setters on both sides of the market

The author argues that the failure of any of these conditions makes simpler and better understood other models. If a platform does not explicitly charge different prices to different groups of users, it is best viewed as a standard, one-sided company. Obviously, the role of a platform will depend on the market where it is operating. In the case of wearables, it is clear that the product sold to users is different from the one sold to developers as well as the prices charged to both sides. The heterogeneity in those prices also reflects some degree of market power. Additionally, it is clear that developers value the presence of users (they can sell their apps to a broader public) and users value the presence of developers (they have access to more content). In this sense, fitness trackers verify the conditions to be analyzed as multi-sided markets.

In summary, definitions of multi-sidedness are controversial. There is no

consensus. However, as it is pointed out by Filistrucchi et al. (2012a): *although at first sight there appears to be still some debate on the exact definition of a two-sided market, the different definitions proposed appear consistent enough to allow the practical identification of two-sided markets.*

3.3 Origins of Multi-sided Literature

The birth of multi-sided literature is not easy to determine. On the one hand, we can consider that this literature was born with the first paper in which indirect network effects were considered, see Parker and Van Alstyne (2000). But this approach has a problem. Then, it is necessary to trace back the literature to the first paper with network effects to understand how this literature was born. However, we consider that this literature was born with the first paper that coined the term “economic platforms”. In that sense, the previous papers were only necessary steps toward this new business model.

The first paper that describes these business models in detail is Caillaud and Jullien (2001), but the take-off of this literature is due to Rochet and Tirole (2003). Their model is defined as a mix between network economy and the multiproduct literature. Nevertheless, the former does not internalize the externalities between end users, and the latter does not consider the externalities that lie at the core of the network economics literature. This difference was enough to justify this new branch in the literature.

After these works, several authors started to look for multi-sided platforms or markets. One of those authors was Evans. In an early work, he pointed out some empirical regularities of those platforms, see Evans (2003). Since then, the idea of multi-sided platforms as devices that internalize the externalities of several sides has been the defining feature of these markets.

In those early stages, the link between platforms and indirect network effects was the defining element, see Jullien (2005). However, recent works such as Hagiu and Wright (2015) have pointed out that indirect network effects may be not an a priori feature,

but a consequence of multi-sided platforms behavior. Nonetheless, in parallel with those early papers, other authors have realized that these platforms have exclusive features. However, for some researchers, the exclusive features of these platforms are not enough to consider them as an independent branch, but this opinion is not shared by everyone.

At the moment, we have two views about how this literature fits in the Economic Science. On the one hand, we can consider it as an independent branch, as it is pointed out by Anderson and Coate (2005) or Economides and Katsamakas (2006). On the other hand, we can consider a technical point of view, as Rysman (2009) suggests, and therefore, multi-sided platforms could be part of the Network Economics literature. We align with those who see this literature as an independent branch because of three reasons:

- It has its own rules. In many cases, traditional insights are not applicable to multi-sided businesses
- Modern papers tend to quote other papers related to multi-sided literature, and it is no longer common to quote papers from other fields in Economics such as the classical literature of Network Economics
- The term “multi-sided platform” is already understood as a specific kind of business model

3.4 Differences with Other Market Structures

An essential characteristic to consider multi-sided market literature as an independent body of the Industrial Organization is that it must present unique and exclusive features. In this section, we focus on highlighting those differences that, in the following sections, we address in more detail.

The first work in which the special nature of two-sided (or multi-sided) markets is pointed out is Wright (2004). In this work, the author explores eight common

statements in the Industrial Organization literature that do not apply to multi-sided markets. Those eight statements (or fallacies as he calls them) are:

- An efficient price structure should be set to reflect relative costs (user-pays)
- A high price-cost margin indicates market power
- A price below marginal cost indicates predation
- An increase in competition necessarily results in a more efficient structure of prices
- An increase in competition necessarily results in a more balanced price structure
- In mature markets, price structures that do not reflect costs are no longer justified
- Where one side of a two-sided market receives services below marginal cost, it must be receiving a cross-subsidy from users on the other side
- Regulating prices set by a platform in a two-sided market is competitively neutral

The reason behind why some traditional insights do not apply is because of the interrelationship between the sides. This interrelationship that emerges from the indirect network effects has been addressed in many works, and all of them conclude that many of our traditional insights may be wrong in multi-sided markets. In this sense, Evans and Schmalensee (2013) argue that *one-sided tools often do not apply, at least not without substantial changes, to multi-sided platforms*.

The difference in the pricing between multi-sided markets and one-sided markets motivates the treatment of multi-sided markets differently. The price structure of multi-sided markets is probably their most known characteristic. **Multi-sided platforms tend to set an asymmetric price structure in which one side is the profitable one and the other one is the loss side⁷.**

⁷Some of these results were pointed out in pioneering works, such as Caillaud and Jullien (2001), Caillaud and Jullien (2003) or Schiff (2003).

But the differences in pricing behavior are not limited to the asymmetric balance. The prices can even be totally disconnected from marginal costs, as it is pointed out by Evans (2003). This contrasts with one-sided markets in which there is a clear relationship between the two. Because of the interrelationship between the sides, it is possible that a platform will respond to an increase in costs on one side with an increase in prices on the other side. Regarding this relationship between prices and costs, Jullien (2005) argues that it is common in multi-sided markets that the welfare-maximizing prices will not coincide with marginal costs. From a social point of view, Rysman (2009) points out that: *Theoretically, it is often hard to establish whether a given price in a two-sided market is higher or lower than socially optimal, or even whether greater competition would make the existing price rise or fall.* This feature contrasts with traditional markets in which it is traditionally believed that more companies imply more competition and more welfare.

Nonetheless, some authors argue that multi-sided market are only a specific case in the Network Economics literature. However, we consider that multi-sided markets are so different, that they deserve a separate treatment. In both, the role of expectation is essential. In a traditional market, if consumers have pessimistic beliefs about the launching of a product, it is difficult to overcome them. However, that is possible in multi-sided markets. Caillaud and Jullien (2003) prove that even when one side believes no one is going to enter the platform (pessimistic beliefs), it can get a positive market share if the platform adopts a divide-and-conquer (DC) strategy. In other words, the platform must subsidize one group to attract the other group.

Optimality will call for subsidies, [...] and one should subsidize more the less profitable side of the market, Jullien (2005). These subsidies come from the fact that one side generates a greater (lower) positive (negative) externality on the other side as Economides and Katsamakas (2006) and Parker and Van Alstyne (2005) point out. However, it is also true that multi-sided markets and one-sided markets have in common other aspects. For instance, Reisinger (2004) is among the first ones in proving that the greater the differentiation, the greater the profits for at least one platform. Hagiu (2004) or Evans (2002) also find that differentiation guarantees the existence

of several platforms in the same market. Rysman (2009) summarizes this feature as follows. *If [platforms] can differentiate from each other, they may be able to successfully coexist.* Caillaud and Jullien (2003) prove that without differentiation, the competition could end in a monopoly equilibrium, like in a classical one-sided model. In a similar vein, Kind et al. (2013) prove that when the horizontal differentiation is lower, platforms will try to differentiate themselves in other dimensions.

A remarkable work in this area is Parker and Van Alstyne (2005). They compare two-sided and one-sided model, and they prove that the two-sided case leads to the internalization of externalities, to bigger profits, and higher welfare levels. However, this result is only true if externalities exist, if not, there is no difference between the two cases. This work shows that the boundaries between traditional and multi-sided models are only one indirect network effect away⁸.

There are also common insights and results between multi-sided platforms literature and network economics, such as the excessive concentration caused by network effects, see van Damme et al. (2010) or OECD (2009). This movement towards concentration is better illustrated by Caillaud and Jullien (2003). In their model, a monopoly platform can be an efficient solution. They call it, the “dominant-firm equilibria”. This result does not only imply that “the winner-takes-all”, it also implies that it is efficient to do that⁹.

Lastly, there is a feeling in the digital sectors that platforms, and in general, all digital markets are prone to permanent monopolies. But that is not true either in platforms markets nor in traditional network markets. In the case of multi-sided platforms, White and Weyl (2016) point out that under certain equilibrium conditions, networks effects can never lead to “entrenched market positions” because a more-efficient but similar entrant may always use a strategy to undercut the incumbent firm. In fact, before the development of the multi-sided literature, Shapiro and Varian stated with regard to network markets that excess inertia is the exception, not the norm in

⁸They also find that under certain conditions, a monopoly is better than a duopoly in terms of welfare. This result is similar to the one found by Hagiu (2004). He finds that a monopoly will create higher product variety.

⁹They define this result as follows. *A “dominant-firm equilibria” is a price system that no pricing strategy allows the other platforms to earn a positive profit.*

digital markets, see Shapiro and Varian (1999). Nonetheless, White and Weyl (2016) argue that *compared to industries without network effects, platform markets are more likely to be inefficiently fragmented*.

3.5 Typologies of Multi-sided Models

Platforms are present in many digital services such as Facebook, Google, Amazon, Netflix, etc. Researchers, managers, and consultants are interested in the implications of these strategies. However, it is easy to get lost when trying to find a suitable model for a specific case. Only in the multi-sided platform literature, more than 80 different models have been developed, and they can be classified in several ways: according to the nature of fees (membership or use), the number of platforms (monopoly, duopoly, or N-platforms), the possibility of being in one or several platforms at the same time (singlehoming vs multihoming), etc.

As is pointed out by Filistrucchi (2008), antitrust authorities, managers, researchers, etc. have to have in mind that different typologies of markets should be treated differently. In this sense, several authors have tried to classify models and platforms with regard to their characteristics. In this section, we highlight those proposals that have attracted more attention. The first taxonomy we are aware of is Evans (2003). He considers three categories:

- **Market-Makers.** They enable members of distinct groups to transact with each other. Each member of a group values more the service if there are more members of the other group. The distinguishing feature is the possibility of monitoring transactions
- **Audience-Makers.** They are those markets where platforms match advertisers to audiences
- **Demand-coordinators.** These platforms do not strictly sell “transactions” like a market maker, or “messages” like an audience-maker. They are a residual category but economically the most interesting for Evans.

However, this classification presents several flaws. On the one hand, the most interesting category is the residual one. But this category should be a minor one, and the rest of categories should be the relevant ones. On the other hand, the definition of the categories is either quite restrictive or quite lax. In the case of Market-Makers, platforms should be able to monitor transactions, which is a lax requisite. But in the case of Audience-Maker, platforms must be in the business of advertising, if not, they are in the residual category. These flaws make impractical this taxonomy nowadays, but it was a useful one at the beginning of the literature.

Later, Evans observed four types of two-sided platforms: exchanges, advertiser-support media, transaction devices and software platforms, see Evans and Schmalensee (2005). However, this taxonomy is, in theoretical terms, worse than the proposed by Evans (2003) because the behavior between “exchange” and “transaction device platforms” is pretty similar. Although this taxonomy is pretty useful in empirical terms, it is not clear where is the advantage of differentiating between exchange and transaction device platforms instead of thinking in “market-makers” (as it was initially proposed). Additionally, from a theoretical point of view, it makes little sense to consider as software platforms all the digital platforms independently of their characteristics.

Filistrucchi (2008) proposes another taxonomy that is quite relevant nowadays. This classification has the advantage of being more accurate than Evans’ classification. Filistrucchi classifies two-sided models in two categories

- **Two-sided non-transaction markets**, or Media type. In these markets, the transaction is not present, or it is unobservable. So, it is not possible to apply transaction fees. These markets only set membership fees. For example, newspapers. Readers read the newspapers with their ads, but the newspaper does not know if the ads are generating transactions for the advertiser.
- **Two-sided transaction markets**, or payment card type. These markets are characterized by the observability of transactions between the sides, like payments with credit/debit cards. The platform can monitor the transaction, and

it can set both transaction and adoption fees.

Filistrucchi argues that the Rochet and Tirole’s definition is better suited for “payment card type” markets, and Evans’ definition is better for “media type” markets, see Filistrucchi et al. (2012a).

In comparison with Evans’, this classification is more useful for research purposes.

It is simple and straightforward, and it allows us to classify platforms unequivocally. However, the only flaw is that the Two-sided transaction markets category may attract all the digital platforms because of the definition: *These markets are characterized by the observability of a transaction between the sides.* In almost all the digital platforms, that is true. However, many of them prefer to use membership fees instead. In this sense, it would be better to classify them in terms of the actual pricing instead of the potential pricing. However, that may lead us to derive wrong conclusions, because we would be assuming that they do not set other prices because they cannot. Nonetheless, all these classifications have their pros and cons, and we have to be aware of what we expect and want from each one of those taxonomies.

Another interesting classification is based on Rysman (2009). He criticizes the use of the term “multi-sided markets” when, in reality, it is more frequent to find “multi-sided strategies”. However, this classification is only useful for theoretical models because in those models is where we can say without error whether or not there are “strategies” see Hagiu and Wright (2015) or Economides and Katsamakas (2006), or “markets” see Armstrong (2006) or White and Weyl (2016).

There are other interesting taxonomies, but their impact is less important. For example, Belleflamme and Toulemonde (2004) divide two-sided markets between horizontal ones (services to several industries) and vertical ones (traditional services of suppliers-consumers). They also divide these two categories with respect to the ownership structure between “third-party” and “consortia”. They define these categories in this way: *third-party marketplaces are neutral communities of many sellers and many buyers, with open criteria for entry, whereas consortia marketplaces are built by a small number of industry leaders that dominate their respective industries.* However, this taxonomy has had little impact because it is more focused on providing a

framework for a specific model than on classifying multi-sided platforms.

As a summary, **in comparison with other lines of research, the classification of two-sided platforms has not been so well studied as other features of these markets**. In all the works we have highlighted, those classifications were developed by the authors' necessity to achieve a specific objective (describe some styled facts, develop an anti-trust analysis, develop a specific model of a market, etc). Nonetheless, the classifications enrich the literature by providing us with different ways of understanding the platforms, and new ways of classifying platforms will be needed because of the development of digital platforms.

In Annex A.2, there is a classification of all the literature considered in this Thesis by the type of competition, the users' behavior, the static-dynamic framework, the ownership structure, the differentiation of the market, the presence of direct network effects, and the previous taxonomies among other categories.

3.6 Research on Multi-sided Markets

In this section, we introduce the reader to the most outstanding works in the multi-sided literature. However, this literature keeps growing each year, so an exhaustive analysis of all the works is not practical. Additionally, each year new and outstanding papers are published, and because of the huge amount of works published, it is difficult to keep an updated review. In this sense, the vast majority of the papers that we highlight are the essential ones. We expect to provide a first approach to the literature to those who are not familiarized with it, as well as a guide to motivate the research in new areas to those familiarized.

3.6.1 Pricing in Multi-sided Markets

In the previous section, we have pointed out that two-sided markets are characterized by a particular pricing scheme. That “unusual pricing scheme” was the focus of many early works, such as Rochet and Tirole (2003), Caillaud and Jullien (2003) or Armstrong (2006). All of them agree that the **equilibrium prices in two-sided**

platforms are different from prices in of markets without network externalities¹⁰.

The pricing scheme in which one side pays a fee while the other side has free access is common in real markets, such as the credit card markets, free newspapers, or even social networks. Rochet and Tirole highlight that this behavior is the consequence of “the Seesaw principle”, and they define it as follows. *A factor that is conducive to a high price on one side, to the extent that it raises the platform’s margin on that side, also tends to call for a low price on the other side as attracting members on that other side becomes more profitable.*

Weyl (2010) states that the Seesaw principle is the most robust result on comparative statics of two-sided markets, but he argues that the notion of “price” is unclear, and he reformulates it as follows. *Factors leading the platform to choose higher participation on side “i” lead it to choose lower participation on side “j”.*

However, this price schema does not imply that the pricing in multi-sided markets is totally disconnected from traditional insights. In fact, approximately 50 papers in this literature review adopt the classical Hotelling framework as the basis for their models, and a Hotelling two-sided market sets prices as the classical Hotelling model, but adjusted by the externalities of the groups of agents, see Armstrong (2006). Armstrong also provides evidence of the Seesaw principle, and he argues that a platform will compete for one group more aggressively than for the other, either if that group is on the more competitive side of the market, or if it causes larger benefit to the other group. This feature highlights that the Seesaw principle requires a certain degree of asymmetry between the sides. Armstrong highlights the case of nightclubs where women have free access, but men have to pay. In his model, this price scheme is explained because men value more the presence of women than the other way around, the externality created by women is larger.

One interesting complication of setting prices in multi-sided markets is that it is not so easy as setting a markup over costs. There are coordination problems. On a dig-

¹⁰For instance, Rochet and Tirole (2003) and Armstrong (2006) study the Lerner index in two-sided markets, and they compare them with the traditional one. They find that non-intuitive behaviors may arise because of network externalities.

ital platform, users will only participate on the platform if the utility they obtain is higher than the price. But, normally, it depends on the developers' decisions on the other side of the platform. And they will only participate if there are enough users on the platform, and so on. This feedback loop creates the multiple equilibria problem because consumers' decisions (users) are not isolated from other consumers' decisions (developers).

Weyl (2010) formulates the platform's problem in terms of its choice of allocation rather than prices. Weyl proves that this formulation mitigates coordination problems¹¹. In this way, prices are a function of the number of participants so, from consumers' point of view, they are isolated from the participation of the other side. Their utility will not be affected by the network effects because the price will change to compensate the number of consumers on the other side. However, to what extent this a realistic depiction of pricing is another discussion¹². In contrast, in the vast majority of models in this literature, platforms set prices expecting a specific allocation of users¹³.

Nonetheless, Weyl makes other two great contributions to the pricing theory in multi-sided markets. First, he proves that private multi-sided platforms have an excessive incentive to serve the marginal user¹⁴, which also leads to an imperfect internalization of externalities¹⁵. On the other hand, his model considers bidimensional heterogeneous consumers. This assumption allows him to consider that consumers have different transaction and membership values. For example, Steam is a digital platform launched by Valve in 2003. Currently, each user can have a library with their purchased games without needing a physical copy. In many of those games, items can be interchanged with other users so, from the users' point of view, users may be het-

¹¹See Section 3.6.2 for an introduction to the multiple equilibria problem in this literature.

¹²Weyl claims that there are real cases of prices schemes that resemble insulating tariffs, such as pay per click ads. Nonetheless, it is not clear that they were chosen because of their "insulating properties".

¹³Other examples of models in which we find that platforms set allocations of users are Kind et al. (2008), Kind et al. (2009) or Kind and Koethenbuerger (2018).

¹⁴This is also a common result in one-sided markets.

¹⁵However, Weyl was not the first one in noticing this fact. Kind et al. (2008) point out that a two-sided monopolist internalizes the intergroup externalities, but not perfectly. A private platform is focused on the marginal user, but a social planner is focused on the average one.

erogeneous in their valuation of membership (accessing the video game platform) and transactions (being able to sell and purchase different digital items for their games)¹⁶. This bidimensional heterogeneity generates two distortions in the prices. First, the classical markup of the market power, and second, the Spence distortion¹⁷. This second distortion appears because of the platform's inability to price discriminate among consumers on one side. The platform imperfectly internalizes network externalities because it takes into account the marginal consumers instead of the average consumer. In his view, private platforms may set prices that may be non-optimal because they cannot set customized prices nor customized products. However, he points out that the Spence distortion may increase (reduce) prices, but it depends on the source of heterogeneity, transaction, and membership values. For example, if there is only membership heterogeneity (users value the entrance the platform in different ways), there is no Spence distortion. An interesting result derived from the sign of the Spence distortion is that it exists the possibility of mitigating the market power distortion with an opposite Spence distortion, which may lead to second-best solutions.

In general, **multi-sided markets can set two different prices, membership and transaction fees**¹⁸. The first makes reference to the price that a user pay for entering the market, for example, the price paid by readers to access a digital newspaper. The latter makes reference to the price paid each time that a transaction occurs, for example, the commission paid by a vendor when a buyer paid by credit card. They are not exclusive, and they can be found together in some markets. For example, a digital streaming platform that has a monthly subscription, but to access specific content you have to pay an additional fee. Nothing prevents platforms from setting one or the other, or both of them. Nonetheless, the literature has focused on analyzing both of them separately.

Additionally, there are not many examples of works that analyze both prices mecha-

¹⁶<http://store.steampowered.com>

¹⁷This distortion was pointed out for the first time by Wright (2004), but it is in Weyl (2010) where we can find an exhaustive analysis.

¹⁸This is the difference that is the basis of the Filistrucci's taxonomy.

nisms, and most of those works are focused on trying to avoid the multiple equilibria problem¹⁹. The most common pattern has been to assume a specific pricing schema, either transaction or membership fees. Nonetheless, there are papers that consider both, such as Armstrong (2006), Schiff (2003) or Rochet and Tirole (2006). The focus has been on the distinctive behavior of multi-sided platforms, and not on the differences that each pricing scheme creates in the market. Although it is not the main focus, several authors have pointed out that we should not ignore the difference between membership and transactions fees. Armstrong (2006) argues that the possibility of setting transaction fees is the main determinant of the structure of prices offered to the groups in two-sided markets, and according to Filistrucchi (2008) this feature is crucial for the development of econometric models and tests like the SSNIP (Small Significant Non-transitory Increase in Price).

The relevance of interaction fees is also pointed out by Caillaud and Jullien (2003). They show that when there is no room for interaction fees, we can have inefficient equilibria, for example, the “dominant-firm equilibria” with positive profits. In that sense, transaction fees are a good tool to reach efficient outcomes. However, it comes at the cost of extracting surplus to consumers, and sometimes that implies we need to assume indirect network effects in terms of interactions. If not, transactions fees are not a good pricing policy. Nonetheless, in theoretical models, this is not an issue because such relationship can be assumed²⁰.

Nonetheless, empirically, we observe much more membership fees than transaction fees. For example, Garmin, Fitbit, Netflix, Amazon Prime, LinkedIn Premium, Tinder Plus, digital journals²¹, etc. But also, theoretically, they have been adopted as

¹⁹Armstrong (2006) is one of the best examples of analyzing both pricing mechanisms. Armstrong proposes a two-part tariff, a combination of membership and transactions fees. Consumers are charged a fixed fee to join a platform and marginal price for each consumer on the other side who joins the platform. However, Weyl (2010) develops further this idea, and he proposes the isolating tariffs that we described before.

²⁰Rysman (2007) studies whether there exists a positive feedback loop between consumer usage and merchant acceptance of a payment network. In his analysis between 1998 and 2001, he suggests there may be a positive feedback loop between the two. However, he argues that the extent to which card usage actually responds to changes in the level of merchant acceptance today is up for debate. A similar work but for the Dutch market is Bolt and Tieman (2005).

²¹Some readers may argue that research journals also set transaction fees when they offer you the possibility of reading an independent paper instead of the whole issue. However, in this case, what

the main pricing scheme in the vast majority of works in this literature, mainly because this pricing mechanism is more aligned with traditional frameworks, such as the Hotelling one, see Annex A.2²².

3.6.2 Coordination Problems. Chicken & egg problem

A key feature of two-sided markets is that platforms have to be able to attract two or more different types of users at the same time. A digital platform with users but without developers has no future, and the opposite is also true. *The demand on each side tends to vanish if there is no demand on the other side – regardless of what the price is. [...] The businesses that participate in these industries have to figure out ways to get both sides on board*, see Evans (2003). This problem is known as “the chicken & egg problem”.

This term was coined by Caillaud and Jullien (2001) when studying how to persuade the sides to join the platform. The coordination problem appears in the simplest equilibrium definitions. In fact, Caillaud and Jullien (2003) state that the uniqueness of equilibrium is hard to justify in many contexts. In the same vein, White and Weyl (2016) point out that *if platforms charge “flat prices” that are not contingent on opposite-side participation levels, then there is a possibility of multiple equilibria*. Nonetheless, there are authors who argue that this problem is only a theoretical one. Song (2013) states *no matter how many equilibria there may be, I do observe one of them in each market*.

From a manager’s point of view, the coordination problem implies that it is not clear how to launch a platform. If there are multiple equilibria, and we cannot discriminate among them, we cannot make predictions about the success/failure of platforms. Jullien (2005) is one of the first works in addressing the coordination problem, he states *[it] exists a set of non-negative prices where no side register. Whether agents will co-*

they sell is the access to the paper, they cannot tax the transactions. In other words, they cannot tax the value you obtain from reading the paper.

²²The first time this framework was used in a multi-sided market was in Armstrong (2006). After that, this has been the most common framework in the literature. Some examples are Rochet and Tirole (2006), Kaiser and Wright (2006), Amelio and Jullien (2012), Weyl (2010), Song (2013), White and Weyl (2016), Ruhmer (2010), or Economides and Katsamakas (2006).

ordinate on the positive participation level or not depends on their beliefs about what the other side is doing. Thus beliefs matter and agents only participate if they are confident in the participation of the others. This argument supports the idea of overcoming the coordination problem by making assumptions about users' expectations. In fact, this approach is used to discriminate among equilibria in many works, such as Caillaud and Jullien (2001), Caillaud and Jullien (2003), Doganoglu and Wright (2006), Hagiu (2006), Bakos and Katsamakos (2008), Chao and Derdenger (2010), Economides and Tåg (2012), etc. However, White and Weyl (2016) point out that it is a risky bet to focus only on consumers' ability to coordinate among themselves. In their vision, although this solution to the coordination problem is a satisfactory one because it allows us to discriminate among equilibria, it implies that consumers are able to coordinate among themselves almost perfectly, which is not realistic.

Ambrus and Argenziano (2004) state that *if there are lots of small consumers on the market then it is practically impossible for them to get together and make explicit agreements on network choices.* They propose a way to overcome the coordination problem without assuming the consumers' ability to coordinate themselves. They propose the “coalitional rationalizability”. A non-cooperative solution concept that assumes *players can coordinate to restrict their play to a subset of the original strategy set if it is in the interest of every participant to do so.* However, this solution concept has not been extensively used. Other solutions have achieved more impact²³.

White and Weyl (2016) point out that the main problem is to show how coordination arises among heterogeneous consumer groups, and they point out that a remarkable answer was given by Rochet and Tirole (2003). White and Weyl explain that, in the Rochet and Tirole's model, consumers proportionally value the number of sellers on the other side. Then, given the prices, every consumer has a dominant strategy to join one platform. In the monopolist model proposed by Armstrong (2006), we find something similar, consumers have homogeneous valuations for externalities, which allows platforms to promise utility levels. In both cases, platforms commit to *offering*

²³For example, Schiff (2003) considers that the coordination problem can be overcome if platforms commit their prices before users form their expectations.

consumers a particular level of utility by adjusting their price in response to changes in the number of users on the other side, fully insuring users against any change in their utility, thus giving them a dominant strategy, White and Weyl (2016). But both cases have two limitations. First, they rely on a particular preference structure. Second, users are unidimensionally heterogeneous. If users are heterogeneous in more than one dimension, it is not possible, using a uniform price, to give all consumers a dominant strategy.

Weyl (2010) proposes a model in which users on one side can be heterogeneous along two dimensions, interaction and membership values²⁴. To address the coordination problem, Weyl proposes the “insulating tariffs”. The basic idea to overcome the coordination problem is to assume that platforms choose user allocations (and not prices) to maximize some objective function. In that way, prices are an insurance instrument of utilities. Platforms charge a price on each side fixing a utility level for users. Therefore, users do not care about the size of the platform on the other side.

Following the previous works, White and Weyl (2016) identify the core of the coordination problem: *In the standard analysis of Nash-in-prices equilibrium of a differentiated products industry, each firm takes as given other firms’ prices and chooses the price(s) for its own good(s) that maximizes profits. The presence of consumption externalities complicates matters. [...] Such games can have multiple Nash Equilibria, since the optimal bundle for consumers on one side of the market depends on the actions of consumers on the other side. [...] Thus, a platform’s optimal strategy may depend sensitively on the particular way it expects consumers to coordinate. And they propose a way to overcome the coordination problem. Rather than considering the large space of potential price functions, the platform can focus on the much smaller space of residual allocations.*

The proposed solution is the adoption of a price that relies on the allocation of users, i.e. they propose the “residual insulating tariffs” as a solution to the coordination

²⁴When there are two dimensions of heterogeneity, even fixing the size on the other side and the price on the side considered, many types of users may be just on the margin between participating and not (users with zero utility from adopting the platform). Some may have high interaction benefits but large membership cost, and others may have low interactions benefits and no membership cost.

problem that is a generalization of Insulating Tariff to environments with rich preference heterogeneity. Despite being a formal and elegant solution, there are not so many works in which insulating tariffs are applied. One reason is that the results cannot be compared with our works based on other frameworks, see Belleflamme and Toulemonde (2018).

If we consider a dynamic context, Cabral (2011) points out that platforms cannot fix a utility level on one side that is independent of the size of the other side because *the platform does not “insure” agents, rather the platform “subsidizes” early adopters to compensate the low utility of joining the platform at that stage*. However, White and Weyl (2016) argue that *there is an exact correspondence between equilibrium prices in the [Cabral’s] dynamic model, and insulating prices in the static [White and Weyl’s] model*. However, the idea proposed by Cabral is another potential solution to the chicken & egg problem that seems to be closer to the actual managerial practices.

On the other hand, some authors have considered that, if the problem is to attract both sides at the same time, platforms may be interested in changing the timing. That is the proposal to overcome the coordination problem developed by Hagiwara (2006). He proposes a model in which software developers arrive before consumers. This asymmetry in timing mitigates the coordination problem on the buyer side, but it does not mitigate it on the developer side. There is also a multiplicity equilibria problem, but for simplicity’s sake, he only focuses on two equilibria. One with “optimistic expectations”, and another one with “pessimistic expectations”. In the former, he finds it is optimal to commit prices as soon as possible, but in the later, he finds the opposite²⁵. Another way to overcome the coordination problem was also proposed by Caillaud and Jullien (2001) and Evans (2003). *[...] [One way to get both sides on board is] to obtain a critical mass of users on one side of the market by giving them the service for free or even paying them to take it*, Evans (2003). This strategy is known as “Divide and Conquer (DC)” because it requires dividing the market between the “profit side” and the “loss side” in order to conquer the market. This strategy solves the coordination problem because it creates an incentive to join the platform on the

²⁵Caillaud and Jullien (2003) find the same result.

loss side, and given the network effects, that creates an incentive on the other side to join the platform.

Despite the theoretical discussion about the correct way to discriminate among equilibria, **this is probably one of the practical solutions to the problem.** If we consider real cases like Facebook, JustEat, Deliveroo, etc. Some users have the service for free, while there are others who pay for the service. This is probably the easiest way to overcome the problem but, as in previous cases, it is also criticized. Jullien (2005) argues that the coordination problem is mitigated but, sometimes, it is difficult or dangerous to subsidize users because it can attract users without their commitment to using the platform. This possibility creates both, the adverse selection and moral hazard problems that are studied by several works, such as Armstrong and Wright (2007) and Parker and Van Alstyne (2005). In fact, Parker and Van Alstyne find that there is another problem because sometimes it is not clear on what side a platform should charge positive prices. Therefore, the consequences can be critical because we can attract a mass of users only because there is a subsidy.

Other authors argue that *it is more natural to observe firms begin with a one-sided model and switch to a two-sided model as they become more established. Doing so allows potential platforms to overcome the “chicken-and-egg” problem*, see Rysman (2009). However, this explanation does not apply to digital platforms that were born as two-sided platforms, such as Facebook. Nonetheless, Evans et al. (2008) argue that expectations about the ownership structure are essential. If users believe that a platform is going to change its strategy toward integration, it sends a message that market is not going to fail in providing that good/service. But also, it sends a message that competition will be more aggressive on one side and, therefore, profits will be lower. From their point of view, integration mitigates the coordination problem, but integration does not solve it by itself. In fact, integration is neither necessary nor sufficient to solve the problem. Additionally, in general, all platforms change its strategy towards disintegration when they are mature. For example, Amazon started as a one-sided book dealer, but right now is a two-sided market in some markets.

As a summary, there are several proposals in the literature, but there is

no consensus. Still, there is a question: Is there a universal solution to overcome this problem? Given the evolution of the literature, it seems that we will not have an answer to this question any time soon. Nonetheless, addressing why some platforms fail and other succeed would be interesting from the coordination point of view. In that sense, we would be able to see which one of those proposals is closer to reality. However, this topic is beyond the scope of this Thesis.

3.6.3 Integration or Disintegration. Should Platforms control the Sides?

Sometimes, it is not clear whether a company has to provide only the platform, or it has to control the intermediation too. The ownership structure is essential, and that is why it has been another common topic in the literature that has attracted the attention of many researchers.

Different organization schemes can coexist, as it is suggested by Rysman (2009). But also, companies can change its organization/ownership over time. In fact, Hagiu and Hałaburda (2014) use as an example the case of Amazon and Zappos. Amazon started off as a one-sided retailer platform but, it has moved to a two-sided platform scheme. On the other hand, Zappos has gone in the opposite direction. The ownership structure has been a major concern for some authors such as Rysman (2009), who defends the idea of focusing on “two-sided strategies” and not on “two-sided markets”. **A platform must choose whether to be one-sided, two-sided or multi-sided.** Being one-sided is an extreme move away from openness, and Rysman argues that the focus should first be on the company, and then on the market in which it operates. In this regard, Hagiu (2007) states that *the main difference between the classic form of market intermediaries - which we will call merchants [...] and two-sided platforms is that pure merchants, by taking possession of sellers’ goods, take full control over their sale to consumers. By contrast, pure two-sided platforms entirely leave that control to sellers and simply determine buyer and seller access to (or affiliation with) a common marketplace.* **Between pure merchants and two-sided markets, there**

is a continuum of ownership structures that depend on the allocation of control rights over the decision variables. Hagiu makes a great contribution by highlighting the relevance of paying attention to the control rights over the good traded. This insight is essential when classifying businesses as platforms because it drives the attention from the price towards the control rights.

Hagiu also analyzes both cases, and he finds that the co-existence of platforms and pure merchants is possible. *The merchant mode is strictly preferred to the two-sided platform mode whenever there is a positive probability that seller expectations are unfavourable [about the platform adoption]. It is easier (cheaper) to convince sellers to sell their products outright than to affiliate to a platform and sell the products to consumers themselves, because the first option eliminates coordination issues [...] there is a trade-off between the merchant mode and the two-sided platform mode [...] between higher costs of managing more products and higher costs of convincing sellers to affiliate. This suggests that intermediaries, especially for new goods, will generally start under a merchant format and, as sufficient sellers become affiliated, move towards a more “open”, platform mode, which is cheaper per seller and thus allows intermediaries to offer a broader variety of products, see Hagiu (2007).* This result is the same than Rysman’s, and it gives us a reasonable idea of how companies deal with the “chicken-and-egg” problem from a practical point of view²⁶.

In a later work, Hagiu and Wright compare the incentives of some customers of being employed by a platform as freelancers or being employed as regular employees, see Hagiu and Wright (2015). This model assumes two different groups of people, consumers and professionals. They compare two possible cases. One in which the platform employs the professionals to produce the goods or services to customers (e.g. consultancy services), and another one in which the professionals are freelancers and can provide those services independently of the platform. The most interesting result is that there is no a first-best solution. **There is not a better structure than the other.** There is always a trade-off between the incentives (and the risk) that people

²⁶Another work that highlights the profitability of the one-sided structure is Carrillo et al. (2006). However, they also subordinate this optimality to the presence of complementarity products. For example, the video-game consoles and the video-games.

have when their salary depends only on them and the safety of a fixed salary. And this trade-off also impacts on the performance of the platform because the incentives to work when you have a fixed salary are different than when it depends on the day-to-day performance.

Hagiu is by far, the author who has devoted more time to this issue. In fact, in an early paper, he analyses the case of open source and proprietary platforms, see Hagiu (2004). His results suggest there is a welfare trade-off between open source and proprietary platforms. A proprietary platform creates a dead-weight loss as consequence of monopoly pricing, but an open source platform does not internalize indirect network effects, so there is no an obvious way to determine which ownership structure creates a higher level of product variety, adoption or welfare. **The preference for one model or the another is not justified economically in his work.**

Other works have been interested in how the value created by multi-sided platforms should be allocated, and who should own the platform. Bakos and Katsamakas (2008) analyze this issue, and they find that: *The optimal ownership is always ownership by the side that enjoys the strongest network effect from the participation of the other side. Independent ownership is never optimal. And most importantly when the network effect that the owner side enjoys is strong enough, then the first-best participation and value are achieved. This happens even though the intermediary market is a monopoly.* Their conclusions highlight that platforms have to be created by those who benefit the most from attracting the other side. In the case of take-away apps, they should be created by users and not by restaurants, and the same also applies to taxis²⁷.

Lastly, other interesting works are Nocke et al. (2007) and Ambrus and Argenziano (2004). The former analyzes a market that has a fixed number of spots for sellers, such as a traditional fair. They find that an independent monopoly that owns all the spots leads to a bigger platform size than a closed platform owned by some incumbents. They find that the monopoly could be socially optimal if network effects are

²⁷ An interesting case analyzed by Bakos and Katsamakas (2008) is the “spin-off case”. In this case, the network is designed by one of the sides, but the platform sets prices independently. They find the platform has a strong incentive to only invest in one of the sides, and marginally in the other.

strong, but if not, the most preferred structure is one in which the platform owns the spots (integrated scheme). The latter finds that, in some cases, it is optimal to split monopolies into two platforms but under a common ownership. The idea is to adopt second-degree price discrimination because, in that way, users coordinate by themselves (higher and lower quality lovers). However, a monopoly network without price discrimination is the most profitable strategy when there is no differentiation among agents. These results are quite relevant for platforms such as JustEat or Ubereats, that normally face a great heterogeneity in the takeaway markets, and that may drive out some medium-high quality restaurants out of the platforms.

As a summary, **multi-sided platforms are not always better than any other market structure**. There are some conditions that should be met, and even when a multi-sided market is optimal, we need to take into account whether it is profitable (or socially optimal) to integrate one or more sides with the platform. This research topic is not closed, and it will become more and more relevant with the rise of many digital platforms in markets that were previously dominated by traditional one-sided businesses. Nonetheless, the Hagiu's and others' works are essential to start developing more complex models to address more critical issues, such as the role of investment and financing in integrated vs disintegrated multi-sided platforms. This topic is beyond the scope of this Thesis. However, it points out a future line of research. Nowadays, wearables are multi-sided platforms, but nothing prevents a change in the future.

3.6.4 Exclusivity in Platforms. Singlehoming and Multihoming

By definition, multi-sided platforms tend to be intermediaries between two or more sides. This feature implies that the cases in which the platform owns one side, or it has control over essential rights of one side are not the rule, but the exception. However, a common feature that we observe in reality is that some agents tend to

use several platforms at the same time²⁸.

In that sense, several works have paid attention to the incentive to be on more than one platform at the same time, also known as multihoming. **Multihoming is a natural part of a lot of markets.** For example, in the newspaper industry, there is no way to prevent readers from reading two or more newspapers, and the same is also true for advertisers²⁹. Multihoming is also common in the payment card industry, where many merchants accept both Mastercard and Visa, and consumers have several payment cards. And in the digital economy, in which developers may support Android, iOS or Windows Phone.

Rochet and Tirole (2006) point out that *multihoming stems from the users' desire to reap the benefits of network externalities in an environment of non-interconnected platforms*. In a similar vein, Caillaud and Jullien (2001) and Caillaud and Jullien (2003) highlight that the consumer interest in multihoming is because it increases the probability of matching, and it also allows them to save on transaction fees because users can adopt the cheaper platform³⁰. On the other hand, Choi (2010) points out that when there is exclusive content on platforms, there is also an incentive to multihoming. **It seems that multihoming is a great advantage because users can benefit from network externalities of several platforms.** But it has a cost, multihoming is not as good as it seems because **the singlehoming side is usually subsidized by multihoming side**. So, their desire to reap the benefits of network externalities incentives platforms to increase the prices to those multihoming users. Another feature of multihoming is that the added-value of multihoming for some users depends on the degree of multihoming on the other side negatively, see Gabszewicz and Wauthy (2004). In other words, some users have incentives to access two different platforms if they can get a non-negative utility from getting in touch with users on those platforms. However, if those users are multihoming too, the incentive is mitigated because you can get in touch with those users on only one platform.

²⁸Drivers that use both, Uber and Lyft. Or couriers on Glovo and Deliveroo.

²⁹However, Evans (2011) considers that it is common to find singlehoming consumers and multihoming advertisers.

³⁰In this case, Jullien (2005) warns that multihoming drives competition towards transaction fees. With multihoming, agents try to concentrate their activity on the low transaction fee platforms.

Gabszewicz and Wauthy point out the three possible multihoming structures that can take place within a market:

- Multihoming and singlehoming agents in each side
- All active agents in a particular side multihome
- All active agents in each side multihome. However, they consider that this outcome is not possible with rational expectations because of the inverse relationship between the degrees of multihoming on each side of the market.

Multihoming relaxes competition on one side, but it increases the competition on the other side, see Rochet and Tirole (2003), Armstrong and Wright (2007), and Armstrong (2006). Realizing that a fraction of users on one or more sides are connected to several platforms modifies the competition because multihoming increases the number of strategy profiles available to all players³¹.

The first work that analyzes this issue in depth is Caillaud and Jullien (2003). They prove that the multihoming side subsidizes the singlehoming side, and they also point out that multihoming mitigates competition. *[Singlehoming] implies a highly contestable market structure where all potential profits are eroded in order to protect a monopoly position, [but with multihoming], intermediaries are then able to avoid fierce price competition and make positive intermediation profits in equilibrium*, Caillaud and Jullien (2003).

Following this idea, Armstrong (2006) proves that, if the multihoming side benefits from a higher externality, platforms will compete for singlehoming agents, and the interest of the multihoming side will be ignored. So, there are two markets, a competitive one (singlehoming side) and a monopolistic one (multihoming side). Platforms have monopoly power over providing access to their singlehoming customers. Rysman (2009) also observes that two-sided markets seem to evolve towards a situation

³¹One interesting contribution to this literature is the “singlehoming index” proposed by Rochet and Tirole (2003). This index measures the possibility of platforms “stealing” agents from each other. For example, if a platform decreases its price on one side by a small amount, this increases demand for that platform in two ways. The platform attracts new agents, and “steers” former multihoming agents.

in which members of one side use a single platform (singlehoming), and the other side uses several platforms (multihoming). This difference between singlehoming and multihoming users also leads to an asymmetric price structure, but this time, it is not motivated by the strength of network effects, but the decisions of consuming one or more platforms.

Nonetheless, a shortcoming of Armstrong’s model is that the population of users is exogenously fixed. Song (2013) introduces the possibility of growing populations, and he compares two models. One in which all agents are singlehomers and another one in which multihoming is allowed. He finds that the two models react to the growth in opposite ways. In the singlehoming model, platforms increase prices for the group which population has increased, but they decrease prices for the other group. On the other hand, in the multihoming model, platforms decrease prices for the group which population has increased, but they increase prices for the multihoming group.

However, consumers only multihome if it is relatively cheap. In this sense, multihoming can be mitigated by introducing exclusive contracts. This is the proposal of Armstrong and Wright (2007). They address the role of exclusive contracts because *platforms might offer exclusive contracts to [one side] to prevent them multihoming, such exclusive contracts can be “cheap” to offer since by tying up one side of the market, the platform attracts the other side. However, by forcing sellers to choose one of the platforms, a platform may instead induce them to choose the rival platform.*

They show that **even when one side multihomes and it is homogeneous, platforms do not directly compete for the multihoming group**. Having attracted the singlehoming agents, they exploit multihoming consumers’ surplus from interacting with their captive singlehoming agents. That is interesting in comparison with a Bertrand model in which the price would be zero as consequence of the competition for the homogeneous group, in this case, the surplus of the multihoming group is totally extracted and prices are not zero.

In this environment, they test the case in which platforms offer exclusive contracts to multihoming agents. The way they introduce this feature is by considering that platforms set prohibitively expensive non-exclusive prices. It ensures that agents will

never want to multihome. They find that **with exclusive contracts, platforms force multihoming consumers to singlehome regardless of competitor's offers**. This behavior also breaks the competitive bottleneck equilibria in which one side was subsidized, and the other was used for earning profits. Additionally, because they assume that multihoming consumers are not differentiated, the winner-takes-all-the-market outcome is an equilibrium.

Instead of making exclusive contracts, another possible strategy is to commit a certain level of prices in advance. That is the case addressed by Hagiu (2006). He analyses four market structures with combinations of multihoming and price commitments. In his model, buyers and sellers get in touch by adopting one or two competing platforms. The four cases are

- Platforms cannot commit, sellers cannot multihome. There is a unique exclusive equilibrium in which platforms make zero profits and sellers are indifferent between platforms.
- Platforms cannot commit but sellers can multihome. There are two equilibria, a dominant-firm equilibrium in which one platform monopolizes the market, and another one with multihoming in which both platforms are active.
- Platforms can commit, sellers cannot multihome. Profits are zero, but the equilibrium is not guaranteed.
- Platforms can commit, sellers can multi-home. There may be a multihoming equilibrium with positive profits.

Hagiu finds two interesting results in his work. First, **multihoming relaxes platforms competition**, and positive profits are even possible in undifferentiated frameworks. And second, **price commitment is always a dominant strategy for platforms**, but it introduces the possibility of an additional divide-and-conquer strategy. However, even when multihoming is possible, platforms can disincentive the multihoming in another way. Rochet and Tirole (2006) state that, if platforms are compatible, there is no incentive to multihome because users will benefit from the network

externalities of all the compatible platforms. However, compatibility is not addressed in their work. Schiff (2003) studies compatibility on multi-sided markets with single-homing users, and he observes that compatibility mitigates the platforms' incentives to rise production, which leads to higher prices. Carrillo et al. (2006) address a multi-sided market with complementary products. Their results point out that in singlehoming case, compatibility erodes market shares but with multihoming that is not the case.

Doganoglu and Wright (2006) also address the compatibility case. They address whether the ability of consumers to multihome means policymakers do not need to worry about compatibility between networks. They analyze several combinations of compatibility/incompatibility and single/multihoming. Without multihoming, they observe that there are excessive incentives for compatibility. **Compatibility mitigates the incentives to multihoming**, and because profits are increasing with respect to multihoming, platforms are less prone to compatibility. So, platforms have excessive incentives for incompatibility when customer multihome.

Another work that addresses compatibility is Salim (2009), she finds that **compatibility may mitigate price competition in two-sided markets**, and the same is found by Doganoglu and Wright (2006). This is an interesting result because it contrasts with the traditional one-sided literature in which the opposite is true, see Farrell and Saloner (1985), or Katz and Shapiro (1985)

Lastly, generally, multihoming has been considered exogenous given. However, recently, Jeitschko and Tremblay (2014) have specifically addressed the endogenous homing decision. In their framework, multihoming is a decision that depends on prices. They obtain results similar to those of Choi (2010), prices will not converge to monopoly prices on the multihoming side because of the endogenous homing decision, which contrasts with previous works that found that result.

3.6.5 Content in Platforms to attract Users. Bundling/Tying Strategies

Some authors have argued that a way to overcome the chicken & egg problem is to offer something to one side to attract consumers. In that sense, tying and bundling strategies become relevant in multi-sided markets not only because they are theoretically relevant, but also because many digital platforms are using them to attract consumers, for example, Netflix.

Bundling means that two distinct products are sold together in fixed proportions, i.e. a pair of shoes. However, we can distinguish between mixed bundling, in which the bundled goods can be purchased individually or together, i.e. menu dishes in a restaurant. And pure bundling, in which the bundled goods cannot be purchased separately, i.e. iPhone and iOS. On the other hand, tying means that a consumer is required to purchase not only a good but also all the subsequent units of another good, i.e. photocopiers and toner cartridges³².

Jullien (2005) and Parker and Van Alstyne (2005) point out that these strategies may overcome the multiple equilibria problem. Other authors argue that it also leads to more efficient outcomes, such as Affeldt (2011), but on the other hand, she argues that traditionally these strategies have been used as a tool to price discriminate and hence extract consumer surplus more efficiently. *Tying and bundling can be used strategically to foreclose competitors and entrants both in the tied and the tying good's market*, see Affeldt (2011). Nonetheless, she argues that tying or bundling will only enhance welfare in two-sided markets if:

- Indirect network effects are large enough
- The side with the lower network effects benefits from bundling/tying
- There are multi-homing costs

Another interesting work which addresses the tying issue is Choi (2010). Choi considers three groups of agents: consumers, content providers, and platforms. He compares

³²See Affeldt (2011) for a short review of these concepts.

two cases. One in which there is no room for tying, and another one in which there is. With tying, Choi states that the effect on welfare depends on the relative strength of externalities and on the level of differentiation. If the former dominates, tying is welfare enhancing, but if the latter dominates, tying reduces welfare. In general, there is a negative effect on welfare because the platform which adopts the tying strategy forces the purchase of the complementary good, over which it has market power. On the other hand, it also creates a positive effect because it mitigates duplicity costs, but there is also an ambiguous third effect. Tying modifies the number of content providers because tying plays a role as a coordinating device for consumers on the platforms, and that attracts providers, but this also increases the price on provider's side, and the increase drives out other providers. He also observes that when both sides are allowed to multihome, tying creates an incentive to multihome, and consumers buy more content from providers. However, without multihoming, consumers will coordinate on the tying platform, so the non-tying platform and its exclusive content will be lost. So tying reduces welfare without multihoming.

Affeldt (2011) extends the Choi's model to consider the existence of users with high and low differentiation. These groups represent agents with low technical skills or knowledge and those who have a great knowledge or skills. She finds that **tying is unlikely a barrier to entry**. A similar result is discussed by Farhi and Hagiu (2008). They consider that tying platforms in multi-sided markets have an incentive to compete *soft* because it could be profitable for both, incumbent and entrant. In contrast with the one-sided case in which tying is considered an aggressive strategy to deter entry sometimes.

These strategies have interesting properties from the subsidizing point of view. As we have observed in previous sections, sometimes it is optimal to subsidize one side to attract the other. However, setting a zero price or a negative price on one side may create an "adverse selection problem". We may attract undesired consumers, those who are only interested in the subsidy. One way to overcome this problem is offering a free complementary product instead of a negative price. One example is Microsoft, it subsidizes developers by giving them the Microsoft APIs (Application

Programming Interface) for free, which only developers value. So, there is no adverse selection problem because it attracts developers only. In that way, the platforms may avoid attracting undesirable customers (free-riders that only want the subsidy), see Amelio and Jullien (2012).

They also find that one side will have a soften competition while the other one will have a hard competition. In general, **in welfare terms, tying has ambiguous effects**, and it depends on parameter values. The authors state that *there is no instance where all customers benefit from bundling nor instances where they all suffer as a result of bundling. Thus there will always be some conflicts between consumers on the issue of bundling.*

Chao and Derdenger (2010) consider a multi-sided monopoly that has an integrated product (proprietary software), but there are also complementary products (independent software). They find that with bundling *prices on the consumer side are lower due to price discrimination, so according to the cross-subsidization rule, we should expect an inflated price on the content developer side. However, we see the opposite. [...] Consumers become more inelastic with respect to their participation on the platform from the fact that bundling can target the consumers more accurately.* That implies that developers' price is also lower. In conclusion, bundling reduces prices on both sides.

Bundling and tying strategies are becoming more relevant with digital platforms, that also implies that these strategies are becoming more and more complex. Evans et al. (2008) show examples of complex bundling strategies. They point out that sometimes, platforms adopt bundling strategies with consumers, i.e. they "tie" consumers. Shopping malls are an example of these strategies. *Malls rent space to stores. But they are selective as to which stores they allow in the mall. They try to offer a diverse group of shops that match their intended customers. That means [...] limiting duplication. Most malls would reject a second bookstore even if it offered to pay the same rent as the first bookstore,* Evans et al. (2008). However, this case is not analyzed in-depth in the literature yet, and some questions remain open. To what extent shopping malls are tying consumers is unknown and, to the best of our knowledge,

there is no empirical work on that. Nonetheless, it is true that many shopping malls send offers to consumers that can be considered as attempts of tying, such as the offer of dinner plus movie, in which you tie two or more people to go to two or more establishments in the shopping mall. Additionally, we have the case of users' data on digital platforms. To what extent that data can be used as tying instrument is unknown.

3.6.6 Dynamic Models. Adoption of Platforms

One interesting feature in multi-sided markets is the static nature of prices. Prices do not change, at least with regard to their structure. Once the platform is stable, prices tend to be stable, as it is pointed out by Evans et al. (2008). However, the nature and structure of those prices can have different origins depending on how the value is created in the platform.

In that sense, dynamic models allow us to adopt larger sets of strategies that can give us a better understanding of markets. In particular, markets in which technological change is a common event. However, dynamic models are not very common. In fact, to the best of our knowledge, there are only a few examples. One of the most interesting contributions is Lam (2014). They study the effect of switching costs with a two-stage game. In this model, there are two groups of users, consumers and developers. If they change their decisions about which platform they join, they will suffer a transaction/switching cost. From a dynamic point of view, they consider there are rational and naive agents. The rational ones make their decisions considering the two stages, and the naive ones only consider the current stage.

They find that the strategy of lowering prices on one side is not only due to network externalities or consumer's characteristics but also, due to switching costs and the dynamic nature of the model. If externalities are weak, and there are small transaction/switching costs they argue that *rational consumers understand that they can easily switch in the second period, and are therefore more responsive to the price cut in the first period. Platforms have strong incentive to compete. Consequently, switching costs are pro-competitive.* However, when switching costs are large, they point out

that *rational consumers recognize that they will be exploited in the second period, and are therefore less tempted by a price cut*. If externalities are strong, the authors highlight that switching costs always make the market more competitive. If consumers are naive, and they only care about the utility at the current period, the authors prove that *[naive consumers] do not anticipate that a first-period price cut will lead to a second-period price rise, and they will react more responsively to the price cut in the first period*.

Dynamic models have been proposed for anti-trust cases too, such as Ruhmer (2010) and Boffa and Filistrucchi (2014). Both of them analyze the collusion problem in two-sided markets by proposing a repeated game. In the last case, Boffa and Filistrucchi find that, in some cases, it may be profitable for the cartel to set quantity levels lower than monopoly levels. When platforms cannot coordinate on the monopoly outcome, the cartel can coordinate on pseudo-competitive outcomes, thus raising the cost of deviation from the equilibrium. They also find that their results are similar to a one-sided market with complementarities.

On the other hand, the most remarkable work on this topic is Cabral (2011). He proposes a model in which the number of agents is not fixed, and they make lasting and non-lasting decisions. The basic idea is that, at certain moments of time, an agent can change its membership decisions. However, at every moment, agents are making decisions over the usage of platforms. There are two kinds of agents. Actives, who reassess their platform membership decisions. And passives, who maintain their memberships.

The main problem of this framework is that utility functions are very complex because it is necessary to take into account the probability of being active, the probability of being in a specific population group, and/or adopting a platform and, at the same time, we need to consider that there are agents who can enter or leave the platform at any time. All these features lead to utility functions with a great number of terms. However, we can identify two terms in the first order conditions, a static one, and a dynamic one. The static one encompasses the profit increase of an additional agent and the dynamic one encompasses the future increase in profits derived from addi-

tional agents.

One interesting result found by Cabral is that **the platform has to subsidize early adopters to compensate them for the low utility of joining the platform at an early stage**. This idea suggests that proprietary platforms may actually perform better than non-proprietary ones³³. A usual pattern of platform growth is when the number of users on both sides increases in tandem. In that sense, Filistrucchi et al. (2012a) state that *it is also fundamental for the platform to attract the different sides in the right proportion*. That is what is found by Cabral. Nonetheless, Cabral also points out that the assumptions over parameter values determine the speed of adoption.

There are other works that highlight several “take-off strategies” for platforms, (Evans, 2011, Chapter 3). One of them is the “tandem-strategy” proposed by Cabral. Evans also describes a fundamental agent in multi-sided platforms that may help in these take-off processes. The catalyst innovator. *They are the ones who discover that it is possible to create economic value by getting two or more groups of economic agents together on a shared platform or develop a more efficient platform for starting and accelerating a catalytic reaction*. It is easy to find a correspondence between those catalyst innovators, and the early-adopters that we can find in the marketing literature. Both are the same type of consumer. The only difference is that their role in multi-sided platforms is more dramatic because of the value of the platform depends on how many people are on the platform.

Lastly, another way to address the launching of platforms is by studying the critical mass problem, see Evans and Schmalensee (2010). They address the dynamic problem of the size of the market in two-sided markets. They point out that when the critical mass is reached, the positive feedback between the sides drives the market to an equilibrium. However, if the critical mass is not reached, the platform may fail. Nevertheless, in the proposed model, the critical mass depends on prices charged, platforms features, agent’s tastes, etc. These characteristics can modify the critical

³³This conclusion is also supported by Economides and Katsamakas (2006). However, Cabral argues that these results depend on the assumption of no heterogeneity.

mass and the stability of the platform. But in general, the authors state that it is always required an initial effort to launch the platform because the number of early adopters is usually not enough to reach the critical mass.

The start-up problem is particularly difficult for firms that are based on multisided platforms. In addition to the usual problems faced by new firms they often must contend with the well-known chicken-and-egg problem. [...] They have to figure out how to get both sides on board their platform. [...] Yet most of the theoretical and empirical research on two-sided businesses have focused on mature platforms. Little attention has been given to critical issues that entrepreneurs must solve to create a viable platform business, Evans (2011).

As we observe, there is a lack of works that address the issue of launching platform, or the role of catalyst innovators. We expect that this part of the literature will grow in relevance in the following years as a consequence of the interest in other interrelated areas, such as Information Economics.

3.6.7 Entry the Market

A common myth about multisided platforms is that monopolies are common. This thought has become popular nowadays because of the rising of social networks, such as Facebook, Twitter, or LinkedIn. However, there is no clear evidence supporting this line of thought. In fact, there are examples in the opposite direction, such as Uber vs Lyft, or like UberEats vs JustEat, or Deliveroo vs Glovo. The reason why this thought is popular is because multi-sided companies can become monopolies in more situations than one-sided companies. Caillaud and Jullien (2003) point out that the “dominant-firm equilibrium” is the only feasible equilibrium in a singlehoming environment³⁴, in that case, the winner-takes-all-the-market.

This possibility has raised concerns in the literature, and many authors have addressed whether or not entrants can break those monopolies. Caillaud and Jullien prove that the incumbent would choose singlehoming services when he/she thought its matching

³⁴If we allow both sides to multihome, this outcome is also an equilibrium, but it is not the only one.

technology is better because it allows the platform to deter entry and to monopolize the market. But this also implies a higher risk of being expelled from the market if the entrant has a better technology. If the incumbent considers that its technology will be worse, the only way to survive is to promote multihoming. However, this result implies zero profits and a large degree of market contestability. In other words, **the threat of entry applies an important competitive pressure**. This result is also found in Jullien (2005). Jullien also points out that intermediation markets may be very contestable. He proposes two ways to mitigate this contestability:

- By increasing differentiation
- By sharing information

In that way, network effects are mitigated, and divide-and-conquer strategies are less effective, which reduces the monopolization problem at the same time. Focusing only on the incentives to enter, White and Weyl (2016) state that the owner of a better technology must have two preconditions to replace an incumbent and to avoid a failure in the launching. First, there must be incentives to enter the market, and the owner must have the ability to do it. The platform must be sufficiently well capitalized in order to finance subsidies to consumers. Second, it must be sophisticated enough to manage consumers' coordination. In that sense, an essential element that creates incentives to enter and isolates the influence of competitors is the differentiation. The differentiation between platforms is essential for allowing coexistence, for example, the differentiation between Uber (city trips) and Blablacar (long trips) may be behind their co-existence. Another feature that allows the co-existence of several platforms is the weakness of networks effects, see Armstrong and Wright (2007) or Rysman (2004)³⁵. Nonetheless, a lack of differentiation and a superior technology may be a killer combination to enter the market, as we have seen with the Facebook case despite it was not the incumbent in several countries³⁶

³⁵<http://www.latimes.com/business/technology/la-fi-0105-lyft-growth-20160105-story.html>

³⁶MySpace in the U.S., Tuenti in Spain or Dol2day in German speaking countries are examples of incumbents.

The most prominent work in analyzing barriers to entry is Farhi and Hagiu (2008). They adapt Fudenberg and Tirole's typology of strategic interactions to multi-sided markets. The basic idea is that the incumbent can invest to deter the entry of the entrant. If the incumbent can deter entry, its investment decision is driven by the entrant's profits. By contrast, if entry accommodation is the most profitable strategy for the incumbent, then its investment decision depends on its own profits. According to the previous insights, we can have four strategies based on the effects of investment on the strategic variable (prices or quantities) and the relationship among these strategic variables (whether they are strategic complements or strategic substitutes). Intuitively, an investment which reduces the marginal cost can only hurt the entrant and benefit the incumbent. But what the authors prove is that, in a multi-sided market, *a cost-reducing investment by one firm can both increase the profits of its rivals and be desirable for the firm undertaking the investment [...]. The set of strategic configurations in a two-sided market is strictly larger than in a one-sided market*, Farhi and Hagiu (2008) .

Another interesting work related to barriers to entry is Belleflamme and Toulemonde (2004). They study the incentives of an independent company to launch a new platform service. They analyze two cases. When there is no previous service, and when there is an incumbent that is providing the service. In the first scenario, sellers and consumers have to trade on the platform because there is no other place to trade. Therefore, the platform can extract all the sellers' and consumers' surplus. So, in this case, **starting a new market is always a profitable strategy**. In the second scenario, the entrant has to subsidize agents on one side of the market to attract them and, by network effects, attract agents on the other side. However, this DC strategy may be not profitable. This work points out two essential conflicting effects when managing a platform

- The higher the number of buyers, the higher the incentive of sellers to be on that platform and the higher the revenue platforms can extract from them.
- The higher the number of buyers, the higher the competition among them, and

the higher the subsidy necessary to attract them.

When the competition among buyers is hard, it is easy to enter the market by attracting buyers. The entrant can isolate a part of them from the competition with the rest of buyers who stay in the old marketplace. They also highlight that when there is strong competition, *the new marketplace gives [buyers] the opportunity to differentiate themselves from their competitors who remain on the existing marketplace. The activity of the intermediary is then beneficial to the industry. By contrast, when buyers produce differentiated products, the intermediary does not offer any value added to the industry.* This is because of direct network effects. If there is a great number of agents on one side, competition is very strong and they are harmed. However, they can switch to the other platform in which there is lower competition. However, if they are very heterogeneous, and the competition among them is weak, they get more benefits from being on the same platform.

As a summary, this branch of the literature has started to analyze some barriers to entry, but there are some open questions, such as the role of classical vendors in the launching of platforms, or how influencers may affect the adoption of platforms when they are entering the market. Nonetheless, the current status of this branch of the literature highlights that multi-sided markets are more complex than one-sided markets, see Farhi and Hagiu (2008). It is an interesting and fruitful field of research given the multiple possibilities that it offers, from the analysis of the monopolization of a previous competitive market to the analysis of strategies that combine network effects with investments.

3.6.8 Digital Platforms

Before two-sided markets were studied in the Industrial Organization literature, Shapiro and Varian (1999) stated that the traditional industrial economy was based on scale economies, but the information economy was based on network economies and on feedbacks. Later, those features have become an essential part of the description of every two-sided market because of the indirect network effects. Nowadays, it is

increasingly common to find multi-sided businesses related to digital services. In fact, Filistrucchi and Klein (2013) state that **multisided businesses are the most common ownership structure on the Internet**. Two examples are the pioneering works of Caillaud and Jullien (2001) and Caillaud and Jullien (2003) that were inspired by what they called *cybermediaries*.

These two pioneering works provide interesting insights about the digital services that we observe today. For example, Caillaud and Jullien (2003) analyze a case that resembles a dating app or a betting house like eBay. They consider a pairwise matching duopoly with singlehoming homogeneous consumers, the idea is that the platform coordinates couples of agents. When a match is done, they assume that *matched partners follow an efficient bargaining process to determine the transaction price, which yields a linear sharing of the total net trade surplus*. In other words, this work reproduce the market case of people negotiating on platforms such as eBay³⁷. Although these models were presented in 2003, their results are still valid today for many matching markets such as dating apps.

One of the most attractive research topics in this literature is the relationship among internet service providers (ISP's), consumers, and producers. The possibility of addressing these relationships has led to a fruitful literature on net neutrality³⁸. However, the majority of works are focused on showing the pro and cons arguments about the net neutrality. There are only few formal economic papers, but they are exhaustive and make an in-depth analysis of the problem.

An early contribution was Musacchio et al. (2009). They address the net neutrality debate with a two-sided model focused on investment decisions. What it is interesting about this work is that the user utility depends on the number of clicks on the Web. However, this work was eclipsed by another contribution, Njoroge et al. (2013). They

³⁷This assumption of negotiation would violate the Rochet and Tirole's condition of multi-sidedness, but the existence of membership fees and externalities avoid it.

³⁸In 2005 the Federal Communications Commission (FCC) changed the classification of Internet transmissions from "telecommunication services" to "information services". Internet Service Providers (ISPs) are no longer bound by the non-discrimination policies in place for the telecommunications industry. As is pointed out by Njoroge et al. (2013): *there is no standard definition of what a net neutral policy is, it is widely viewed as a policy that mandates ISPs to provide open-access, preventing them from any form of discrimination against Content Providers (CPs)*.

propose a model to investigate net neutrality considering pricing and investment incentives. The model is based on two interconnected ISP (platforms) competing for content providers (CPs) and consumers. Intuitively, this model explains the relationship between Comcast or Verizon (ISP), Netflix or Wuaki.tv (CPs), and the consumers. They compare two regimes, a neutral one and a non-neutral one:

- In the neutral regime, consumers and CPs are charged membership fees, and CPs can communicate with consumers subscribed to either platform.
- In the non-neutral regime, a CP pays additional fees to reach off-network consumers. In that sense, under the non-neutral regime, ISPs have control over the access to its consumer base, i.e. there is bottleneck competition.

In the neutral model, the authors prove that *platforms are viewed as substitutes by both CPs and consumers. Hence at equilibrium, platforms maximally differentiate to corner different consumer and CP niches in the markets. [...] One platform opts not to invest while the other picks the highest quality permitted by investment costs.* In the non-neutral model, they show that *platforms are viewed as substitutes only by consumers. In contrast, from the CPs' perspective, each platform has a monopoly over the access to its consumer base. Consequently, CPs decide whether to connect to each platform independently, causing different platforms' investment patterns from those in the neutral regime.*

In the neutral regime, the investment made by the high-quality platform allows it to earn significant revenues. However, the low-quality platform does not invest. The reason for this behavior is that investing does not pay off because it would increase price competition on the consumer side, thus reducing revenues extracted from consumers. So, a profitable differentiation strategy for one platform is not investing at all. In the non-neutral regime, each platform has monopoly power over the access to its consumer base, and there is a trade-off between adopting a differentiation strategy based on quality investment (as in neutral regime) or exploiting their monopoly power over the access to their consumer bases.

They argue that **the non-neutral regime leads to higher social welfare** because

the higher investment levels resulting in the non-neutral regime increase consumer and CP gross surplus. However, the low-quality platform prefers the non-neutral regime while the high-quality one prefers the neutral regime. With regard to investment, in the neutral regime, only the high-quality platform invests. But in the non-neutral regime, the low-quality platform invests too. In general, the authors conclude that every agent in this model prefers the non-neutral regime, except the high-quality platform.

Economides and Tåg (2012) also address the net neutrality debate by considering the model proposed by Armstrong (2006). They find that network effects between consumers and content providers can provide a rationale for network neutrality regulation, but only for some parameter values. The authors consider monopolistic and duopolistic frameworks, but both cases show similar results in terms of welfare. However, in the duopoly case, **platforms prefer the neutrality regime**, but the opposite is true in the monopoly case.

Krämer and Wiewiorra (2012) also analyze a monopoly that coordinates CPs and consumers. They consider the number of clicks as an indicator of the network use, such as Musacchio et al. (2009). But also, they are focused on the investment decisions on network quality, such as Njoroge et al. (2013) and Musacchio et al. (2009). The main result is that, in the short run, the non-neutrality regime leads to the same level of content variety as the neutrality regime. In the long run, the non-neutrality regime is likely to result in higher investments, but the authors also point out that there are special cases in which that is no longer true. This result was also found by Economides and Tåg (2012).

However, what is more interesting about this work is the analysis of minimum quality standards as an instrument to ensure a minimum level of investment³⁹. Nevertheless, the authors point out that this instrument could have no effect or even negatives effects. On the other hand, the strategic quality degradation provides the ISP with means through which it can manipulate the relative attractiveness of high-quality

³⁹The minimum quality standard could be set such that the ISP is required to offer to CPs under non-neutral regime a congestion level in the low-quality class that is at least as low as the equilibrium quality level under network neutrality.

connections, but the authors prove that, although it is not socially optimal, the platform would find it profitable.

As a summary, **it is not clear whether or not the neutral regime is better than the non-neutral regime**. There is evidence in both directions, and it also depends on which parameter regions we consider, and which agents we take into account. This issue remains open, and because of the recent decisions of the FCC regarding the net neutrality, it will keep growing in the following years⁴⁰. Nonetheless, many of those works rely on assumptions that are not realistic, such as the linear relationship between the utility and the number of clicks, see Musacchio et al. (2009), or the assumption that the quality of CPs is the only dimension valued by users, see Njoroge et al. (2013), or that users only value the number of CPs, see Economides and Tåg (2012). Probably, overcoming those limitations will be the next step in this part of the literature.

Another topic that has attracted the attention of researchers is the competition between private and open source systems⁴¹. One of the most interesting examples is Economides and Katsamakas (2006). They analyze a multi-sided market in which software platforms coordinate users' and developers' demands. They highlight the fact that an open source platform cannot adopt two-sided strategies because this ownership structure imposes a null price on at least one side and a non-profit behavior⁴².

Economides and Katsamakas show that when the cost of users switching to the open source platform is large, it is optimal for the application provider to subsidize all the users that adopt the open source platform. The authors also highlight that **the proprietary system is more likely to dominate** in this case. Another work that analyzes this case is Hagiu (2004). Hagiu observes that it is not possible to say whether or not a proprietary system is better than an open source system in terms

⁴⁰<https://www.washingtonpost.com/news/the-switch/wp/2018/02/22/the-fccs-net-neutrality-rules-will-die-on-april-23-heres-what-happens-now/?noredirect=on>

⁴¹This topic has also been addressed from a one-sided perspective, a good example is Schröder and Bitzer (2003), that proposes a model of technological competition a la Cournot.

⁴²However, apps running on open source operating systems can be for-profit, and developers can earn positive profits.

of welfare. However, both, the proprietary and the open platforms, induce socially insufficient product variety and user adoption. In that sense, he argues that **open source platforms can induce a socially excessive entry of developers**, and if users care more about diversity, it would be optimal to make profits on developers' side⁴³. He also shows that positive royalties on developers' side can mitigate the coordination problem between both sides because they are an effective way of committing the platform to charging lower user prices, and thereby to induce more user adoption. Lastly, another digital market that has started to attract the attention of researchers is the video game industry, in particular, the video-console market. This market is characterized by the presence of platforms that coordinate players and developers. It is pretty similar to the PC market, both have platforms coordinating consumers and developers, but their pricing schemes are different, see Evans et al. (2008). However, there is a lack of works that analyze those market from a two-sided perspective. In fact, we have only found two works in which the video-console market is analyzed properly. Hagiu (2006) is the first one in analyzing this market theoretically. He shows that if developers hold favorable expectations, committing buyer and developers prices at the same time is a dominant strategy for monopolies but, if developers' expectations are unfavorable, then the platform may prefer no commitment at all. In the duopoly case, commitment is always a dominant strategy for both platforms. This result may explain why all the video-console producers announce the prices of those devices in advance.

The other interesting work is Lee (2013). Lee studies the sixth generation of video consoles in the US between 2000 and 2005. There are two main assumptions in his model. First, consumers do not view software products as substitutes for one another, and second, consumers' and firms' utilities follow first-order Markov processes. Empirically, the latter is a reasonable assumption, but theoretically, it has the flaw of the memoryless property (or Markov property). It is worth pointing out that each consumer makes its purchase decision of a title independently of the rest of titles.

⁴³Hagiu argues that this is the case in video-consoles markets, where the pricing structure is balanced towards developers in contrast with operating systems, where diversity is less relevant.

However, this is not always true, because there are video games sagas, which may bias the results. Nonetheless, we do not expect a great bias because these sagas do not represent the majority of the titles launched each year. Another interesting feature of Lee (2013) is that he follows the timing of Hagiu (2006). Developers arrive before users, this is a critical feature of software markets where one side enters the market before the other. The justification is that they might need significant time to make their products available for the platforms they have decided to support. He proves that this market is a truly two-sided market, and he finds that prohibiting exclusive arrangements would have benefited the incumbent and harmed the smaller entrant platforms. He makes a counterfactual experiment without exclusive arrangements, and he shows that the total hardware and software adoption would have increased by 7% and 58% respectively. That means a welfare gain of more than a billion US dollars.

This section is probably the one more likely to grow in the following years. We are aware that each year many works are published with the words “digital platforms”. But that it does not necessarily imply that a proper multi-sided market analysis is carried out. Nonetheless, this section does not pretend to show the state of the art of the digital platform modeling, but to show that it is also a part of the literature.

3.6.9 Anti-trust Literature on Multi-sided Markets

In parallel with the development of these theoretical models, there is a growing interest in how competition authorities have to regulate multi-sided platforms because, in some cases, it is possible to find counter-intuitive conclusions, such as prices below marginal costs, socially optimal monopolies, competitive tying/bundling, etc, see Filistrucchi et al. (2012a). In this section, we point out the most relevant works on this topic and their results. However, we do not try to make an exhaustive analysis of the development of the anti-trust policies regarding multi-sided markets. The idea is to present another open field that is attracting the attention of researchers. Nonetheless,

more exhaustive analyses can be found in some of the cited papers⁴⁴.

Evans (2002) is one of the first works in addressing the anti-trust topic in multi-sided markets. He points out that it is essential to consider network effects in the anti-trust analysis because they create externalities that make the one-sided analysis no longer suitable. Filistrucchi et al. (2012a) also argue that **the traditional anti-trust analysis cannot be applied without taking into account network effects** because, if we adopt the traditional tests, our conclusions will be biased⁴⁵. Goos et al. (2011) also find that, if we do not take into account frictions and network externalities when there is evidence of their presence, our market power measures will be biased. Recently, and following these ideas, Lam (2014) point out that: ***Relying on a one-sided logic may overestimate potential anti-competitive effects.*** Filistrucchi (2008) proposes a modification of the SSNIP (Small Significant Non-transitory Increase in Price) test to identify the relevant market in two-sided markets. The author highlights the complexity of adapting this one-sided tool to two-sided markets. *In a two-sided market, the profits of the hypothetical monopolist are determined by both, the price level and the price structure. It is not a priori clear whether the hypothetical monopolist should be thought of as raising:*

- *The price level while optimally adjusting the price structure*
- *Both prices together keeping fixed the price structure*
- *Each of the two prices separately allowing the other price to be adjusted optimally*
- *Each of the two prices while keeping the other price fixed*

Answering these questions requires using Filistrucchi's taxonomy of two-sided markets (see Section 3.5). In a "payment card" market, the hypothetical monopolist would increase the price level and optimally adjust the price structure. In a "media" market, that is not true, and the hypothetical monopolist would increase each one of the two

⁴⁴Some interesting reviews about the anti-trust issues in two-sided markets are Filistrucchi et al. (2012a), Filistrucchi et al. (2012b) and Filistrucchi and Klein (2013).

⁴⁵Under the assumption of at least one positive network effect, any price increase tend to be less profitable in two-sided markets than in one-sided markets because of feedbacks.

prices separately but optimally.

The author also states that, *from a practical point of view, allowing the hypothetical monopolist to optimally adjust the price structure would have the positive side-effect to mitigate the [...] worries of antitrust authorities that in a two-sided market with two positive indirect demand externalities [the definition of the market] would lead to a very wide market [definition]*. However, Evans and Noel (2008) also distinguish between short and long-term effects of the price increase, but Filistrucchi does not think in that way. *The distinction is probably useless from a practical point of view in the case of SSNIP test*, see Filistrucchi (2008).

Filistrucchi also highlights that non-transaction markets tend to be more complicated than transactions markets. Non-transaction markets require a more extensive analysis of which feedbacks we should take into account. On the other hand, the profits in transactions markets came from the transactions, in which all the externalities are included. Following this idea, Filistrucchi and Klein (2013) point out that, if we study a non-transaction market, it has to be considered as two interrelated markets. Whereas in payment card markets, we have to define only one market because in these markets there is a basic service, the transaction, that is linking both markets⁴⁶. Empirically, Argentesi and Filistrucchi (2007) estimate the market power in the Italian newspaper industry, and they highlight that the standard mark-up formula is no longer correct. In a similar way, Filistrucchi and Klein (2013) analyze a merger in Dutch newspaper industry and point out the same result⁴⁷.

Song (2013) also analyzes the German magazine industry. He estimates mark-ups based on one-sided and two-sided approaches. He finds that one-sided markups on the consumers' and advertisers' sides are positive. However, he also finds that two-

⁴⁶From a theoretical point of view, it is worth mentioning Alexandrov et al. (2011). Their model has no network effects. However, there are cross-side effects that arise from shortages, so both sides are interdependent as we expect in two-sided markets, but they are not truly two-sided platforms. What is interesting about this work is that it is necessary to take into account the relationship between both sides even in markets beyond the canonical definition of two-sided markets/platforms. Some of their results are common to those found by Filistrucchi.

⁴⁷Affeldt et al. (2013) also analyze this market using the UPP test. Their conclusions are roughly the same. Other empirical works related to the Dutch newspaper industry are Affeldt et al. (2013), van Damme et al. (2010), and Filistrucchi and Klein (2013).

sided mark-ups on the advertisers' side are pretty similar to those under the one-sided approach, but that is not the case on the consumers' side because they have negative mark-ups under the two-sided approach. He considers a merger simulation, and he observes that the one-sided approach leads to an increase in prices, by contrast, the two-sided approach leads to ambiguous conclusions, prices may increase or decrease, **so it is not clear that a merger in a two-sided market would be harmful.**

Another interesting work related to antitrust issues is Evans and Noel (2008). They propose a two-sided framework for Critical Loss Analysis and SSNIP tests, and they realize that the one-sided framework creates two biases.

- The bigger the network effects, the larger the biases
- One-sided approaches underestimate merger effects

However, this last result is not found by Chandra and Collard-Wexler (2009) when analyzing the Canadian newspaper industry. They prove that a higher concentration would not lead to higher prices on consumers' side. In general, **it is not obvious that a higher concentration would lead to higher prices** because they do not observe significant changes in advertisers' prices. Two other interesting works in this area are Weyl (2010), that proposes an extension of his own model to measure market power, but also to evaluate predation, and White and Weyl (2016) that make recommendations about estimating discrete choice models and UPP tests (Upward Pricing Pressure)⁴⁸.

Lastly, two interesting topics for competition authorities are market collusion and tying. With regard to market collusion, only a few works have explicitly addressed it, such as Ruhmer (2010). She finds that the higher the network effect, the harder to collude in repeated games with a grim trigger strategy. She also finds that collusion is harder to maintain in two-sided platforms than in one-sided ones, and sometimes, it is not profitable at all. Another related work is Boffa and Filistrucchi (2014). They

⁴⁸They consider that public subsidies may be very useful for platforms, but also that there is a need for regulation because: *development subsidies may help to some extent with raising capital and are generally useful in addressing problems with appropriability, direct subsidies on adoption are likely to achieve more socially desirable ends at once. [...] [However] If every start-up in a new platform market or every entrant could call for subsidies this could easily degenerate into chaos.*

argue that there is a similarity between collusion in two-sided markets and collusion in one-sided markets with complementarities.

With regard to tying, Affeldt (2011) argues that although tying/bundling may seem to be a tool to deter entry, this use is unlikely in a two-sided market because *when anti-competitive effects can be clearly identified, these should be weighed against potentially offsetting pro-competitive efficiencies*. Choi (2010) also points out that, only if the platforms design their products in a way such that a competitor's products cannot interoperate with them, that could be considered anti-competitive. The rest of tying cases cannot.

To conclude, Evans (2011) points out that *most standard approaches to market definition such as the SSNIP test, diversion ratios, conditional logit demand analyses, and other economic models and formulae, do not apply to two-sided markets without modification*. In that sense, this part of the literature will potentially grow in the next years not only from a theoretical point of view but also, from an empirical one because many questions remain open about the applicability of standard approaches to multi-sided markets.

3.6.10 Empirical Multi-sided Markets. A glimpse

The empirical literature on multi-sided markets is not so developed as the theoretical literature. Nonetheless, this field is growing fast and, for simplicity's sake, we only highlight some of the most known works up to date, and we mainly point out their results. The main shortcoming in this case is the necessity of data. In contrast, one-sided markets normally require fewer data. Another problem is that the estimation of two-sided models is not easy. White and Weyl (2016) point out that two of the most cited works in the literature, Rochet and Tirole (2006) and Armstrong (2006), are not suitable for estimation. In contrast with one-sided models, in the two-sided market literature, it is usual that every empirical work uses as framework an ad hoc model, but not a previous theoretical one.

The first empirical work that uses a two-sided approach is Rysman (2004). He studies the yellow pages industry. The author observes that the “winner-takes-all” equilibrium

may be not common in all two-sided markets. In fact, his results support the idea that only when there are strong network effects, there will be a “winner-takes-all” outcome.

Another interesting work is Ivaldi et al. (2011). The authors study whether or not airports are two-sided platforms⁴⁹. *Airlines prefer to operate at airports which are attractive to passengers and passengers enjoy airports where they can access more air links and destinations, as well as a wide range of shops and restaurants, and convenient parking and transportation facilities*, Ivaldi et al. (2011). They find that *without any doubt, airports should be considered as two sided platforms*. However, they also state that the airports they analyze are not behaving like two-sided markets.

Nonetheless, the most outstanding empirical work up to date is Lee (2013). He analyses the sixth-generation of the U.S. video game industry (2000-2005). His main conclusion is that exclusive arrangements (that guarantee a singlehoming position for some software titles) would have benefited the incumbent (Sony PlayStation) and harmed the smaller entrant platforms (Microsoft Xbox, Nintendo Wii, etc.). An interesting result is that many software titles have not individual impact on hardware sales. However, hit titles have an important impact, the earlier the launch of a hit title, the higher its impact. Chao and Derdenger (2010) also study the video console market, but they focus on the portable video game console market during 2000-2005 when Nintendo was the only portable video console manufacturer. Their empirical work verifies that prices are lower when products are sold separately.

On the other hand, another interesting market that has been empirically addressed is the credit card market. Credit cards were used as an example of two-sided markets from the very beginning of the literature, see Rochet and Tirole (2003). However, empirically, it is not clear if large networks, such as Visa or American Express still exhibit a measurable positive feedback loop. At some level, consumers’ and sellers’ demands should be independent, see Rysman (2007). However, he only focuses on credit cards and not on debit cards, although he argues that the results are similar. TV-channels can be considered another example of two-sided markets. Some works

⁴⁹Wright (2004) was the first work in which airports are considered two-sided platforms.

have empirically addressed this issue, such as Wilbur (2008) for TV-channels in the U.S. or Song (2013) for TV magazines in Germany. In this work, the author shows that advertisers are more sensitive to price changes on consumers' side than the other way around. He concludes that the empirical results show that magazines choose prices on consumers' side below marginal cost, and they make profits on the advertisers' side.

Another interesting work is Kim et al. (2013). They analyze the online daily deals promotion industry. This industry has several distinctive features. Consumers tend to multihome, and sellers tend to singlehome. The authors find that the incumbent (Groupon) enjoys an advantage which appears attributable to its greater network size. On the other hand, they show that the main competitor (LivingSocial) has successfully entered the market by adopting a DC strategy.

Lastly, among all the empirical works stand out those oriented to the estimation of the market power, or those oriented to guide the economic policy. One of those works is Argentesi and Filistrucchi (2007). They study the Italian newspaper industry with a two-sided approach from 1976 to 2003, and they find that mark-ups on consumers' side are non-positive, but mark-ups on advertisers' side are positive. Another work which addresses the market power in the newspaper industry is Filistrucchi et al. (2012b). Their estimation shows that consumers are price-sensitive and ad-adverse. Other interesting contributions in this topic are Kaiser and Wright (2006), that estimate a two-sided model to study the German magazine industry from 1972 to 2003. Or Jeziorski (2014), that addresses the merger wave in U.S. radio industry from 1996 to 2006.

3.6.11 Other Research Topics in the Literature

In this section, we address other interesting topics that have not attracted the attention of many researchers. Either because it is a new topic, or because it is considered as a minor problem, or because it is a very specific problem of one industry.

For example, many digital platforms are built on top of other previous platforms or technologies. In this sense, a critical question is to what extent backward compatibil-

ity may influence the market equilibrium. To the best of our knowledge, there is only one work that addresses this topic despite its relevance. Tremblay (2016) assumes a two-stage model with two technology generations to reproduce the idea of backward compatibility. He considers that, at the second stage, users on the platform with backward compatibility obtain a proportion of the utility they have received on the previous stage. In this model, there is a monopoly incumbent at the first stage, and he finds that when an entrant and the incumbent with backward compatibility have the same technology at the second stage, the incumbent will drive the entrant out of the market. However, if the entrant has a technology advantage three scenarios are possible. Either the incumbent sets low prices to deter entry, or the entrant has a superior technology and it sets prices with mark-up, or the incumbent is expelled from the market. This result points out the relevance of having a better technology when entering the market.

Another interesting topic that is poorly addressed in literature is the role of “quitters” and “switchers”. The first ones are those that when prices increase, they quit the market. The second ones are those who change the platform when prices increase. To the best of our knowledge, only two works have considered this topic. See White and Weyl (2016) and Chandra and Collard-Wexler (2009).

White and Weyl (2016) address the difference between these two types of users. The question they address is which type of user is more representative when there is a change in prices. They find that, if there is no correlation between membership values and usage externalities then, switching buyers are more representative than exiting buyers because platforms are differentiated primarily on a dimension orthogonal to externalities. But, if there is a correlation between membership values and usage externalities then, exiters will be more representative of average users than switchers. Exiters and switchers are also addressed by Chandra and Collard-Wexler (2009), but they are focused on addressing the effects of mergers in prices⁵⁰.

Another issue that is starting to attract the attention of researchers is the influence

⁵⁰They find that mergers in two-sided markets may not necessarily lead to higher prices. This is a remarkable result because it is opposed to the traditional insights of one-sided markets.

of information in two-sided markets. Hagiu and Halaburda (2014) propose a model in which developers have full information, but users have no information about the developers' fee. Therefore, in their framework, users differ in how they form their expectations about the size of developers' side. **They prove that a monopoly has incentives to avoid asymmetries in information**, but the opposite is true in a duopolistic framework. Following Hagiu and Halaburda's work, we find Sun (2014). She addresses the same issue, but she considers a market with bundling/tying strategies. She obtains the same result than Hagiu and Halaburda but also, she finds that **bundling is more effective to stimulate consumer demand when there are more informed consumers**.

Lastly, an interesting and relevant issue is the role of taxes in multi-sided markets⁵¹. The first work that addresses this issue was Kind et al. (2008). They find that a higher value-added tax on one side may make profitable for the platform to shift revenue from that side to the other one (from the heavily taxed to the untaxed side). Because of this balance, the output on both sides may increase. In other words, **it is possible that taxing a two-sided platform may increase the number of affiliates on both sides**⁵². Nonetheless, they also find that a higher specific tax on one side leads to lower affiliation, as in one-sided markets⁵³.

The role of taxes also expands to more subtle areas. For example, Kind et al. (2013) prove that taxes may affect the optimal location of horizontally differentiated platforms. In other words, **taxes may affect the political views of newspapers**. Taxation on digital platforms is more complex than in one-sided markets, and in some cases, it requires a completely new design. *The innate characteristics of digital products and digital platforms modify the effects and the optimal design of taxes in*

⁵¹See Belleflamme and Toulemonde (2018) for a short review of this topic.

⁵²In a posterior work, the authors also found that this effect may lead to a reduction of the differentiation, see Kind et al. (2010). In a similar work, the authors provide a comparison between one-sided markets and two-sided markets that clarifies why the principle of minimum differentiation dominates, see Kind et al. (2013).

⁵³These authors also compare both taxation schemes in terms of welfare, and they show that the dominance of ad-valorem taxes that is common in one-sided markets does not hold in two-sided markets. In fact, they conclude that unit taxes may yield higher welfare than ad-valorem taxes, see Kind et al. (2009).

potentially unexpected ways, see Kind and Koethenbuerger (2018). In this work, the authors point out that statement by highlighting that even if consumers dislike ads, a tax aimed to reduce ad levels may affect them negatively. A recent work on this topic is Belleflamme and Toulemonde (2018). They compare two different taxes, ad valorem and transaction taxes. They find many ambiguous results about the impact of such taxes but also, they obtain interesting insights about their role. For example, they find that transaction taxes hurt agents on both sides and benefit platforms. On the other hand, they also confirm the result found by Kind et al. (2008) that ad valorem taxes may benefit the users that are taxed, but it may hurt agents on the other side of the market. Another interesting result is that taxes in those markets may affect prices through three channels: contamination, leverage and ricochet channels. The contamination channel implies that taxes on one A-side discourage participation on the B-side, which reduces the price on that side. The leverage channel implies that taxes on one side may increase prices on the opposite side. Because A-side users value the interaction with B-side users, the reduction of price on the B-side attracts more A-side users, which incentive a higher price on the B-side. The ricochet channel is an ambiguous effect that explains the optimal adjust of price on the A-side as the consequence of the adjustment on the B-side⁵⁴. To this date, the issue of tax incidence on competing two-sided platforms is largely underexplored, and the emphasis nowadays in taxing digital platforms will attract the attention towards this literature. Therefore, we expect a significant increase in works in this area in the following years. Especially, from an empirical point of view and in combination with other research areas, such as multihoming or bundling.

There are many other research topics that have been started to be addressed using the multi-sided market literature. However, the list is so large that we cannot cover all of them here. In this section, we only want to remark that this is a growing literature in which many questions remain open.

⁵⁴Other interesting works in this area are Bourreau et al. (2018), Kind et al. (2010) and Tremblay (2018).

3.7 Wrap-up and Open Questions

In this Chapter, we present a general literature review of multi-sided markets. This aim of this work is not to provide a very specialized literature review on a narrow topic, but to provide to new readers with an introduction to the literature, and to experienced researchers with an overall view of the state of this literature. We first introduce the definition of multi-sided markets in which we discuss the different contributions of several works in defining these markets. We conclude that no standard definition is yet available, but there is a consensus on the main characteristics of these markets. We observe that those characteristics are defining features of the fitness tracker market, as we point out in Chapter 2. **In that sense, multi-sided platforms help us in describing the fitness tracker market.** We have also observed that these markets have exclusive features that make them different from other markets. Especially regarding pricing and costs. Prices may differ from what is expected in other markets, and costs may be unrelated to the prices in some cases. These conclusions open an immediate question: *How to properly price fitness trackers? Which are the main drivers of pricing?*

We have also highlighted that platforms can be classified using different taxonomies. In that sense, we have stated that these classifications are essential in understanding the results of theoretical models, and the behavior of platforms. To properly analyze a market, it is fundamental to be able to identify those taxonomies. **In the case of fitness trackers, none of the previous taxonomies is valid because of the digital nature of the market.** Nonetheless, if we consider the current pricing mechanisms and not the potential one, they are “Non-transaction markets” in the sense of Filistrucchi. Therefore, a theoretical model that aims to explain this market should be in this category.

We have pointed out the main lines of research of this literature as well as the main conclusions. We have seen that **asymmetric pricing is the norm.** Depending on the consumer group (users, developers, advertisers, etc), it is normal to find different fees because of the different valuation of the presence of other groups. Nonetheless,

the most extended price pattern in both, theoretical models and real markets, is one based on membership fees, which we will also consider as the basic framework because it is observed in the fitness tracker market⁵⁵.

We have observed that there is an ongoing discussion about how to properly price platforms at their launching to overcome the chicken & egg problem. Several proposals have been addressed in the literature, but there is not a clear better one. But the evidence highlights that **platforms will set low initial prices to foster adoption among early-adopters, and they will change those prices as the number of users on each side changes**. This evidence will help us later in defining how to launch a successful platform because prices are an essential part of the launching. And the evidence in this sense is clear, but it is not clear how to proceed when users have to get aware of the product first, or how should start-ups address the launching of their platforms. In that sense, several questions remain open. *What is the optimal pricing policy of a platform for a successful launching? What does foster their adoption? Is it a matter of how users transmit the information?* To answer those questions, we have a starting point, prices should be lower at the launching, as the theoretical evidence points out. Additionally, the evidence highlights that **platforms launchings will be harder than one-sided markets**, but it is not clear to what degree. We will also explore this issue in the following chapters.

We have discussed which organization scheme is better, and we have highlighted that **there is no economic model that is always better**. Nonetheless, we have observed that some platforms were born as traditional business models, and only when they were mature enough, they adopted a multi-sided platform business model. However, currently, we observe in new digital markets that platforms born as multi-sided markets (see Facebook, or JustEat for example). So, **it makes sense to start analyzing the fitness tracker companies as multi-sided platforms**. We have considered the possibility of multihoming, and we have seen that it has strong consequences on how platforms set prices, and how the market power is shared among

⁵⁵For example, the price of the device is the equivalent to the membership fee, and the price for accessing to the API is the membership fee for developers.

platforms. However, the current evidence points out that, in the presence of compatibility, in the sense that network effects are shared among platforms, such behavior may not be an issue, but it will be the compatibility itself. We have also observed that compatibility is not well addressed in the literature, and only two works consider it but without providing many insights. So, one of our previous questions remains open. **It is clear that multihoming is not going to be an issue in the fitness tracker market in the short run** because of the presence of compatibility networks. However, *what are the implications of compatibility in the market? What are the consequences of sharing network effects among platforms?* Platforms tend to be related with one another by complex networks. Compatibility allows us to create new platforms on top of previous ones using common communication protocols but also, it allows us to send and receive data from other platforms, partners and competitors alike. Global platforms such as Facebook or Google have created vibrant ecosystems full of users and developers that are generating huge amounts of data that they interchange. But, *to what extent the use of data in these networks influences our economic intuitions? Can we rely on our traditional insights? Or is this time different?*

Afterward, we have addressed the use of content in platforms as a coordination mechanism. We have shown that tying and bundling additional services may be useful when setting negative prices on one side has the risk of creating adverse selection problems. Nonetheless, many empirical works have to be done because there are contradictory evidence in terms of welfare creation/destruction as a consequence of these strategies. **From the point of view of the fitness tracker market, up to date, there is no evidence of tying/bundling strategies in this market.** Then, we have addressed the current state of the study of digital platforms. We have observed that the main focus has been on operating systems (OS), or on the network neutrality debate. **There is a lack of works that address the Internet-of-Things (IoT) technologies, so to what extent this theory helps explaining wearables market is unknown.** On the other hand, we have observed an increasing interest in the development of anti-trust methods in this literature. However, given the current evolution of the fitness tracker markets, it is not an immediate concern,

but a clear concern in the medium and long-run.

However, after this literature review, there are some questions that are totally open, such as *What is the role of users expectations? Is it matter if users care about the device but not about the connecting with other people? What is the optimal pricing policy of a platform for a successful launching? What are the implications of commoditization of users' data?* These questions are essential in the context of wearables and IoT markets. Nonetheless, the lack of works that address these issues is related to the lack of works that address these markets. This theme is essential in digital markets, and its relevance will be vital in the near future. For that reason, we address these questions in the following Chapters.

Chapter 4

Theoretical Modeling

4.1 Introduction

We have seen that fitness trackers are suitable to be analyzed with theoretical multi-sided platform models. After analyzing the current features of the fitness tracker market (Chapter 2), and the literature review of multi-sided markets (Chapter 3), we know that any model that pretends to reproduce this market will be based on multi-sided platforms, so it implies that we only need to lay out a multi-sided platform model and not two different market frameworks.

In Chapter 2, we have also observed that the fitness tracker market has some interesting features, such as the quality races, the compatibility networks or the brand expansion. In order to find a suitable model that reproduces these characteristics, we need to identify the economic dimensions behind those characteristics. For example, in the case of quality races or the brand expansion, it is a clear desire of differentiation. In that sense, to understand those features, we need to study the differentiation. In the compatibility case is different because compatibility is a dimension by itself, so we also need to know the implications of this behavior in conjunction with the

others¹.

In this chapter, we develop a set of different theoretical models to address three essential issues:

- Pricing and Expectations. What are the main drivers of pricing? How do users' beliefs influence the optimal strategies of platforms?
- Compatibility. What incentives do platforms have to establish compatibility networks? What are the implications of compatibility in the market? What are the consequences of sharing network effects among platforms?
- Differentiation. What is the role of differentiation when pricing digital platforms? What are the consequences of commoditizing data?

Another big concern in the literature is how to price the launching of platforms. In other words, *what is the optimal pricing policy of a platform for a successful launching?* In that sense, we develop a dynamic model that establishes the optimal pricing rule in dynamic settings with full information. We are especially interested in the suitability of these kinds of models to address the take-off phase of digital platforms, which we address in the last section of this Chapter.

The organization of this Chapter is as follows. In Section 4.2, we lay out the most simple model, the monopoly. In this scenario, we start analyzing the role of users' expectations and quality. In Section 4.3, we lay out the duopoly model. This is the main body of this Chapter. In this section, we describe the different cases of differentiation, and we analyze several practical questions regarding compatibility, expectations, and barriers to entry. We conclude this Section by presenting a critical review of these models, and by describing their limits. Then, in Section 4.4, we lay out a sequential decision model to analyze these markets from a dynamic point of view. We conclude the Chapter with Section 4.5, in which we wrap-up the questions that remain unanswered, and summarize the findings of our models.

¹Compatibility in the digital era can take two different forms. On the one hand, compatibility in telecommunications protocols, which study does not differ from the results pointed out in the early literature of the 80s and 90s on compatibility in network economics. On the other hand, this term may refer to the use of compatible databases or the use of shared data. In this Chapter, we consider this case.

4.2 A Platform Monopoly. The basic Case

This case assumes there is only one platform in a market. It is the most simple case because there is no interaction with other companies, and the platform only interacts with their customers. To keep the model as simple as possible, we assume that the platform only competes in prices in a mature market, and all the customers and the platform have full information. At this stage, we do not want to depict a realistic view of a digital market but to lay down the most simple case that will be the cornerstone of the rest of the theoretical modeling.

We consider three scenarios: a pure two-sided market, a two-sided market with only one side having indirect network effects, and a two-sided market that has direct network effects on one side, and indirect network effects on the other side. These three cases correspond to different possible markets such as a pure digital platform, a digital service that encompasses a digital device and a platform, and a social network respectively. This part of the work is a modification of the Gabszewicz and Wauthy's model. In fact, the pure two-sided case is the same than the one proposed by Gabszewicz and Wauthy. We use it as the basic framework to address and compare the other two cases. The model comprises three classes of agents. There are two different types of buyers that can interact with each other, and one intermediary who provides the platform to enable the interactions among buyers.

- **Platforms:** They are denoted by j , where $j = 1$ in this scenario. Platforms sell their product in two markets that we describe as “users’ market” and “developers’ market”. We assume both, users and developers, pay an access fee when entering the platforms. Platforms maximize their profits by setting prices on both sides. We denote v_j the price paid by users, and T_j the price paid by developers when consuming the platform j ².
- **Users:** We denote by n_j the number of users who participate on platform j , and we denote by θ_i their type, which is uniformly distributed in the $[0,1]$ interval. The utility of an user θ_i consuming the platform j in the pure two-sided

²For simplicity's sake, we do not consider the subscript in the monopoly section.

case is $U_{(i,j)} = \theta_i m_j^e - v_j$, with m_j^e denoting the expectations that users have about the number of developers on the platform j . When considering the case with only one side having indirect network effects, we assume users perceive an exogenous quality level. The utility of consuming the platform j in this case is $U_{(i,j)} = \theta_i s_j - v_j$, with s_j denoting the quality of the device provided by the platform j (normalized to 1)³. Lastly, when considering the case in which users have direct network externalities, the utility of the user is $U_{(i,j)} = \theta_i n_j^e - v_j$, with n_j^e denoting the expected number of users on the platform j . In any other case, their utilities will be normalized to zero.

- **Developers:** We denote the number of developers who participate in platform j by m_j , and we denote their type by δ_i , which is uniformly distributed in the $[0,1]$ interval. The utility of a developer δ_i consuming the platform j is $U_{(i,j)} = \delta_i n_j^e - T_j$, with n_j^e denoting the expectations that developers have about the number of users on the platform. If developers do not access any platform, their utilities will be normalized to zero. Lastly, for simplicity's sake and without loss of generality, we assume developers only consider the pure two-sided market case as in the Gabszewicz and Wauthy's model.

Our idea is to compare how those small changes in users' utilities affect the market outcome without eroding the two-sidedness of the model⁴. When we consider the pure two-sided case, the willingness to enter the platform of both customers depends on his/her own type (δ_i or θ_i), the access fee (T_j or v_j) and the number of other customers he /she expects to address (n_j^e or m_j^e). But when we consider the case in which only the developers have the indirect network effects, the users' willingness to adopt the platform depends on the platforms' quality (s_j) and the price (v_j), but the developers' willingness does not change. These modeling choices represent different cases of the fitness tracker markets. In some situations, users only value the fitness tracker device and its quality, in other cases, users value the apps they can use or

³We assume $s_i \in [0.5; 1]$ to guarantee that the platform generates enough utility to attract some users.

⁴At least one side has to have indirect network effects to maintain the two-sidedness of the model. In this case, it is the developers' side.

Table 4.1: Users' Demands. Monopoly Model

Pure two-sided	Exogenous quality level	Direct network effects
$n(v, m^e) = 1 - \frac{v}{m^e}$	$n(v, s) = 1 - \frac{v}{s}$	$n(v, n^e) = 1 - \frac{v}{n^e}$

the user communities that are on the platforms. In all these situations, consumers may have expectations about the number of other consumers, or they can observe the quality of the product. The point is to know to what extent these different behaviors modify the optimal pricing of platforms.

4.2.1 Monopoly. Equilibrium Analysis

We consider the Gabszewicz and Wauthy's definition of active agents (the ones who buy one of the platforms) and their assumption of rational agents with passive beliefs⁵. We use the users' and developers' preferences to derive demands addressed to the platform by the users and developers as a function of their expectations (or as a function of the quality level)⁶. The users' demands in the different cases that we consider are depicted in Table 4.1. On the other hand, developers' demand is $m(T, n^e) = 1 - \frac{T}{n^e}$. Given the expectations m^e and n^e and the quality level s , the monopolist maximizes their profits⁷

$$\max_{T, v} vn(v, \cdot) + Tm(T, n^e)$$

⁵In the literature, authors normally assume responsive beliefs. The difference relies on how we assume consumers reacts to a change in prices. When facing a change in prices, consumers with responsive beliefs anticipate that the rest of consumers will react to that change immediately. In other words, their expectations change. On the other hand, consumers with passive beliefs know that such change will trigger a change in the other consumers' decisions, but it will not take place immediately. Nonetheless, because in both cases is assumed rational expectations, the equilibrium must verify that $n^e = n$. From a technical point of view, the difference between both cases is that, in the passive beliefs case, we only consider $n^e = n$ after solving the first order conditions. In the other case, we consider $n^e = n$ before solving the first order conditions. Nonetheless, the reason because we do not assume responsive beliefs is because those beliefs require the following expression to be true in the case of indirect network effects: $v > 2\sqrt{T} + T + 1$ and $T > 2\sqrt{v} + v + 1$, which is not possible. Nonetheless, in the case of direct network externalities, responsive beliefs can be assumed. Proof in the Annex.

⁶As it is pointed out by Gabszewicz and Wauthy: *products' quality in one [platform market] reflects agents' expectations relative to the network's size in the other market. We may therefore characterize optimal pricing strategies in each market, conditional on these expectations.*

⁷For simplicity's sake and without loss of generality, we normalize the marginal costs to zero.

Table 4.2: Optimal Strategies Conditional on Expectations or Quality. Monopoly

Pure two-sided	Exogenous quality level	Direct network effects (Passive beliefs)
$v^*(m^e) = m^e/2$ $T^*(n^e) = n^e/2$	$v^*(s) = s/2$ $T^*(n^e) = n^e/2$	$v^*(n^e) = n^e/2$ $T^*(n^e) = n^e/2$

$n(v, \cdot)$ denotes users' demand in one of the three previous cases (Table 4.1). In Table 4.2, we show the optimal strategies conditional on expectations (or qualities). The corresponding networks' sizes at equilibrium are $m = n = 0.5$ in all cases. However, in the case with direct network externalities and responsive beliefs on users' side, three potential equilibrium arise:

1. $n = 0$
2. $n = \frac{1}{2} + \sqrt{\frac{1}{4} - v}$
3. $n = \frac{1}{2} - \sqrt{\frac{1}{4} - v}$

As it is pointed out by (Belleflamme and Peitz, 2015, Pag. 589), those equilibria rely on self-fulfilling prophecies. The first equilibrium corresponds to the case in which each consumer expects no other consumer will adopt the platform; and the other two also correspond to the case in which, at a given price, users expect a high adoption (case 2), or they expect a low adoption (case 3). To avoid the multiplicity of equilibria, we consider that the platform maximizes their profits on users' side with respect to the size of the network⁸

$$\max_{n, T} vn(v, \cdot) + Tm(T, n^e)$$

In this case, the optimal prices are $v^* = 0.222$, $T^*(n^e) = n^e/2$. The corresponding demands at these prices are $n = 0.667$ and $m = 0.5$.

Lemma 1. *An optimal strategy for the monopolist is to set $v^* = T^* = 0.25$, except in the exogenous quality case because it depends on the quality level. In the direct network effect case with responsive beliefs, an optimal strategy is to set $v^* = 0.222$; $T^* = 0.333$.*

Table 4.3: Monopolist's Optimal Payoffs

Pure two-sided	Exogenous quality level	Direct network effects	
0.25	0.125+0.25s	Passive beliefs	Responsive beliefs
		0.25	0.315

Depending on the exogenous quality level we assume, profits may range from 0.25 to 0.375. It is interesting to highlight that, in the pure two-sided case and in the case in which users have direct network effects with passive beliefs, the platform earns the same profit. Another interesting result is that profits are higher under responsive beliefs than under passive beliefs. As a matter of fact, this difference between beliefs is also found by Hagiu and Halaburda (2014) when analysing the impact of expectations and information in two-sided markets.

Lemma 2. *A monopoly platform makes larger profits when users have responsive beliefs and direct network effects than in any other case. However, a high-quality two-sided market in which users perceive an exogenous quality level may make larger profits because of their larger willingness to pay.*

The intuition is the following. **It is easier to convince people to buy a high-quality product than to convince them to buy a product that will be high-quality only when other consumers adopt it.** And it is easier to convince similar people than to convince heterogeneous people to adopt the product. However, these are not the only equilibria that can be found in the model. There are other equilibria. In the pure two-sided model of Gabszewicz and Wauthy, we find two symmetric equilibria in which the product is given for free in one side, and the other side pays. In this case, profits are equal to 0.25, but that also implies that **monopolies may arise in these markets**. That gives us an intuition of why monopolistic social networks may arise, e.g. Facebook, Instagram or LinkedIn.

In the exogenous quality model, depending on what values of s we assume, several equilibria may arise. For example, at $s = 0.5$, an equilibrium is $v = 0$ y $T = 0.5$. But

⁸This assumption is standard in the network economics literature, see Belleflamme and Peitz (2015)

at $s = 1$, there is no other equilibrium than the one pointed out in Table 4.3⁹.

In the case with direct network effects, if users have passive beliefs, another equilibrium is $v = 0$ and $T = 0.5$ (like in the pure two-sided case). However, there is no incentive to subsidize developers given that users do not value their presence in this framework. On the other hand, in the case with responsive beliefs, there is no other equilibrium. In fact, fixing $v = 0$ is suboptimal.

Lemma 3. *The interior equilibrium in the model with direct network effects and responsive beliefs is the only one. However, in the other cases, other equilibria can be found in which one side has free access, and the other one pays the monopoly price*

4.2.2 Monopoly. Scope and Wrap-up

Some digital platforms operate as temporal monopolies during the initial phases of a market or, in some cases, they operate as monopolies after a strong competition in markets that ends in a winner-takes-all outcome. A simple monopoly model does not provide a lot of information or insights, but it is a simple and powerful tool that allows us to describe an abstract market easily. This simple model highlights two essential results.

On the one hand, **expectations matter, and the profit that platforms earn depends on those expectations so, it is relevant their management.** On the other hand, **network effects can accelerate the adoption, but they create a multiple equilibria issue that may result in a failure in launching a platform.** However, selling a device with a standardized quality is enough to attract consumers, and it may lead to a constant adoption. Nonetheless, this adoption may not be so explosive as with network effects.

This simple model has highlighted two essential issues regarding digital platforms. However, this model is an oversimplification of markets, and it is fundamental to take into account the strategic interactions among companies.

⁹Although values below 0.5 have been ruled out, it worth pointing out that those cases present interesting equilibria, for example, at $s = 0.25$ and with $v = 0$, $T = 0.25$ and $T = 0.75$ are also equilibria.

4.3 Duopoly. Strategic Interactions, Differentiation and Price Competition

The introduction of the second platform in our scheme implies that we need to consider the relationship between these two companies in the market, the degree of heterogeneity of the market, and the nature of that heterogeneity among other factors. We also need to determine how the customers (users and developers) value both platforms, that for simplicity's sake, we assume the same than in Section 4.2. In this situation, two schemes of heterogeneity are possible¹⁰. The vertical and the horizontal ones.

The vertical one is also known as the framework of differentiation in qualities. The intuition is that, at the same price, all the customers prefer one product over the other. For example, at the same price, everyone prefers a Ferrari to a Fiat. In the fitness tracker case, at the same price, everyone always prefers a device with one more extra functionality. On the other hand, the horizontal differentiation scheme is also known as the framework of differentiation in tastes. The intuition is that, at the same price, some customers prefer one product, and other customers prefer the competitor's product. For example, at \$1, some customers prefer Coke to Pepsi, and the opposite can also be true. In the fitness tracker case, at the same price, some customers prefer Garmin and others prefer Fitbit. These two different ways of differentiation have direct implications in the market strategies and pricing policies.

In the next sub-section, we expand the previous monopoly model, and we consider the second platform. In this environment, we address the three essential issues that we highlighted in the Section 4.1: Pricing, Compatibility, and Differentiation in digital platforms.

¹⁰Other schemes are possible, and a combination of these two is also feasible. However, these two schemes are the most common ones in the literature, and they tend to be analyzed separately. We proceed in that way.

Table 4.4: Users' Demands. Vertically Differentiated Duopoly

Pure two-sided	Exogenous quality level	Direct network effects
$n_1(v_j, m_j^e) = 1 - \frac{(v_1 - v_2)}{m_1^e - m_2^e}$	$n_1(v_j, s_j) = 1 - \frac{(v_1 - v_2)}{s_1 - s_2}$	$n_1(v_j, n_j^e) = 1 - \frac{(v_1 - v_2)}{n_1^e - n_2^e}$
$n_2(v_j, m_j^e) = \frac{v_1 m_2^e - v_2 m_1^e}{m_2^e(m_1^e - m_2^e)}$	$n_2(v_j, s_j) = \frac{v_1 s_2 - v_2 s_1}{s_2(s_1 - s_2)}$	$n_2(v_j, n_j^e) = \frac{v_1 n_2^e - v_2 n_1^e}{n_2^e(n_1^e - n_2^e)}$

4.3.1 Vertical Differentiation. The role of Quality and Expectations

Let's assume two platforms compete in prices, $j = 1, 2$. We assume all agents singlehome. They buy one and only one product (the platform). Using the previous users' and developers' preferences, we derive demands addressed to each platform¹¹ (Table 4.4). These demands depend on customers' expectations (except in the exogenous quality case). Without loss of generality, we assume $n_1^e > n_2^e$ and $m_1^e > m_2^e$ (and $s_1 > s_2$ in the exogenous quality case)¹², and we refer to the platform 1 as the leader, and to the platform 2 as the follower. The intuition of the model is the following. *For given network's sizes, the platform housing the larger number of [developers] appears, in the eyes of all [users], as a good of higher quality than the other one. Thus at given network's sizes, the two platforms are vertically differentiated*, see Gabszewicz and Wauthy (2004). In other words, the size of the network effects on the platforms can be considered as measures of quality. Symmetrically, developers' demands are

$$m_1(T_j, n_j^e) = 1 - \frac{T_1 - T_2}{n_1^e - n_2^e} \quad m_2(T_j, n_j^e) = \frac{T_1 n_2^e - T_2 n_1^e}{n_2^e(n_1^e - n_2^e)}$$

Conditional on expectations (or quality levels) and price levels, platforms maximize the following profit function (with the exception of the case with direct network effects

¹¹We rewrite the utility functions of Section 4.2 to take into account the quality, demand, and prices of each platform j .

¹²We assume expectations are not the same because, if not, users will spread evenly across the two platforms and prices will be identical. However, this assumption does not rule out symmetrical equilibria. They may appear because of our assumption of rational agents.

Table 4.5: Optimal Strategies Conditional on Expectations or Quality. Vertically Differentiated Duopoly

Pure two-sided	Exogenous quality level	Direct network effects
$v_1(m_1^e, m_2^e) = \frac{2m_1^e(m_1^e - m_2^e)}{4m_1^e - m_2^e}$	$v_1(s_1, s_2) = \frac{2s_1(s_1 - s_2)}{4s_1 - s_2}$	$v_1(n_1^e, n_2^e) = \frac{2n_1^e(n_1^e - n_2^e)}{4n_1^e - n_2^e}$
$v_2(m_1^e, m_2^e) = \frac{m_2^e(m_1^e - m_2^e)}{4m_1^e - m_2^e}$	$v_2(s_1, s_2) = \frac{s_2(s_1 - s_2)}{4s_1 - s_2}$	$v_2(n_1^e, n_2^e) = \frac{n_2^e(n_1^e - n_2^e)}{4n_1^e - n_2^e}$

and responsive beliefs).

$$\begin{aligned} & \underset{T_j, v_j}{Max} \\ & v_j n_j(v_1, v_2) + T_j m_j(T_1, T_2) \end{aligned} \quad (4.1)$$

In which $n_j(v_1, v_2)$, denotes the users' demand in one of the three previous cases (Table 4.4). The optimal strategies conditional on expectations (or quality) on users' side are in Table 4.5. To obtain those expression, we derive and solve the first order conditions (FOC) of the previous optimization program, Eq. 4.1. Given the symmetry of the model, the optimal price strategies on developers' side are.

$$T_1(n_1^e, n_2^e) = \frac{2n_1^e(n_1^e - n_2^e)}{4n_1^e - n_2^e} \quad T_2(n_1^e, n_2^e) = \frac{n_2^e(n_1^e - n_2^e)}{4n_1^e - n_2^e} \quad (4.2)$$

However, in the case with direct network effects and responsive beliefs, the maximization problem considered is

$$\begin{aligned} & \underset{T_j, n_j}{Max} \\ & n_j v_j(n_1, n_2) + T_j m_j(T_1, T_2) \end{aligned} \quad (4.3)$$

In this case, the optimal strategy on users' side is to set prices that lead to the following demands $n_1 = 0.636$ and $n_2 = 0.243$. Replacing those demands in T_1 and T_2 allows us to derive the optimal prices (Table 4.6), and equilibrium payoffs (Table 4.7) in this case¹³. Lastly, we solve the models with passive beliefs by replacing the optimal price strategies in the demands, and then, solving the system of demand equations assuming $m_j^e = m_j$ and $n_j^e = n_j$. Straightforward computation yields the other columns of Table 4.6.

¹³Note that the optimal strategy on developers' side is the same than in Table 4.5.

Table 4.6: Platforms' Prices. Vertically Differentiated Duopoly

Pure two-sided	Exogenous quality level	Direct network effects	
$v_1 = 0.1633$ $v_2 = 0.0408$ $T_1 = 0.1633$ $T_2 = 0.0408$	$v_1 = \frac{2s_1[s_1-s_2]}{4s_1-s_2}$ $v_2 = \frac{s_2[s_1-s_2]}{4s_1-s_2}$ $T_1 = \frac{4s_1}{7(4s_1-s_2)}$ $T_2 = \frac{s_1}{7(4s_1-s_2)}$	Passive beliefs $v_1 = 0.1633$ $v_2 = 0.0408$ $T_1 = 0.1633$ $T_2 = 0.0408$	Rational beliefs $v_1 = 0.173$ $v_2 = 0.03$ $T_1 = 0.217$ $T_2 = 0.042$

Table 4.7: Platforms' Payoffs. Vertically Differentiated Duopoly

Pure two-sided	Exogenous quality level	Direct network effects	
$\pi_1 = 0.1866$ $\pi_2 = 0.0233$	$\pi_1 = \frac{4s_1^2[s_1-s_2]}{(4s_1-s_2)^2} + \frac{16s_1}{49(4s_1-s_2)}$ $\pi_2 = \frac{s_1s_2[s_1-s_2]}{(4s_1-s_2)^2} + \frac{2s_1}{49(4s_1-s_2)}$	Passive beliefs $\pi_1 = 0.1866$ $\pi_2 = 0.0233$	Rational beliefs $\pi_1 = 0.23$ $\pi_2 = 0.019$

Depending on what exogenous quality levels we assume, profits range from 0 (when $s_1 = s_2$) to 0.1866 (when $s_1 = 1$; $s_2 = 0.5$)¹⁴. However, payoffs in the exogenous case depend on the difference between quality levels and only differences higher than 0.5 between quality levels lead to larger profits for both companies than the profits pointed out before, but those cases were ruled out by our assumptions. Nonetheless, the equilibria of Table 4.7 are not the only ones. As it is pointed out by Gabszewicz and Wauthy (2004), in the pure two-sided model there are other two equilibria: the Bertrand equilibrium and the “dominant platform”¹⁵, in which one company monopolizes the market by setting a zero price on one side and setting the monopoly price on the other side. However, both platforms have this incentive, and if both of them deviate, they end in a Bertrand equilibrium. So, this threat may avoid any deviation¹⁶.

Nonetheless, in the exogenous quality case is different, if there is symmetry between

¹⁴If we assume that a platform has a quality level close to zero, the monopoly can be an equilibrium.

¹⁵See Gabszewicz and Wauthy (2004) for a definition of these concepts.

¹⁶Although we have assumed $n_1^e > n_2^e$ and $m_1^e > m_2^e$, this assumption does not limit the Bertrand equilibrium. The assumption of rational expectations implies that, if company 2 sets $v_2 = 0$ (and company 1 sets a positive price), at equilibrium, all users realize that company 2 is cheaper, and they will “expect” all users changing to company 2. Initially, one platform may have a larger expected demand but, at equilibrium, users correctly predict the demands. If there is a deviation, there is a change in the demands (and expectations) at equilibrium. That is what we observe here that was also found by Gabszewicz and Wauthy (2004).

platforms, platforms will reach a Bertrand equilibrium but, if there is an asymmetry between platforms, the presence of heterogeneity guarantees that the interior equilibrium is an equilibrium. However, the “dominant platform equilibrium” may appear when the leader has a low “quality”. For example, at $s_1 = 0.5$, the leader has an incentive to fix $v_1 = 0$, which leads to $n_1 = m_1 = T_1 = 0.5$, and $\pi_1 = 0.25$.¹⁷

When we consider the case with direct network effects and passive beliefs, both equilibria, the dominant one and the Bertrand equilibrium, are possible. Nonetheless, the dominant platform equilibrium is only possible if the subsidized side is the users’. We can rule out the case in which developers are subsidized because there is no indirect network effect on users’ side. Lastly, if we consider the case with responsive beliefs, there are two interior equilibria. One in which the company 2 is active, and another one in which it is not. In this second case, the monopoly is possible without needing to set a zero price on users’ side because, in this equilibrium, the follower platform has no users’ base, but it is active. However, the other equilibrium is the one depicted in Table 4.6 and 4.7 in which both companies have positive demands.

Nonetheless, the dominant platform equilibrium and the Bertrand equilibrium cannot be ruled out. In the first case, because a deviation towards $v_j = 0$ is profitable. It will lead to the monopoly equilibrium but also, the other company can do the same, which may lead to a Bertrand equilibrium.

Lemma 4. *In a vertically differentiated duopoly with singlehoming agents, the set of Nash equilibria with respect to prices is*

- *The quadruples of Table 4.6, which define the interior equilibrium in which both companies enjoy positive profits, as in Gabszewicz and Wauthy (2004).*
- *The dominant platform equilibrium, or monopolist equilibrium*
- *The Bertrand equilibrium $v^* = T^* = 0$*

¹⁷This result implies a convergence toward the monopoly case. In that sense, the s -value of Table 4.3 can be considered as a measure of the difference in qualities between the duopolists. Only if $s > 0.2464$, this deviation is not profitable.

It is not possible to rule out the dominant and Bertrand equilibria, only in the exogenous quality case under specific parameter values. **In vertically differentiated two-sided markets, monopolies are possible.**

Proposition 5. *In a vertically differentiated duopoly with singlehoming agents, without data sharing agreements and with qualities endogenously determined by agents on platforms, a “winner-takes-all-the-market” outcome is likely to arise given that a deviation from the asymmetric interior equilibrium is profitable for the leader. However, the follower is indifferent between staying or leaving the market, so a Bertrand equilibrium is also possible.*

The intuition of this theorem is the following. **When what really matters is the bulk number of users, platforms have an incentive to give for free the product to users and set a positive price on developers’ side.** Because developers value the number of users, they will coordinate themselves on the largest platform. Therefore, **developers unconsciously support the creation of monopolies.** However, we cannot reject the possibility of competition between platforms. In that sense, if platforms are capable of perfectly dividing the market, developers will be indifferent between the two, and two platforms may coexist but profits will be zero. Nonetheless, these results are not true when users only value the quality of the device, in that case, both platforms may coexist, but at least one platform earns positive profits.

Vertical Differentiation. Data sharing among Platforms

In the previous case, we have assumed that platforms can only take into account the users in their networks. However, in real markets, some platforms also consider users that are not their customers. One illustrative example are MyFitnessPal users. Some of those users are wearing a wearable such as Fitbit or Garmin, and both companies have their own platforms. However, both platforms are compatible with MyFitnessPal, and all users have the chance of exporting all his/her data to the other platforms. In other words, users can be on two or more platforms at the same time.

Although sometimes they cannot transfer all the information, a question arises. *Why do platforms allow users to do that? Is there an economic incentive?* Let's extend our previous model to address this new feature.

Suppose that platforms allow their consumers to access to a proportion ρ_j , $j = 1, 2$, $\rho \in [0, 1]$ of competitor's network throughout their own network¹⁸. This is the case of some digital platforms such as Fitbit, Garmin or Under Armour that allow users to import/export data from other platforms. In this sense, the network considered by developers is composed of the original users of one platform plus a proportion of the users of the other platform. Therefore, we assume that the expected network size of any platform is given by the following expressions¹⁹

$$n_j^{(e,c)} = n_j^e + \rho_{-j}n_{-j}^e \quad m_j^{(e,c)} = m_j^e + \rho_{-j}m_{-j}^e$$

We derive the demands addressed to platforms considering these new network effects. Without loss of generality, we assume $n_1^{(e,c)} > n_2^{(e,c)}$ and $m_1^{(e,c)} > m_2^{(e,c)}$ (and $s_1 > s_2$ in the exogenous quality case). Replacing the new network effects in the utility functions, we derive the new users' demands.

- Users' Demand. Pure two-sided

$$n_1(v_j, m_j^e) = 1 - \frac{(v_1 - v_2)}{(1 - \rho_1)m_1^e - (1 - \rho_2)m_2^e}$$

$$n_2(v_j, m_j^e) = \frac{v_1(m_2^e + \rho_1 m_1^e) - v_2(m_1^e + \rho_2 m_2^e)}{(m_2^e + \rho_1 m_1^e)[(1 - \rho_1)m_1^e - (1 - \rho_2)m_2^e]}$$

- Users' Demand. Exogenous quality level

$$n_1(v_j, s_j) = 1 - (v_1 - v_2)/(s_1 - s_2)$$

$$n_2(v_j, m_j^e) = \frac{v_1 s_2 - v_2 s_1}{(s_2)(s_1 - s_2)}$$

¹⁸Companies are not the ones who access competitors' databases. It is the consumers. From companies' point of view, that implies they can offer more data to developers.

¹⁹This formulation is also adopted by Salim (2009) and Doganoglu and Wright (2006) when analyzing compatibility.

- Users' Demand. Direct network effects

$$n_1(v_j, n_j^e) = 1 - \frac{(v_1 - v_2)}{(1 - \rho_1)n_1^e - (1 - \rho_2)n_2^e}$$

$$n_2(v_j, n_j^e) = \frac{v_1(n_2^e + \rho_1 n_1^e) - v_2(n_1^e + \rho_2 n_2^e)}{(n_2^e + \rho_1 n_1^e)[(1 - \rho_1)n_1^e - (1 - \rho_2)n_2^e]}$$

Symmetrically, developers' demands are

$$m_1(T_j, n_j^e) = 1 - \frac{T_1 - T_2}{(1 - \rho_1)n_1^e - (1 - \rho_2)n_2^e} \quad m_2(T_j, n_j^e) = \frac{T_1(n_2^e + \rho_1 n_1^e) - T_2(n_1^e + \rho_2 n_2^e)}{(n_2^e + \rho_1 n_1^e)[(1 - \rho_1)n_1^e - (1 - \rho_2)n_2^e]}$$

Platforms simultaneously choose prices to maximize profits (Eq. 4.1). Taking the first order conditions of platform j with respect to v_j and T_j , and solving the corresponding system of equations, we obtain the optimal strategies conditional on expectations (or quality) on users' side.

- Optimal strategies conditional on expectations. Pure two-sided

$$v_1(m_1^e, m_2^e) = \frac{2[m_1^e + \rho_2 m_2^e][(1 - \rho_1)m_1^e - (1 - \rho_2)m_2^e]}{(4 - \rho_1)m_1^e - m_2^e(1 - 4\rho_2)}$$

$$v_2(m_1^e, m_2^e) = \frac{[m_2^e + \rho_1 m_1^e][(1 - \rho_1)m_1^e - (1 - \rho_2)m_2^e]}{(4 - \rho_1)m_1^e - m_2^e(1 - 4\rho_2)}$$

- Optimal strategies conditional on quality. Exogenous quality level

$$v_1(s_1, s_2) = [2s_1(s_1 - s_2)]/(4s_1 - s_2)$$

$$v_2(s_1, s_2) = [s_2(s_1 - s_2)]/(4s_1 - s_2)$$

- Optimal strategies conditional on expectations. Direct network effects

$$v_1(n_1^e, n_2^e) = \frac{2[n_1^e + \rho_2 n_2^e][(1 - \rho_1)n_1^e - (1 - \rho_2)n_2^e]}{(4 - \rho_1)n_1^e - n_2^e(1 - 4\rho_2)}$$

$$v_2(n_1^e, n_2^e) = \frac{[n_2^e + \rho_1 n_1^e][(1 - \rho_1)n_1^e - (1 - \rho_2)n_2^e]}{(4 - \rho_1)n_1^e - n_2^e(1 - 4\rho_2)}$$

Given the symmetry of the model, optimal strategies on developers' side are

$$T_1(n_1^e, n_2^e) = \frac{2[n_1^e + \rho_2 n_2^e][(1 - \rho_1)n_1^e - (1 - \rho_2)n_2^e]}{(4 - \rho_1)n_1^e - n_2^e(1 - 4\rho_2)} \quad (4.4)$$

$$T_2(n_1^e, n_2^e) = \frac{[n_2^e + \rho_1 n_1^e][(1 - \rho_1)n_1^e - (1 - \rho_2)n_2^e]}{(4 - \rho_1)n_1^e - n_2^e(1 - 4\rho_2)} \quad (4.5)$$

It worth pointing out that users' demand in the exogenous quality case does not depend on the sharing proportions (ρ_j). Nonetheless, as we see in the optimal strategies on developers' side, developers' prices (and demand) depend on those sharing proportions, so the total payoff will depend on the sharing proportions.

On the other hand, we solve the direct network externalities and responsive beliefs case as before. We assume that users are rational and they anticipate that their demand depends on their expectations. Therefore, we replace $n_j^e = n_j$, and fulfilled-expectations demand curves are

$$v_1(n_1, n_2) = (n_1 + \rho_2 n_2)(1 - n_1) - n_2(n_2 + \rho_1 n_1)$$

$$v_2(n_2, n_1) = (n_2 + \rho_1 n_1)(1 - n_1 - n_2)$$

Platforms simultaneously choose the demand level on users' side and the price level on developers' side to maximize profits (Eq. 4.3). Taking the first order conditions of platform j profits with respect to n_j and T_j , and solving the corresponding equations system, we obtain the equilibrium payoffs, Fig. 4-2²⁰. Lastly, we solve the case with passive beliefs. We replace the optimal price strategies in demands and then, we solve the system of equations assuming $m_j^e = m_j$ and $n_j^e = n_j$. Payoff functions depend on (ρ_j, ρ_{-j}) and they tend to have a complex expression. For simplicity's sake, we depict them in Fig. 4-1. Nonetheless, their analytical expressions are in the Annex.

The case with data sharing agreements is a generalization of the previous one. When $(\rho_1, \rho_2) = (0, 0)$, this model converges to the case without data sharing agree-

²⁰The equilibrium payoffs have a non-intuitive expression. To obtain a clear insight, we represent the equilibrium payoff in tridimensional graphs. In the Annex, we show how to compute the equilibrium for the case in which $(\rho_1, \rho_2) = (0, 0)$. The computation of equilibria in other cases is similar.

Figure 4-1: Interior Equilibria. Vertically Differentiated Duopoly with Compatibility. Source: own

ments. However, when $(\rho_1, \rho_2) \neq (0, 0)$, we find new behaviors. An interesting point about data sharing agreements is that **the most preferred case is the one in which the follower platform shares its data with the leader, $(\rho_1, \rho_2) = (0, 1)$** . In this scenario, the differentiation (the difference between the network sizes) is higher, and profits are higher too. This case is preferred because, when there is no data sharing, $(\rho_1, \rho_2) = (0, 0)$, the differentiation is lower and lower are the profits. However, when the sharing is total and symmetrical, $(\rho_1, \rho_2) = (1, 1)$, platforms are not differentiated from developers' point of view. Therefore, the only equilibrium is the Bertrand equilibrium. On the other hand, the case in which $(\rho_1, \rho_2) = (1, 0)$ there is no interior equilibrium for the same reason. As a matter of fact, in this case, the equilibrium is the Bertrand's. The intuition is straightforward. If the leader shares its database alone, that mitigates all the differentiation between the companies. In that sense, the model converges to a Bertrand model²¹. The comparison between $(\rho_1, \rho_2) = (1, 0)$ and $(\rho_1, \rho_2) = (0, 1)$ is the most interesting one. In the first case, the

²¹A table with all of these values is in the Annex.

equilibrium is not stable, and platforms will converge to the Bertrand equilibrium. However, in the second case, no deviation is profitable, and the interior equilibrium is the only equilibrium.

In the case with exogenous qualities and $(\rho_1, \rho_2) = (1, 1)$, we can rule out the Bertrand equilibrium and the dominant platform equilibrium. If the leader fixes $v_1 = 0$ and tries to monopolize the market, given the data sharing agreements, platforms will not be differentiated from developers' point of view, in that sense, the Bertrand equilibrium is the only equilibrium on developers' side. Platforms anticipate this, and they prefer the interior equilibrium. However, if we consider $(\rho_1, \rho_2) = (1, 0)$, the interior equilibrium is not an equilibrium. As a matter of fact, platforms prefer to sell the product to users and give it for free on developers' side (because there is no differentiation, Bertrand equilibrium is the only equilibrium). On the other hand, if we consider $(\rho_1, \rho_2) = (0, 1)$, the interior equilibrium is the only equilibrium because no deviation is profitable.

When we consider direct network effects with passive beliefs, we observe that it is closely related to the pure two-sided case. In both cases, when $(\rho_1, \rho_2) = (1, 1)$, Bertrand's is the only equilibrium. Although the case when $(\rho_1, \rho_2) = (1, 0)$ seems to be different, it is not. The leader will prefer to play a Bertrand game and set prices at zero than to have negative profits. Lastly, in Fig. 4-2, we consider the case with

Figure 4-2: Interior Equilibria with Direct Network Effects and Active Beliefs. Vertically Differentiated Duopoly with Compatibility. Source: own

responsive beliefs and direct network effects. In this case, there are two potential

equilibria. Nonetheless, in both cases, there is a parameter region for ρ_1 and ρ_2 in which no solution exists in the real numbers, those cases are the blank spaces. Although, when ρ_1 is less than 0.5, the 1st equilibrium seems to be the only equilibrium (in this case, there are no blank spaces). Only the 2nd equilibrium is valid.

The reason is that in the 1st equilibrium, the demand on users' side is negative, and that is impossible. However, profits are positive, that happens because there are developers who enter the platform expecting users there. In this equilibrium, the assumption of rational expectation is violated. Developers enter the platform expecting users that are not there. So, this outcome cannot be an equilibrium. However, in the 2nd equilibrium, the demands are positive, and the expectations of both, users (with direct network effects) and developers (with indirect network effects) are fulfilled²².

On the other hand, either with responsive or passive beliefs, the Bertrand equilibrium is the only equilibrium if $(\rho_1, \rho_2) = (1, 0)$. In contrast, if $(\rho_1, \rho_2) = (0, 1)$, the interior equilibrium is the only equilibrium because there is no profitable deviation.

Proposition 6. *In a vertically differentiated duopoly with singlehoming agents and with data sharing agreements (compatibility in databases):*

- *Platforms are better-off when the follower platform shares its data than in the case without data sharing. The interior equilibrium is the only equilibrium of all cases if the follower is the only one who shares its database*
- *A market without data sharing at all is preferred by all players than one with total sharing of databases*
- *If the leader is the only one who shares its database, the only equilibrium is the Bertrand equilibrium*
- *Only in the exogenous quality model and the model with direct network effects and responsive beliefs, the interior equilibrium is a profitable equilibrium if there is a total sharing of databases*

²²This case is solved in the Annex for illustration purposes. Also, the equilibrium depicted in Table 4.7 is the same than in the 2nd equilibrium in Fig. 4-2 when $(\rho_1, \rho_2) = (0, 0)$.

All cases share a common feature, the $(\rho_1, \rho_2) = (1, 0)$ case leads to the Bertrand equilibrium. However, given that platforms are indifferent between being active or not, the monopoly case may arise. This is a relevant issue because **the market may jump to the extreme cases of monopoly or Bertrand competition**. Nonetheless, what we observe in reality is monopolies, such as Facebook, Instagram, Google or LinkedIn. **Open data initiatives or open Application Programming Interfaces (APIs) may be locking in some markets**. Big companies will be interested in importing data from small companies to keep their dominant positions. **Nonetheless, small players would be interested in sharing their databases. This movement can accelerate the ecosystem around an emerging new product**. For example, Garmin and Under Armour did it. Some years ago, they offered open and free APIs. But once they became relevant players and the market started to grow, they fixed a fee for developers. On the other hand, the case with exogenous qualities represents the situation in which users only value the device (as it may be the case for some users in the wearable market). This case is the only one in which a total share of databases could be profitable because a high-quality device is profitable by itself, so data can be offered free of charge to developers because the profitable item is the device. Lastly, these results could be interesting for antitrust analysis. **When the follower opens its network to the leader, it increases the differentiation between the two. Therefore, it may lead to the creation of segmented monopolies**. One platform for users, and another platform for developers, but both platforms linked by network effects. This behavior may be in a grey area of regulation because it cannot be considered as a merger, collusion or a price pact.

Insights, Limits and Contributions of the Vertical Differentiation Model

This model has allowed us to have a first insight about the role of data sharing agreements (compatibility) among platforms but also, the role of different network effects (direct, indirect or exogenous) in services in which the number of users is what matters. In this sense, we have obtained interesting answers to some of our questions.

We have found that, without data sharing agreements, the asymmetric interior equilibrium coexists with the dominant platform equilibrium. This result points out **the excessive incentive towards concentration in vertically differentiated two-sided markets**, but we do not know yet whether this is a common feature of all the platforms markets or only a feature of vertically differentiated ones. In other words, **multi-sided markets at risk of data commoditization are prone to monopolization**.

When we consider that platforms may allow users to export their data, we find that the most preferred case for all companies is the one in which the follower platform shares its data with the leader. On the other hand, the less preferred case is the one in which the leader shares its database. From a strategic perspective, these results imply that platforms have incentives to share their data when they consider they are not leaders of a vertically differentiated market. A follower will always want to share their data with their competitor to maximize the differentiation between them. In other words, **there are clear incentives to become compatible, it increases profits because it increases differentiation**.

Lastly, in the cases with direct network effects, platforms with more market power prefer responsive users, in contrast with Hagiu and Halaburda (2014). However, in our model, we assume vertically differentiated users and direct network effects, and Hagiu and Halaburda assume horizontally differentiated users and indirect network effects. In comparison, feedback loops in our model tend to benefit the one with the initial advantage, and with responsive beliefs, those loops are stronger than with passive beliefs. This result highlights the relevance of choosing the correct and adequate theoretical model to study a market, wrong conclusions may lead to wrong decisions that may weaken the position of digital platforms in their markets.

As a summary, compatibility may increase prices because it can increase differentiation. This compatibility may lead to platform monopolies in which one platform controls the devices, and another one controls the data. This analysis does not cover all possible cases of data sharing in two-sided markets. We do not know to what extent these results are also common in horizontally differentiated markets (in which

the brands are relevant). In other words, we do not know yet to what extent these results are robust to other frameworks.

4.3.2 Horizontal Differentiation. The role of Subjective Tastes and its distribution

The horizontal differentiation is the other side of the coin. In this Section, we modify the previous model to include the horizontal differentiation. In other words, users are not only driven by the quality of the products or the number of users in the platform but also, by subjective features, such as the interface and the user experience. To capture these new ideas, we assume the Hotelling quality-augmented framework, that is the most common framework to deal with horizontal differentiation in the Industrial Organization literature.

In this section, we are interested in the role of the subjective tastes so, for simplicity's sake and without loss of generality, we assume users are only interested in the quality of the product or platform, but developers are interested in the number of users using that product or platform²³. The intuition is the following. Platforms sell devices that capture data from the users that can be sold to other companies interested in such data. For example, sports companies may be interested in sports trends (intensity, duration, or type of activity) because that information may be useful to make decisions about a new product, or even developers can use that data to build new services on these platforms.

Users' and Developers' behavior in Horizontally Differentiated Markets

- **Users:** We assume there is a mass of potential consumers n that is normalized to 1. To consume a platform, the utility they receive on that platform must be non-negative. The utility of a user i consuming the platform j is $U_{i,j} = c^u + \theta_i s_j - v_j - t^u |l_j - x_i|$. We consider users are differentiated in two

²³In this way, we reduce the complexity of the model but, we keep the two-sidedness. On the other hand, in this case, assuming different users' expectations is not so relevant as before because the role of expectations is mitigated. For that reason, we do not take them into account here.

uncorrelated dimensions, the vertical one ($\theta_i \sim U[0, 1]$)²⁴ and the horizontal one ($x_i \sim U[0, 1]$)²⁵. Users face a transportation cost (t^u). The intuition of this parameter is the following: The distance between products and users in that interval can be interpreted as a “cost” because users have to go from their positions (that represents their ideal product) to companies’ positions (that represents the position of the real product). Therefore, the term that controls the horizontal differentiation is $t^u * |l_j - x_i|$. To guarantee that all consumers buy at least one platform, theoretical models assume that all consumers have an identical (and sufficiently high) reservation value, c^u , that we also assume. Lastly, each user pays the same price for entering the platform, v_j . This behavior is the standard in the literature, see Belleflamme and Peitz (2015), Armstrong (2006), or Salim (2009).

- **Developers:** We assume there is a mass of potential developers m that is normalized to 1. To consume a platform, the utility they receive on that platform must be non-negative. The utility of the developer i consuming the platform j is $\pi_{i,j} = c^d + \delta_i C_j(n_j^e(v_1, v_2)) - T_j - t^f |l_j - x_i|$. We consider that developers are also horizontally differentiated. The intuition is the same than before. However, developers face different transportation costs. In other words, the differentiation could be other than the one on users’ side. We also assume an identical (and sufficiently high) reservation value, c^d and a common price for all developers, T_j . Nonetheless, we assume that developers value the presence of users on the platform, but we do not know how exactly, $C_j(n_j^e(v_1, v_2))$. We only know that, the higher the number the users, the more valued are the platforms, $\frac{\partial C_j(\cdot)}{\partial n_j^e} > 0$ ²⁶. In contrast with the previous model, we assume responsive beliefs because this time is feasible.

- **Platforms:** They sell two products in two markets that we describe as “users’

²⁴The interpretation of s_j is the same than in the previous model. θ represents how much the user value the quality/functionalities provided by the platform.

²⁵This assumption is essential. It allows us to consider the previous case but, without changing the conclusions that we would obtain in a purely horizontally differentiated case.

²⁶Nonetheless, we assume this parameter is also normalized to 1.

market” and “developers’ market”. We assume both, users and developers, pay an access fee for entering the platform. The platforms maximize their profits by setting prices on both sides. We denote by v_j the price paid by users and by T_j the price paid by developers on platform j . Nonetheless, in contrast with the previous section, we assume that providing the service to users has a cost that represents the cost of selling a device. Formally: $\Pi_j = T_j M(T_1, T_2) + (v_j - c_j)n(v_1, v_2)$; $j = 1, 2$ Lastly, we assume that both platforms are at the extremes of the Hotelling segment ($l_j \in [0, 1]$) on both markets. See Armstrong (2006), Hagiu (2004), Choi (2010), or Doganoglu and Wright (2006).

During our discussion, we have made several assumptions. However, we need another assumption to guarantee the stability and tractability of this model. We assume $c^u \geq \frac{3}{2}t^u$; $c^f \geq \frac{3}{2}t^f$. This assumption ensures the total participation of users and developers. Armstrong and Wright (2007) or Salim (2009) make a similar assumption. Without it, the interpretation of our results becomes more difficult. We also assume that the parameters t^u and t^f are big enough to guarantee that there is only one equilibrium, and it is the one pointed out by the FOC. In this sense, we assume $|v_2 - v_1| + |s_2 - s_1/2| < t^u$ and a similar condition on developers’ side.

The role of Horizontal Differentiation

Let’s assume platforms compete in prices to attract users and developers. We assume agents singlehome, and they choose the platform that maximizes their utilities if and only if that utility is non-negative. Formally

$$B \equiv \{(\theta_i, x_i); c^u + \theta_i s_j - t^u |l_j - x_i| - v_j \geq c^u + \theta_i s_{-j} - t^u |l_{-j} - x_i| - v_{-j} \geq 0\}$$

Following Weyl (2010), we can define users’ demand in platform j as $n_j(v_j, v_{-j}) = \int \int_B f(\theta_i x_i) \partial x_i \partial \theta_i$. The intuition of this framework is the following. In the fitness tracker market, there are devices with different designs and qualities, and people value them differently. Some people love specific designs (subjective taste) but, these people may not be the same than those who love the “sleep monitoring” features (objective

feature). What is interesting about this approach is that users are in a bidimensional world and not in a unidimensional one. Therefore, the demands in this framework are

$$n_1(v_1, v_2) = \int_0^1 \int_0^{\tilde{X}_j} f(\theta, x) \partial x \partial \theta = 1/2 + \frac{s_1 - s_2}{4t^u} + \frac{v_2 - v_1}{2t^u} \quad (4.6)$$

$$n_2(v_2, v_1) = \int_0^1 \int_{\tilde{X}_j}^1 f(\theta, x) \partial x \partial \theta = 1/2 + \frac{s_2 - s_1}{4t^u} + \frac{v_1 - v_2}{2t^u} \quad (4.7)$$

Where $\tilde{X}_j$ is the marginal user in this framework²⁷. If we compare these demands with the demands of a classical Hotelling two-sided market, we observe that this demand is smaller because of the bidimensional differentiation.

Figure 4-3: Marginal User ($\tilde{X}_j$). Adopters of Platforms 1 (blue) and 2 (green). Horizontally Differentiated Model. Source: own

In Fig. 4-3, we depict the market situation. On the X-axis, we represent the horizontal differentiation, and on the Y-axis, we represent the vertical one. The black area represents those who quit the market because of the vertical differentiation. The blue and green areas represent the demands addressed to platforms. The white area

²⁷We do not depict developers' demands because they are symmetric.

represents those who are more prone to abandon the market because of the horizontal differentiation²⁸.

Considering these users' and developers' demands, we derive the optimal prices conditional on expectations assuming that platforms choose prices simultaneously, as we did in the previous section²⁹.

$$T_1^* = t^f + \frac{C_1(n_1^e(\cdot)) - C_2(n_2^e(\cdot))}{6} \quad T_2^* = t^f + \frac{C_2(n_2^e(\cdot)) - C_1(n_1^e(\cdot))}{6} \quad (4.8)$$

$$v_1^* = t^u + \frac{s_1 - s_2}{6} + \frac{2c_1 + c_2}{3} - \left(1/4 + \frac{C_1(\cdot) - C_2(\cdot)}{72t^f}\right) \left(\frac{\partial C_1(\cdot)}{\partial n_1^e(\cdot)} + \frac{\partial C_2(\cdot)}{\partial n_2^e(\cdot)}\right) \quad (4.9)$$

$$v_2^* = t^u + \frac{s_2 - s_1}{6} + \frac{2c_2 + c_1}{3} - \left(1/4 + \frac{C_2(\cdot) - C_1(\cdot)}{72t^f}\right) \left(\frac{\partial C_1(\cdot)}{\partial n_1^e(\cdot)} + \frac{\partial C_2(\cdot)}{\partial n_2^e(\cdot)}\right) \quad (4.10)$$

Prices are quite different in this model. In the previous section, prices depend on the differences in qualities between the platforms (See Table 4.5). In this new model, this effect is not the only one. There are other effects such as the relative difference in marginal cost ($\frac{2c_j + c_{-j}}{3}$), or the degree of differentiation of the market (t^u). But the most relevant difference is that, there is an incentive to reduce prices on users' side because of the externality they create on developers' side. This effect is a consequence of both, the horizontal differentiation and the responsive beliefs. They create a connection between prices on users' side and the developers' demand. Without such connection, users' prices would be disconnected from developers' demand, as in the previous model (See Table 4.5).

Lemma 7. *The degree of differentiation in horizontally-differentiated two-sided markets impacts on prices directly, in contrast with vertically-differentiated markets, where the distribution of the heterogeneity is what matters.*

Only in a pure two-sided market, in which the price on one side depends on the expected demand on the other side, the link between prices on both sides can be observed. But, if one side values exogenous quality levels, this link is weaker.

²⁸Nonetheless, we have assumed full participation, so the black and white areas do not exist in our model. We consider them for illustrative purposes.

²⁹At these points, the Hessian matrix is negative semi-definite.

Nonetheless, the responsive beliefs, *ceteris paribus*, enhance this linkage.

Lemma 8. *Responsive beliefs are essential in creating stronger links between the sides.*

Although we have assumed an orthogonal bidimensional differentiation, our conclusions are robust in a unidimensional model. In fact, the Equations 4.8, 4.9 and 4.10 are roughly the same. The only difference is in some denominators³⁰.

If we solve the model, we observe the equilibrium demands only emphasize the previous insights about difference the between the models again. In this sense, let's test how the introduction of compatibility between platforms affects the structure of the market.

$$M_j^* = 1/2 + \frac{C_j(\cdot) - C_{-j}(\cdot)}{12t^f}$$

$$n_j^* = 1/2 + \frac{s_j - s_{-j}}{12t^u} + \frac{c_{-j} - c_j}{6t^u} + \left(\frac{C_j(\cdot) - C_{-j}(\cdot)}{72t^f t^u} \right) \left(\frac{\partial C_1(\cdot)}{\partial n_1(\cdot)} + \frac{\partial C_2(\cdot)}{\partial n_2(\cdot)} \right)$$

Horizontal Differentiation and Compatibility

To know the real effects of compatibility in digital platform markets, we need to consider the case of the horizontally differentiated markets. This Section complements Section 4.3.1, in which we address the impact of compatibility in a vertically differentiated two-sided market. We follow the same scheme, and we consider asymmetric and partial compatibility. The intuition is the same than before. Platforms have access to competitor's databases but, they may or may not have access to all the data, e.g. legal boundaries. For example, the Withings body scale is compatible with Fitbit platform but, the Fitbit platform is not compatible with the Withings platform directly³¹.

Formally, we use the same definition of compatibility than in Section 4.3.1, $n_j^{(e,c)} = n_j^e + \rho_{-j} n_{-j}^e$. However, for simplicity's sake, in this model, we only focus on the case in which one side has indirect network effects and the other one value an exogenously

³⁰See Salim (2009) or Hagiu and Halaburda (2014).

³¹Indirectly, Fitbit platform is compatible with Withings platform, but the Withing platform is not directly compatible with Fitbit's.

fixed quality level. Later on, we relax this assumption. Additionally, developers in this model consider $C_j(n_j^e(v_1, v_2))$. But if we take into account the compatibility, that expression is $\overline{C}_j(n_j^{(e,c)}(v_1, v_2)) = \overline{C}_j(\cdot)$.

In this framework, users' demands will be the same than before. However, there is a small change in developers' demands. This behavior is common to both models, the vertical differentiated one and the horizontally differentiated one. If we consider the previous change in developers' utilities, and we solve the model again, the new prices conditional on expectations are³²

$$T_1^* = t^f + \frac{\overline{C}_1(\cdot) - \overline{C}_2(\cdot)}{6} \quad T_2^* = t^f + \frac{\overline{C}_2(\cdot) - \overline{C}_1(\cdot)}{6} \quad (4.11)$$

$$v_j^* = t^u + \frac{s_j - s_{-j}}{6} + \frac{2c_j + c_{-j}}{3} - \left(1/4 + \frac{\overline{C}_j(\cdot) - \overline{C}_{-j}(\cdot)}{72t^f}\right) \left(\frac{\partial \overline{C}_1(\cdot)}{\partial n_1^e(\cdot)} + \frac{\partial \overline{C}_2(\cdot)}{\partial n_2^e(\cdot)} - \rho_2 \frac{\partial \overline{C}_1(\cdot)}{\partial n_2^e(\cdot)} - \rho_1 \frac{\partial \overline{C}_2(\cdot)}{\partial n_1^e(\cdot)}\right) \quad (4.12)$$

We observe that between Eq. 4.8 and Eq. 4.11 there are no big differences. The only difference is how developers address the new externalities. However, if we compare Eq. 4.9 and 4.10 with Eq. 4.12, it is clear that there is a big difference in how externalities influence prices. **We find that the competition is more intense in the incompatible case.** This result is common to the previous Section, and we have evidence to believe that it is a robust result. However, our results prove that compatibility does not necessarily lead to a one-sided equilibrium, as it is pointed out by Salim (2009) or Doganoglu and Wright (2006). In fact, our results highlight that the one-sided equilibrium may only be reached if there are symmetric externalities and full compatibility³³.

This result contrasts with the exogenous quality case in Section 4.3.1, in which prices on users' side were not influenced by the compatibility. However, in this case, we find the opposite as a consequence of both, the horizontal differentiation and the responsive beliefs. However, if we pay attention to the prices on developers' side, the price is influenced by the compatibility in both cases. But there is an important

³²Hessian matrix is negative semi-definite.

³³If $\frac{\partial \overline{C}_1(\cdot)}{\partial n_1^e(\cdot)} + \frac{\partial \overline{C}_2(\cdot)}{\partial n_2^e(\cdot)} - \rho_2 \frac{\partial \overline{C}_1(\cdot)}{\partial n_2^e(\cdot)} - \rho_1 \frac{\partial \overline{C}_2(\cdot)}{\partial n_1^e(\cdot)} = 0$.

difference, in the vertically differentiated market, prices can be less or equal to the one in the incompatible case³⁴. Nonetheless, the way compatibility influences both prices is totally different.

Lemma 9. *In horizontal differentiated two-sided markets, compatibility reduces the price competition. In a vertically differentiated market, it may not happen if compatibility is exogenously fixed but, if companies can choose the degree of compatibility, they will choose the configuration that mitigates price competition.*

If we solve the optimal demands, it is clear that the expressions of developers' demands are similar, but we have to change $C_j(\cdot)$ by $\overline{C}_j(\cdot)$. The users' demands also change, but that change only affects the externality term that changes from $\left(\frac{C_j(\cdot) - C_{-j}(\cdot)}{72t^f t^u}\right) \left(\frac{\partial C_1(\cdot)}{\partial n_1(\cdot)} + \frac{\partial C_2(\cdot)}{\partial n_2(\cdot)}\right)$ to $\left(\frac{\overline{C}_j(\cdot) - \overline{C}_{-j}(\cdot)}{72t^f t^u}\right) \left(\frac{\partial \overline{C}_1(\cdot)}{\partial n_1(\cdot)} + \frac{\partial \overline{C}_2(\cdot)}{\partial n_2(\cdot)} - \rho_2 \frac{\partial \overline{C}_1(\cdot)}{\partial n_2^e(\cdot)} - \rho_1 \frac{\partial \overline{C}_2(\cdot)}{\partial n_1^e(\cdot)}\right)$. In the horizontally differentiated market, we observe that compatibility monotonically leads to an outcome that is closer to the equilibrium of a market without any network externality (the one-sided Hotelling equilibrium). However, that equilibrium can only be reached if full-symmetric compatibility is assumed among all the platforms in the market.

Lemma 10. *In the horizontally differentiated case, compatibility does not necessarily lead to one-sided equilibria. But in contrast with a vertically differentiated market, any increase in compatibility monotonically leads to an equilibrium that is closer to the one-sided Hotelling equilibrium.*

However, an interesting contrast between both models is the following. In the vertically differentiated market, full compatibility leads to the Bertrand equilibrium but, in the horizontally differentiated one, it leads to the Hotelling equilibrium³⁵. The compatibility affects both models in a different way. **In the vertically differentiated model, the leader has no incentive to share data with the follower but, in the horizontally differentiated case, that incentive exists.** Because of the

³⁴For example, when $(\rho_1, \rho_2) = (1, 1)$ or $(\rho_1, \rho_2) = (1, 0)$. Nonetheless, the most preferred case by platforms is $(\rho_1, \rho_2) = (0, 1)$, in which prices increase.

³⁵It exists the possibility of the Hotelling equilibrium converging to the Bertrand one. However, we rule out such possibility here, which is an extreme case of the Hotelling framework.

horizontal differentiation, being the leader or follower is not so relevant, and survival is easier. In this sense, an interesting result is that the winner-takes-all outcome is less likely this time.

Lemma 11. *In a vertically differentiated multi-sided market, platforms prefer an asymmetric compatibility scheme in which the follower shares all the data with the leader but the leader shares nothing. In contrast, in a horizontally differentiated multi-sided market, platforms prefer a full-symmetric compatibility scheme.*

In the horizontally differentiated market, full compatibility increases the users' base of both platforms and their value for developers. In contrast, in a vertically differentiated market, full compatibility increases the users' base but, it makes the platforms less differentiated. In this sense, it is essential for platforms to differentiate themselves from competitors in subjective dimensions such as the graphical user interface (GUI), in that way, having the same users on both platforms is not a handicap.

Proposition 12. *Vertically and horizontally differentiated multi-sided platforms have two essential differences:*

1. *Platforms can easily survive if they are horizontally differentiated. The winner-takes-all outcome can be avoided with horizontal differentiation. In a vertically differentiated market, there are incentives to create monopolies on different sides of the market*
2. *In horizontally differentiated multi-sided markets, full compatibility is desired by all players. Nonetheless, in vertically differentiated multi-sided markets, all the players want asymmetric compatibility schemes*

A similar conclusion is pointed out by Jullien (2005) who states that: *Differentiated intermediaries may soften competition by sharing their information and allowing their customers to access the competitors' networks.*

Platforms have an incentive to create compatibility networks in horizontally differentiated markets. In our model, for example, platforms can increase

their profits by setting high prices on users' side because there is no need to subsidize users to attract developers. Both platforms share the same users' base. This result explains why in the fitness tracker market is so common to find compatibility agreements among platforms. Nonetheless, compatibility may generate other two effects:

1. It may attract competitors because of the higher profits. In that sense, the incumbent platforms have more incentives to try to deter the entry.
2. It may create de facto monopolies if the horizontal differentiation is too low.

Compatibility has to be carefully handled by public authorities because it may have the opposite result of what is intended, (to promote competition in markets and increase the consumers' welfare). To deal with this issue, let's analyze whether or not compatibility increases the incumbents' incentives to deter entry.

Extension: Addressing the Entry of a Third Competitor

The previous model proves that, **in horizontally differentiated multi-sided markets, compatibility leads to higher prices and profits**. Prices can even converge to the equilibrium prices of a classical one-sided Hotelling model if we assume full compatibility among all the platforms. However, the previous model relies on a closed-market framework with only two platforms. In this section, we keep the assumption of horizontal differentiation, but we adopt a Salop's model to consider the entrance of a third platform³⁶. The idea is to prove whether or not compatibility increases the incentives to deter entry. In Section 4.3.2, we prove that the inclusion of an orthogonal dimension does not provide us with more insights than a pure horizontally differentiated multi-sided market³⁷. In this sense, for simplicity's sake and without loss of generality, we assume that $\theta = \delta = 1$. We also assume there are three platforms (Fig. 4-4). To consider a situation in which two platforms are established and a third one is trying to enter the market, we assume platforms have an exogenous position.

³⁶The Salop's model is a modification of the Hotelling model. In the Hotelling model, we assume consumers are distributed in a line. In the Salop model, they are distributed in a circle.

³⁷See Equation 4.6 and 4.7, and compare them with the ones derived by Salim (2009).

Figure 4-4: Salop's Circle. Positions of Platforms. Horizontally Differentiated Model

As it is depicted in Fig. 4-4, Platform 1 and Platform 2 are at the points 0 and $1/2$ respectively, and the third one is at $1/4$.

This assumption represents the idea that incumbents cannot easily change their brands (their positions)³⁸. Platforms do not accommodate their position to the new entrant. This assumption is essential. If we assume platforms change their positions to accommodate the new entrant, it is more difficult to prove whether or not there are incentives to deter entry that come from compatibility but also, it less realistic in the short run. Changing a brand takes time. First of all, let's consider the case when there are only two platforms (platforms 1 and 2) that are totally compatible. Following Salop (1979), we define demands as follows³⁹.

$$n_j(v_j, v_{-j}) = 2\widetilde{X}_u = \frac{s_j - s_{-j} + v_{-j} - v_j}{t^u} + 1/2$$

$$m_j(T_j, T_{-j}) = 2\widetilde{X}_f = \frac{C_j(\cdot) - C_{-j}(\cdot) + T_{-j} - T_j}{t^f} + 1/2$$

³⁸The optimum is to be at $1/3$ one another.

³⁹In this model, we have to assume that $c^u \geq \frac{3}{4}t^u$; $c^f \geq \frac{3}{4}t^f$ to guarantee the total participation of all users and developers.

Where $\widetilde{X}_u$ and $\widetilde{X}_f$ are the marginal agents in the users' and developers' markets. Assuming that both platforms set prices simultaneously, the optimal prices are⁴⁰.

$$T_j^* = \frac{t^f}{2} + \frac{C_j(\cdot) - C_{-j}(\cdot)}{3}$$

$$v_j^* = \frac{t^u}{2} + \frac{2c_j + c_{-j}}{3} + \frac{s_j - s_{-j}}{3}$$

We have assumed that they are totally compatible. Therefore, we obtain that the optimal prices are the same than in a model without network externalities. As in the previous Section, the full and symmetric compatibility mitigates the subsidizing incentive. In this case, the equilibrium demands are

$$m_j^* = 1/2 + \frac{C_j(\cdot) - C_{-j}(\cdot)}{3t^f}$$

$$n_j^* = 1/2 + \frac{c_{-j} - c_j + s_j - s_{-j}}{3t^u}$$

The equilibrium prices, demands, and profits are the same than in a one-sided market or a market without network externalities. **Platforms mitigate the competition because of the compatibility.** It does not matter who attract whom. Both platforms are part of the same shared network of users. In this situation, let's consider that a third platform enters the market. We assume the entrant is not different in terms of size and technology. However, we assume it is not compatible with the incumbents. We have assumed that platforms do not change their position, so the entrant is established at the maximum distance of the incumbents at 1/4,(Fig. 4-4). The new demands are

$$n_j(v_j, v_{-j}, v_3) = \widetilde{X}_u + \widetilde{X}_{3,u} = \frac{s_j - v_j}{t^u} + \frac{v_{-j} - s_{-j} + v_3 - s_3}{2t^u} + 3/8$$

$$n_3(v_j, v_{-j}, v_3) = 2\widetilde{X}_{3,u} = \frac{s_3 - v_3}{t^u} + \frac{v_{-j} - s_{-j} + v_j - s_j}{2t^u} + 2/8 \quad (4.13)$$

$$m_j(T_j, T_{-j}, T_3) = \widetilde{X}_f + \widetilde{X}_{3,f} = \frac{C_j(\cdot) - T_j}{t^f} + \frac{T_{-j} - C_{-j}(\cdot) + T_3 - C_3(\cdot)}{2t^f} + \frac{3}{8}$$

$$m_3(T_j, T_{-j}, T_3) = 2\widetilde{X}_{3,f} = \frac{C_3(\cdot) - T_3}{t^f} + \frac{T_j - C_j(\cdot) + T_{-j} - C_{-j}(\cdot)}{2t^f} + \frac{2}{8} \quad (4.14)$$

⁴⁰Hessian matrix is negative semi-definite.

We consider that $j = 1, 2$ are the incumbents, and $j = 3$ is the entrant. Our assumption of large switching costs implies that the position of the three companies is suboptimal. That makes sense when platforms have invested resources in positioning themselves in the market. Therefore, the demand addressed to Platform 3 is lower than the demands addressed to the other two platforms. Considering these new demands, we can solve the model again.

$$\begin{aligned} T_j^* &= \frac{2C_j(\cdot) - C_{-j}(\cdot) - C_3(\cdot)}{5} + \frac{7t^f}{20} \\ T_3^* &= \frac{2C_3(\cdot) - C_{-j}(\cdot) - C_j(\cdot)}{5} + \frac{6t^f}{20} \end{aligned} \quad (4.15)$$

$$\begin{aligned} v_j^* &= \frac{7t^u}{20} + \frac{2s_j - s_{-j} - s_3}{5} + \frac{3c_j + c_{-j} + c_3}{5} - \frac{3}{5t^f} \left(T_j^* \varepsilon_j + \frac{T_{-j}^* \varepsilon_{-j} + T_3^* \varepsilon_3}{3} \right) \\ v_3^* &= \frac{6t^u}{20} + \frac{2s_3 - s_{-j} - s_j}{5} + \frac{3c_3 + c_{-j} + c_j}{5} - \frac{3}{5t^f} \left(T_3^* \varepsilon_3 + \frac{T_{-j}^* \varepsilon_{-j} + T_j^* \varepsilon_j}{3} \right) \end{aligned} \quad (4.16)$$

A relevant term in these prices is the externality (ε), specially in the Eq. 4.16. This term stands for

$$\varepsilon_j = \frac{\partial C_j(\cdot)}{\partial n_j^e(\cdot)} - \frac{\partial C_j(\cdot)}{\partial n_{-j}^e(\cdot)} + \frac{1}{2} \left(\frac{\partial C_{-j}(\cdot)}{\partial n_{-j}^e(\cdot)} - \frac{\partial C_{-j}(\cdot)}{\partial n_j^e(\cdot)} + \frac{\partial C_3(\cdot)}{\partial n_3^e(\cdot)} \right) \quad (4.17)$$

$$\varepsilon_3 = \frac{\partial C_3(\cdot)}{\partial n_3^e(\cdot)} + \frac{1}{2} \left(\frac{\partial C_{-j}(\cdot)}{\partial n_{-j}^e(\cdot)} + \frac{\partial C_j(\cdot)}{\partial n_j^e(\cdot)} \right) \quad (4.18)$$

The entrance of the third platform has disrupted the market. This third company is not compatible with the other two so, the new optimal prices have to take into account that there are new network externalities. In this situation, the incumbents have incentives to reduce prices to attract users to their networks. They have to compete with the entrant, and with each other although their shared network mitigates this competition. This model points out that we only need an incompatible company to increase the competition.

Lemma 13. *A new entrant in the market can increase the competition in two ways:*

- *By reducing the level of differentiation among companies in the market*
- *By mitigating the relevance of the network effects derived from compatibility agreements among incumbents*

The demands also reflect this situation, compare Eq. 4.13 and 4.14 with Eq. 4.19 and 4.20. On developers' side, compatibility provides an advantage to the compatible platforms at the expense of the incompatible one. However, on users' side, compatible platforms are less willing to compete, but the presence of the third platform forces them to compete. Obviously, this competition erodes the profits of the compatible platforms in comparison with the case of total compatibility and, especially, with the full compatible duopoly.

$$\begin{aligned} n_j(v_j, v_{-j}, v_3) &= \frac{14}{40} + \frac{2s_j - s_{-j} - s_3 - 2c_j + c_{-j} + c_3}{5t^u} + \frac{2}{5t^u t^f} (T_j^* \varepsilon_j - T_{-j}^* \varepsilon_{-j} - T_3^* \varepsilon_3) \\ n_3(v_j, v_{-j}, v_3) &= \frac{12}{40} + \frac{2s_3 - s_{-j} - s_j - 2c_3 + c_{-j} + c_j}{5t^u} + \frac{2}{5t^u t^f} (T_3^* \varepsilon_3 - T_{-j}^* \varepsilon_{-j} - T_j^* \varepsilon_j) \end{aligned} \quad (4.19)$$

$$\begin{aligned} m_j(T_j, T_{-j}, T_3) &= \frac{2C_j(\cdot) - C_{-j}(\cdot) - C_3(\cdot)}{5t^f} + \frac{14}{20} \\ m_3(T_j, T_{-j}, T_3) &= \frac{2C_3(\cdot) - C_{-j}(\cdot) - C_j(\cdot)}{5t^f} + \frac{12}{20} \end{aligned} \quad (4.20)$$

Platforms earn more profits in the duopoly case, so they have an incentive to deter entry. Platforms will be individually willing to sacrifice the difference between the profits in the duopoly and the profits in the case with three platforms to deter the entry⁴¹. But, if compatibility is considered, profits in the duopoly case are higher, and therefore, higher is the incentive to deter entry.

Lemma 14. *Compatible platforms have more incentives to block the entrance of a new entrant than incompatible platforms.*

This conclusion requires the next condition to be true $\Pi_2^c - \Pi_2^{nc} > \Pi_3^c - \Pi_3^{nc}$, where the subscripts c and nc stand for the compatibility and non-compatibility cases. This condition can be rewritten as $\Pi_2^c + \Pi_3^c > \Pi_3^{nc} + \Pi_2^{nc}$. That implies that profits of platforms in a duopoly market are higher than in an oligopoly with three platforms, and the difference in profits is higher when platforms are fully compatible. This is a reasonable assumption because, with full compatibility, platforms set one-sided market prices, but when they are not compatible, platforms compete harder to attract some agents. Compatibility creates incentives to deter entry because profits are higher.

⁴¹We acknowledge that there is a problem of coordination. Who should sacrifice their profits? However, we do not want to focus the discussion on the coordination problem but, on the existing incentives to deter entry.

This feature would explain why, in fitness trackers markets, incumbents like Fitbit, Withings or Jawbone try to deter entry by introducing new brands. In fact, if we consider that the third platform is a secondary brand of one of the incumbents, it is clear that this strategy is profitable, especially when transportation costs are high. But even if they are not high enough, it may be a profitable strategy in comparison with competing with a third company. Platforms prefer to compete in markets with less differentiation (three brands and two platforms) rather than in markets less differentiated and with more competitors (three platforms). In that sense, **it may be optimal to deter entry by launching new brands.**

Let's assume the platform $-j$ launches a new brand that is represented by the previous third platform. In this situation, and with the assumption of full compatibility between the platforms, we have that the optimal prices and demands are

$$\begin{aligned} T_j^* &= \frac{11t^f}{24} + \frac{C_j(\cdot) - C_{-j}(\cdot)}{3} & T_{-j}^* &= \frac{13t^f}{24} + \frac{C_{-j}(\cdot) - C_j(\cdot)}{3} \\ v_j^* &= \frac{11t^u}{24} + \frac{2c_j + c_{-j}}{3} + \frac{s_j - s_{-j}}{3} & v_{-j}^* &= \frac{13t^u}{24} + \frac{2c_{-j} + c_j}{3} + \frac{s_{-j} - s_j}{3} \end{aligned} \quad (4.21)$$

$$\begin{aligned} M_j^* &= \frac{11}{24} + \frac{C_j(\cdot) - C_{-j}(\cdot)}{3t^f} & M_{-j}^* &= \frac{13}{24} + \frac{C_{-j}(\cdot) - C_j(\cdot)}{3t^f} \\ n_j^* &= \frac{11}{24} + \frac{c_{-j} - c_j + s_j - s_{-j}}{3t^u} & n_{-j}^* &= \frac{13}{24} + \frac{c_j - c_{-j} + s_{-j} - s_j}{3t^u} \end{aligned} \quad (4.22)$$

In comparison with the symmetric duopoly, the platform that launches a new brand increases its profits on all sides. If platforms can launch different brands in highly differentiated markets, it is optimal to be the first one in launching new brands. This strategy has two consequences. On the one hand, it increases profits. On the other hand, it makes more difficult the entry of a new competitor. This explains why, in fitness tracker markets, incumbent platforms tend to launch new products from time to time. In fact, brand expansion is a good strategy to deter entry. On the other hand, **if the entry cannot be blocked, this model points out that the best strategy is to become compatible with the new entrant.** In fact, this increase in compatibility among platforms is what we observe in the market.

Lemma 15. *When the market is highly differentiated, platforms can launch new brands with the idea of foreclosing that market or expanding its business.*

Proposition 16. *A new entrant can increase the competition in the market by reducing the differentiation and the network effects of the compatible incumbents. In that sense, incumbents have incentives to deter entry. Nonetheless, they face prisoner dilemma.*

- *They have incentives to deter entry by being the first one in launching new brands. It will increase their profits at the expense of other competitors*
- *But if the competitors do the same, profits will be lower because of the increase in competition*

Insights, Limits and Contributions of the Horizontally Differentiated Market

This model complements the one presented in Section 4.3.1, and it allows us to have a complete picture that answers the questions regarding pricing and differentiation in digital platform markets.

We have found that, as in traditional models, the degree of horizontal differentiation impacts directly on prices. In these markets, it is easy to decompose the influence of differentiation in prices. However, in contrast with vertically differentiated platforms, we have found that compatibility always reduces the competition. Even symmetric compatibility leads to higher prices and profits. The opposite was true in vertically differentiated platforms. That implies that **it is easy to sustain a duopoly in a horizontally differentiated market than in a vertically differentiated one.** Nonetheless, **platforms have incentives to differentiated themselves horizontally because it increases their profits, it reduces competition, and it guarantees survival.** And on top of that, they have a great incentive to become fully compatible, because they can mitigate the competition and reduce the incentives to subsidize one side.

This incentive to become compatible and to reduce subsidies has risen a concern, may it create incentives to deter entry? We addressed this issue too, and we have found that new entrants threat the status quo of the incumbents, and therefore, **incum-**

bents have larger incentives to deter entry than in traditional markets or in incompatible multi-sided markets. In that sense, platforms have incentives to launch new brands from time to time because it may foreclose niche markets to entrants, and it improves their position with respect to other competitors.

As a summary, **compatibility reduces competition and increases profits**. Differentiation is essential. The consequences of vertical and horizontal differentiation in pricing are different as well as the role of compatibility. Nonetheless, the increase in profits as consequence of compatibility raises our concerns about the creation of incentives to foreclose the markets. However, the commoditization of data may help in introducing competitiveness in the market. In the next section, we address this issue.

4.3.3 The Relevance of Differentiation. A Homogeneous World

In previous Sections, we have argued that the differentiation is essential for platforms. However, we have not pointed out what happens if companies have to face a commoditized market, a market without differentiation. Although we have had a glimpse in Section 4.3.1, we did not address this case in-depth. In the last decade, we have observed some platforms trying to imitate the success of competitors by copying them. A clear example is Tuenti in Spain, a social network that until 2016 was a competing with Facebook⁴², they copied many features of Facebook such as the instant messaging application or the games. They reduced the differentiation with the big player, and as a consequence, Tuenti was expelled from the market.

This is not the only case, the digital economy is full of examples of big players that have expelled many companies out of the market. In many of those cases, it was a low level of differentiation the reason because there is only one big company in the market at the end⁴³. For example, we observe this pattern in social networks. There are social networks for friends (Facebook), for research purposes (Researchgate), for

⁴²<https://www.elconfidencial.com/tecnologia/2016-02-01/tuenti-cerrara-su-red-social-sus-20-millones-1141970/>

⁴³There are other reasons that are consequences of the low level of differentiation, such as strong network effects, the first-mover-takes-all-the-market, etc.

Table 4.8: Users' Utilities and Marginal Users. Vertically Differentiated Model. Homogeneous Framework

Users' Utilities	$U_{i,j} = \theta_i s_j - v_j$
Marginal user between platforms	$\tilde{\theta} = \frac{v_j - v_{-j}}{s_j - s_{-j}}$
Marginal user of the market	$\hat{\theta} = \frac{v_{-j}}{s_{-j}}$

professional issues (LinkedIn), etc. All of them have expelled other competitors. In this section, we address the risks of a commoditized market and how platforms can survive in it.

This issue is especially relevant in digital platform markets because platforms tend to consider that investing in differentiation in one side is enough to guarantee the survival. In the wearable market, there are companies that make profits by selling devices to users and data to developers. However, they sell data as a commoditized item. This situation raises a concern, to what extent may the homogeneity in the data influence other markets, such as the users market? or more specifically, how important is the homogeneity of data for platforms and its competitors?

Competition between Homogeneous Platforms

We assume that users behave as in Section 4.2 and 4.3.1. They are vertically differentiated. We can also consider the horizontal differentiation, but conclusions do not change. In this framework, we have two different marginal users, the one indifferent between consuming both platforms ($\hat{\theta}$), and the one indifferent between consuming and not consuming at all ($\bar{\theta}$). Without loss of generality, we assume that the plat-

Figure 4-5: Distribution of Users and Marginal Users. Vertically Differentiated Model. Homogeneous Framework

form $j = 1$ covers the blue segment (high-quality platform) and the platform $j = 2$ covers the pink one (low-quality platform). On the other hand, to reproduce the ho-

homogeneity in data, developers are differentiated by their intrinsic values (δ_i), but all of them value the same the data provided by platforms. The utility of developer i is $\pi_{i,j} = \delta_i - T_j + C(n_j)$. Developers are heterogeneous with respect to the market itself, but once in the market, they value the same the product offered by both platforms. If a platform can attract the developer with $\delta_i = 0$, that platform will attract the rest of developers. Obviously, the marginal developer between the platforms cannot be identified as easy as before. In this case, it will be the set of developers who verified the following condition $T_j - T_{-j} = C(n_j) - C(n_{-j})$. If we define $\Omega_i = C(n_j) - T_j$ as the developers' surplus when they consume platform j , it is easy to prove that the demands are similar to those of the Bertrand model⁴⁴.

$$M(T_j, T_{-j}) = \begin{cases} M(T) & , if \ \Omega_j > \Omega_{-j} \\ M(T)/2 & , if \ \Omega_j = \Omega_{-j} \\ 0 & , if \ \Omega_j < \Omega_{-j} \end{cases} \quad (4.23)$$

Following our example, developers can consider that it does not matter who offers the data because the information may be similar. For example, the difference in the running metrics of Garmin users or Fitbit users may not differ too much.

We assume each platform maximizes their profits with respect to T_j and v_j . Because there is no network effect on users' side, when platforms choose the price on developers' side, they behave like one-sided platforms. In other words, they only consider that side. However, when platforms set the prices on users' side, they have to take into account both sides because the number of users influences the developers' adoption. This feature is the same that we find in Sections 4.2 and 4.3.1. We also keep the assumption of responsive beliefs in this Section because it does not create the problems we described in Section 4.3.1.

Nonetheless, the assumption of homogeneity on developers' side creates a relevant issue. The demand is not continuous. We cannot derive the FOC to address this case as before. This is an extreme case, but it illustrates that when differentiation is low, the market can suffer big changes. Lastly, without loss of generality, we assume that

⁴⁴We assume the marginal consumer between the platforms verifies $\Omega_i \geq 0$

marginal costs are normalized to zero and they are symmetric.

Let's address the differences in how platforms make decisions in this framework in comparison with the previous ones. If we consider the developers' side, although the demand is not continuous, it is the set of strategies (prices). In this scenario, platforms compete harder than in any other case because the winner-takes-all. Developers choose the platform that provides them the highest utility. In other words, they will choose the platform that verifies $\Omega_j > \Omega_{-j}$. However, that parameter depends on both, the developer prices and the users demand. There are three possible prices (higher, equal or lower) and two companies. In total, there are nine possibilities. Three of them consider $C_1 = C_2$, but only one of them is feasible. When $T_1 = T_2 = 0$. It is important to highlight that $T_j = T_{-j} > 0$ is not feasible because of the Bertrand competition, there will always be an incentive to reduce prices. We have other six cases that are symmetric, three by three.

1. $\Omega_j < \Omega_{-j}$
2. $\Omega_j > \Omega_{-j}$
3. $\Omega_j = \Omega_{-j}$

In the first two cases, there is at least one platform that has incentives to reduce prices and to move towards the third case. But the third case may be not the equilibrium. It will be an equilibrium if and only if the prices are zero⁴⁵. In that case, they create the maximum incentive to attract developers but without becoming unprofitable. However, there may be another equilibrium. If $T_{-j} = 0$ and $C_j > C_{-j}$, then the platform j will set the price $T_j \approx C_j - C_{-j}$. In this case, the platform j will become a monopoly, and it will keep those prices to avoid others entering the market.

Lemma 17. *When the product sold to customers with indirect network effects is homogeneous (developers demanding data), the only optimal pricing is to set zero prices if there is total symmetry. If not, the leader sets a price that is the difference between its added-value and competitors', or zero otherwise.*

⁴⁵This is only true in the framework with marginal costs normalized to zero.

On the other hand, because of the indirect network effects and the null differentiation on developers' side, changes in prices on the users' side create discontinuities in the developers' demand. A small change in users' prices may represent a small change in users demand, but a big change in developers demand. The prices on this side play a bigger role than in previous models because of the extreme competition on developers' side. However, in this case, the challenge is that we cannot use calculus to derive the equilibrium prices as in Sections 4.2 and 4.3 because the profits function is discontinuous on users' side. The Bertrand competition on developers' side creates that discontinuity. To solve this model, we have to use the Bertrand intuition⁴⁶.

Although we do not know the specific expression of the optimal users' prices, we know they encompass two terms, the classical one-sided term, and the network externality term because of the influence of users on developers' side. Before addressing the optimal price level, it is interesting to study how those non-continuous externalities may influence the prices on users' side. We know from the previous sections that the net effect of the externalities in prices depends on the relative difference between the network effects of each platform, so two cases are possible. $C_j(n) = C_{-j}(n)$ or $C_j(n) > C_{-j}(n)$. In the first case, the symmetry implies that the externality term will be zero⁴⁷. However, the second case is the interesting one. For simplicity's sake and without loss of generality, we assume $C_1(n) > C_2(n)$ ⁴⁸. If we assume $v_1 = v_2$, it is direct to prove that $n_1 = n$ and $n_2 = 0$, where n is the monopoly demand. In this case, the platform 2 has an incentive to reduce the price (if it is positive) to that point in which both platforms can coexist with non-negative profits (if it exists that case, if not, we will have the previous case in which $v_1 > v_2 = 0$, and $n_1 = n$). If both

⁴⁶See Tirole and Matutes (1990).

⁴⁷This also may imply that this market will converge to the Bertrand equilibrium. If network sizes are equal, it is because platforms are symmetric on users' side, or users are indifferent between the two. In other words, the symmetry of the platforms on users' side leads us to this result.

⁴⁸We also assume $s_1 > s_2$. It makes no sense the opposite because better data cannot be obtained with worse devices. The framework we use is based on a vertical differentiation scheme, so there is no reason to prefer the worse device at the same prices.

platforms can coexist, the demands will be

$$\begin{aligned} n_1 &= 1 - \frac{v_1 - v_2}{s_1 - s_2} \\ n_2 &= \frac{v_1 - v_2}{s_1 - s_2} - \frac{v_2}{s_2} \end{aligned}$$

To guarantee that the platform 2 has the incentive to reduce prices, we need to assume the following condition, $\frac{v_1}{s_1} \geq \frac{v_2}{s_2}$. In other words, the marginal agent between the platform 1 and 2 has a θ -value that is higher than the marginal user of the market. By definition, this condition is fulfilled. Let's consider for a moment the equilibrium prices of the users' side only ($\Pi_k = v_k n_k$). In such case, we can derive the equilibrium prices and demands using the FOC⁴⁹.

$$\begin{aligned} v_1^* &= \frac{(s_1 - s_2)2s_1}{4s_1 - s_2} \\ v_2^* &= \frac{(s_1 - s_2)s_2}{4s_1 - s_2} \end{aligned} \tag{4.24}$$

In this case, $v_1 > v_2$, and it is optimal. However, up to now, we have neglected any relationship with the developers' side. If we again observe the demands functions, those demands do not consider the impact on developer' side. Also, the profits function does not consider the developer' side. If we consider it, the immediate concern is the following. If we reduce prices, that will increase the users' demand, and that may increase $C(\cdot)$, which may increase profits.

To address this concern, we have to consider the effect of a change in users' prices on developers' side. In this case, we can state that this effect is continuous. The effect of C_k on M_k is not continuous, but we can assume that C_k is continuous and twice differentiable with respect to n_k . Although this effect is continuous, profits are not. So, we need again to use the Bertrand intuition to address the optimal prices. Let's consider the incentives to change prices. For that purpose, let's consider the optimal profits of the users' side only.

$$\begin{aligned} \Pi_1^* &= (s_1 - s_2) \left(\frac{2s_1}{4s_1 - s_2} \right)^2 \\ \Pi_2^* &= (s_1 - s_2) \frac{s_1 s_2}{(4s_1 - s_2)^2} \end{aligned} \tag{4.25}$$

⁴⁹This will correspond to the case in which externalities are symmetric and equal.

Our starting point is the following. In this situation, $n_1 > n_2$, and therefore $C_1 > C_2$. So, it makes sense to assume $\Omega_1 > \Omega_2$. In this case, the profits will be $\Pi_1 = \Pi_1^* + T_k M_k$ and $\Pi_2 = \Pi_2^*$. Has platform 2 incentives to reduce the users' price?

If we consider that the platform 2 sets a price $v_2^{(\epsilon)} = \frac{(s_1 - s_2)s_2}{4s_1 - s_2} - \epsilon$, where ϵ is a small but positive number. It is clear that this reduction implies losing profits on users' side. However, this reduction of profits implies an increase in n_2 that may lead to $C_2 > C_1$ and to conquer the developers' market. This reduction leads to an increase in the demand $(\frac{\epsilon s_1}{(s_1 - s_2)s_2})$ and to a reduction of profits on users' side $(\frac{\epsilon^2 s_1}{(s_1 - s_2)s_2})$. The platform 2 has incentives to reduce their prices if and only if $T_2 M_2 \geq \frac{\epsilon^2 s_1}{(s_1 - s_2)s_2}$. In other words, the earnings from the developers' market have to be larger than the losses from the users' side. If this decision is profitable for the platform 2, the platform 1 will again consider if it is profitable to reduce the users' price to avoid platform 2 entering the developers' market. We have two platforms trying to capture the whole market, as in a Bertrand model. As it happens in the Bertrand model, platforms will reduce prices up to the point in which one platform is indifferent between the earnings from developers' side and the losses from users' side.

In this situation, it is direct to prove that the platform 1 sets a price $v_1 = v_1^* - \epsilon$, where $\epsilon = \sqrt{(s_1 - s_2)T_1 M_1}$. Setting that price, platform 1 deters the entry of platform 2 in the developers' market.

Therefore, two equilibria are possible. It depends on how sensitive are C_1 and C_2 to n_1 and n_2 . If the initial condition $C_1 > C_2$ is sensitive to demands, platforms will compete until one of them (or both) dissipates profits. But, if the condition is insensitive, and demands cannot change that relationship. Then, platform 1 and platform 2 will compete on users' side softly, and platform 1 will monopolize developers' side.

Proposition 18. *Multi-sided platforms that sell commoditized data may earn positive profits. If network effects are sensitive to changes in prices on users' side, platforms compete hard for users in order to capture the developers' market (data market). However, if the network effects are relatively insensitive to changes in prices on users' side, that may imply the possibility of monopolizing the commoditized side (monopoly of data).*

Compatibility in an Homogeneous Market

We can also address the impact of compatibility in this market. Let's assume full compatibility. Formally: $C_j(n = n_1 + n_2)$. In this case, platforms cannot use users to compete for developers. They share the same users' base. Therefore, platform 1 monopolizes the developers' market, and both platforms compete on users' side *à la one-sided* (Eq. 4.24) because of the initial assumption $C_1 > C_2$. Nonetheless, if we assume this time $C_1 = C_2$. Then, platforms compete *à la Bertrand* in the developers' market, and they set the one-sided prices on users' side (Eq. 4.24).

However, we can assume that this compatibility is neither total nor symmetric. We can assume $C_j(n_j^c = n_j + \rho_j n_{-j})$. This case is only an intermediate case between full compatibility and total incompatibility. This new variable, ρ_j , is a parameter that reduces the differentiation between platforms on developers' side. Nonetheless, if $\rho_j > \rho_{-j}$, this asymmetry may benefit one platform over the other. In this sense, partial compatibility ($\rho_j \neq 0$) only mitigates the competition of platforms partially. The full compatibility and the incompatibility cases are the extreme cases. In between, there is an infinite set of cases that are out of the scope of this work.

Proposition 19. *In commoditized markets, the competition is mitigated by shared databases or compatibility in databases. Platforms have a dominant strategy of setting shared databases.*

4.3.4 A generalized Multi-sided Market with Unidimensional Heterogeneity

In the previous sections, we have pointed out the role of the vertical and horizontal differentiation but also, the role of the non-differentiation. To test to robustness of those results, we develop a generalized model that encompasses all the duopoly models presented in the previous sections as well as all the compatibility models that are available in the literature. In this model, we consider a generalization of the competition to any arbitrary number of platforms, users, or developers as well as any arbitrary number of compatibility relationships.

The model comprises three classes of agents: users, developers, and platforms. Users (developers) can interact with developers (users) and platforms. Platforms are intermediaries that enable the interactions between the two groups.

Let's assume the utility of a user i consuming the platform k depends on the prices on the users' side (V_k) and on individual features (θ_i) such that $U_{i,k} = U(V_k, \theta_i)$. Users choose the platform that maximizes their utilities, if and only if the utility is non-negative. Thus, users who choose the same platform k will form the demand for that platform k . Formally⁵⁰

$$D_k(V, \theta) = \sum_{\forall i \in A} i, \text{ where } A \equiv \{(V, \theta_i); \quad U_{i,k} \geq 0, \quad U_{i,k} \geq \max(U_{i,-k})\}$$

In a similar way, the profit of a developer j on a platform k depends on the prices on developers' side (T_k), on individual features (δ_j), and on the technical features of the platform (that are related to the number of users on the platform), $C_k(D_k(\cdot))$ such that $\Pi_{j,k} = \Pi(T_k, \delta_j, C_k)$. Developers choose the platform that maximizes their profits, if and only if the profit is non-negative. Thus, developers who choose the same platform k will form the demand for that platform k . Formally:

$$G_k(T, \delta, C) = \sum_{\forall j \in B} j, \text{ where } B \equiv \{(T, \delta_j, C); \quad \Pi_{j,k} \geq 0, \quad \Pi_{j,k} \geq \max(\Pi_{j,-k})\}$$

In both cases, we assume demands are continuous and differentiable with respect to prices, and agents consume one platform only, i.e. agents singlehome.

Given the symmetry of the model, for simplicity's sake and without loss of generality, we assume one externality on developers' side only. This assumption does not change the conclusions but simplifies the exposition. Lastly, we consider platforms maximize their profits with respect to prices. Formally:

$$\max_{T_k, V_k} \pi_k = T_k * G_k + V_k * D_k - c_k(G_k, D_k) \quad (4.26)$$

⁵⁰We make a small change in the notation because it is necessary for this generalization.

$c_k(\cdot)$ denotes the twice continuously differentiable cost function. It is important that the first-order conditions represent the optimal allocation for platforms. In this sense, we can assume that the platform's profit function is concave, but some authors consider that this assumption is overly restrictive, Weyl (2010). Therefore, we assume log-concavity.

To rule out the multiplicity of equilibria, we assume the first-order conditions represent the unique global interior equilibrium, and agents are “sufficiently differentiated”. In that sense, deviations towards zero prices are not profitable, and platforms cannot monopolize a part of the market by giving the platform for free to one side⁵¹.

The model without compatibility nor shared data

Taking the first order conditions of the equation (4.26) with respect to prices we get the Lerner indexes⁵². On developers' side, the Lerner index is:

$$\frac{1}{|\varepsilon_{jj}^k|} = \frac{T_k - MC_k^d}{T_k} \quad (4.27)$$

$MC_k^d = \frac{\partial c_k(\cdot)}{\partial G_k}$ denotes the marginal cost of providing the service to developers, and $\varepsilon_{jj}^k = \frac{\partial G_k}{\partial T_k} \frac{T_k}{G_k}$ denotes the own-price elasticity of demand for the platform k on the developers' side. However, on the users' side, the Lerner index is more complex:

$$\frac{1}{|\varepsilon_{ii}^k|} - \frac{T_k}{V_k} \frac{\partial G_k}{\partial C_k} \frac{\partial C_k}{\partial D_k} = \frac{V_k - MC_k^u}{V_k} \quad (4.28)$$

$MC_k^u = \frac{\partial c_k(\cdot)}{\partial D_k} + \frac{\partial c_k(\cdot)}{\partial G_k} \frac{\partial G_k}{\partial D_k}$ denotes the marginal cost of providing the service on users' side. However, note that $\frac{\partial c_k(\cdot)}{\partial D_k}$ is the marginal cost of providing the service to users, and $\frac{\partial c_k(\cdot)}{\partial G_k} \frac{\partial G_k}{\partial D_k}$ is the extra marginal cost generated by developers that are attracted to the platform because of the larger number of users on the platform. Additionally, $\varepsilon_{ii}^k = \frac{\partial D_k}{\partial V_k} \frac{V_k}{D_k}$ represents the own-price elasticity of demand for the platform k on users' side.

⁵¹We acknowledge that the differentiation condition is rather vague. However, it cannot be described better without making further assumptions about the utility functions.

⁵²The Lerner index is a standard metric of market power in the Industrial Organization literature. It depicts a relationship between the mark-ups and the price-elasticity of demand. See Tirole and Matutes (1990) or Belleflamme and Peitz (2015)

side.

If shared networks among platforms are not allowed, the market power is lower than in a market without network effects (a one-sided market). The difference between a case with and without network effects is $\frac{T_k}{V_k} \frac{\partial G_k}{\partial C_k} \frac{\partial C_k}{\partial D_k}$, which is positive. So the Lerner Index is lower. The intuition is the following: Developers value the presence of users, and platforms need to attract developers and users. To do so, platforms reduce prices on users' side, and that decrease mitigates their market power on users' side⁵³.

The model with a network of compatibility

Let's assume that a set H of platforms make a sharing agreement. Those platforms can access a proportion ρ_k of her partners' networks. In this framework, $C_k^*(D_k + \rho_k \sum_{\forall l \neq k \in H} D_l(\cdot))$ represents the technical features of platform k . Therefore, if platform l shares her network with platform k , the number of users on platform l influences the developers' decisions on platform k .

On the one hand, the Lerner index on developers' side will have the same expression than in (4.27). However, this does not imply that the market power is unchanged, as a consequence of the increase of technical features from C_k to C_k^* , prices and market power on developers' side can be higher. On the other hand, the Lerner index on users' side will have a different expression:

$$\frac{1}{|\varepsilon_{ii}^k|} - \frac{T_k}{V_k} \frac{\partial G_k}{\partial C_k} \frac{\partial C_k}{\partial D_k} + \frac{T_k}{|\varepsilon_{ii}^k|} \frac{\partial G_k}{\partial C_k} \frac{1}{V_k * D_k} \left(\rho_k \sum_{\forall l \neq k \in H} \frac{\partial C_k}{\partial D_l} \varepsilon_{ii}^{k,l} * D_l \right) = \frac{V_k - MC_k^u}{V_k} \quad (4.29)$$

$\varepsilon_{ii}^{k,l} = \frac{\partial D_l}{\partial V_k} \frac{V_k}{D_l}$ denotes the cross-price elasticity of demand for the platform l with respect to the price fixed by platform k on users' side.

Proposition 20. *Sharing networks increases the market power of platforms in the agreement.*

Proof. In comparison with the case without agreements, the Lerner index has an extra element that represents the effect of shared networks in the market power. This

⁵³Because of the large number of users attracted, the market power may increase on developers' side. Developers will be willing to pay higher prices, and platforms may exploit this feature.

element is positive and is countervailing the effect of the two-sidedness in the market power. So this new term is increasing the market power. $\square$

In the case without shared networks, platforms set a low price on users' side to attract them because developers prefer platforms in which there are a lot of users. On the other hand, when platforms share their networks, developers can access users on other platforms through one platform. In this case, there is no need to set low prices on the users' side to attract them, and developers are willing to pay higher prices because they can find more users so, the market power of platforms increases. Additionally, the market power can increase in three ways: a) an increase in the rights to access to the competitors' networks (increases in ρ_k); b) the number of platforms in the agreement ; c) other individual features of platforms⁵⁴.

Proposition 21. *Sharing networks among platforms does not necessarily mitigate the subsidizing effect of the two-sided market totally.*

Proof. If we assume $\rho_k = 1$, we can prove that $\frac{T_k}{|\varepsilon_{ii}^k|} \frac{\partial G_k}{\partial C_k} \frac{1}{V_k * D_k} \left(\rho_k \sum_{\forall l \neq k \in H} \frac{\partial C_k}{\partial D_l} \varepsilon_{ii}^{k,l} * D_l \right)$ does not equal $\frac{T_k}{V_k} \frac{\partial G_k}{\partial C_k} \frac{\partial C_k}{\partial D_k}$ unless we make further assumptions. $\square$

The intuition is the following: if developers can get in contact with any user in other platforms, platforms have an incentive to set higher prices than when developers can only get in contact with a few platforms. However, unless we assume that every platform is in the agreement and developers can reach all users on any platform, there will be an incentive to try to attract some users by setting low prices.

Opening your network to competitors is common in the fitness tracker market. In Fig. 4-6 is depicted a network that represents the compatibility relationships among the databases of the relevant players in the fitness tracker ecosystem⁵⁵. The most connected player is Under Armour. As theory predicts, the professional access to their API is not free, however, some years ago it was free. Garmin is another example

⁵⁴There are other factors that influence the market power. However, we omit this part of the analysis because all those effects are positive. Therefore, they only increase the market power.

⁵⁵We only consider those companies which sell a fitness tracker. There are other players that influence the market such as Google Fit, Apple Health or Runkeeper, but they do not sell a fitness tracker with a complementary platform.

of this behavior. They have a one-time license fee of \$5000. Nonetheless, in 2014, it was completely free. However, other companies have open APIs because: a) fitness tracker is not the main line of business (as Nokia-Withings), or b) their ecosystems are not so vibrant as those of Garmin or Under Armour.⁵⁶

Figure 4-6: Relationships among Databases of Fitness Tracker Companies. Summer 2016. Source: own

Incentives to share data with competitors

Companies are interested in profitable strategies, so it makes sense to analyze the incentives of platforms to share their networks with competitors (third-party access). Let's consider the equilibrium profits of platforms when there is no sharing at all (π_k^{ns}) and when they can access their competitor's network (π_k^s). The difference between these two cases is the following: in the first case, the technical features of platforms are $C_k(D_k)$, in the second case, the technical features are $C_k^*(D_k + \rho_k \sum_{l \neq k \in H} D_l(\cdot))$. Thus, sharing networks can be profitable if, and only if, profits increase when the access to other platforms increases. Analytically: $\frac{\Delta \pi^*}{\Delta D_l} = \pi_k^s(C_k^*(\Delta D_l)) - \pi_k^{ns}(C_k(\cdot)) >$

⁵⁶Under Armour: <https://developer.underarmour.com/>, Garmin: <https://goo.gl/nLUw35> and <https://goo.gl/QkHfHu>

the increase in revenues is higher than the increase in costs⁵⁸.

Although this condition seems to support any non-costly third-party access, this is not always true. **In real markets, two barriers limit the widespread adoption of third-party access or compatibility.** On the one hand, **there are negotiation and coordination costs**, and the larger the companies or the networks, the larger those costs are. On the other hand, **the larger the network effects, the larger the incentive towards concentration in only one platform.** This effect implies that incumbents with big networks are less willing to grant access to their networks to new and small entrants because they may attract developers and may reduce incumbents profits. Sharing networks only make sense in markets where network effects are moderate and independent platforms have little market power because, in that way, they increase both, network effects and market power. For example, without sharing networks, the fitness tracker companies would be less attractive to developers, because there would be fewer potential users. But, if they share their networks, developers are attracted to platforms because they offer a large pool of users, and their market power increases.

However, in contrast with a merger in the Cournot model, even when only a subset of companies agrees on sharing networks, third-party access can be profitable. Sharing networks increases the network effects, so developers have a large willingness to pay, and platforms can exploit this characteristic to increase profits. An important difference between a merger in the Cournot model and shared access to networks in two-sided markets is the following: the merger in a Cournot model does not affect the consumers' utilities, but in a two-sided market consumers' utilities may vary because of the changes in network effects. Prices may increase because of a large willingness to pay and not because there are fewer players in the market.

In Fig. 4-7 we can observe the situation of the fitness tracker ecosystem in June 2017. The bold lines represent the new connections that have appeared between July 2016 and July 2017. We observe that nine new connections have appeared among

⁵⁸We can express inequality (4.30) as: $T_k^* G_k^* (\varepsilon_{T,C}^k + \varepsilon_{G,C}^k) > C_k^* (\Delta D_l) (\mu + \gamma)$. Where $\mu = \frac{\partial c_k}{\partial G_k} \frac{\partial G_k}{\partial C_k}$ and $\gamma = \frac{\partial F_{k,l}}{\partial D_l} \frac{1}{\rho_k (\partial C_k / \partial D_l)}$.

companies that benefit bilaterally from the third-party access.

Proposition 22. *Sharing of networks in two-sided markets can be profitable even if only a subset of companies agrees on sharing such networks. The increase in network effects can expand the market and offset the costs of coordinating platforms. If there are no costs and platforms are symmetric in size, shared access to networks is profitable for all companies.*

Comparison with the previous literature. What is new with regard to compatibility

Doganoglu and Wright (2006) and Salim (2009) show that prices converge to the equilibrium of a market without network effects. They assume that platforms grant full access to their networks and no side is subsidized, so the Lerner index is: $\frac{1}{|\varepsilon_{jj}^k|} = \frac{T_k - MC_k^d}{T_k}$. To obtain this expression in our framework, the following condition must be satisfied:

$$\frac{T_k}{|\varepsilon_{ii}^k|} \frac{\partial G_k}{\partial C_k} \frac{1}{V_k * D_k} \left(\rho_k \sum_{\forall l \neq k \in H} \frac{\partial C_k}{\partial D_l} \varepsilon_{ii}^{k,l} * D_l \right) = \frac{T_k}{V_k} \frac{\partial G_k}{\partial C_k} \frac{\partial C_k}{\partial D_k} \quad (4.31)$$

This condition requires the two-sided effect or the subsidy effect (the right-hand side) to be equal to the “shared networks” effect or the disincentive to subsidy the other side (the left-hand side). However, this expression can be simplified. Straightforward computation yields:

$$|\varepsilon_{ii}^k| * \varepsilon_{C,D}^k = \frac{1}{C_k} \left(\rho_k \sum_{\forall l \neq k \in H} \frac{\partial C_k}{\partial D_l} \varepsilon_{ii}^{k,l} * D_l \right) \quad (4.32)$$

$\varepsilon_{C,D}^k = \frac{\partial C_k}{\partial D_k} \frac{D_k}{C_k}$ denotes the elasticity of the technical features of the platform k with respect to the demand for the platform k .

Proposition 23. *Only if we assume total symmetry, full access to other networks, and constant values, we obtain the same conclusions than Doganoglu and Wright (2006) and Salim (2009).*

Proof. To obtain the same result than Doganoglu and Wright (2006) and Salim (2009),

we need to assume:

1. Full access to networks, $\rho_k = 1$
2. The benefit an agent enjoys from interacting with the opposite side is constant and equal for all platforms, $\frac{\partial C_k}{\partial D_l} = \frac{\partial C_k}{\partial D_k} = c$
3. The effect of prices in demands is symmetric, $\frac{\partial D_k}{\partial V_k} = \frac{\partial D_k}{\partial V_l} = c$

If we make those assumptions, the condition (4.32) is satisfied. To the best of our knowledge, there is no work in the two-sided market literature which does not consider the assumption 3. Also, the assumption 2 is common in the literature, although sometimes it is relaxed, see Weyl (2010). $\square$

Another interesting result is that **shared access to networks can lead to a larger market power** than in the cases predicted by Doganoglu and Wright (2006) or Salim (2009). The proof is trivial: the left-hand side has to be smaller than the right-hand side in Eq. 4.32. The market power could be higher because developers may value the presence of users a lot. In this way, platforms have no incentive to subsidize users. In fact, they may have an incentive to charge them higher prices. Although this may price out of the market some users, this effect can be offset by users in other networks.

Lastly, if we consider the inequality Eq. 4.30, we can obtain the conditions to guarantee the profitability of sharing networks in Doganoglu and Wright's and Salim's frameworks. In the case of Doganoglu and Wright (2006), they state that compatibility among networks is profitable if $\frac{\beta}{2} > F$. Where β denotes the value of the network benefits, and F denotes the cost of sharing networks. If we compare prices and demands with and without compatibility: $\frac{\partial T_k}{\partial C_k} G_k = \frac{\beta}{2}$ and $\gamma = F$. This is a particular case of the inequality (4.30). In the case of Salim (2009), no inequality represents the profitability of accessing to competitors' networks in her original work, but we can obtain such inequality from Eq. 4.30⁵⁹. As a summary, **profits are not**

⁵⁹We do not derive the expression because it will require explaining Salim's framework. However, the intuition is straightforward, if network effects are higher than differentiation effects, access to competitors' networks is profitable.

always larger when sharing networks. It depends on the assumptions we make about the utility functions and demands.

4.3.5 Limits and Issues out-of-the-scope of our Models

Reality is more complex than these models. For example, it is easy to confuse multihoming agents with data sharing agreements. In both cases, users get in touch with agents on several platforms. The difference is in how they get in touch. For example, Withings is a fitness tracker company that has partial access to Fitbit's network. A user can use a Fitbit device and later, he/she can use the Withings' platform. In this case, the user is not multihoming because he/she is using a device and a third-party platform, but he/she is not using both devices and both platforms at the same time. Fitbit is capturing the user's data because he/she is using a Fitbit device, but Withings can capture that data if and only if the user adopts the Withings' platform.

Another example but with direct network effects are the fitness apps. They focus on the social aspect of fitness, so having a big network is an important issue, which is the reason to allow cross-synchronization among platforms. One user of Endomondo can synchronize their data with MyFitnessPal, which avoid the need to use both platforms (multihoming). The user can adopt a platform for a while and then, he/she may change to the other one, but that user will carry all the information with him/her. However, from a technical point of view, he/she is still on both platforms. Additionally, many ways of accessing other platforms are available: third-party platforms, synchronizers, multihoming, etc. This heterogeneity implies that each particular analysis of these markets requires taking into account that several behaviors may coexist, and it requires an extra effort in isolating those behaviors to have a clear picture of their implications in the market outcome. In this work, we only consider one of those behaviors, the compatibility in databases. However, other behaviors could be interesting, but that is beyond the scope of this Thesis, and more importantly, we do not know to what extent those behaviors are relevant in the fitness tracker market nowadays.

Nonetheless, compatibility in databases has not been totally addressed, and some

questions remain open. To what extent antitrust practices may be disguised as data sharing agreements or compatibility agreements is unknown already. Users may have the opportunity of changing platforms without suffering many barriers. But this behavior may be creating big differences in other markets, such as the developer’s markets, in which some platforms may arise as “monopolies of data” and other may remain as “device monopolists”. However, we have no evidence that this is the case right now, and therefore, we have not considered it.

On the other hand, the models described in Section 4.3 allow us to deal with the pricing and expectations, the compatibility, and the differentiation. These models have answered the questions we laid out in Section 4.1. However, there is a set of questions that we are not able to answer with those models. We refer to the launching of platforms and the optimal pricing rule. In the following section, we address this concern by proposing a dynamic model to address the launching of a platform and the optimal pricing rule.

4.4 Dynamic Modeling. Addressing the Launching of a Digital Platform

In this Section, we propose an extension of the previous models to consider the different stages of a market (introduction, growth, and maturity). In the multi-sided platforms literature, there are good examples of dynamic models, but the most interesting one is Cabral (2011). This model proposes a dynamic multi-sided duopoly. However, we want to consider changes in the framework, such as the entry of a new competitor or the creation of a new market. In this sense, the easiest way to do that is to consider a dynamic game with several stages and sequential decision⁶⁰.

Sequential decision games allow us to have an idea of how companies or other players make decisions about the future when *the rules of the game* change. In that sense, they are useful to analyze possible reactions to new events before they happen. For

⁶⁰For a dynamic setting with continuous timing, see Cabral (2011), and Evans and Schmalensee (2010). See White and Weyl (2016) for a critic.

example, platforms may expect to sell data in the future, so maybe their pricing today is taking that into account, although they are not selling the data yet. How does that possible strategy influence prices today? What if they expect new competitors? And more importantly, *what is the optimal pricing policy of a platform for a successful launching?*

Many digital platforms (Facebook, eBay, Fitbit, etc.) are characterized by being small monopolies at the beginning. In the early stages, companies are so small that they only address the demand in small areas where they do not face direct competitors. However, when the market grows and the competitors appear, new market interactions have to be taken into account. Once the market is mature and there are a lot of users, many of those services may consider the idea of selling data. This simple description of the evolution of these market is the one we consider here⁶¹.

4.4.1 Sequential Decisions Models

Let's assume there are three stages in our theoretical market. In the first stage, there is a monopoly that represents the launching of a new device (a wearable). At this moment, this product is so innovative that there are no competitors in the market. Then, we consider there is a second stage in which two companies share the market, so they have to compete with each other for users. Then, in the last stage, both companies realize that they can earn money with their users base, so they start offering their databases to other companies or developers. This framework reproduces some stylized facts about many digital markets that have evolved in this way.

To solve this sequential decision model, we have to use the backward induction algorithm. In that sense, we start solving the model at the third stage, and later, we solve the second and the first stage respectively. Let's describe the stages.

⁶¹To keep the model as simple as possible, we mainly rely on the assumptions of previous models.

Third Stage

In this phase, both platforms have well-established user bases that attract the attention of developers. In other words, in this phase, platforms set the price of data. That implies that platforms only set prices on developers' side. We assume that both, users' market and developers' market, are horizontally differentiated. We assume users and developers behave as in Section 4.3.2, but for simplicity's sake and without loss of generality, we assume $\theta_i = 1$.

We assume that the utility of a developer i interested in data of platform j is $\pi_{i,j} = c^d + C(\cdot)_j - T_j - t^f |l_j - x_i|$. Therefore, the demands addressed to the platforms are $M_j = 1/2 + \frac{C(\cdot)_j - C_{-j}}{2t^f} + \frac{T_{-j} - T_j}{2t^f}$. In this stage, platforms maximize their profits with respect to the price on developers' side. Platforms are already earning profits on users' side, so we consider those profits are exogenously given at this stage.

$$\Pi_k = \Pi_k^u + T_k M_k$$

Π_k^u are the profits on users' market, and $T_k M_k$ are the profits of selling the data.

We assume that both platforms operate in a market with full information, and we assume they set the prices that maximize their profits. In this case, in comparison with other models, there is no coordination problem because there are well-established user bases, so they do not need to set prices to attract consumers, as it was assumed in the one-shot games of Section 4.3.

This scenario is quite simple. Platforms only set the price on developers' side. Therefore, we have

$$T_j^* = t^f + \frac{C(\cdot)_j - C(\cdot)_{-j}}{3} \quad (4.33)$$

$$M_j^* = 1/2 + \frac{C(\cdot)_j - C(\cdot)_{-j}}{6t^f} \quad (4.34)$$

$$\Pi_j^f = \frac{t^f}{2} + \frac{(C(\cdot)_j - C_{-j})^2}{18t^f} + \frac{C(\cdot)_j - C(\cdot)_{-j}}{3} \quad (4.35)$$

We assume there are no marginal costs when selling data. Also, because we assume users are already on the platforms, the prices and demands on users' side are fixed.

This is a strong assumption because it implies that companies do not change how they set prices on users' side when they sell data⁶².

As we observe in Eq. 4.33 and Eq. 4.34, prices and demands at this stage are influenced by the differentiation of the market (t^f), and by the relative difference in the perception of quality of the data provided by the two platforms ($C(\cdot)_j - C(\cdot)_{-j}$). Obviously, this is an extreme case of simplification, but it highlights two important issues. Even in such simple framework, **data is priced following the tastes of the potential customers (developers) and the relative difference in the quality of the data**⁶³.

Let's consider the previous stage in which platforms compete for users. However, this time, platforms have to take into account that in the future (the third stage) they will sell data. Let's see how pricing change when platforms take into account future events or actions that are not taking place in the present.

Second Stage

Platforms compete for users and developers, but not simultaneously, as in Section 4.3. In this case, platforms compete for users now, and for future developers or companies that will buy the access to data. We assume users behave as in Section 4.3.2 at this stage but also, at the first stage. In this sense, we denote t_u^0 the transportation costs of the first stage, and t_u^1 the transportation costs of the second one, and we assume $t_u^1 < t_u^0$.

We introduce a novelty with respect to the previous sections. In this case, we assume that users have direct network effects (n_j). In other words, they value the presence of other users on the platform⁶⁴. We consider this effect at this stage but also, at the first stage. The idea is to reproduce that, sometimes, platforms try to create communities. We assume that the platform which has been the most successful in creating a large

⁶²We do not address in this work how realistic is this framework. We make this assumption because the framework is simpler and tractable.

⁶³Quality is a word that may mean too many things. In this framework, it can refer to the number of variables of the dataset provided, the quantity of data, the granularity of such data, etc. Everything that is valuable to developers interested in such data.

⁶⁴The value of each additional user is measured by μ . Therefore, μn_j is the valuation in terms of utilities of the platform community.

user base at the “monopoly stage” (first stage) will have an advantage in competing at this stage. We use the Salop’s framework of Section 4.3.2 to reproduce this feature. We assume that the “most successful monopoly” is able to launch another brand that competes directly with the other platform, that is how this platform takes the advantage.

Figure 4-8: Salop’s Platforms. Sequential Decision Model. Second and First Stages. Source: own

At this stage, both platforms compete for new users, but we assume that, at the first stage, they were successful in attracting some users. We denote by n_j^0 the proportion of users that were attracted at the first stage. This user base is used by platforms to attract more users. This proportion defines the position of platforms at the second stage $l_j^1 = l_j - n_j^0$. The more users you attracted, the larger the market you can deal with⁶⁵.

Because we assume a Salop’s model, there are two marginal users that are located between E.1.1 and E2.1, and between E1.2 and E2.2⁶⁶. The utility of a user i on the platform j is $U_{i,j} = s_j + \mu n_j - v_j - t^u |l_j^1 - x_i|$. After computing the marginal users,

⁶⁵The number of users has a negative sign because the higher the number of users, the less costly is for users the platform in terms of utility.

⁶⁶We keep the original positions of platforms at 1/2 and zero.

we can obtain the demands addressed to each platform⁶⁷. At this stage, demands are composed of the users of the first stage (that we consider fixed), and the new users that are attracted to the platform. Therefore, the demands addressed to platforms are⁶⁸

$$n_1 = \frac{(1/2 + n_1^0 - n_2^0)t_1^u}{t_1^u - 2\mu} + \frac{s_1 - s_2 + v_2 - v_1 - \mu}{t_1^u - 2\mu} \quad (4.36)$$

$$n_2 = \frac{(1/2 + n_2^0 - n_1^0)t_1^u}{t_1^u - 2\mu} + \frac{s_2 - s_1 + v_1 - v_2 - \mu}{t_1^u - 2\mu} \quad (4.37)$$

Platforms maximize profits ($\Pi_j = (v_j - c_j)n_j$) with respect to prices (v_j). In this case, we consider that platforms sell a device, and such device has a marginal cost of production (c_j)⁶⁹. Therefore, the optimal prices and demands are

$$v_1 = \frac{(1.5 + n_1^0 - n_2^0)t_1^u}{3} + \frac{s_1 - s_2}{3} - \mu + \frac{2c_1 + c_2}{3} - \left(\frac{C_1(\cdot) - C_2(\cdot)}{27t^f} + 1/3 \right) \left(\frac{\partial C_1(\cdot)}{\partial n_1} + \frac{\partial C_2(\cdot)}{\partial n_2} \right) \quad (4.38)$$

$$v_2 = \frac{(1.5 + n_2^0 - n_1^0)t_1^u}{3} + \frac{s_2 - s_1}{3} - \mu + \frac{2c_2 + c_1}{3} - \left(\frac{C_2(\cdot) - C_1(\cdot)}{27t^f} + 1/3 \right) \left(\frac{\partial C_1(\cdot)}{\partial n_1} + \frac{\partial C_2(\cdot)}{\partial n_2} \right) \quad (4.39)$$

$$n_1 = \frac{(1.5 + n_1^0 - n_2^0)t_1^u}{3(t_1^u - 2\mu)} + \frac{s_1 - s_2 - 3\mu}{3(t_1^u - 2\mu)} + \frac{c_2 - c_1}{3(t_1^u - 2\mu)} + \left(\frac{C_1(\cdot) - C_2(\cdot)}{13.5t^f} \right) \left(\frac{\partial C_1(\cdot)}{\partial n_1} + \frac{\partial C_2(\cdot)}{\partial n_2} \right) \quad (4.40)$$

$$n_2 = \frac{(1.5 + n_2^0 - n_1^0)t_1^u}{3(t_1^u - 2\mu)} + \frac{s_2 - s_1 - 3\mu}{3(t_1^u - 2\mu)} + \frac{c_1 - c_2}{3(t_1^u - 2\mu)} + \left(\frac{C_2(\cdot) - C_1(\cdot)}{13.5t^f} \right) \left(\frac{\partial C_1(\cdot)}{\partial n_1} + \frac{\partial C_2(\cdot)}{\partial n_2} \right) \quad (4.41)$$

We can observe that platforms take into account not only the users but also, how their pricing today will affect the market tomorrow. **Platform set lower prices on users' side to try to attract more uses to increase the attractive of the platforms for future developers.** However, it is interesting to observe that

⁶⁷ Demands without network effects would be:

$$n_1 = 1/2 + n_1^0 - n_2^0 + \frac{s_1 - s_2 + v_2 - v_1}{t_1^u}$$

$$n_2 = 1/2 + n_2^0 - n_1^0 + \frac{s_2 - s_1 + v_1 - v_2}{t_1^u}$$

⁶⁸If we compare the demands with and without the network effects, we observe that changes are more abrupt with network effects. In other words, it is more likely to find winner-takes-all outcomes.

⁶⁹At this stage, we set prices for new users only. Early adopters are already on the platform, and developers will come in the future stage.

platforms use their early-adopters (the users who adopted the platforms at the first stage) **to increase the prices for new users**⁷⁰.

In comparison with our previous models, in this case, platforms are not selling data, but they expect to do that in the future. Prices can be even lower than predicted by one-shot games. In other words, **even when platforms are not using data for commercial purposes, setting zero prices can be profitable if they expect to sell data in the future**. This result implies that detecting predatory prices in multi-sided markets can be even more difficult than expected.

Lemma 24. *Future and current network effects tend to call for low prices. However, past network effects call for high prices. Nonetheless, there are timeless factors such as the differentiation, that always calls for higher prices.*

This model also reproduces the fact that prices goes up with time because of the growth of the user base. But this effect may be offset by the subsidies to future customers, such as developers.

Platforms may set lower prices today expecting tomorrow to sell data. Optimal prices can be below marginal cost even if platforms do not behave as multi-sided markets. But it could not be considered predatory behavior if those prices correspond to a future decision of selling data.

First Stage

At this Stage, each company is a temporal monopoly. The intuition is the following. Each platform starts in a market niche without competitors. We assume there are network effects among the early-adopters. They do not only influence other early-adopters, their decisions also influence “the big majority” that will come later (at the second stage). So, their role expands to all the other stages. This relevance of the early-adopters is well-known by companies, but one-shot games cannot deal with such effect because of the lack of temporal dimension. We assume that companies operate in the Salop’s circle, Fig. 4-8. This schema is similar to the one at the second stage.

⁷⁰Note also that these equations verifies $n_1 + n_2 = 1$.

However, transportation costs are higher. That is why companies do not compete with each other, $t_u^1 < t_u^0$.

We assume that the utility of an early-adopter i when consuming the platform j is $U_{i,j} = s_j - v_j - t_u^0 |l_j - x_i| + \mu n_j$. So, the demand addressed to platform j is the horizontal sum of all those early-adopters with non-negative utilities. Because we are considering monopolies, we can normalize the position of both monopolies to zero ($l_j = 0$). Therefore, the demand is $n_j = \frac{2(S_j - v_j)}{t_u^0 - \mu}$. This demand function considers that all the early-adopters are equal. However, some early adopters are more relevant than others. Nonetheless, introducing such heterogeneity may make this model intractable⁷¹.

Let's analyze how platforms set prices in this case. At this stage, platforms consider profits are $\Pi_j^0 = v_j^0 n_j^0 + \delta v_j^1 n_j^1 + \delta^2 T_j^1 M_j^1$. For simplicity's sake and without loss of generality, we assume no marginal costs. Assuming marginal costs do not change our conclusions, but it leads to complex expressions without extra insights. δ represents the discount parameters that control how platforms value the future when choosing prices at this stage. In this case, optimal prices have a much more complex expression than before.

$$v_j^{*,t=0} = \underbrace{\frac{s_j}{2}}_{\text{Monopoly}} + \underbrace{\delta \left(-\frac{t_1^u}{6} - \underbrace{\left(\frac{\partial C_{-j}^2}{\partial n_{-j}} - \frac{\partial C_j^2}{\partial n_j} \right) \left(\frac{13.5 t_1^u t^f}{6\epsilon(t_1^u - 2\mu)} \right)}_{\text{Externality via Prices}} n_1^* + v_1^* \left(\frac{t_1^u}{6(t_1^u - 2\mu)} + \underbrace{\left(\frac{\partial C_{-j}^2}{\partial n_{-j}} - \frac{\partial C_j^2}{\partial n_j} \right) \frac{t_1^u}{6\epsilon(t_1^u - 2\mu)}}_{\text{Externality via Demands}} \right)}_{\text{Duopoly. Users}} \right) +$$

⁷¹A possible way to introduce this idea is by considering a potential law ($F(x) = x^2$). In this way, if we weight each user by this parameter, we can estimate a new demand $n_k = \sum_{U_i \geq 0} i z_i(x)$. The demand will not only increase because of the network effects but also, because of the relevance of each user. Let's imagine that the platforms do not care about which users they attract, in that case $z(x) = \frac{1}{\int_0^1 x f(x) \delta x} = 3/2$. So, ($n_j^0 = n_j z(x)$). We consider this case, but other cases could be analyzed, for example, if platforms pay attention to the 90% of the most influential people, then: $z(x) = \frac{1}{\int_0^{0.9} x f(x) \delta x} = 2$

$$+ \delta^2 \underbrace{\left(\left[\frac{C_j - C_{-j}}{3t^f} \left(\frac{\partial C_j}{\partial n_j} - \frac{\partial C_{-j}}{\partial n_{-j}} \right) + \left(\frac{\partial C_j}{\partial_j} + \frac{\partial C_{-j}}{\partial n_{-j}} \right) \right] \frac{13.5t_1^u t^f}{18\epsilon(t_1^u - 2\mu)} \right)}_{\text{Duopoly. Companies}} \quad (4.42)$$

The intuition is similar than before. Platforms take into account all the future events, and they incorporate that information into the prices. However, this new stage gives us an unsatisfactory answer to how to price new-comers. In other words, **how to price early adopters versus late majority is not clearly defined.**

On the one hand, it is not realistic to think that this expression is how companies make the pricing decision. **This expression implies that companies are able to perfectly forecast the long run, which is far from true.** Nonetheless, it could be argued that this expression only points out that it is optimal to think “in the future”. That is true. However, this expression does not provide us with more insights that the ones we obtained at the second stage, i.e. subsidize early-adopters. Additionally, **it is not realistic to think that an emergent start-up in a new market is setting prices considering a future in which the market is well established.**

On the other hand, to keep tractable the model, we need to assume a homogeneous entry of users. Users have to make the buying decision at the same time. This issue is especially relevant for emerging markets, in which users are adopting the products little by little and, in some cases, following a sequential timing. Nonetheless, we are interested in what happens when users chose one platform and this decision influence other users. However, this model does not provide us with a clear statement of this effect because of the necessary assumption of simultaneous decisions, which limits the potential equilibria of the model, that in this case is assumed to be this one only.

For simplicity's sake, we do not derive the optimal demand expression at this stage. That expression is as complex as the optimal price function, and it does not provide us with further insights.

4.4.2 Alternative Approach to model the Adoption and the Diffusion based on Individual Actors

There are other ways to model the decision of agents with regard the adoption of platforms. In the previous sections, we have assumed that users make simultaneous decisions. We made such assumption to keep the tractability of the model. However, we miss an analysis of users' decisions. Normally, users do not choose to buy at the same time. They either tend to observe what others did and they decide, or they decide without waiting for others. In this Section, we explore this idea. We lay out a simple model of coordination and sequential decisions to study how different patterns of decision-making modify the expected user base of a platform. This model is a modification of the classical framework of coordination in standardization proposed by Farrell and Saloner (1985). However, our modified model considers three agents instead of only two.

We assume only three agents because is the minimal number of required agents to guarantee asymmetries between two competing platforms. We define the utility of an agent i on a platform j is $U_{i,j} = U(K_j, n_j), i = 1, 2, 3; j = A, B$. Where K_j represents the quality or technical features of the platform, and n_j the user base.

In order to model the decisions, we assume two preference sets and three scenarios. We distinguish between the brand-lover users (those who love to use one platform or brand), and the neutral ones (those who prefer the biggest platform).

First Set Lover user.

$$U_j(K_j, 3) > U_j(K_j, 2) > U_j(K_j, 1) > U_{-j}(K_{-j}, 3) > U_{-j}(K_{-j}, 2) > U_{-j}(K_{-j}, 1)$$

Second Set Neutral user.

If $K_j = K_{-j}$:

$$U_j(\cdot, 3) > U_j(\cdot, 2) > U_j(\cdot, 1)$$

If $K_j > K_{-j}$:

$$U_j(K_j, 3) > U_{-j}(K_{-j}, 3) > U_j(K_j, 2) > U_{-j}(K_{-j}, 2) > U_j(K_j, 1) > U_{-j}(K_{-j}, 1)$$

In both sets, we implicitly assume that $K \in [0, 1]$. Nonetheless, this assumption does not change our conclusions. The first set represents the idea that the brand-lover user always prefers its brand. The second set represents the idea that a neutral user always prefers the biggest platform.

Sequential Decision of Representative Agents

Let's consider three types of sequential decisions. Each one of them is similar, but there are differences in the sequentiality of decisions. The first case represents when one user decides, then another one, and lastly, the last one. All of them know what has happened before they make their decision. The second case represents when the first and the second users decide at the same time, and then the third make the decision knowing the decisions of the previous users. The last case represents when all of them make their decision at the same time, as in previous Sections.

- **First case. The sequential model.**

If we solve the model using the backward induction algorithm, we observe that, if all users are neutral, there are two Nash equilibria, AAA and BBB. However, if we assume there is one brand-lover user (A-lover), it does not matter when he makes the decision, the only equilibrium will be AAA (or BBB if the brand-lover user loves platform B)

- **Second case. The semi-sequential model.**

If we solve the model using the backward induction algorithm, we observe that, if all users are neutral, there are two Nash equilibria, AAA and BBB. However, if we assume there is one brand-lover user, there are two possible outcomes. If the brand-lover is the last-mover (A-lover), then AAA and BBA are the Nash equilibria, but if the brand-lover is a first-mover, only AAA is the Nash equilibrium.

- **Third case. The non-sequential model.** If we solve the model using the backward induction algorithm, we observe that, if all users are neutral, there are four Nash equilibria, AAA, ABB, BAA, and BBB. However, if there is one brand-lover (A-lover), there are two Nash equilibria, AAA and ABB.

These results point out that **sequentiality matters**. The less sequential the decisions are, the larger the set of equilibria. In the non-sequential model, we have found four different equilibria. In other words, all the possible combinations of one platform being the leader and the other a follower or both symmetric. Another interesting result is that **brand-lovers help in the coordination**. Their presence reduces the multiplicity of equilibria. This result implies that users' heterogeneity is also essential in the take-off phase. These results illustrate that the timing and the heterogeneity matter.

These two features are essential if we want to study the launching of platforms. Nonetheless, these features are not constraining when we analyze issues of mature markets, such as compatibility or competition among platforms. It clearly depends on the topic we are interested in. If we want to investigate how platforms take-off or how they must handle early-adopters, we must consider that heterogeneous users make sequential decisions.

However, introducing such heterogeneity in the previous models make them intractable without further assumptions. The previous model is a clear example of how complexity can arise if we have to consider that at each stage some users have to make the adoption decision based on what others have made. So, we face a trade-off between complex models to solve and interpret and simplifying assumptions that limit the utility and insights of the models.

Proposition 25. *The sequentiality of users' decisions is essential to understand the adoption of platforms. The sequentiality and the users' heterogeneity can impose a specific dynamic of adoption.*

As a summary, an optimal pricing policy considers both, the past and the future network effects. However, to launch a new platform and to overcome the multiple

Figure 4-9: Sequential Decision Tree. Three Agents

Figure 4-10: Semi-Sequential Decision Tree. Three Agents

equilibria problem, we cannot rely on previous models. On the one hand, some models assume the markets are complete. On the other hand, even if we relax those assumptions, the models become quite complex. In a nutshell, their complexity in-

Figure 4-11: No-Sequential Decision Tree. Three Agents

creases too much if we want to address questions as *How can platforms influence their adoption? What does foster their adoption? Is it a matter of how users transmit the information?* In this situation, a different tool is needed. We need a tool that allows us to keep the same framework, relax those assumptions, and avoid the increase in complexity.

4.5 Theoretical Modeling. Wrap-up and Conclusions

In this Chapter, we have laid out several models that reproduce the fitness tracker markets. These theoretical models allow us to answer some of the open questions about the optimal pricing scheme, the role of expectations, compatibility or differentiation in these markets. However, there are other questions that we have been partially addressed, such as how can platforms influence their adoption, or how does a platform take-off.

Initially, we have considered a monopoly framework. Although it may seem unrealistic, many digital platforms start as temporal monopolies. This simple model has

highlighted two relevant issues. On the one hand, **users' expectations matter**. The optimal pricing policy and profits heavily depend on the expectations so, successful platforms have to invest time and resources to address their customers' expectations. On the other hand, **network effects can accelerate adoption**, but it is also more complex than other approaches. In that sense, we have observed that launching a service with a device can be a way to guarantee the take-off, but its adoption may be slower than with network effects.

Later, we have introduced another company, and we have addressed the role of competition and strategic interactions between companies. In this scenario, we have confirmed the previous results, and we have also observed that **platforms have incentives to become compatible**. However, these incentives are not symmetric. In a vertically differentiated framework, the follower has incentives to share its database with the leader. In this way, the differentiation is maximized, and both companies increase their profits. Nonetheless, other configurations of compatibility may drive the market to extreme cases of competition. These results highlight one essential issue. When platforms are differentiated by the number of customers, or by the quality of their products only, there are incentives to separate both markets. In that sense, **there is a risk of creating “monopolies of data” and “competitive markets of users”**. These results provide us with an answer to the role of compatibility and its consequences in the market. However, it is necessary to address to what extent these results are induced by the vertical differentiation we assume.

To provide an answer to the question about the role of differentiation, we extend the model to address the other type of differentiation, the horizontal one. In that way, we compare the three models and observe to what extent pricing depends on the differentiation we assume. We have found that, as in traditional models, the degree of horizontal differentiation impacts directly on prices. In these markets, it is easy to decompose the influence of differentiation in prices. However, in contrast with vertically differentiated platforms, we have found that **compatibility always reduces the competition**. This incentive to become compatible has risen a concern, *may it create incentives to deter entry?* We addressed this issue too, and we have found that

new entrants threat the status quo of the incumbents, and therefore, incumbents have larger incentives to deter entry than when platform are incompatible. In that sense, **platforms have incentives to launch new brands because it may foreclose niche markets to entrants**, and it improves their position with respect to other competitors. The steady increase in brands in the fitness tracker market since 2011 is clear evidence of this finding.

These results about compatibility generate two immediate questions. *May commoditization of data help in improving competitiveness? Or may it lead to monopolies of data?* We have also addressed these questions. We find that the pricing on the side that generates the network effects depends on the relative strength of the network effects that they generate. **If network effects are weak, there is a possibility of a platform becoming a monopoly of data. However, if the network effects are relatively strong, the market will be competitive.**

To prove that our conclusions about compatibility can be applied to any market, we have also developed a generalized model. In that framework, we prove that **compatibility increases the market power of the platforms involved**, and it may be in the interest of all the parties to create such agreements. We illustrate our findings with the evolution of compatibility networks in the fitness trackers market.

Lastly, we address the questions regarding the launching of platforms. We propose a theoretical dynamic model of three stages, and we find that prices on the subsidized side can be lower than static theory points out because of the necessity of attracting not only current consumers but also, future consumers. These prices highlight two issues: **previous consumers increase prices for future ones, and predatory prices are harder to detect in these markets** than in one-sided markets or static two-sided markets. However, the complexity of this model quickly increases, and its tractability is compromised. Additionally, we observe that this framework does not allow us to have a clear picture of how users make their adoption decisions because it assumes simultaneous decisions on all the stages. To try to address the complexity of the adoption process, we laid out a model with three agents. We test their adoption decisions in three scenarios, sequential decision, semi-sequential decision,

and simultaneous decision. We find that the timing and users' heterogeneity matter. However, our previous models were based on simultaneous decision even when we consider sequential stages. This feature imposes a limitation on the answers we can provide to the questions on launching/adoption of digital platforms. In a nutshell, we cannot answer *how do platforms attract users over time, or how is platform adoption influenced by the spread of information among consumers?* Relaxing the necessary assumptions of the previous models make them either intractable or not suitable to be addressed analytically. In that sense, **a desideratum is a tool that allows us to keep the same framework, relax their assumptions, and avoid the increase in complexity.**

Therefore, to address adoption, we need to study the literature of diffusion of innovations. To narrow the scope of that literature, we only focus on those approaches that deal with individual decisions of the economic agents. In other words, instead of focusing on the overall adoption of a product, we pay attention to the individual consumers that try to maximize their utility by adopting a product/technology. That implies that our analysis is focused on the use of multi-agent systems. In the following chapter, we introduce this concept and its application to the analysis of complex systems, such as markets.

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Chapter 5

Multi-Agent Systems and the Diffusion of Products

5.1 Introduction to Multi-Agent Systems or Agent-based Models

If we consider the works in Chapter 3, none of those models have considered other network structures than the full connected network¹. Maybe, some authors would argue that this topic is not relevant, or its relevance is small, or the main conclusions of the literature would not change. However, we only need to read the news to realize how relevant are influencer marketing and networks nowadays². Nonetheless, some authors provide us with preliminar insights, such as Rochet and Tirole (2003) that pointed out that “marquee buyers” make platforms more attractive, and that may change the price structure.

However, up to the date, the questions *What does foster the adoption of platforms?* *Is it a matter of how users transmit the information?* are unanswered. One of the reasons is because the previous models addressed in Chapter 3, and the ones in

¹In this network, the diffusion of information is instantaneous. This feature explains why this issue has not been considered before.

²A simple search in Google Scholar with the terms “Influencer marketing” gives us 43.600 results. On the other hand, “multi-sided markets” gives us only 10.700 results. Accessed on 04.16.2018.

Chapter 4 cannot address those issues without substantial changes. Normally, those changes also imply a lack of tractability that may blur the intuitions. Some authors have proposed the adoption of multi-agent systems or agent-based modeling to overcome the lack of tractability, see Farmer and Foley (2009).

The agent-based modeling has been around for more than two decades, but its adoption in the mainstream economics is slow, and many opposing forces ignore its utility in addressing economic problems³.

Agent-based modeling (ABM) is not so different from the traditional equation-based modeling of the Industrial Organization literature. *The key feature of agent-based modeling is that it involves a bottom-up approach to understanding a system's behavior*, see Twomey and Cadman (2002). This statement also represents the theoretical models of the Industrial Organization literature. However, in comparison with the equation-based modeling, **there is a lack of standardization in the way those agent-based models are built**. This lack of standardization has been one of the major sources of discredit, see Rand and Rust (2011). Nonetheless, **this approach cannot be viewed as a substitute of the traditional equation-based modeling, but as a complement** for those cases in which *the appropriateness can be called into question, especially, for those markets characterized by non-linearity and complexity, for example, telecommunications markets*, see Twomey and Cadman (2002). Tesfatsion and Judd (2006) define Agent-based Computational Economics (ACE) as the *computational study of economic processes modeled as dynamic systems of interacting agents. Here agent refers broadly to bundled data and behavioral methods representing an entity constituting part of a computationally constructed world*. This is not the only definition in the literature, and many authors have proposed other definitions that emphasize different details. For example, Rand and Rust (2011) define agent-based modeling as *a tool that can help researchers understand and analyze complex patterns. By describing simple rules of behavior for individual agents and then aggregating these rules, researchers can model complex systems*. Kiesling et al.

³This approach has been applied in finance, industrial organization, labor market, innovation, transportation, land use, climate policy, etc. See Rai and Robinson (2015) and Bargigli and Tedeschi (2013) among others.

(2012) define them as *a bottom-up, disaggregate approach and thus not limited in its capacity to account for heterogeneity and social structure*. Lastly, Macal and North (2009) consider ABM to be a computer model in which the objects are self-contained autonomous entities that interact with each other within an environment.

These definitions emphasize an essential feature of the ABM, its flexibility. It can deal with both, complex or simple models. This feature also opens the door to use agent-based models as a verification tool. *Simulations models may reproduce and replicate results from analytical models. Simulations models are useful to test different scenarios with potential intervention on micro-level*, see Faber et al. (2010). In that sense, the flexibility of ABM can help us to answer questions regarding the launching of platforms, and the role of network topologies and information flows. At the same time, we can keep the same frameworks we highlighted in Chapter 4 with less restrictive assumptions but without the intractability⁴.

5.2 Agent-based Models. Worth it?

In the early 00s, some authors highlighted the potential benefits (and risks) of this way of modeling, such as Berger (2001), Twomey and Cadman (2002), or Bunn and Oliveira (2003). But it was after the publication of the book “Handbook of Computation Economics. Agent-Based Computational Economics”⁵ when the methodology started to attract the attention of others researchers.

Currently, some relevant authors claim that we need the agent-based approach, see for example Farmer and Foley (2009) in Nature. But it seems that nothing has changed in how we do research on Economics. On the one hand, mainstream economists argue that there is no need to change the methodology when the current one has proved to be able to deal with the economic problems. They also add that, agent-based models did not provide us with useful insights in the last two decades. This line of thought

⁴However, we have to be careful when introducing new layers of heterogeneity or complexity because the model can easily get out of control, and the intuitions may get blurry. That is why is so important to identify the correct micro-behavioral rules because if those rules have flaws, or they are not well defined, the model will be a mere “toy” without scientific value.

⁵See Tesfatsion and Judd (2006).

argues that agent-based models are more a toy or a video-game than a scientific tool. The statements made by Jesus Fernandez-Villaverde, professor at the University of Pennsylvania and researcher at the CEPR and NBER, are a good example of this line of thought: *There are research programs in computational economics that I think they make no sense. One example is the Agent-based Computational Economics. [...] After 30 years of research, we have learned nothing. A direct consequence is that it has a null impact in the economic area. [...] Do we think differently about inflation, unemployment, industry structures, human capital, auctions, contracts, game theory or financial frictions? No.*⁶

This statement is valid in some cases in which those groundbreaking works have not appeared. But not in all the cases. However, the reason, because the contribution of ABM is so small, is because the ACE literature suffers a major shortcoming. The lack of standardization. This flaw has been an ongoing issue from the very beginning, and it seems that this standardization is not going to take place any time soon⁷.

One of the consequences of this lack of standardization is that agent-based models are obscure for many researchers. If we develop a DSGE model with overlapping generations and households with Cobb-Douglas utilities, macroeconomists will know what we are talking about. On the other hand, if we present an agent-based model on consumer's decisions, it is not clear how our model performs this task. **It is not standardized how to compute demands, prices or expectations.** And if we do not prove in advance that the model is capable of computing demands, prices or expectations properly, no one can trust on our results.

Despite these limitations, the agent-based modeling can complement other approaches because *economic phenomena are often complex because they are the emergent result of many individual agents*, see Rand and Rust (2011). **Agent-based models can include characteristics that are difficult to include in traditional models,**

⁶[Translated] <http://nadaesgratis.es/fernandez-villaverde/guia-para-aprender-metodos-cuantitativos-en-economia-iii>

⁷See Rand and Rust (2011), Farmer and Foley (2009) or Richiardi et al. (2006). All of them claim for the standardization.

such as non-differentiability, non-continuity or layers upon layers of interactions⁸. Rand and Rust argue that *the strongest benefit of using agent-based models [...] is that the actions of firms and consumers within the model can be constructed based upon strong theories of behavior, but at the same time, the results can be validated against empirical data*⁹. However, this power came at a cost. **It is the researcher's burden of proof to show that the model corresponds to reality.** As a summary, despite *the power of agent-based models, widespread acceptance and publication of this method in the highest-level journals has been slow*, see Rand and Rust (2011). Nonetheless, there are areas in which this literature has flourished, and they provide us with new insights. One example is the literature on the adoption of innovations.

5.3 The Agent-based Models in the Literature on Adoption/Diffusion of innovations

In the last two decades, the limits of aggregate models in this literature have become clear. *[The aggregate models] do not capture individual interactions. For innovation diffusion, this is an important drawback*, see Zhang and Vorobeychik (2016). Their explanatory power is limited because the aggregation of these models implies that the level of heterogeneity that can take into account is limited, see Kiesling et al. (2012). Other approaches have been proposed such as the statistical-based. But this approach has been criticized because the adoption of technology should not be based on previous experiences. *Whereas extent empirical studies mainly use data of successful diffusions in order to explain the critical factors, most new products introduced into the market fail*, see Delre et al. (2007). In this sense, Mahajan et al. (1991) also point out that ***parameter estimation for diffusion models is primarily of historic***

⁸Faber et al. (2010) point out that *the attractiveness of simulations tools like agent-based modeling is largely due to the fact that they do not constrain the adoption of any functional form [...], allowing, for example, non-linear, non-derivable functions. [...] Aggregate analytical models have difficulty modeling discontinuities and non-linearities, specifically when they arise from a large number of interlinked micro-variables.[...] Aggregate models bear the risk that relevant micro-dynamics are hidden in aggregated functions in order to maintain analytical tractability.*

⁹They are not the only ones. Muduganti et al. (2005) also argue that *agent-based models can overcome the linear and static limitations of traditional empirical research methods.*

*interest; by the time sufficient observations have developed for reliable estimation, it is too late to use the estimates for forecasting purposes*¹⁰.

Therefore, in this literature, the use of agent-based models has found a fertile field to grow because it facilitates the modeling of agent heterogeneity, and it enables fine-grained modeling of interactions, especially, on social networks, and the requirements of data are lower. Bonabeau (2002) perfectly explains the added-value of agent-based models and why we cannot consider them as a stand-alone method. *A number of researchers think that the alternative to agent-based models is traditional differential equation modeling; this is wrong.* His reason to use agent-based models is that *individual behavior is nonlinear and can be characterized by thresholds, if-then rules, or nonlinear coupling. Describing discontinuity in individual behavior is difficult with differential equations.* This author also highlights one essential benefit for the adoption of this method in business. ***ABM makes the model seem closer to reality.*** *For example, it is more natural to describe how shoppers move in a supermarket than to come up with the equations that govern the dynamics of the density of shoppers. [...]* *Everything can be done with equations, in principle, but the complexity of differential equations increases exponentially as the complexity of behavior increases. Describing complex individual behavior with equations becomes intractable.* Other authors also state that another advantage is that agent-based models can consider the topological features of interactions that are often neglected in the traditional literature, see Kim and Hur (2013).

This situation has sparked a clear necessity of comparison between both approaches, the equation-based and the agent-based models. Rahmandad and Sterman (2008) are the first ones in addressing this issue. They find that when data is available, the approach based on differential equations remains valid. This is straightforward. If we have aggregate data, the aggregate approach works fine. However, they highlight that the flexibility of agent-based models is more helpful when heterogeneity is important. They conclude that both types of modeling can incorporate random

¹⁰Other authors argue that the statistical approach does not support changes or external shocks that can be exclusive of the technology or product analyzed, see Pellon et al. (2010).

events, non-linearities, delays, etc. However, agent-based models can incorporate heterogeneity in all the agents and networks, although the computation required can be prohibitive. In contrast, differential equations often make unrealistic assumptions to keep tractability. They conclude *that mixing both approaches can enhance the ability of analysts to model important policy issues efficiently and effectively*. Their conclusion is that there is no better approach. They state that *in addressing a particular policy issue, [...] there may be elements best modeled with explicit agents, and some best modeled as aggregates*. This result points out the utility of using agent-based models as a complement of other techniques.

Agent-based models would be considered as a suitable tool if they were seen as a complement of other approaches and not as a competing one. But first, we need a standardized environment or rules. This is one of the contributions of this Thesis. We want to provide a standardized environment that helps researchers and practitioners to overcome the apparent lack of rules in agent-based models, especially, with regard to the individual behavior of consumers. However, to understand why it is needed a set of standardized rules, we first need to understand the situation in the literature on the diffusion/adoption of innovations.

5.4 The Agent-based Literature on Adoption/Diffusion of Innovations

There is one essential reason to focus on the agent-based literature on the adoption/diffusion of innovations¹¹. **To model the effects of individual efforts or variables in the global adoption, the only approach that is suitable is the agent-based modeling.** Other methods are not tractable, or they are oversimplified.

¹¹Although adoption and diffusion are interrelated, they are different concepts. The adoption involves the decisions made by agents to incorporate a new product or technology in their activities. The diffusion is concerned with the economic significance and the impact over time of such product or technology, see Leite and Teixeira (2012). In this Thesis, we are interested in the adoption. Nonetheless, we will use both terms interchangeably when the intuitions or the results apply to both of them.

There is also another reason. **To the best of our knowledge, digital multi-sided platforms have not been addressed by the literature on adoption/diffusion of innovations.** Normally, it is assumed that platforms are successful, and they compete in a mature market¹². However, neither all platforms are successful, nor all the successful platforms are launched symmetrically. We are interested in why some platforms are successful and others not, but we are especially interested in the individual role of users, developers, companies, and platforms. We are not interested in the whole literature on the adoption/diffusion of innovations, but in the literature that allows us to study the individual contribution of those “actors” to the launching of platforms. In other words, we are interested in the literature that uses agent-based modeling.

In 1961, Katz stated that *it is unthinkable to study diffusion without some knowledge of the social structures*, see Kiesling et al. (2012). That implies not only social influence at the macro level but also, at the meso and micro levels, see Kiesling et al. (2012).

We do not pretend to lay out an exhaustive literature review¹³. We only want to highlight the current state of the literature and provide a glimpse of what is needed in the literature. There are two relevant branches in the literature. On the one hand, the empirical literature that is based on developing models to predict demands, profits, adoption of products, etc. On the other hand, the methodological literature that provides us with the concepts, methods, and support to implement agent-based models.

5.4.1 Empirical Works. Simulations of Product Adoption/Diffusion

When we simulate a market, there are many features that we have to take into account such as the pricing, the consumers/providers networks, how fast information spreads, etc. In the following sub-sections, we focus on those features that are essential in the

¹²See Chapter 3.

¹³For a review on the different approaches see Kiesling et al. (2012). Another interesting literature review is made by Kim and Hur (2013) or Leite and Teixeira (2012). See Zhang and Vorobeychik (2016) for a literature review on empirical methods.

simulation of the adoption of a new product.

Competition: Prices and Information

Competition among companies that patronize different products or technologies is essential to describe why some companies succeed and others fail. However, competition can take many forms, and the literature is a reflection of this feature. **Pricing is probably the most important characteristic.** Leite and Teixeira (2012) highlight that the diffusion process is extremely sensitive to price changes. It can completely dominate the diffusion process¹⁴. It does not matter what types of customer we face, all of them face in the same way the price. They may have different rents or willingness to pay, but the price they observe is the same for all¹⁵. **Despite its relevance, research on the price, the most important attribute of a product, is very rare**, see Diao et al. (2011). In fact, a common pattern in the literature is to consider prices as an exogenous parameter, see Fuks and Kawa (2009), Leite and Teixeira (2012), Faber et al. (2010), Günther et al. (2011) or Zutshi et al. (2015).

There are other works that consider variable but non-optimal prices. These works allow us to study the impact of volatility in prices. For example, Diao et al. (2011), address the dynamic pricing of durables. Zhang and Zhang (2007) consider non-linear prices but, they do not follow any optimizing process to set them¹⁶.

However, a common issue of those works is that **there is no way to prove that those prices are optimal or even realistic**. Nonetheless, there are some attempts in the literature. One example is Zhang and Brorsen (2011). They propose two algorithms of price and quantity competition. However, they work independently and simultaneously. The first creates a problem of inconsistency with the theory, the second creates an endogeneity problem. Another flaw is that they assume a Cournot model as a framework, and they assume that companies' decisions are not influenced

¹⁴This result is also found by Faber et al. (2010).

¹⁵In some cases, some groups may pay different prices because companies are able to discriminate among people. However, in this case, we refer to a homogeneous group of people that is not price-discriminated.

¹⁶Other works that set non-optimal prices are Berger (2001), Günther et al. (2011), Zhang and Nuttall (2007), Terano and Naitoh (2004)

by other companies, which is against the theoretical model they assume. This inconsistency is clearly depicted in their results. They obtain that with four sellers the model converges to a Bertrand model. With three they have a result between the monopoly and Bertrand's cases.

It seems that the price competition is quite complex to model and a lot of effort has to be made to achieve a generalized algorithm to perform that task. In fact, **to the best of our knowledge, there is only one work that proposed a price competition algorithm.** van Leeuwen and Lijesen (2016) considers a market with endogenous price competition but, it is limited to a Hotelling model, it is designed *ad-hoc*, it cannot be applied to other cases, it makes small but systematic errors when predicting prices, and it is not efficient when there are many consumers or companies.

Prices are not the only factor that influences competition. Another critical factor is how information spreads in the market. Pegoretti et al. (2012) consider two substitute products in two different scenarios, one with perfect information and another one in which there is imperfect information. They find that, with perfect information, it is important to reach as many early adopters as possible, in this scenario, the random network is the fastest in achieving the overall diffusion. With imperfect information, small-world networks are the most effective in the propagation process¹⁷. Other works that have focused on competition highlight that intensifying competition increases the adoption of the product, see Rixen and Weigand (2014). However, they highlight that, in monopolies, information policies are less effective than in duopolies. They show that any information policy aimed to increase the awareness of consumers increases the speed of adoption but, low prices increase both, adoption and speed.

An interesting work that derives a winner-takes-all outcome without focusing on price competition but on the information spread is Broekhuizen et al. (2011). They investigate social influence in the cinema market, and they find that *some movies, although entering the market with a low advertising budget, have characteristics that closely meet agents' preferences [...] [which] allow these movies to grow substantially in the*

¹⁷They also find that winner-takes-all outcomes are common in the case of imperfect information.

following weeks.. In other words, targeting homogeneous groups fosters the adoption. Kim and Hur (2013) address how local networks, followers, and influencers affect the diffusion of innovations. In their model, followers can be influenced by other followers or influencers, but influencers can only be influenced by other influencers. They find that winner-takes-all outcomes are very unlikely. However, they argue that this result is because, in their framework, the network effects are locally limited, so the influence is localized within regional boundaries. Nonetheless, they argue that, if there are many followers and only a few influencers, the winner-takes-all is likely. However, as the number of influencers increases, the monopoly outcome is less likely¹⁸.

Lastly, a market that has gone unnoticed by the literature is the digital market. Only a few works have addressed it, but they are far behind the theoretical literature of multi-sided platforms that is much more exhaustive and rich. **The adoption of digital services is a relevant topic nowadays, but it seems that the agent-based literature is more focused on devices or technologies than on digital platforms.** To the best of our knowledge, only three papers have considered digital platforms in some way. Muduganti et al. (2005) compare the adoption of information technologies across different types of users (laggards, innovators, etc). Their model is extremely simple but powerful. It considers only two parameters, but that is enough to show that the failure or success of any product can depend on the stand-alone value (perception) of the product, and on the network effects. Lastly, an interesting work is Zutshi et al. (2015). They try to simulate the pricing model of an online two-sided platform. However, for simplicity's sake, they only consider one side and without taking into account the network effects. These assumptions create an inconsistency problem because their theoretical model does not correspond to the real simulated model. In the end, they simulate the customer's behavior with different prices that are exogenously given.

There are many open issues in the literature right now. From the lack of standardized price-competition algorithms to the study of digital platforms. Another problem that

¹⁸Another work that considers the role of influencers is Günther et al. (2011). They find that targeting experts (influencers) accelerates the diffusion process.

remains open is the lack of proper use of Economic Theory. In some cases, the results are counter-intuitive. **Agent-based models need to be based on Economic Theory** but also, they need to provide the same intuitions than the theoretical models, or at least a well-grounded and justified explanation of why not.

Networks, Spread of Information and Expectations

The early adoption of products or technologies may be the difference between a success or a failure. The relevance of the dynamics of adoption of new products has sparked a great interest in the analysis of social networks and their topologies. *The fundamental problem in information diffusion is to model and predict how information is propagated through interpersonal connections over social networks*, see Zhang and Vorobeychik (2016).

People talk to other people, they share their opinions, and the information they have about products. This word-of-mouth may be much more effective than any other marketing campaign. The analysis of word-of-mouth processes need to take into account the heterogeneity among the different agents in the market, their individual relationships, and their individual decision-making processes.

Agent-based modeling allows researchers to address this issue, and many works have analyzed the role of different network topologies in the last decade. Probably, the most relevant paper in the last decade regarding the role of network topologies is Kiesling et al. (2012). The authors analyze all the relevant works in the agent-based literature of diffusion of innovations and conclude that the network topology is essential in the process of adoption/diffusion. They highlight that three fundamental readings can be extracted from the literature:

- Innovations diffuse faster in more regular (clustered) networks than in random networks because individuals are exposed to more social influence and may, therefore, decide to adopt sooner
- Scale-free networks lead to markets dominated by fewer products as opposed to small-world networks

Table 5.1: Types of Networks in this Thesis

Type of Network	Random	Preferential Attachment	Small-World	Others
Number*	5	5	14	5
*Number of works with that type of network in this literature review.				

- In scale-free networks, a small proportion of consumers may have an exceptional influence on the consumption of others

The authors also recognize that because of the good properties of the small-world network as a representation of social networks it has become the most studied. As we observe in Table 5.1, there are clear differences in the number of works that have considered the small-world network in comparison with other network topologies. The use of small-world networks is quite extended, and this pattern is not exclusive of this literature. Zhang and Vorobeychik (2016) also highlight that this pattern is also common in the psychologic literature. Although it is clear that different network topologies lead to different diffusion processes, there is a result that is common to any network topology, **any increase in the connectivity of the network increases the speed of diffusion**, see Pegoretti et al. (2012). This is probably one of the most common results in the literature, see Leite and Teixeira (2012), Günther et al. (2011), Palmer et al. (2015) among many others¹⁹.

However, **the network can play even a more relevant role when consumers value the number of other consumers or users who adopt the same product or technology** (network effects). Pegoretti et al. (2012) also analyze this case, and they find that the assumption of local networks implies that the influence is localized within regional boundaries. In other words, the network size influences the timing and the diffusion process. This result is also found by Leite and Teixeira (2012). However, they focus on global networks, but they consider that users are heterogeneous in the valuation of those network effects²⁰.

¹⁹See Kiesling et al. (2012) for a more exhaustive review of network topologies assumed in the literature.

²⁰Other works that consider global network effects are Muduganti et al. (2005), Broekhuizen et al. (2011), Choi et al. (2010) or Xing and Wang (2015).

On the other hand, an interesting result of Broekhuizen et al. (2011) is that when network effects are strong, consumers are hesitant and that leads to failures in launching. The imitation effect or the network effect can be an accelerator but also a barrier. This result is also found in the industrial economic literature in which this phenomenon is known as “the multiple equilibria problem”²¹. When network effects get stronger, the expectations about the consumption of that product by others becomes essential. Then, how to deal or influence those expectations becomes relevant to companies launching those products.

Companies must take into account their customers’ expectations to anticipate changes in the market. Those expectations can be passive, statics, responsive, rational, etc. One of the first works in addressing the role of different expectations was Berger (2001). He simulates the adoption of new agricultural technologies under three different expectations regimes, passive, static, and perfect forecasting. However, in the last decade, there are only a few works that have addressed the relevant role of expectations. The vast majority of works that assume networks effects assume either static expectations (a fixed parameter), such as Günther et al. (2011), or passive expectations, the most common case. For example, Delre et al. (2007) and Pegoretti et al. (2012) assume that users react to other users consuming the same product, but this assumption implies that users have passive expectations, they do not try to infer the future²².

However, **a common feature of all those works is they only consider users’ adoption, but not the behavior of other players that may be essential in that process, such as developers, sellers or companies.** We cannot study the adoption of digital newspapers without paying attention to the advertisers, or the platform itself that sets the prices. However, this is the most common scenario in the literature. Only a few works address other agents different than users.

²¹On the other hand, other authors such as McCoy and Lyons (2014) state that mild network effects can lead to a higher adoption. However, in this case, the evidence is scarce. The most common result is that network effects can boost the adoption, see Choi et al. (2010), Kiesling et al. (2012).

²²Expectations can be formed by considering the number of consumers adopting a product but also, by prices, see Zhang and Zhang (2007) or Choi et al. (2010)

Another relevant topic in the literature is the how the adoption takes place. Neither all the launching are equal, nor all the adoption processes follow the same rules. In the literature, we can find many ways to describe the adoption process. The two commoner ones are the infection and the threshold processes. The infection process consists in a probabilistic method by which some users in a specific state can “infect” other users in another state with a specific probability. This process is adopted from epidemic studies, see Jackson (2010). The second one is a method by which a consumer will adopt one product if the utility he/she obtains from the adoption of that product is higher than a determined threshold level. This process can be used in combination with the previous one. **The infection process describes the transmission of information, and the threshold process defines the decision-making.** Many examples of these two processes can be found in the literature because they are considered one of the workhorses of the literature, see Berger (2001), Delre et al. (2007), Zhang and Vorobeychik (2016), among others.

Lastly, one of the essential issues when analyzing the adoption of a new product is who adopt it first, and how that influences the overall adoption. McCoy and Lyons (2014) state that **random diffusion yields a higher adoption than the clustered seed**. This result is also found by Zhang and Nuttall (2007). They found that, in clustering, it is more difficult the adoption. However, this work is not based on economic theory, and it makes some mistakes that invalidate some of their findings. For example, they assume that the market shares are initially equally shared among companies. That makes no sense if you are addressing adoption. On the other hand, Delre et al. (2007) compare scattered and clustered promotional activities. They find that neither both of the extreme strategies are the most efficient in launching the product. They also find that the timing is key. But it clearly depends on the type of product we want to promote. However, Kiesling et al. (2012) conclude after an in-depth review of the literature that **diffusion appears to be faster in clustered networks**.

5.4.2 Risks of Agent-based Modeling

Agent-based models are a powerful tool. Technically, it is possible to simulate any social environment. This feature allows us to perform simulations in which we can introduce as much heterogeneity at agents' level as we want.

The most interesting feature is that agent-based models can increase their complexity almost indefinitely. But this feature comes at a cost, the difficulty to understand the whys behind our results. However, this is not an issue in other modeling techniques such as equation-based modeling. The only way to overcome this issue is to use standard protocols, algorithms, or packages. These standardized solutions must be simple, and its consequences in the simulations must be well known. In this way, other researchers can focus on addressing other issues that rely on those standardized solutions. For example, we cannot address the launching of digital platforms without considering the prices, and we need to rely on well-known or well-tested algorithms that guarantee us that the prices we observe are the optimal ones for that market. In this way, we can focus on addressing other issues that rely on top of that, such as the adoption or the profitability of the launching.

This idea of creating “modules” is not new, and many authors have stated this necessity. However, it seems that **such convergence in criteria and modules is not taking place**. One early paper in proposing that was Berger (2001), and a recent paper emphasizes that idea is Rand and Rust (2011). It seems that we are not close to that objective than a decade ago.

On the other hand, the lack of theoretical foundations and the slopiness in its use are clear shortcomings. Richiardi et al. (2006) state that *methodological pitfalls are common in papers employing agent-based simulation [...] each article should include references to the theoretical background..* They propose a set of common guidelines for agent-based models to standardize its development. However, this kind of advice seems to be unnoticed by the vast majority of agent-based researchers.

Linking the agent-based models with the theory is essential to be understood by the mainstream economics, but *showing an equation is not enough to establish a*

link. Many works offer equations that show how the model works but, in most cases, these equations does not define or represent a theoretical model previously established nor a common link about the most basic ideas of theoretical literature, Zhang and Vorobeychik (2016).

One example of this critic is Rixen and Weigand (2014). They study the adoption of smart meters, and they adopt a Cournot model for that purpose. However, the demands are extracted from the theoretical model without any change, and they assume a correlation between wealth and price sensitivity, which is not found in the original Cournot model. This assumption clearly changes the basis of the Cournot model. A similar issue is found in Bunn and Oliveira (2007) and Barr and Saraceno (2005). They assume a Cournot model that is solved analytically, and then they simulate a model on top of that changing some basic assumptions that were not considered at the beginning.

Other researchers have pointed out that another critical issue is how to validate agent-based models²³. Moss (2008) studies and compares different methods of validation based on theory or empirical methods respectively. The first case is the more “econometric” one, and the second case is more based on engaging stakeholders in the modeling process. There is no clear answer to which process is better. The first one is better understood by mainstream economists but, it may lack some realism when dealing with specific cases. The second one is not related to the way economists do science, but it much more aligned with stakeholders’ point of view²⁴.

Despite this debate and its relevance, it is easy to find many works that have omitted these warnings, and they present works that lack theoretical foundation, or in the worse case, there is no theoretical foundation at all, and obviously, its validation is compromised, or in the best case, it is difficult to trust on their results.

²³Verification is the process by which the implemented model is shown to correspond to the conceptual model. Validation is the process by which the implemented model is shown to correspond to the real world, Rand and Rust (2011).

²⁴Our work is closely related to the first case. And its validation follows the econometric way. Nonetheless, as we prove in the following chapters. This approach does not imply that we cannot address realistic frameworks or specific markets.

5.4.3 Conclusions, Caveats and Opportunities

The lack of standardization and the lack of groundbreaking works have limited the expansion of agent-based models in the Economic Science. However, there is a branch that has extensively adopted this methodology because its utility to address complex individual interactions. We refer to the literature on diffusion/adoption of technologies and products. The reason because this methodology has flourished in this literature is mainly because,

- it does not need to rely on aggregate equations, so it can tackle individual interaction
- it does not need to rely on statistical data of past events

We are interested in why some platforms are successful and others not, but we are especially interested in the individual role of users, developers, companies, and platforms. This implies that we are interested in the study of the individual contribution of those “actors” to the launching of platforms. In other words, we are interested in the literature that uses agent-based modeling. We have observed that the situation of agent-based models in Economics can be summarized as follows: *Despite the power of ABM, widespread acceptance and publication of this method in the highest-level journals has been slow. This is due in large part to the lack of commonly accepted standards of how to use ABM rigorously*, see Rand and Rust (2011). This problem is not new, but although some advances are taking place, there is plenty of room for improvement.

Rand and Rust (2011) argues that, a common perception of agent-based models is that they are “toys” because of the lack of documentation, proper testing or theoretical background. Although some attempts have been made, theoretical economic models are rarely considered in the agent-based model literature²⁵. Those works which consider a theoretical framework are a minority, and we can highlight some examples

²⁵In this work, we consider only microeconomic models because they tend to be simpler in the number of relationships they take into account than macroeconomic models.

such as Rixen and Weigand (2014), Hamill and Gilbert (2016), Barr and Saraceno (2005) and Chang (2011). Nonetheless, they present three shortcomings:

- They rely on the equilibrium equations of the theoretical models, so the simulated markets are constrained by the theoretical assumptions
- They tend to assume other interactions among the agents even when the equilibrium of the theoretical model does not consider such interactions, and they may change the equilibrium
- They tend to consider competition in quantities, particularly, the Cournot model²⁶

Therefore, there is no standard rule or procedure to consider the implementation of theoretical frameworks, especially, those with price competition. But there is also no standard about how to consider other interactions on top of these theoretical models without violating the equilibrium conditions/assumptions. Given this situation, two questions arise:

- *Can theoretical models be simulated following a set of standard rules?*
- *Can price competition be implemented in agent-based models following a set of common rules in concordance with Game Theory and economic intuitions?*

The first question represents the common problem that each economist faces when dealing with agent-based models and, probably, it will take some decades to achieve a convergence in standards and criteria. On the other hand, the second question is one of the questions we are going to answer in this Thesis.

²⁶For instance, Barr and Saraceno (2005) investigates how environmental and organizational factors affect the equilibrium outcome of a repeated Cournot model. Chang (2011) analyzes entry and exit in an industrial market characterized by turbulent technological processes and by quantity competition. Rixen and Weigand (2014) analyzes the diffusion of smart meters.

5.5 Launching of Digital platforms: A current Caveat, but an Opportunity

Only a few works have considered the relevance of the launching phase in the Industrial Organization literature, see Evans and Schmalensee (2010) or Cabral (2011). The first one focuses on the role of the critical mass to guarantee the survival of the platform. The second one focuses on the dynamic features of pricing.

However, **the launching phase is not so well developed as the analysis of equilibria because it is more complex than the equilibria analysis.** But this one is not the only reason. Another cause is that **many theoretical models are based on assumptions that are incompatible with addressing the launching of a platform.** For example, the Hotelling framework assumes every consumer wants to buy the platforms from the very beginning, which is not realistic when we address the launch of a new product or service. **Another common assumption is that it is assumed that networks are fully connected, which is unrealistic.** These two assumptions are common in a lot of models, see Hagiu and Halaburda (2014), Salim (2009) or Armstrong (2006). The problem is that relaxing them generates intractability problems. In many cases, the models become quite complex, and it is not easy to derive intuitions.

Although those theoretical models are very popular among economists, the vast majority of them lacks the dynamism to address issues out of their original scope. One interesting proposal to overcome this issue is the adoption of agent-based models to address how platforms are adopted. **We can find agent-based models that have adopted theoretical economic models as frameworks.** However, those works only consider the equilibrium equations. Therefore, **those works remain constrained by the same set of assumptions than theoretical models,** and the applicability of agent-based models is limited, see Rixen and Weigand (2014), or Bunn and Oliveira (2007).

On the other hand, there are cases that address the adoption of innovations without considering those equilibrium equations, but they do not take into account the be-

havior of companies, Choi et al. (2010) or Pegoretti et al. (2012). This is especially relevant because prices are essential in the adoption process, and companies are the ones that set them²⁷.

In that sense, *how do platforms attract users over time, or how is platform adoption influenced by the spread of information among consumers?* are questions that remain unanswered. Additionally, given the current state of the literature on the diffusion/adoption of technologies and products, there are no means to address them properly. As a summary, **no empirical or theoretical literature is available regarding the diffusion of innovation literature to simulate the launching of platforms, optimal prices, or competition.** We know that pricing matters, so we consider a new question, *Can price competition be implemented in agent-based models following a set of common rules in concordance with Game Theory and economic intuitions?* We also know that network effects may play an essential role as well as network topologies, so both of them have to be part of any model that pretends to simulate the adoption of digital platforms. In the following Chapter, **we lay out an agent-based algorithm that allows us to simulate pricing in any market** that is theoretically based, and afterward, we simulate the adoption of platforms in several scenarios.

²⁷For example, Diao et al. (2011) state that prices are the most important attribute in diffusion, but the least studied.

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Chapter 6

Agent-Based Modeling. Algorithms and Market Simulation

6.1 Introduction

Up to the date, the questions *What does foster the adoption of platforms? Is it a matter of how users transmit the information? How do platforms attract users over time? How is platform adoption influenced by the spread of information among consumers?* were unanswered in the previous chapters. To answer those questions, we proposed to use agent-based modeling. However, we have observed that prior to providing a functional agent-based model that simulates the adoption of platforms, we need to find a way of simulating the theoretical framework, especially, the price competition. In that sense, another question is open. *Can price competition be implemented in agent-based models following a set of common rules in concordance with Game Theory and economic intuitions?*

Prices play an essential role in any market and understanding how they are fixed is a fundamental part of the Economic Science. To address this issue, in this chapter, **we propose an algorithm for agent-based models that simulates price competition among companies.** This algorithm is based on Game Theory, and it guarantees the optimality of consumers' and companies' behavior without needing to use the equilibrium equations of any theoretical model, nor relying on maximiz-

ing (minimizing) any real function¹. Intuitively, this algorithm resembles the best response map but without assuming any particular theoretical model or function. In this sense, it is possible to address markets with heterogeneous decisions-makers, asymmetric information flows and levels, continuous or discontinuous behaviors, etc. and without assuming that decision-makers carried out complicated mathematical manipulations, and at the same time, it is also possible to guarantee the optimality and rationality of our results².

The Chapter is organized as follows. In Section 6.2.1, we test the algorithm in five different theoretical models, and we prove that the algorithm reproduces the Nash equilibria of those models. We also consider four extensions, two with relaxed assumptions and other two that are either based on quantity competition or on dynamic frameworks. We prove that the algorithm also works in those cases. Once we prove that the proposed algorithm reproduces our desiderata, we address two simple cases of launching. In Section 6.6, we consider both, the launching of a device and the launching of a platform. To keep the model tractable, we use as frameworks the Hotelling's and Hagiu and Halaburda's models.

Afterward, we extend the platform model to address other network topologies, and we study the role of "influencers" and third-options, such as traditional vendors in Sections 6.7 and 6.8. Finally, we conclude by highlighting the main results we find regarding the launching of platforms.

¹It works in both, discrete and continuous frameworks. If the optimum exists, the algorithm can identify it. If it does not exist, the algorithm chooses a second-best solution that maximizes the utility (profits) of users (companies) given the actions of companies (users) in the local area.

²We define a rational agent as the one who makes those choices that maximize their subjective utility given a specific set of information.

6.2 The Price-competition Algorithm. Applications to Theoretical Models

6.2.1 The Algorithm

The algorithm is designed in a modular way. In this sense, each part of it can be used in different contexts and for different purposes. It consists in two sub-algorithms: The consumers' and the companies' algorithm. The consumers' reproduces the buying decisions of consumers and allows us to generate demands. The companies' sub-algorithm reproduces the process by which companies choose the price levels. The continuous interaction of both leads us to the equilibrium (or equilibria).

The Consumers' Algorithm

Our framework considers that each consumer at each moment of time t has an utility function $U(\cdot)$. Each consumer considers the utility he/she obtains from each company he/she knows. If no company offers a worthy product, $U(\cdot) < 0$, the consumer abandons the market; but if there is a company which offers a valuable product, $U(\cdot) \geq 0$, the consumer will compare those products and will buy the one that maximizes its utility. All the consumers who buy the same product from the same company form the demand addressed to that company. In the Fig. 6-1 is depicted a schematic version of the algorithm. Up to this point, this algorithm is not new, and similar algorithms can be found in other works. However, this algorithm is scalable. It presents four features that differentiate it from other proposals³:

- Its modularity. This algorithm can be used independently of the price competition.
- We do not impose any demand function, the demands are the emergent result of the consumers' decisions. It only matters how consumers make decisions.

³The pseudo-code is available in the Annex. The consumer's algorithm corresponds to the first two sub-algorithms of the "Static situation of the market", i.e. utilities and demands.

- Consumers make decisions based on their utility functions, which can be discrete or continuous and have as many parameters as necessary. However, those functions are flexible, and each consumer has its own utility function. That implies the possibility of introducing multi-dimensional heterogeneity, externalities, etc. Also, we do not impose fixed utility functions, those utilities can be dynamic.
- Although we assume perfect information, the algorithm can be adapted to deal with those cases in which information is not perfect. For example, we can assume there is a network that connects consumers and by which information flows.

Figure 6-1: Consumers' Algorithm. Schematic depiction

The Companies' Algorithm

This sub-algorithm is composed of four sub-sub-algorithms.⁴

⁴The pseudo-code of those sub-sub-algorithms is in the Annex.

1. In the first algorithm, each company considers a change in prices (increase or decrease). The parameter ϵ controls this change (iteration parameter). The algorithm requires a starting price that can be any real number.⁵
2. In the second one, each company considers how that change in prices will affect the demands. To estimate the impact of that change in the demands, they estimate the change in the utilities taking other companies' prices as given. Because all consumers compare the utility that each company's product provides them, the price decisions of companies influence the other companies. If we assume that all companies are rational and fully-informed, they will perfectly forecast the decision of consumers⁶. Nonetheless, the algorithm can consider other assumptions about how companies make their decisions.
3. The third algorithm is an optional one. It is designed to control externalities such as direct and indirect network effects. It addresses the case in which the change in prices affects the decisions of other consumers that, at the same time, influences other consumers and so on. In some cases, when a company changes their prices, that decision attracts other consumers that, at the same time, attract more consumers and so on. This algorithm simulates these feedback loops until this effect disappears (convergent feedback loops or the attraction of all the consumers).
4. Companies compare the three actions: increase, decrease or maintain the prices, and they choose the most profitable one.

As it was stated before, the algorithm resembles the best response map, so the convergence towards the price equilibria depends on the initial price and the size of the changes in prices (ϵ)⁷. Once the algorithm has reached an equilibrium, the

⁵There is no range of prices previously fixed. The prices are free to vary, but it is important which is the initial price that we choose. It is recommendable to try several different prices with the only condition of not being so high that all the utilities are negative.

⁶This is the case in the vast majority of theoretical models that we simulate in this work.

⁷This opens a discussion about how the algorithm tackles the convergence, but as long as this algorithm resembles the best response map of price competing markets, the convergence towards the equilibrium is similar to the one expected using Bertrand's Intuition, (Tirole and Matutes, 1990, Chapter 5).

Figure 6-2: Companies' Algorithm. Schematic depiction

algorithm will be continuously testing if any deviation is profitable. This algorithm can be considered as a helpful tool to look for local optima. To find global ones, we need to consider different ϵ -values and different suitable starting prices.

6.2.2 Theoretical Frameworks

To prove that the proposed algorithm is capable of reproducing theoretical models, we need to apply it in several frameworks. We choose five theoretical economic models. All of them share only one feature: companies compete in prices for consumers⁸.

⁸This is de facto behavior assumed throughout the literature on multi-sided platforms, see Chapter 3. On the other hand, it is the most realistic depiction of the wearables market, in which prices are a fundamental dimension, see Chapter 2.

This framework only requires knowing the utility functions, so we will not solve those models analytically. All the assumptions made in the following sections are the original assumptions of the models. Some of them are very restrictive, but those models are very well known in Economics, and it is easier to prove the algorithm in an environment that is well-known. Later, we will show how the algorithm is capable of dealing with those models but relaxing some of their assumptions.

Horizontal Differentiation: The Hotelling Framework

This model⁹ assumes there is a large pool of small consumers that are uniformly distributed in a line. At the extreme of that line, there are two companies that compete in prices to attract consumers. Each consumer has to move from his/her position to the company's position he/she prefers. In Economics, this heterogeneity among consumers is called “horizontal differentiation”. At the same level of prices, some consumers prefer one company but other consumers prefer the competitor. For example, at the same price, some consumers prefer Coke over Pepsi. In the classical version of this model, the utility of a consumer i buying the product of company j , $j \in 1, 2$ is

$$U_{i,j} = c^u + q_j - t * |l_j - x_i| - p_j \quad (6.1)$$

All consumers are identical with the exception that they are uniformly located (x_i) between 0 and 1. Consumers face a transportation cost (t) for reaching companies which are located at the extremes of the interval ($l_j \in [0, 1]$). The intuition of this parameter is the following: The distance between products and consumers in that interval can be interpreted as a “cost” because consumers have to go from their position (that represents their ideal product) to companies' position (that represents the position of the real product). Therefore, the term that controls the differentiation is $t * |l_j - x_i|$.

To guarantee that all consumers buy at least one platform, the theoretical model assumes that all consumers have an identical (and sufficiently high) reservation value,

⁹See (Belleflamme and Peitz, 2015, Chapter 5.2).

c^u . Lastly, we assume each company sells a product that has an exogenous quality level q_j , and they fix a price p_j .

Vertical Differentiation Model

In this case ¹⁰, consumers' preferences are

$$U_{i,j} = \theta_i * q_j - p_j \quad (6.2)$$

All consumers pay a price p_j when consuming the product $j, j \in 1, 2$, which has a quality q_j . Without loss of generality, we assume $q_1 > q_2$. The parameter θ represents the taste for quality. It is uniformly distributed across the population of consumers between $\underline{\theta} \geq 0$ and $\bar{\theta} = \underline{\theta} + 1$ with density 1.

We make two extra assumptions that are common in the literature to guarantee enough differentiated consumers and a covered market respectively:

Assumption 26. $\bar{\theta} \geq 2\underline{\theta}$

Assumption 27. $\frac{(\bar{\theta} - 2\underline{\theta})}{3}(q_1 - q_2) \leq \underline{\theta}q_1$

The intuition of the vertical differentiation is the following: at the same level of prices, all consumers prefer one company over the rest. For example, at the same price, all consumers prefer a Ferrari over a Fiat.

Externalities: Two-sided Markets

We consider two cases. Both of them are extensions of the previous models. In the first case, we consider the two-sided market proposed by Hagiu and Halaburda (2014) in which two platforms compete in prices for users and developers. This model can be considered an extension of the Hotelling's in which there are indirect network externalities between two independent groups of consumers: users and developers. Following the original work, we assume all consumers are rational and buy one and

¹⁰See (Belleflamme and Peitz, 2015, Chapter 5.3).

only one platform. In this case, the utility of a user i consuming the platform $j, j \in 1, 2$ is given by¹¹

$$U_{i,j} = c_i^u - t * |l_j - x_i| - p_j + \delta n_{-j} \quad (6.3)$$

Users are uniformly located in the interval $[0,1]$, and they suffer a cost when going from their position to the platforms', like in the Hotelling model. However, instead of valuing exogenous qualities, users (developers) value the number of developers (users) they can meet in the platform (n_{-j}). We assume all users (developers) value the presence of the other group in the same way (δ).

The second model is proposed by Gabszewicz and Wauthy (2004), which is another example of two-sided markets. However, it has two interesting features: first, it presents vertical differentiation. This characteristic is unusual among the two-sided market literature, mainly because it generates multiple equilibria. Second, there is no information about the stability of the equilibria, so we have the opportunity to test the algorithm in an environment in which several potential equilibria are possible.

It consists of two platforms that represent exhibition centers that compete for visitors and exhibitors. In this case, visitors' preferences are described by

$$U_{i,j} = \theta x_j^e - p_j \quad (6.4)$$

And exhibitors' preferences are

$$U_{i',j} = \gamma v_j^e - \pi_j \quad (6.5)$$

Parameters θ and γ are best understood as a measure of how each visitor (exhibitor) values an additional exhibitor (visitor) in the exhibition centers. The intuition underlying the model is the following. From an exhibitor's point of view¹², the willingness to rent a stand in the exhibition center depends on his personal value of an additional visitor (γ), on the number of additional sales this exhibitor may expect (that depends

¹¹The case of developers is symmetric. We omit it for simplicity's sake.

¹²The intuition is symmetrical in the case of visitors.

on the number of visitors, v_j^e)¹³, and on the rental fee, π_j . At the same price, all exhibitors will prefer the exhibition center with more visitors.

In the original work, the authors assume that $\theta, \gamma, v_j^e, x_j^e \in [0, 1]$. In other words, they assume a normalized market.

Warranties Model

This model is taken from (Belleflamme and Peitz, 2015, Chapter 13). We suppose that a firm offers a product that breaks down with probability $1 - \lambda$, and consumers are willing to pay for a product that works a quantity $r > 0$. The authors make four assumptions:

- There is a unit mass of homogeneous consumers
- There are two firms. A high-quality one (λ_1) and a low-quality one (λ_2). Therefore, $\lambda_1 > \lambda_2$
- Consumers do not know the quality of each company
- Both companies have constant marginal costs, c

From consumers' point of view, a firm can be the high-quality one with probability ρ and the low-quality one with probability $1 - \rho$. Thus, the expected utility of consumers is

$$U_i = [\rho\lambda_1 + (1 - \rho)\lambda_2]r - p \tag{6.6}$$

Up to now, the model does not consider warranties. Let's introduce full warranties (the company replaces the broken product by a new one). The expected cost of introducing a warranty is c/λ_1 for the high-quality one, and c/λ_2 for the low-quality one. The interesting point about this model is that consumers only observe prices and warranties. Warranties can play a decisive role in shaping prices and market shares because they provide information about which company could be the high-quality

¹³Symmetrically, x_j^e represents the number of expected exhibitors.

one. Companies can use warranties to “prove” they are the high-quality one¹⁴. To guarantee the stability of the equilibrium, the authors assume $\lambda_2 r < c$.

6.3 Results and Simulation Tests

We create a world with 314 consumers (in the case of the market with two-sided platforms, there are 628 consumers divided into two groups: users and developers) and two companies. We run one thousand simulations for each case in NetLogo. In all those cases, we compare the theoretical and the simulated equilibria. We consider two ε -values, 0.1 and 0.05. For each case, we only consider a set of parameters values, for example, different transportation costs or quality levels, etc. to show how the algorithm is capable of reaching the theoretical equilibria. We can consider other cases with other parameters but, for simplicity’s sake and without loss of generality, they are not included (although they are available upon request)¹⁵.

6.3.1 Horizontal Differentiation: The Hotelling Framework

We run the simulations considering different transportation costs and with symmetric quality levels ($q_1 = q_2$). As depicted in Fig. 6-3, depending on what ε -values we assume, we obtain different simulated prices that reproduce the theoretical prices¹⁶. To test if simulated prices are able to reproduce the theoretical prices accurately, we run a linear regression in which the dependent variable is the theoretical price, and the explanatory variable is the simulated one. In Table 6.1, we observe that the r-squared is close to 99% in both cases. So, the simulated prices explain 99% of the variations in theoretical prices. Let’s consider the difference between theoretical and simulated prices. We test if those errors are normally distributed. To do so, we consider three normality test, all of them assume the null hypothesis of normality. The first one is the D’Agostino’s K-squared test, or the Skewness and Kurtosis test.

¹⁴The model predicts that only the high-quality company will be willing to introduce the warranties.

¹⁵The number of users and developers is arbitrarily selected, other numbers can be considered and conclusions will not change.

¹⁶The code can be downloaded at: <https://goo.gl/XSV97N>

Figure 6-3: Simulated and Theoretical Prices. Hotelling's Model

Table 6.1: Regression of Prices. Hotelling Model

(a) Hotelling. Iteration 0.1		(b) Hotelling. Iteration 0.05	
Variable	Coefficient (Std. Err.)	Variable	Coefficient (Std. Err.)
Simulated Price	1.0459** (0.0073)	Simulated Price	0.9821** (0.005)
N	90	N	90
R ²	0.9957	R ²	0.9977
F _(1,89)	20558.99	F _(1,89)	38519.85

This test is based on the kurtosis and skewness measures, it can be considered a default normality test. We also consider the Shapiro-Wilk test, which is another traditional normality test. Lastly, we consider the Shapiro-Francia test, which is indicated as the best test to detect deviation from normality in a recent work, see Mbah and Paothong (2015). In Table 6.2, we observe the p-values associated with those tests. Let's consider first the case in which $\varepsilon = 0.1$. In this case, at 95% confidence level, only in the D'Agostino's K-squared test we can reject the null hypothesis of normality. It is reasonable to think that errors are normally distributed and therefore, the average (-0.036) is a good representation of the simulations errors. In this case, it is an underestimation of 3.6%. However, given that the algorithm works considering 10%

Table 6.2: P-values of Normality Tests. Hotelling Model

ε / p-values	Skewness and kurtosis test	Shapiro-Wilk test	Shapiro-Francia test
<i>0.10</i>	0.0205	0.09909	0.60196
<i>0.05</i>	0.0000	0.0000	0.001

of change in prices ($\varepsilon = 0.1$), this error is negligible.

On the other hand, when $\varepsilon = 0.05$, all the tests suggest that the difference between simulated and theoretical prices is not normal. We run a variance-comparison test, and we find that, at 99% confidence level, the standard deviations between the cases with transportation costs in the interval $[0.1;0.59]$ and in the interval $[0.60;0.99]$ have different variances. Given that each simulation for each parameter is independent of the rest, we can analyze both sub-samples separately. The first one considers transportation costs between 0.1 and 0.59 and the other one between 0.60 and 0.99. In those intervals, at 95% confidence level, we cannot reject the null hypothesis of equal variance.

If we run the normality tests again, we cannot reject the null hypothesis of normality at 95% confidence level, see Table 6.3. Therefore, the average error in simulated prices is an underestimation of 1.3% in the first part (-0.013), and an overestimation of 2% in the second part (0.02). But given that the algorithm works considering 5% of change in prices, in this case, those errors are also negligible.

Table 6.3: P-values of Normality Tests. Hotelling Model. Iteration at 0.05

Intervals	Skewness and kurtosis test	Shapiro-Wilk test	Shapiro-Francia test
$[0.1;0.59]$	0.5595	0.23156	0.86565
$[0.60;0.99]$	0.2468	0.67779	0.68322

6.3.2 Vertical Differentiation Model

In this case, we run the simulations by considering different quality levels for company 2. Nonetheless, we maintain $q_1 = 1$. In Fig. 6-4, we observe the simulated and the theoretical equilibrium prices considering different quality levels (company 2). As in

the previous case, the simulated prices reproduce the theoretical ones accurately¹⁷. We run a linear regression for each ε . The dependent variable is the theoretical

Figure 6-4: Simulated and Theoretical Prices. Vertical Differentiation Model

price, and the explanatory variable is the simulated price. We find the algorithm reproduces the behavior of the theoretical companies properly. In Table 6.4, we

Table 6.4: Regression of Prices. Vertical Differentiation Model

(a) Iteration 0.1		(b) Iteration 0.05	
Variable	Coefficient (Std. Err.)	Variable	Coefficient (Std. Err.)
Simulated Price	1.0385** (0.0104)	Simulated Price	1.0314** (0.0054)
N	85	N	85
R ²	0.9917	R ²	0.9977
F _(1,84)	10066.75	F _(1,84)	36883.17

observe that the r-squared is close to 99% in all cases. The simulated prices are able to explain 99% of the variations in the theoretical prices. As in the Hotelling model, simulations reproduce the optimizing behavior of companies accurately. Let's consider the differences between the theoretical and simulated prices. As before, we consider

¹⁷The code can be downloaded at: <https://goo.gl/WnfPhk>

three normality tests. In Table 6.5, we observe that all the normality tests point

Table 6.5: P-values of Normality Tests. Vertical Differentiation Model

ε	Skewness and kurtosis test	Shapiro-Wilk test	Shapiro-Francia test
0.1	0.3097	0.77471	0.94308
0.05	0.2197	0.22636	0.24974

out that, at 95% confidence level, we cannot reject the null hypothesis of normality. Therefore, the average of the errors can be interpreted as the average error of the algorithm in this model. In this case, the algorithm yields an average error of -1.5% (-0.015) when $\varepsilon = 0.1$ and 1% (0.01) when $\varepsilon = 0.05$. Nonetheless, the algorithm considers changes in prices of 10% and 5% respectively, so these errors are negligible. In this model, demands are not equal. In contrast with the rest of the models, companies will not equally share the market. Nonetheless, the algorithm is also capable of simulating demands. In Fig 6-5, we observe demands are well reproduced at the beginning, but there are divergences at high-quality levels. This effect depends on the ε we assume, and it is exclusive of vertically differentiated models.

Figure 6-5: Simulated and Theoretical Demands. Vertical Differentiation Model

When both qualities are similar, prices tend to be similar too but, because the algorithm works in “discrete jumps (ε)”, when both qualities are similar, little increments of quality may not change the simulated prices but may change utilities,

which leads to changes in demands. The more similar the platforms are, the more relevant are these changes. For that reason, those unusual behaviors are concentrated in the region where platforms are less differentiated (when $q_2 \rightarrow 1$). If we omit that region, we observe that the difference between theoretical and simulated demands (hereinafter, the errors) are normally distributed and, on average, the algorithm predicts without errors the demand level. However, we cannot omit the fact that some errors arise. To prove that those errors come from the ε -value assumed, we also consider the case in which $\varepsilon = 0.01$.

Table 6.6: P-values of Normality Tests. Vertical Differentiation Model. Demands

ε (Δ)	Skewness and kurtosis test	Shapiro-Wilk test	Shapiro-Francia test
0.1(0.14)	0.0037(0.0674)	0.00000(0.13764)	0.00001(0.07698)
0.05(0.09)	0.0009(0.0396)	0.00001(0.09888)	0.00002(0.04154)
0.01 (0.05)	0.000(0.6848)	0.00000(0.69446)	0.00001(0.55921)

In Table 6.6, the Δ represents the difference between companies' quality levels at which the errors are normal. For instance, when $\varepsilon = 0.01$, only if the difference in quality is bigger than 0.05, the errors are normal. In parenthesis, there are the p-values that correspond to those cases in which we remove the observations with a differentiation less than Δ . In Table 6.7, we observe the case in which $\varepsilon = 0.01$ is the best one in reproducing demands because prices are more sensitive to differences in qualities.

Table 6.7: Regression of Demands. Vertical Differentiation Model

(a) Iteration 0.1		(b) Iteration 0.05		(c) Iteration 0.01	
Variable	Coefficient (Std. Err.)	Variable	Coefficient (Std. Err.)	Variable	Coefficient (Std. Err.)
Simulated Demand	0.9556** (0.0231)	Simulated Demand	0.9850** (0.0165)	Simulated Demand	0.9987** (0.0067)
N	85	N	85	N	85
R ²	0.9534	R ²	0.9771	R ²	0.9962
F _(1,84)	1717.66	F _(1,84)	3585.43	F _(1,84)	22024.81

In contrast with the previous case, the lower the ε , the more accurate are the simulated prices and demands in all cases. The Fig 6-6 depicts the comparison between the cases in which $\varepsilon = 0.05$, $\varepsilon = 0.1$ and $\varepsilon = 0.01$.

Figure 6-6: Comparison of ε -values. Vertical Differentiation Model. Prices

6.3.3 Externalities: Two-sided Markets

Hagiu and Halaburda's Model

This model considers that two platforms compete in prices for consumers (users and developers). Consumers value the presence of the other group so, the more, the better. For simplicity's sake and without loss of generality, we assume both sides are symmetrical, and we only analyze one of them, in this case, we focus on users. We run simulations considering different transportation costs. In Fig 6-7, we observe that the simulated and theoretical prices behave in a similar way. As in the previous cases, the simulated prices reproduce the theoretical ones properly¹⁸. If we regress the theoretical prices with the simulated ones, we find that, in all cases, the r-squared is superior to 99%, which shows that simulated prices predict quite well the theoretical prices, see Table 6.8.

In Table 6.9, we analyze the differences between the simulated and the theoretical prices. We observe that when $\varepsilon = 0.1$ and at 95% confidence level, we cannot

¹⁸The code can be downloaded at: <https://goo.gl/RDwsDD>

Figure 6-7: Simulated and Theoretical Prices. Hagiu and Halaburda’s Model

Table 6.8: Regression of Prices. Hagiu and Halaburda’s Model

(a) Two-Sided. Iteration 0.1		(b) Two-sided. Iteration 0.05	
Variable	Coefficient (Std. Err.)	Variable	Coefficient (Std. Err.)
Simulated Price	0.9924** (0.0068)	Simulated Price	0.9201** (0.0055)
N	90	N	90
R ²	0.9959	R ²	0.9968
F _(1,88)	21373.90	F _(1,88)	27492.02

reject the null hypothesis of normality. On the other hand, given that the average is approximately zero, we can state that, in this case, the algorithm makes no error. However, when we consider $\varepsilon = 0.05$, we can reject the null hypothesis of normality at 99% confidence level. However, this rejection is a consequence of an unusual behavior at high transportation costs. When transportation costs are higher than 0.9, simulated prices show great differences with theoretical prices as depicted in Fig 6-7. If we omit that interval, in all normality tests, the null hypothesis cannot be rejected at 95% confidence level. The average is approximately equal to 0.03. So, we can state that when $\varepsilon = 0.05$, the algorithm makes an average error of 3% (3.8% if that interval is not omitted). As in previous cases, given that the algorithm works with

percentages bigger than the average errors, those errors are negligible.

Table 6.9: P-values of Normality Tests. Hagi and Halaburda's Model

ε	Skewness and kurtosis test	Shapiro-Wilk test	Shapiro-Francia test
0.1	0.2179	0.14804	0.77307
0.05	0.0000(0.2568)	0.0000(0.3255)	0.0000(0.4511)

Gabszewicz and Wauthy's Model

In contrast with the previous model, the Gabszewicz and Wauthy's model¹⁹ considers vertical differentiation between the platforms. However, this is not the only difference. The essential difference is that this model presents three different equilibria in the duopolistic framework. These equilibria are also different than the previous ones. They do not depend on parameters values. Each price-equilibrium is defined by constant prices and demands. Table 6.10 shows the different equilibria found by Gabszewicz and Wauthy. However, some of those equilibria are not stable, and the simulations are affected by this feature.

Let's prove that some of those equilibria are not stable. On the one hand, the duopolistic equilibrium is not stable. If any company fixes a zero price on one side and the monopoly price on the other side, this deviation is profitable. If any company deviates, the other one will abandon the market²⁰. If we analyze the other equilibria, only the "Monopoly equilibrium" is stable²¹. This happens because Gabszewicz and Wauthy assume "passive beliefs". That implies that when a platform changes prices on one side, the other side does not change their expectations immediately. So, it is always profitable a deviation from the zero price because, given the passive beliefs, the platforms earn an extra profit from deviating. And once they have moved from that equilibrium and the expectations have changed, they will move to the "Monopoly equilibrium" to keep their profits. In this case, the theoretical equilibrium is a con-

¹⁹This model can be found at <https://goo.gl/S6i3rn>

²⁰Technically, they will be indifferent, but we can only observe one reality, in this case, we assume it is the abandon.

²¹This makes sense because of the vertical differentiation. The network effects are so strong that there is an incentive towards concentration in only one platform.

Table 6.10: Gabszewicz and Wauthy's Equilibria

Equilibria	Prices	Demands	Profits
Duopolistic Equilibrium	$p_1 = \pi_1 = 2/49$ $p_2 = \pi_2 = 8/49$	$x_1 = v_1 = 2/7$ $x_2 = v_2 = 4/7$	$\Pi_1 = 0.0233$ $\Pi_2 = 0.1866$
Monopoly Corner Eq.	$p_1 = 0, \pi_1 = 1/2$	$x_1 = 1, v_1 = 1/2$	$\Pi = 1/4$
Monopoly Equilibrium	$p_1 = \pi_1 = 1/2$	$x_1 = v_1 = 1/2$	$\Pi = 1/4$

stant value, so we present in Table 6.11 the simulation results with different ϵ -values and the theoretical equilibrium values. As we stated in the Subsection 6.3.2, the vertical differentiation can have dramatic effects on the equilibrium because it may lead to big changes. In the case of indirect network effects and vertical differentiation, those changes can be even more dramatic. For example, when $\epsilon = 0.01$ or $\epsilon = 0.005$ the model collapses to the Bertrand equilibrium (which is another possibility considered by the authors). This result is a consequence of the extreme sensitivity of the model to changes, and the existence of several equilibria.

As we move towards small ϵ -values, the monopoly equilibrium becomes the predominant outcome. However, in comparison with other models, it seems that there is a big divergence in demands but not in prices. This characteristic is a consequence of the simulation model. While the theoretical model considers an infinite amount of users uniformly distributed, our model only considers 314 users. That implies that one percent in the γ and θ parameters represents 1% of population in the theoretical model, but 1.3% of population in the simulated model. This small difference leads to a huge difference between the demands of the theoretical and the simulated model because the vertical differentiation. Again, these results show the relevance of testing different ϵ -values. In comparison with previous models, different equilibria appear when choosing different ϵ -values. All of them are equilibria of the theoretical model. So, testing different ϵ -values helps us to identify global equilibria.

Table 6.11: Prices, Demands and Profits. Simulation of Gabszewicz and Wauthy's Model

Equilibria	Passive Beliefs	Responsive Beliefs
$\epsilon = 0.1$	$P = x = \Pi = 0$	$P = 0.21$ $x = 0.698$ $\Pi = 0.293$
$\epsilon = 0.05$	$P = x = \Pi = 0$	$P = 0.21$ $x = 0.647$ $\Pi = 0.291$
$\epsilon = 0.01$	$P = x = \Pi = 0$	$P = 0.24$ $x = 0.599$ $\Pi = 0.287$
$\epsilon = 0.005$	$P = x = \Pi = 0$	$P = 0.22$ $x = 0.672$ $\Pi = 0.296$
$\epsilon = 0.001$	$P = 0.215$ $x = 0.685$ $\Pi = 0.294$	$P = 0.136$ $x = 0.8375$ $\Pi = 0.228$

6.3.4 Warranties Model

In this case, the theoretical model predicts two different equilibria when there are warranties and when there is no warranty. If there is no warranty, both companies fix the same price, ($p = (\rho\lambda_1 + (1 - \rho)\lambda_2)r$), but if warranties are used, consumers can identify the quality of each company, and prices will be different, ($p_1 \leq r$, $p_2 = \lambda_2 r$). However, in the last case, only the high-quality company remains in the market. For simplicity's sake and without loss of generality, we analyze the former case²².

In Fig. 6-8, we depict the theoretical prices and the average simulated ones with different values of λ_1 . In Fig. 6-9, we observe the theoretical price and two simulated prices during the first 50 iterations. In this model, prices are not always stable at a specific point, but they oscillate around that point. This oscillating pattern is due to the discrete nature of the algorithm, that is applied in a continuous environment that is quite sensitive to small changes. To test if simulated prices are able to reproduce the theoretical prices accurately, we run a linear regression in which the

²²Nonetheless, the code and the software to simulate both cases are available at: <https://googl/zFvY7t>

Figure 6-8: Average Simulated Prices and Theoretical Prices. Warranties Model

Figure 6-9: Simulated and Theoretical Prices. Warranties Model

dependent variable is the theoretical price, and the explanatory variable is the simulated one. In Table 6.12, we observe that, in both cases, the r-squared is around 99%, so our simulated prices are able to explain 99% of the variations in theoretical prices. Nonetheless, in this case, we have seven observations only, so we cannot test the normality of these cases properly²³. However, the Fig. 6-8 and the Fig. 6-9 leave little room for doubt that the algorithm is capable of simulating the theoretical optimal prices.

²³We have only seven observation because we are working with the averages of simulated prices. The only test that we can properly run is the Wilk test and, in both cases, at 95% confidence level, we cannot reject the null hypothesis of normality.

However, the algorithm presents two limitations in this model. First, sometimes the algorithm is not capable of reaching the equilibrium and predicts a situation in which all companies abandon the market. This happens because of the discrete nature of the algorithm, small changes in the parameters correct this situation, e.g. instead of using $\lambda_1 = 0.89$, use $\lambda_1 = 0.9$. Second, extreme cases such as $\rho = 0$ or $\rho = 1$ will not work. This is a limitation of the current model because it is not programmed to consider the cases in which the model converges to others with full information.

Table 6.12: Regression of Prices. Warranties Model

(a) Warranties. Iteration 0.1		(b) Warranties. Iteration 0.05	
Variable	Coefficient (Std. Err.)	Variable	Coefficient (Std. Err.)
Simulated Price	0.9756** (0.0111)	Simulated Price	0.9304** (0.008)
N	7	N	7
R ²	0.9992	R ²	0.9996
F _(1,6)	7621.27	F _(1,6)	14831.19

6.4 Extensions and Relaxation of Assumptions. New directions in Agent-Based Modeling

Up to now, we have considered the theoretical models under their original assumptions. However, we can use the algorithm to address cases in which some assumptions are relaxed or even cases that are out of the scope of theoretical models. For instance, we can consider the market is not covered, utility functions are not linear, users are distributed following a normal, an exponential, or any other distribution, etc. In all of those cases, the algorithm works properly. We can even include new layers of complexity by assuming more than two companies, or by assuming that users are heterogeneous in several dimensions. In this section, we consider two different cases in which we relax such assumptions.

First, we briefly show how this algorithm can address other theoretical models in the

industrial organization literature that are based on quantity competition or consider a two-stage competition (dynamic frameworks). I consider those models as extensions of the price competition algorithm, but not as extensions of the other theoretical frameworks.

Second, we simulate the Hagiu and Halaburda’s model presented in Section 6.2.2 and simulated in Section 6.3.3, but this time we test the model outside of the parameter region defined by the authors. What is relevant about that region is that the theoretical model predicts negative profits, which is not realistic because platforms will prefer to fix zero prices in both sides than to lose money.

Extension 1: The Perfect Competition Framework. Competition in Quantities

Although we assume the algorithm can be applied to simulate price competition, it can also simulate quantity competition. To prove this point, we test a small modification of the algorithm. This is the simplest model of quantity competition. It assumes there is a large number of companies and consumers, all of them are so small with respect to the market that no one can influence the market. So, every participant is a price taker. In that sense, consumers have to choose how many products they want to buy (given a fixed level of rent), and companies have to choose how many products they will produce at given prices. For simplicity’s sake, we consider only two companies (but we can consider any other number). In this case, we consider the

Table 6.13: Consumers’ Choices. Simulation of the Perfect Competition Model

Parameter Values at $a = 1$	Quantities Consumed	Parameter Values at $a = 1$	Quantities Consumed
$d = 0; b = 1$	$q_1 = q_2 = 1$	$d = 0.7; b = 1$	$q_1 = 1$ or $q_1 = 0$ $q_2 = 0$ or $q_2 = 1$
$d = b$	$q_1 = 1$ or $q_1 = 0$ $q_2 = 0$ or $q_2 = 1$	$d = 0.7; b = 0$	$q_1 = q_2 = 1$
$d = -1; b = 0$	$q_1 = q_2 = 1$	$d = 0.1; b = 1$	$q_1 = q_2 = 1$
$d = -1; b = 1$	$q_1 = q_2 = 1$	$d = 0.2; b = 1$	$q_1 = q_2 = 1$

utility functions defined by (Belleflamme and Peitz, 2015, Page 65). In particular,

the utility function takes the form

$$U(q_1, q_2) = 1 + aq_1 + aq_2 - (bq_1^2 + 2dq_1q_2 + bq_2^2)/2$$

We consider companies can produce natural quantities of each product (1,2,3,..), and they sell their products at a fixed price²⁴. Depending on the values of b and d , we can address several cases considering complements or substitutes. In Table 6.13, we compare different cases. In all of them, the algorithm points out that the consumers' decisions about their quantities are the optimal ones²⁵.

For example, when $d = 0$ and $b = 1$, it is optimal for consumers to buy products from both companies. So, both companies will produce enough products for all the consumers. But when $d = b$, consumers only demand one product, and only one company will produce it.

Extension 2: Milgrom-Roberts' Model of Barriers to Entry

The algorithm is flexible, and it can deal with dynamic frameworks too. To test this statement, we chose the Milgrom-Roberts model²⁶. The model assumes two stages: At the first stage, there is a monopoly that produces a good with a marginal cost that may be high c_h or low c_l . The information about the cost is not available outside of the monopoly. At the second stage, a newcomer has the opportunity to enter the market. However, his/her decision of entering depends on the marginal cost of the incumbent and on its own marginal costs c_e . If the cost of the incumbent is high, the entrant will have positive profits; if the cost is low, the entrant will have negative profits.

The original model considers two different equilibria: the separating one and the pooling one. For simplicity's sake and without loss of generality, we focus on the pooling

²⁴ q_1 and q_2 refer to the quantity produced by company 1 and 2 respectively.

²⁵Simply computation with the parameter values and the utility function prove this point. The model can be downloaded at <https://goo.gl/bjDP5E>

²⁶This model is an adaptation of Milgrom and Roberts (1982) that can be found in (Tirole and Matutes, 1990, Chapter 9). Code at <https://goo.gl/djiCWh>

one²⁷. This equilibrium predicts that the incumbent will block the market forever. Independently of the high or low marginal costs. This happens if the Eq. 6.7 holds. This equation states that the duopoly profits of the entrant when the incumbent has high costs must be larger than zero. But they must be negative with low costs, see (Tirole and Matutes, 1990, Condition 9.8)

$$c_l < c_e < c_h \quad (6.7)$$

If this equation does not hold, for example, if the entrant has lower marginal costs than the incumbent with low marginal cost. The entrant will always enter the market, and two outcomes are possible:

- Competition: if both have low costs and profits are non-negative.
- Expulsion: the incumbent will be expelled from the market

In Table 6.14, we observe the outcome of the simulated model. The idea is to have an intuition of how works the algorithm in this model. We consider two cases. One in which the incumbent has high marginal costs. And another one in which it has low marginal costs. In all those cases, the result predicted by the agent-based model is the same than the one predicted by theory.

Table 6.14: Simulation of the Milgrom-Roberts Model. Outcomes

Parameters Values when $c_{incumbent} = c_h$	Market Outcome	Parameters Values when $c_{incumbent} = c_l$	Market Outcome
$c_l = 0.1; c_h = 0.84$ $c_e = 0.1$	Incumbent is expelled	$c_l = 0.1; c_h = 0.84$ $c_e = 0.1$	Duopoly competition
$c_l = 0.1; c_h = 0.84$ $c_e = 0.2$	Incumbent is expelled	$c_l = 0.3; c_h = 0.84$ $c_e = 0.1$	Incumbent is expelled
$c_l = 0.1; c_h = 0.84$ $c_e > 0.2$	Block to entry	$c_l = 0.1; c_h = 0.84$ $c_e > 0.2$	Block to entry

²⁷The Milgrom-Roberts model presents two different equilibria that are based on different assumptions. In contrast, the Gabszewicz and Wauthy's model has multiple equilibria under the same assumptions.

Relaxed assumptions: Hagiu and Halaburda’s Model

One of the assumptions of this model to guarantee that “*all optimization problems with competing platforms are well-behaved*” is $t^2 > \delta^2$, Eq. 6.3. If we assume this condition does not hold, the theoretical model predicts negative profits. Obviously, this is not optimal because a better option is to fix zero prices or to abandon the market, which guarantees zero profits.

If we consider that such assumption does not hold and we run the algorithm, platforms always find that prices near zero are an equilibrium²⁸. In Table 6.15, we consider two different starting prices for the algorithm (-0.05 and 0.25) and two different scenarios²⁹. We find that simulated profits make more sense than their counterparts, the theoretical ones. The algorithm is capable of finding the best outcome in those cases in which the theoretical model provides unsatisfactory results. This result implies the algorithm can be used as a verification tool for theoretical models but also, it can be used to deal with cases that are theoretically complex or non-tractable.

Table 6.15: Comparison between Theoretical and Simulated Models when Conditions regarding the “well behavior” of Equilibria are relaxed. Hagiu and Halaburda’s Model

Variables / Cases	Starting Price	Deltas	Transportation Costs	Equilibrium Prices Users (Developers)	Equilibrium Profits
Simulated Case	0.25	0.65	0.15	-0.05 (0.15)	0.05
	-0.05	0.65	0.15	0.05	0.05
	-0.05	0.8	0.4	0.05 (-0.05)	0
Theoretical Case		0.65	0.15	-0.5	-0.5
		0.8	0.4	-0.4	-0.4

6.5 Similarities and Dissimilarities between the Algorithm and other Approaches

The proposed algorithm resembles the optimization programs that are used in Economic Theory or Game Theory. In these cases, it is common to compute an optimiza-

²⁸Prices equal to zero or less than the ϵ assumed.

²⁹In other scenarios with other starting prices, we have the same qualitative result.

tion program from which the first and second order conditions are derived to identify the reaction functions and the equilibria. The algorithm is closely related to the idea of reaction functions. However, there are relevant similarities and differences. On the one hand, **the algorithm acts in a similar way than reaction functions**; the output of both is the best reply to a specific situation, and the continuous interaction of reaction functions or agents with the algorithm leads to the Nash equilibria. If it does not exist, **the algorithm can find corner solutions or second best equilibria**³⁰.

On the other hand, there are three relevant differences in comparison with the classical optimization programs used in Economics:

- First, the algorithm does not provide a stylized expression that represents the equilibria. It computes a numerical one.
- Second, tractability is not an issue. Traditionally, researchers make simplifying assumptions, such as linear demands, constant values, continuity of functions, concave profits functions, etc. that may not be realistic. This is done to guarantee tractability and well-behaved equilibria. However, that is not necessary with the algorithm. If there is no equilibrium, the algorithm chooses a second-best solution (one which produces the most favorable outcome for the agent, taking other agents' strategies as given). In some cases, several second-best solutions can be found, in such cases, the algorithm may pivot from one to another. But, if the equilibrium is global, the algorithm will prove that by showing always the same outcome.
- Third, we do not assume continuity or differentiability. The algorithm is discrete, and it approximates a continuous environment.

There are other features that make the algorithm interesting. For example, the algorithm puts emphasis in the process of reaching the equilibrium, and not in the

³⁰For example, in a Cournot model, the equilibrium can be reached using the reaction functions only. Those functions also reproduce an interactive behavior among companies that leads to the equilibrium. The algorithm works in a similar way.

equilibrium itself. This allows us to study the impact of shocks not only in the equilibrium but also, in the process of reaching it. Nonetheless, **the most important contribution is the possibility of relaxing assumptions and guarantying the optimality of results at the same time.** In this way, we can introduce new dimensions that were quite complicated in theoretical models, such as introducing a network structure among the consumers.

Nonetheless, some researchers may argue that the algorithm is not different than solving the model numerically. However, this is not true. To solve a model numerically requires solving the theoretical model analytically in advance in most of the cases³¹, but with this algorithm, that is not necessary. The algorithm does not assume that agents make complicated mathematical manipulations. It consists of simple actions (consumers make their best decision, the one that maximizes their utility: buy one of the product or not; and companies increase, decrease or maintain prices, what it is more profitable at each time), and we prove that, with those simple actions, the theoretical equilibria predicted by many theoretical models can be reached.

This is the first time a generalized algorithm that reproduces the behavior of agents of theoretical models is assumed. So, it is possible to build agent-based models that are closely linked to traditional economics by using economic intuitions. We do not pretend to present the agent-based modeling as an alternative to the traditional industrial organization literature. Instead, this work presents the agent-based modeling as a complement of that literature. If we can agree that the rules presented in Section 6.2.1 represent the same rules that we take as given (or we assume) in the consumer's and company's decision problems. Then, we can agree that **the algorithm is a representation of the process of maximization of utility (profits) of users (and companies).**

Nonetheless, the algorithm we propose is also critizable. It is a tool designed to look for local equilibria. So, to address global equilibria, it requires different starting points, different number of iterations or even a different discrete “jump” in prices. If

³¹We can argue that some models cannot be solved analytically, and it is required solving them numerically. But that is not the point here. We argue that even such models require a previous theoretical work, in which optimization programs are defined, and some expressions are derived.

not, we are at risk of identifying local optima that are not the global ones.

Highlight 28. *The algorithm is capable of reaching the equilibria predicted by theory. It also works in cases that were not considered by theory, or in parameter regions where the theoretical model was not suitable to be analyzed. These results open the door to implementing endogenous pricing in agent-based models but also, to test theoretical models in new environments in which we can relax some of the assumptions that were limiting us before.*

We have proved that price competition can be implemented in agent-based models following a set of common rules in concordance with Game Theory and economic intuitions. However, the questions regarding the launching of platforms remain open. In the following Sections, we test our statements about the generality and the power of this algorithm to address cases out-of-the-scope of theoretical models. We pretend to test to what extent this algorithm can be used to simulate the adoption of platforms and products. In that sense, it is essential to consider not only the buying decision but also, the dynamics of adoption, the influence of third competitors or options, the role of influencers, etc.

6.6 Information Flows, Prices, and Adoption

Prices and information play a major role in the launching processes of new products and understanding when and why they accelerate or slow down adoption is essential for both predicting the penetration of a new technology (or product) and for developing business strategies.

We simulate the Hotelling's and Hagiu and Halaburda's models presented in Section 6.2.2, but this time, we assume that not all the consumers enter the market at the same time. In fact, we assume that there is diffusion of information process that determines who enters the market and when. Analytically, it is quite complex to derive an expression that describes the dynamics of these markets. However, we

can adopt the price competition algorithm presented in Section 6.2.1 and simulate the adoption of products. Our contribution is twofold. In the diffusion of innovation literature, **the novelty of our approach is that we consider endogenous companies' decisions**. In the Industrial Organization literature, **we prove that simple models can be extended to address new issues such as diffusion of information**.

Therefore, let's define which assumptions we need to simulate the diffusion of information, and which assumptions we should relax in the theoretical models to address this issue.

6.6.1 Market Framework and Theoretical Background

We consider two theoretical sources to simulate the diffusion of information. First, we consider the literature on diffusion of innovations from which we adopt three of the most common assumptions in this literature:

1. Agents are related by a random network, as in Günther et al. (2011), Leite and Teixeira (2012), and Pegoretti et al. (2012)
2. The diffusion process depends on an infection process (word-of-mouth)
3. Agents have a propensity to adopt the product that is normally distributed to simulate the existence of innovators, early-adopters, laggards, etc.

Second, we consider two theoretical models from Section 6.2.2 that provide us with a framework to simulate the market. The first one is the classical Hotelling model, in which there are two price-competing companies and horizontally differentiated consumers. We also consider the Hagiu and Halaburda's model, in which platforms compete for horizontally differentiated users and developers in a two-sided market. We consider users and developers adopt one and only one platform.

Users (and developers in the two-sided case) want to buy the product which provides them with the largest non-negative utility. The utility that each agent obtains from

products depends on the following parameters. A reservation value (or a propensity-to-buy), c_u . The consumers' subjective tastes for the ideal product (x_i), which are distributed uniformly on the interval $[0,1]$. In this case, the distance between products and users in that interval can be interpreted as a “cost” because users have to go from their position (that represents their ideal product) to companies' positions (l_j , that represents the position of the real product) that we assume are at the extremes of that interval. This cost is called “transportation cost” or “nuisance cost” (t) and we consider three different transportation costs to show how market differentiation affects the overall adoption.

Each consumer pays a price p_j for consuming the product j . Given that all consumers pay the same price, the utility of a consumer i buying the device j in the Hotelling's model can be written as:

$$U_{i,j} = c_i^u - t * |l_j - x_i| - p_j \quad (6.8)$$

And the utility of a consumer i on the platform j in the Hagiu and Halaburda's model can be written as:

$$U_{ij} = c_i^u + -t * |l_j - x_i| - p_j + \delta n_{-j} \quad (6.9)$$

In the Hagiu and Halaburda's case, there are indirect network effects (n_{-j}), which implies that users (developers) value the presence of all developers (users) in that platform.

This small difference between both utilities is relevant. In the Hotelling's case, users are not influenced by the number of consumers buying the product, but in the Hagiu and Halaburda's case, they are. When competing in prices, platforms have to take into account that changes in prices also lead to changes in participation on one side which also lead to changes in participation on the other side that, at the same time, influence the participation. Companies try to maximize their profits by competing in prices. To reproduce the pricing behavior, we adopt the algorithm proposed in Section 6.2.1.

Although all agents try to maximize their utility functions, initially, the vast majority

of them do not know about the existence of the products/platforms. We assume agents know about technology or the products by “infection” through other agents. We consider that the process of adoption follows an infection process as in Kim and Hur (2013) or Günther et al. (2011). Once one user has knowledge of the product or technology, there is a probability of “infecting” other users in his/her network. On one hand, infection can be independent of consumption and agents can spread their information even when they do not consume the products. This is the most common case in the literature. On the other hand, we assume the spread of information depends on consuming the products. Agents have to consume to infect other agents with their knowledge about products. Additionally, in this case, two cases can be addressed: when agents know about technologies, which implies that users know about all companies that sell products; or when agents only know about none, one or two companies. In this case, when an user is “infected”, he/she only gets information about the company that sells one product, but not about all the companies at the same time. We consider all these cases.

In the simulated market, users (and developers in the two-sided case) want to buy the product which provides them with the largest non-negative utility. However, we relax some assumptions of the theoretical models. First, we assume that the parameter c_u is drawn from a normal distribution with negative mean to reproduce the existence of innovators, laggards, etc. Previously, it was assumed that it was high enough to guarantee that all potential consumers were willing to buy the product/platform. Each consumer pays a price p_j for consuming the product j , but prices are not at equilibrium since the beginning. Prices will start at zero in the case of the platform market because it is the normal pricing scheme in all digital platforms like Spotify, LinkedIn, etc. However, prices will start at 1 in the Hotelling’s case because it represents the pricing scheme of the launching of devices like fitness trackers or smart TVs that tend to be expensive at the beginning. Other prices can be considered without loss of generality. Lastly, following Hagiu and Halaburda, δ is constant for all users

(developers)³².

Simulation Framework

We create a world with 314 users (and 314 developers in the two-sided case) and two companies (or platforms). A random network is created among each category of agents with a link-probability of 1%. Five percent of those agents are categorized as “innovators”, and they know about products before the beginning of the simulations. Those agents are selected by clustering so, all innovators are less than one node away from one another.

At each step, users that know about at least one product will evaluate if the utility they obtain when buying a product is larger than not buying at all. If they are consuming, they will “infect” other users in their networks with that knowledge with a probability of 14%. To influence users’ decisions, companies can change prices while they try to maximize profits³³.

One thousand simulations have been carried out for each case in NetLogo³⁴, which has been used extensively in diffusion literature, see Diao et al. (2011), Kim et al. (2011), Fuks and Kawa (2009), Zhang and Zhang (2007), Kim and Hur (2013) or Rixen and Weigand (2014).

6.6.2 Results

Hotelling’s Model

This case resembles the adoption of a device, such as smart TVs or tablets. The essential assumption is that people are not influenced by the number of users. Let’s consider first that information about the product spreads in the network indepen-

³²Fitness trackers are more related to the Hagiu and Halaburda model. Nonetheless, some companies may behave as the Hotelling model predicts.

³³The number of users and developers is arbitrarily selected, other numbers can be considered and conclusions will not change. The link-probability of 1% is chosen because it is small enough to avoid a full-connected network and to guarantee the presence of no-connected nodes. We choose 5% of innovators because it is a common assumption throughout the diffusion of innovation literature. Lastly, we chose 14% of probability of infection arbitrarily, other probabilities can be considered too, but the main conclusions of this work will not change because it only affects the speed of diffusion.

³⁴See Wilensky (1999).

dently of its consumption (classical infection process). In this environment, the first interesting question to ask is what happens with prices. The lefthand graph of Fig. 6-10 depicts the convergence to an equilibrium price in three cases that represents low ($t_c = 0.2$), intermediate ($t_c = 0.5$), and high ($t_c = 0.7$) differentiation levels. The

Figure 6-10: Prices and Adoption. Relaxed Hotelling model. Spread of Information: common technology

simulations show prices will be higher in more differentiated markets (as the theory predicts). The intuition of this behavior is the following: if users have n options but they prefer one of them because of their tastes, they will be willing to pay more for that option. Companies recognize that their products are not easily substitutable by competitors', and they set higher prices.

On the right side of Fig. 6-10, we observe how prices affect the adoption of products. In the case with the lowest differentiation, the adoption is almost 80%, while in the case with the highest differentiation, the adoption is almost 20%. The reasoning is the following: in the differentiated market, companies are aware that users are loyal, and it will be difficult to reach users in other segments, so they prefer a low adoption and higher prices to a high adoption and lower prices. The opposite is true when markets are not differentiated. If we consider that the spread of information about the products depends on its consumption, there will be no big differences with respect to the previous case in terms of prices and adoption, so this slightly change is not

critical when considering diffusion.

Lastly, let's consider that companies spread information about their own products but not about the competitors'³⁵. On the left side of Fig. 6-11, simulations show that prices are more volatile. This behavior is normal because new users are entering the market at each moment, then companies try to adjust prices because of the expansion of the market, but companies are also competing so they try to reduce prices. Prices only reach a stable position in the case with low differentiation because the competition is stronger than the expansion effect, which is mitigated when the market approximates its full capacity.

Figure 6-11: Prices and Adoption. Relaxed Hotelling model. Spread of Information: individual products

On the right side of Fig. 6-11, simulations show the case with low differentiation is the only one that reaches a point where it is not growing anymore (the expansion effect is over). However, the other two cases are so volatile because the spread of information is less regular and slower than before.

High prices are a barrier that block other users from becoming a node of infection, which limits the adoption. On the other hand, users only know about the individual products, so there are cases where users are only aware of one product and, because information initially spreads from clusters, there will be clusters that

³⁵The opposite may be true when both companies promote the same technology.

will never know about the existence of other companies. In this situation, volatility in prices and adoption appear because there is a trade-off between rising prices (because of the differentiation levels and the market expansion) and reducing prices (because of the competition between platforms and the boosting effect that it has on the demands).

Hagiu and Halaburda's Model

Intuitively, this case is close related to the launching of a digital platform, such as a social network, or a digital market like Apple Store or Play Store where there are two sides (users and developers) that need each other in some way. Given the symmetry of the model, for simplicity's sake and without loss of generality, we address only the users' side. Let's consider that information about the products only spreads if users consume a platform³⁶.

Figure 6-12: Users' prices. Righthand - Spread of Information: common technology. Lefthand - Spread of Information: individual products

In Fig. 6-12, simulations show a similar result to that of the Hotellings' case, the more differentiation, the higher the price. On the left side, there is the case in which platforms spread information about both products at the same time, and we

³⁶We will not consider the case in which information about the technology spreads in the network independently of consumption because it does not provide additional insights.

Figure 6-13: Users' adoption. Righthand - Spread of Information: common technology. Lefthand - Spread of Information: individual products

observe that prices increase at the beginning but then they reach a maximum and they start to slowly converge to a lower price. The higher the differentiation, the slower the convergence. The intuition is the following: the initial increase in prices is consequence of recognizing users are willing to pay more because of the differentiation levels and/or because users value the growing number of developers on the other side and they will continue buying the platform even with high prices. But after a few iterations, platforms realize they have to compete for users, and they reduce prices. This reduction will be faster in less differentiated markets because a price reduction attracts more users than in other cases. However, when platforms spread information about their products only (right side), prices increase quickly at the beginning and then continue to increase, but more slowly. The continuous increase in prices in this case is due to the following: information about platforms spreads so slowly that the set of users that is indifferent between buying one platform or the other one is so small that platforms can focus on the users who are loyal and will buy the platform anyway, so platforms set higher prices. Note that, the higher the differentiation, the smaller the set of indifferent users and the higher the prices. In Fig. 6-13, simulations show how price dynamics translate to the diffusion of the platforms. Just as before, **the higher the differentiation, the lower the adoption.**

Table 6.16: Failures in Launching. Relaxed Hotelling and Hagiu and Halaburda's models. Random Network.

Failures. Information/Models		Hotelling			Hagiu and Halaburda		
Independent	Differentiation	<i>Low</i>	<i>Intermediate</i>	<i>High</i>	<i>Low</i>	<i>Intermediate</i>	<i>High</i>
	Failures	24	219	334	0	0	0
By technology	Differentiation	<i>Low</i>	<i>Intermediate</i>	<i>High</i>	<i>Low</i>	<i>Intermediate</i>	<i>High</i>
	Failures	272	700	802	0	0	0
By products	Differentiation	<i>Low</i>	<i>Intermediate</i>	<i>High</i>	<i>Low</i>	<i>Intermediate</i>	<i>High</i>
	Failures	245	716	796	0	3	45

As a summary, one interesting point about those two models is the role of how information spreads. If companies focus on spreading information about their own products, the adoption is lower. Although price seems to be relevant, it is **the differentiation levels and the role of information that are most relevant because they define the price levels.**

Failures in Launching

One of the most terrifying scenarios for entrepreneurs or managers is the failure in the launching of their products. The literature focuses on diffusion and analyzing successes. However failures are the other side of the coin, and they are neglected in many works. Nonetheless, we can address the cases in which at least one platform has failed to enter the market. To do that, we create a variable that takes value 1 when the demand of at least one platform is null and 0 otherwise. In Table 6.16, simulations show that cases with high differentiation are more prone to failure. The intuition is the following: highly differentiated market tend to have higher prices, which is by itself a barrier to adoption, but if the information does not spread properly, **high prices and the lack of information will lead to a failure in launching.** On the other hand, Hagiu and Halaburda's model is less prone to failure due to two reasons: prices start at a low level, so there is always more willingness to buy the platform, and network effects increase as new users or developers adopt the platform.

6.6.3 Wrap-up and first Conclusions

This Section has shown us that agent-based models can be a useful tool to complement theoretical models. We have observed that simple models such as the Hotelling's or the Hagiu and Halaburda's can be adapted to simulate the adoption of platforms or devices.

We have assumed that users (and developers) are connected by a random network, in contrast with the implicit assumption of a fully connected network. We have found that **the sequential process of adoption matters in both, prices and demands**. If companies only spread information about their own products, prices are more volatile and adoption is lower than when both companies spread information about all the products. New users are entering the market at each moment, then companies try to adjust prices because of the expansion of the market, but companies are also competing, so they try to reduce prices. This feature generates volatility in prices and demands that is not captured in theoretical models.

Nonetheless, some conclusions of the theoretical models still apply. For example, **highly differentiated markets tend to have higher prices**. However, these high prices are by themselves a barrier to adoption. Another interesting result is that prices are essential in the adoption process, but **the level of those prices is determined by the market differentiation** (as Theory predicts) **and by the sequential flow of information** (and the sequential adoption).

Although we have observed that the spread of information plays a relevant role in determining the prices of platforms and companies, we have assumed only one type of network, a random network. To address the role of the spread of information properly, we have to consider other networks. An implicit assumption we made is that all nodes are similar in their relevance, but in real social networks, that is not true. There are people who influence a lot of people, and the opposite is also true. These features are essential to address the launching of a new product such a digital platform. In the next Section, we focus on the case of multi-sided digital platforms, and we address the role of different types of networks and nodes, especially, the role

of *influencers*.

6.7 On “Influencers” and their Impact on the Diffusion of Digital Platforms

Influencers, people who influence other people, are the marketing tool of the social media era. Many of those influencers are well-known because their role in shaping opinions in Twitter, Instagram or Youtube. They are capable of reaching a lot of people, and as Google points out, they are trendsetters more important than other celebrities³⁷. Although influencers play a relevant role in transmitting information in the social media, it is not evident which features make them relevant³⁸. *Is it their followers? Is it their position in the networks? Does it matter this type of heterogeneity?* There are many open questions about the role of influencers. Although influencers and their role in the Internet is a trendy topic, **there is a lack of works in which the role of influencers is addressed**. Companies assume that influencers are essential in their marketing campaigns, but it is not clear to what extent they modify the behavior of these companies, or the adoption of their products.

In this Section, we extend the Hagiu and Halaburda’s model to address the role of different types of networks and nodes in the launching phase. We consider three types of networks: random, preferential attachment and small-world, and we use four metrics of network centrality to identify influencers: degree, closeness, betweenness, and page rank.

³⁷<https://www.thinkwithgoogle.com/consumer-insights/youtube-stars-influence/>

³⁸Influencers can be passive or active. Active ones are those who are targeted by companies to promote their products. Passive ones are those who are not directly targeted by companies. In this work, we focus in passive influencers.

6.7.1 Market Framework, Diffusion of Information and Node Removal

Let's consider that two platforms launch a digital service. For example, an application such as the Garmin Connect or the MyFitnessPal, in which users and developers get in touch. In this framework, there are $j \in [1, 2]$ platforms that compete in prices for users and developers.

Both, users and developers, only adopt the platform that maximizes his/her utility, and if the utility is non-negative. We define the utility of the i -user who adopts the platform j as follows³⁹

$$U_{ij} = c_{i,j}^u - t_u * |l_j - x_i| - p_{u,j} + \delta_u n_d \quad (6.10)$$

All users (and developers) pay a price for using the platform. That price is the same for all users (developers) and depends on each platform ($p_{u,j}$)⁴⁰. Each user has a constant stand-alone value when consuming platform j ($c_{i,j}^u$), and a specific set of tastes that we represent with their position (x_i) in the Hotelling segment, $[0,1]$. Each platform offers a service that coincides with a specific set of tastes (l_j). We assume that platforms are totally differentiated between them. So, they will be at the extremes of the Hotelling segment. The difference between the service offered by platforms and the users' tastes is considered a cost that is weighted by the parameter (t_u), commonly known as "transportation cost or nuisance cost". In this way, the expression $t_u * |l_j - x_i|$ represents the disutility of having a product that does not fit users' tastes perfectly. All users (and developers) value the presence of developers (users) in the other part of the market. In this way, the larger the number of developers in the platforms, the larger the utility that users obtain from using the platform (n_d)⁴¹. Up to this

³⁹The developers' utility function is symmetric. Despite this symmetry, users value the number of developers on the platform, and developers the number of users. The platform has to be able to set prices that attract both groups at the same time.

⁴⁰The subscript U refers to users, analogously, the developers' is D, but because of the symmetry, and for simplicity's sake, we omit it.

⁴¹The parameter δ_u controls how users value the presence of an additional developer. For simplicity's sake and without loss of generality, we assume that this value is constant and equal for all users and developers, $\delta_u = \delta_d = \delta$.

point, we have described the market framework proposed by Hagiū and Halaburda (2014). Nonetheless, we need to relax some of their assumptions to address the role of influencers. We assume that users (and developers) are linked with other users (developers). This network has no impact on utilities, but it is through the network that users (and developers) are informed about the platforms following an infection process. Our framework has five differences with Hagiū and Halaburda's:

- When a user or developer considers the possibility of adopting a platform, he/she assesses the stand-alone value of the platform ($c_{i,j}^u$). We assume it is normally distributed with a positive mean. In this way, we can simulate the presence of early-adopters, laggards, etc. In contrast, Hagiū and Halaburda assume a constant high value
- Agents are not fully informed. In our framework, some users and developers do not know the platforms at the beginning
- In the original framework, all users and developers have non-negative utilities. In our framework, some users and developers would have a negative utility if they use the platform. So, adoption may not be total
- In the original framework, there is no adoption process. All users consume one of the platforms from the very beginning. In our framework, there is an adoption process.
- In the original framework, no network is considered. In our framework, we assume a network among users and another one among developers

The two platforms compete in prices during one hundred periods⁴². At each moment, there will be three types of users and developers: Those who do not know any platform, those who know one platform only, and those who know both platforms. Although we consider the framework proposed by Hagiū and Halaburda, we do not assume their equilibrium equations. If we assume that, it will make no sense to simulate

⁴²We define a period as an iteration in the simulation model. We choose one hundred iterations arbitrarily. Other number of iterations can be considered as well.

adoption because one of their main assumptions is that there is no adoption process. Instead, we consider their utility and profit functions, and we set the platforms' prices by using the algorithm of Section 6.2.1.

Infection Process and Node Removal

We assume that 5% of users and developers know the platforms at the beginning of the simulations. These users and developers represent the “innovators”. They can “infect” others users or developers with their information. We consider that the adoption follows an infection process. Once users (or developers) know one platform, there is a probability of infecting other users in his/her network with that information. The infection process depends on consuming the platform: users and developers have to consume to infect other agents with their information about platforms. However, if a user (or developer) knows one platform only, he/she will spread the information about that platform only. If that user (or developer) knows the two platforms, he/she will only spread information about the platform he/she consume. Lastly, if they know one or two platforms but they do not consume any platform, they will not spread the information⁴³. On the other hand, there is no a standard definition of “influencer”. We only know that influencers play an important role because they influence other people, so we have to consider different influence measures. Influencers can be relevant because of their degree (how connected a node is), closeness (how easily can a node reach other nodes), betweenness (how important is a node in terms of connectivity), or because of other neighbors' characteristics. To identify those influential nodes, we consider four centrality measures: degree, closeness, betweenness and page rank⁴⁴. Then, we order the agents by their relevance in each metric. For each metric, we remove the 10% with the largest values⁴⁵. We analyze three cases: When no node is

⁴³The probability depends on the normalized degree of each node. The higher the degree, the higher the chance of being infected. We divided the degree of each user/developer by 4. In this way, the most connected node will only be infected in 1 out of 4 cases.

⁴⁴The page rank of a node is the proportion of time that an agent walking forever at random on the network would spend at one node. Nodes that are connected to a lot of other nodes that are themselves well-connected get a higher page rank.

⁴⁵The experiment has been carried out by removing the 5 and 15 percent also. The conclusions are the same.

Table 6.17: Correlations between Centrality Metrics

<i>Measures</i>	Betweenness & Degree	Betweenness & Closeness	Betweenness & Page Rank	Degree & Closeness	Degree & Page Rank	Closeness & Page Rank
Small-World Correlations						
Average	.5585	.7298	.6480	.7420	.9453	.6861
Std. Dev.	.0464	.0463	.0367	.0427	.0134	.0390
Preferential-Attachment Correlations						
Average	.7678	.3079	.7574	.2911	.7754	-.0120
Std. Dev.	.0226	.0474	.0228	.0477	.0267	.0414
Random Network Correlations						
Average	.9323	.8124	.9243	.8064	.9616	.7357
Std. Dev.	.0075	.0375	.0120	.0373	.0086	.0246

removed, when only the 10% is removed in one of the sides (users or developers), and when the 10% is removed in both sides (users and developers).

6.7.2 Simulation and Results

We create a world with 314 users and 314 developers, and two platforms⁴⁶. We consider three types of networks: small-world, preferential attachment, and random. The first two are created by the “network” extension of Netlogo. The small-world network is created by considering the proximity between agents in the simulated world and adding some random links (1% chance)⁴⁷. The “innovators” are selected by clustering. Therefore, all innovators are less than one node away from one another. To study the role of “influencers” in the diffusion process, we need to know the relationship among the different centrality measures that we consider. As we observe in Table 6.17, most of the cases are partly correlated. Therefore, each centrality measure addresses different types of “influence”. These correlations are robust to different network topologies, so the interpretation of influence does not seem to depend on the network topology we assume.

⁴⁶The number of users and developers is arbitrarily selected. We can consider other numbers, and conclusions will not change.

⁴⁷These networks are generated following the $G(n,p)$ variant of the Erdős–Rényi model, the Barabási–Albert algorithm for preferential attachment networks, and the Watts-Strogatz small-world network.

Table 6.18: Average Adoption in the different Network Topologies. No prices

<i>Networks & Removal</i>	Small-World Network	Preferential-Attachment Network	Random Network
No removal	83.05%	33.88%	74.11%
Betweenness (one-side)	73.52%	2.62%	49.22%
Betweenness (both)	71.91%	2.52%	44.26%
Closeness (one-side)	74.30%	1.15%	54.42%
Closeness (both)	73.53%	0.75%	51.47%
Degree (one-side)	74.88%	2.59%	47.98%
Degree (both)	74.31%	2.59%	42.62%
Page Rank (one-side)	74.32%	2.81%	48.80%
Page Rank (both)	72.92%	2.75%	45.79%

The Infection with Price Competing Platforms

Traditionally, adoption processes have been analyzed as stochastic processes of infection in which some nodes infect other nodes following a probability or a threshold distribution. However, the process of adoption may be influenced by prices or users' perception of products. Let's consider first that prices are zero. In this way, we can focus on the "infection" process. This case may represent the diffusion of open source platforms, such as Python or Android, in which no one pays for using them. But also, this case allows us to establish a framework in which we can compare the impact of prices in the adoption process. In Table 6.18, we observe the average infection in each network after 100 periods. The results are in accordance to those of literature: **The scale-free networks are very sensitive to the removal of the higher degree nodes**, see (Jackson, 2010, Chapter 7), and **the small-world networks are the most robust ones**, see Mishkovski et al. (2011). Nonetheless, the overall adoption cannot be directly compared with other works because it depends not only on the network topology but also, on the utility functions that we assume for users and developers and on the word-of-mouth process. Both, the overall adoption and the speed of adoption, are affected by the node removal. Obviously, this removal reduces the adoption. Let's introduce the idea of price competition between two platforms. We start all the simulations fixing a zero price and then, we let the platforms choose

the prices that maximize their profits at each step. At the same time, the spread of information among users and developers keeps going on. This situation can be considered as the simulation of the launching of a private platform such as Wolfram Mathematica. Let's begin analyzing the degree centrality. The degree is the most common and simple centrality measure in the literature. So, it makes sense to adopt it as a common framework to compare the three network topologies. In Table 6.19, we compare the three networks in three different cases: No removal, removal of 10% of users, and removal of 10% of users and developers. The first interesting result is that the preferential attachment network is critically damaged if we remove the 10% of agents with the larger degrees. This is not new. What is new is that, even when platforms can use the prices to try to boost adoption, the network is so critically damaged that nothing can be done. The launching will fail. If we adopt the other three centrality measures, we have the same conclusion.

On the other hand, a striking result in both, small-world network and random network, is that the adoption is lower in all the cases than in the previous case. This result is what we observe in reality, the number of users of Wolfram Mathematica is much smaller than the number of Python users⁴⁸. This result seems to be counter-intuitive because platforms are limiting the adoption of their products. However, the intuition is straightforward. A private platform has to face a trade-off between adoption and profits. If the platforms want to earn profits, they have to set positive prices on one side at least. A positive level of prices may change some users' decisions, given that the number of users is lower, fewer developers will enter the platform. Because the number of developers is lower, fewer users will enter the platform, and so on. As we observe in Table 6.19, **when we remove 10% of higher-degree agents, the percentage of users who adopt the platform in the random network case falls more than 50%. In contrast, in the small-world network, it “only” falls 23%.** Also, it does not matter if we remove the 10% of users or the 10% of users and developers, the overall adoption will be similar. Except in the small-world network, we can consider that platforms fail in launching their platforms, so there is no point in

⁴⁸We only consider the adoption, not the profitability. We will analyze it later.

Table 6.19: Average Adoption and Profits at the end of the Simulations. Endogenous Pricing

<i>Networks & Sides without Influencers</i>	Small-World		Preferential Attachment		Random	
	Average Adoption	Average Profits	Average Adoption	Average Profits	Average Adoption	Average Profits
No influencers removal	45.98%	0.2340	8.55%	0.0456	19%	0.0901
Betweenness (one side)	30.43%	0.1847	1.17%	0.0196	8%	0.0518
Betweenness (both)	29.77%	0.1467	1.12%	0.0022	4.63%	0.0207
Closeness (one side)	35.46%	0.1956	0.96%	0.0192	10.79%	0.0482
Closeness (both)	28.32%	0.1393	0.43%	0.0012	6.90%	-0.0632
Degree (one side)	35.69%	0.1958	1.23%	0.0220	6.3%	0.0056
Degree (both)	35.68%	0.1645	1.35%	0.0025	4.5%	0.0178
Page Rank (one side)	35.17%	0.1977	1.16%	0.0177	6.41%	0.0565
Page Rank (both)	31.53%	0.16	1.15%	0.0038	4.25%	0.0192

analyzing those cases. This result also emphasizes two issues: a) the well-known fact in the literature that **small-world networks are more resilient** than the random or preferential attachment networks to the removal of some relevant nodes, and b) **the topology of the network is important**. Let's consider now the other three centrality measures in the small-world network case⁴⁹.

Adoption of Platforms

In Table 6.19, we have observed the first interesting difference between the cases with and without influencers. In the latter, platform adoption is lower. However, **the level of adoption depends on the centrality measure we assume**. In this sense, there are no big differences between the cases in which we remove the influencers on one side or both. However, it is interesting that the effect in the final adoption depends on the metric we consider. For example, if we consider the betweenness, although we have removed the 10% more influential, the drop in demands is more than 10%. In fact, the demand is around fifteen percentage points lower than in the case with those influencers. However, with the rest of metrics, the drop is around ten percentage points if we only consider one side, but when we consider both sides, that drop is slightly lower. On the other hand, we observe that the speed of adoption is slower when we remove the influencers. They are the catalyst that guarantees a

⁴⁹Networks are critically damaged when we remove the influencers in the random and preferential attachment networks, so their analysis make no sense.

Table 6.20: Speed of Adoption. First 25 iterations

<i>Speed of adoption</i>	Betweenness	Closeness	Degree	Page Rank
Original Case	.0132	.0134	.0127	.0126
One side	.0061	.0072	.0077	.0075
Both	.0058	.0051	.007	.0063

Figure 6-14: Adoption of Products with and without the 10% Influencers

quick launch. In Table 6.20, we observe that, in all the cases, the speed of adoption is two times faster with influencers than without them. However, in comparison with a case with only an infection process, the speed is significantly slower⁵⁰. Lastly, in the cases in which we consider the closeness and the page rank measures, the adoption of platforms is slightly different when we only remove 10% of users than when we remove the 10% of users and developers. This is the first evidence that **different centrality measures influence the adoption process of platforms differently**. In Table 6.18, we depict the final adoption of platforms when prices were zero. In that case, there was no such difference in the adoption process, so this difference seems to be the consequence of how platforms set prices.

⁵⁰In the same simulations but without platforms setting prices, the speed of infection is around 3-4% per iteration.

Prices of Platforms

In Fig. 6-15, we compare the prices of the four previous cases. Our results show that there are differences in how platforms set prices when we remove users with large closeness or page rank than when we remove users with large betweenness or degree. This result suggests that the most connected users play a different role than those who are “close” to everyone in the network. Nonetheless, there is always a case in which prices are similar with and without influencers. The intuition of this result is the following. When we consider the betweenness and the degree metrics, we remove those nodes that are either very connected or those who play a relevant role in connecting other nodes. So, when we remove those nodes, the information spreads more asymmetrically. In this situation, platforms have market power over some users because they do not know about the existence of competitors. Therefore, platforms have an incentive to set higher prices. Nonetheless, when we remove 10% of influencers in both sides (users and developers), we are again in a symmetric framework. Therefore, prices behave symmetrically (in both sides). On the other

Figure 6-15: Average Prices on Users' Side with and without the 10% Influencers

hand, when we consider the closeness and the page-rank metrics, we pay attention

to nodes that are “close” to the rest of nodes in the network (closeness), or to nodes that attract a lot of “traffic” from other nodes. This case is interesting because prices behave differently. The intuition is the following. The closeness measures the distance to all other nodes. The page-rank pays attention to how important neighbors are. So, when we remove the nodes that seem to be the most important ones under these metrics, we may not disrupt the flow of information enough. Only when we remove the 10% of users and developers, we remove enough agents to affect how the information flows. If we pay attention to Fig. 6-14, only in these cases the overall level of adoption is different when we remove users only or users and developers. This change happens after ten iterations, the exact same moment in which prices start to rise in Fig. 6-15.

Profits of Platforms

In Fig. 6-16, we compare the profits that platforms earn when we remove the influencers in the four cases analyzed in the previous section. In all cases, **profits grow faster and are larger when there are influencers**. In contrast with prices, which behavior depends on the centrality metric we assume, profits behave in a similar way in all cases. This result points out that the different price behavior of the previous section may be the way in which platforms mitigates the removal of some nodes. On the other hand, independently of what centrality metric we use, influencers have an impact on profits. In Table 6.19 and in Fig. 6-16, we observe that the cases without influencers have lower profits. We can summarize the role of influencers in two points: **Profits are more sensitive than demands to influencers, and the way platforms react to the absence of those influencers vary among the different centrality measures**.

6.7.3 Conclusions on the Role of Influencers and Network Topologies

In this section, we have addressed not only the role of different network topologies but also, the role of the most relevant nodes in the network. We show **the adoption**

Figure 6-16: Average Profits with and without the 10% Influencers

is overestimated when we do not consider the price competition. Platforms do not want to maximize adoption, they want to earn profits, and they face a trade-off between boosting adoption and earning profits. We also show that **adoption is higher and faster when there are influencers**. Without influencers, the profits, the adoption, and the speed of adoption are much lower than the case with them. We also show that the speed of adoption may be overestimated if we only assume a word-of-mouth process. We find that **prices are sensitive to influencers**, but that influence depends on which centrality measure we consider. Lastly, an interesting result is that, in all the cases, independently of what centrality measure we consider, profits are higher with influencers. They help in accelerating the adoption and in increasing profits.

These results provide us with answers to the open questions on how relevant is the position of users in the network, or in other words, we prove that **it matters the connectivity and the flow of information among consumers when addressing the launching of digital platforms**. The adoption of platforms clearly depends on the spread of information. Platforms can foster their adoption by using influencers, and even if they do not exist, it is profitable to “create” them. Additionally, in

this simulation, we reinforce our previous conclusions on the launching of platforms. Companies have to attract both sides in tandem, as Cabral (2011) pointed out. However, we have omitted the relevance of other players in the market. Platforms are not alone in the market, and in many cases, they are competing and disrupting well-established markets. In the Industrial Organization literature, there are a lot of works that address the issue of entering the market. Although some works address the issue of launching a digital platform in an established market, such as Belleflamme and Toulemonde (2004) or Evans and Schmalensee (2010), to the best of our knowledge, **there is no work which addresses the diffusion of information, the launching of platforms, and the influence of established companies.** We are the first ones in addressing this issue in the next section.

6.8 On “Third Options” and their Influence on the Diffusion of Digital Platforms

Each year, new platforms appear in markets that were dominated by traditional business models like the taxi sector (Uber), the takeaways (JustEat) or the real estate sector (Airbnb). However, these markets are not only formed by platforms but also, by one-sided companies (third-options). **We cannot omit the fact that platforms compete with each other and with other companies that are not platforms.** In the fitness tracker market, some companies only sell a device, and they do not care about creating a platform. Nonetheless, the mainstream market is going in the other direction. For example, Garmin is a two-sided platform, but Swarovski is not. In more general terms, the vast majority of companies in the fitness tracker market are platforms, in the sense that they put in touch two types of customers that need each other in some way (users and developers). Nonetheless, in other markets, it is different, and two different business models compete with each other. For example, you can watch a movie on Netflix, or you can buy the DVD.

In this Section, we simulate the launching of digital platforms, and the impact of a

competing one-sided company (third-option). To do so, we extend the Hagiu and Halaburda’s framework by considering there is a third alternative that it is not a platform. We study which market features (differentiation, prices, etc.) influence the adoption of digital platforms, and the impact of the impact of the one-sided company (hereinafter, third option) in those markets. Therefore, in this Section, we try to answer **to what extent is different the launching when platforms have to compete with business models that are not based on network effects.**

6.8.1 Market Framework and Theoretical Background

We consider the two-sided market proposed by Hagiu and Halaburda (2014) in which two platforms compete in prices for users(u) and developers(d). For simplicity’s sake and without loss of generality, we assume the same set of assumptions than in Section 6.7 with regard the utility functions and the diffusion of information. Nonetheless, in this case we assume that users are linked by a small-world network and, we relax a new assumption.

In theoretical models is normal to consider that alternative options are nonexistent. This assumption implies that all users value the same not consuming than consuming other products that are not platforms. Nonetheless, some users may value alternative options that are not provided by platforms. For example, many restaurants send information about their menus by postal mail even if they are using a digital platform that connects them with consumers. In some cases, users order their takeaways without using the digital platform (by phone for example), but not all users value this option in the same way. In this framework, we consider there is a one-sided company that offers an imperfect substitute of the platforms’ services. A fitness tracker without platform, for example. The utility of a user- i choosing the one-sided product is⁵¹

$$U_{io} = c_{i,t}^u + a^o - t_u * |l_o - x_i| \quad (6.11)$$

⁵¹We assume that the third-option only exists on the users’ side.

In this case, we also consider the existence of consumers' subjective taste ($t_u * |l_o - x_i|$), and the stand-alone value of the good or service ($c_{i,t}^u$) with respect to the third-option. However, we consider a new parameter. The a^o represents the attractiveness index. It is an exogenous variable that is exclusive of the third option, and it represents an additional stand-alone valuation of this option. We do not assume that the third option can change the price of their products. The idea is to show how platforms can adapt their behavior to the third option, not the other way around. Nonetheless, nothing prevents platforms from fixing zero or lower prices on one side if that is profitable.

The Third Option

We also consider that, once that one user knows at least one platform, he/she also knows the “third-option”. Then, three scenarios are possible:

- The utility of consuming one of the platforms is positive, and it is the maximum utility
- The utility of consuming both, the platform and the third option, are not positive
- The utility of consuming the third option is positive, and it is a better option than the platforms (it is the maximum utility)

In the first case, the user will consume the platform. In the second case, the user will remain outside of the market. The third case is the interesting one because the user will consume the third option. Nonetheless, we introduce a bias. We assume that, only after three consecutive periods in which this utility is the highest, the user will consume the third option⁵².

⁵²This is an ad hoc assumption. We can consider other number of periods. The intuition is the following. Sometimes, you order food from a restaurant using an app like JustEat, but if you always choose the same restaurant, maybe you can avoid using the platform, and you decide to order food by phone. We test whether or not there are incentives to avoid the intermediation of platforms.

6.8.2 Simulation and Results

The simulation framework is the same than the one depicted in Section 6.7. The only difference is that, at each step, users that know about at least one platform will evaluate if the utility they obtain when joining a platform is larger than not joining any platform at all or joining the third option. To influence users' decisions, companies can change prices following the algorithm proposed in Section 6.2.1⁵³.

We analyze two different situations: First, the symmetrical case, in which users have the same stand-alone value when consuming platforms or the third option ($c_{i,t}^u = c_i^u \sim N(0.3, 0.25)$). And second, the asymmetrical case, in which users have a larger stand-alone value when consuming the platforms ($c_i^u \sim N(0.3, 0.25)$) than when consuming the third option ($c_{i,t}^u \sim N(-0.7, 0.25)$)⁵⁴. For each set of values, we run thirty simulations with one hundred iterations in NetLogo, see Wilensky (1999). All the simulations start with a zero price.

Results: Without the Third Option

In this section, we focus on the case in which users have only the option of quitting the market or using the platforms. This case is symmetrical to the one presented in Section 6.6.2. Let's consider first the impact of the contagion probability. In Fig. 6-17, we compare two cases with a low and a high probability of infection.

When probability of infection is low, we observe that the adoption is very slow. Although the increment is constant, after one hundred iterations, less than the 40% of the market is covered. However, when the probability of adoption is high enough, we observe that the adoption is quite fast. In fact, after 25 iterations, the platforms reach their maximum adoption at 60% of the market. The intuition is straightforward. The spread of information is essential to guarantee the adoption of platforms. This is the other side of the coin of our results in Section 6.6.2. The faster, the better

⁵³One of the main issues of the agent-based methodology is the over-parametrization of the models. We have to take into account many variables and, the complex the model, the harder to know what "is going on under the hood". For simplicity's sake, we omit the exact specifications of the simulated model, but they are available upon request. Nonetheless, the results presented here represent the vast majority of cases of the parameter space.

⁵⁴Additionally, the model can be downloaded at: <https://goo.gl/bGLRDP>

because more users will be willing to join the platform. Let's consider now how the

Figure 6-17: Adoption. Different Probabilities of Infection. Without one-sided Platforms

market differentiation (or transportation costs) influences the adoption of platforms. In Fig. 6-18, we observe that the transportation cost is the parameter that limits the maximum adoption of the market. The intuition is the same than in Section 6.6.2. The higher the heterogeneity of the market, the more difficult is to attract users. In that sense, many users do not adopt any platform, and the maximum adoption is lower than when heterogeneity is low. These cases shed light on the relevance of

Figure 6-18: Adoption. Different Transportation Costs. Without one-sided Platforms

transmitting information and market differentiation in the launching of platforms. However, even if we assume that quitting the market is the same than choosing the

third option, the model does not give us answers about the role of the third option. That is why it is necessary to consider the third option explicitly.

Results: With a Third Option

In this section, we consider the third option is available. We consider two cases: in the first one (that we call “symmetrical”), we assume all consumers value the product offered by platforms and the third option in the same way, ($c_{i,t}^u = c_i^u \sim N(0.3, 0.25)$). In this case, the difference between the platforms or the one-sided company is at network effects level. In the second one (that we call “asymmetrical”), we assume that, on average, users value more the product offered by the platforms, ($c_i^u \sim N(0.3, 0.25)$), than the third option, ($c_{i,t}^u \sim N(-0.7, 0.25)$). For example, the idea of using a platform to order food that allows you track your order, to pay using several credit cards, etc. versus the idea of ordering the food by phone directly. We compare these two cases to point out the differences in the competitive pressure that the third option generates.

The Symmetrical Case

On the one hand, if we consider a low and a high probability of infection, we obtain the same result. The third option is more attractive than the platforms. In Fig. 6-19, we observe that users tend to quit from platforms, and they choose the third option. However, the level of adoption of the third option is not relevant for us. It depends on which parameters we assume. What is truly relevant is that, if the third option is attractive enough, the increase in the probability of infection may reduce the adoption of platforms. The intuition is the following. First, the platforms cannot attract enough users, and they need them. However, the users who enter the platform get in touch with a few developers, and then, they get out of the platform because the platforms do not provide any additional services than a few apps that users can use outside of the platform. In other words, as Evans (2011) states, *platforms must create a significant value as a result of getting two sides together that exceeds what they can do on their own or on alternatives platforms*. The presence of a third option

Figure 6-19: Adoption. Different Probabilities of Infection. With one-sided Platforms (Symmetrical Case)

is more relevant in this case, in which platforms do not create enough value, and it can be linked to a higher chance of failure in launching the platforms. In other words, **it is easier to launch a one-sided service** first.

If we consider the market differentiation, it is clear that the adoption of platforms is affected by the presence of the third option. However, this effect is not homogeneous and depends on the market differentiation. In Fig. 6-20, we depict two cases with different levels of market differentiation. It is clear that the presence of the third option has a large impact in markets with low differentiation. Nonetheless, that impact seems to be non-linear because when market differentiation is decreasing, the impact of the third options is increasing more than linear. In the case with transportation costs of 0.6, the percentage of users who quit the platforms is less than 5%, but in the case with transportation cost of 0.2, it is more than 40%. This may suggest that platforms face a trade-off. In highly differentiated markets, it is more likely to fail because the potential market is smaller, but the threat of the third options is low. But in markets with low differentiation, platforms will face a stronger competition with the third option. This stronger competition also limits the potential market of platforms. Some authors suggest that **the best strategy is to focus on small and homogeneous markets**, see Evans (2011). These markets are easy to understand, and it is easy to identify the adequate technology and strategies to grow up later. However, as we have shown, there is a risk of being locked in a small market

(a) Transportation Cost at 0.2

(b) Transportation Cost at 0.6

Figure 6-20: Adoption. Different Transportation Costs. With one-sided Platforms (Symmetrical Case)

with a small market share.

These results highlight that **platforms have to offer significant value**. If not, it is quite difficult to attract people that want to know other people because they will abandon the platforms quickly afterward. These results give us an intuition of why so many start-ups based on platforms fail⁵⁵.

The Asymmetrical Case

Let's consider that platforms have some extra features that make them more attractive (better technology, better marketing campaigns, an outstanding idea, etc.). To do so, we assume that the third option is relatively less valued than platforms.

Obviously, this environment favors the launching of platforms. However, it is interesting to point out to what extent, the third option influences platforms. In Fig.6-21, we compare two cases with differences in the probability of being infected. When the probability is low, we observe that the adoption is very slow, although the increment is constant, after one hundred iterations, only 40% of the market is covered. However, when the probability of adoption is high, we observe that the adoption is fast. In fact, after 25 iterations, the platforms reach its maximum adoption (60% of the market). These are the same results that we obtained in Section 6.8.2. In this case, it is clear that the third option has little impact on the launching of platforms. The

⁵⁵Forbes, 90% of the start-ups will fail <https://goo.gl/ptyNrM>

third option does not influence the performance or the market shares of platforms, which are constrained by the market. Let's consider now how the differentiation af-

Figure 6-21: Adoption. Different Probabilities of Infection. With one-sided Platforms (Asymmetrical Case)

fects the adoption process. In Fig. 6-22, we observe how market differentiation limits the maximum adoption in the market. In contrast with the previous case, the market differentiation affects both services, platforms and the third option. The higher the differentiation, the less attractive are both, platforms and the third option. The third

Figure 6-22: Adoption. Different Transportation Costs. With one-sided Platforms (Asymmetrical Case)

option seems to be irrelevant in the launching process of platforms. However, we have assumed that the stand-alone value of platforms was higher than the third option's. Nonetheless, we can test what happens if we increase the attractiveness of the third

option. This parameter helps us to compare cases by increasing the stand-alone value of the third option. In Fig. 6-23, we observe an intermediate case between the symmetrical and the asymmetrical ones. In this case, we depict another asymmetrical case, but in which the advantage of the platforms is smaller.

At the beginning of this Section, we observe that when the attractiveness index is low, the adoption of platforms is not affected by the third option. However, when the attractiveness index is high, the adoption of platforms is not only slower than before but also, it is more irregular, Fig. 6-23. We can derive three interesting insights from

Figure 6-23: Adoption. Different Degrees of Attractiveness. With one-sided Platforms (Asymmetrical Case)

these results:

- First, when the platforms have a clear advantage, but this advantage is not large enough, (more specifically, $c_i^u \sim N(0.3, 0.25)$ and $c_{i,t}^u \sim N(0.15, 0.25)$), the third option is able to slow down and limits the adoption of platforms. **It imposes a competitive pressure on platforms by stealing customers.**
- Second, at the beginning, a lot of users prefer the third option because there are not enough developers on the platforms. However, when platforms succeed in attracting enough developers, some users start to join the platform. Nonetheless, the number of users on the platforms will be lower than without the third option.

- Third, with the third option, platforms set a lower price on users' side than on the case without the third option. This is because platforms recognize the threat of the third option, the fewer users, the fewer developers, the lower the profits. To avoid that outcome, they prefer to compete harder for the users. This behavior is depicted in Fig. 6-24⁵⁶.

Figure 6-24: Comparison of Prices. Attractiveness at $c_{i,t}^u \sim N(0.15, 0.25)$. With one-sided Platforms (Asymmetrical Case)

As a summary, we can extract two relevant insights. On the one hand, **the competitive pressure of the third option is not linear, and it depends on the relative attractiveness of platforms with respect to one-sided companies.** The lower this attractiveness, the stronger the competition, and the more difficult the launching of platforms. In this case, **the recommendation is to launch a one-sided company.** These results complement those of the multi-sided literature and prove that the intuitions of these models are robust in more heterogeneous frameworks. On the other hand, we can point out two killer combinations of strategies to succeed.

- If the platform does not create value enough by itself, integrate one of the sides and become one-sided
- If the platform creates value but it is moderate, there are two options. Either it should be prepared to suffer a strong competition with previous incumbents

⁵⁶In this case, the competition is also stronger for the developers.

or one-sided platforms. Or it should become one-sided at the beginning until the take-off.

Failures in Launching

One of the most interesting cases to analyze is when platforms fail in reaching the market. We define a failure as a situation in which at least one platform has no user in the platform. Given that we analyze several parameters, it is interesting to divide them into two classes: those cases related to the perception of the platform (stand-alone value), and those related to the market characteristics (probability of being infected and market differentiation). In Table 6.21, we observe the average

Table 6.21: Failures in Launching. With one-sided Platforms

Perception of platforms External dimensions.	<i>Asymmetrical</i>	<i>Symmetrical</i>
<i>Avg. Prob Infection</i>	8.933(6.713)	8.267(5.007)
<i>Market differentiation</i>	6.750(3.715)	8.875(3.117)

failure. This value is computed as follows. For each parameter value, we run thirty simulations. For all those cases, we compute the average of those cases in which a platform has zero users on it. Then, we compute the average of all the failures for all the parameter values. That is the value presented in Table 6.21. In this way, we know which parameters are more associated to market failures.

On average, both cases seem to be equally prone to failures. However, there is a difference in the standard deviations between those characteristic linked to the perception of platforms, and those linked to the market. That is because the cases with a low probability of infection are more predisposed to failure than those with a high probability. In general, it seems that both variables are similar, the only difference is that the probability of infection tends to have a lot of failures concentrated in a specific region. Although there is a relationship between a high market differentiation and more failures, that relationship is more evenly distributed than the one between the probability of infection and failures. In Fig. 6-25, we depict these results in the

asymmetrical case. However, the results are similar in the symmetrical case⁵⁷.

(a) Failures with Different Probabilities (b) Failures with Different Trans. Costs

Figure 6-25: Number of Failures. With one-sided Platforms (Asymmetrical Case)

6.8.3 Conclusions on the Role of the Third-option

Our results confirm our previous insights that when market differentiation is low, platforms can attract more users. In this case, that also implies that the third option may attract more users too, which may slow down the adoption of the platforms. However, if the market differentiation is high, platforms are not so influenced by the third option. But the maximum level of adoption is lower, and the failure rate is higher. Those results point out that **the management of the market differentiation is essential for survival**. The old rules still apply in this case. Additionally, we compare two cases. One in which the platforms are better valued than the third option, and another one in which they are symmetric. We find that, if platforms cannot create a significantly large value, the third option will be able to attract consumers, and the platform will fail. On the other hand, if platforms can create a significantly large value, the third option will not influence the adoption of platforms. However, in the middle, there are interesting insights. We have found that price competition is stronger, but this effect is not linear in the relative attractiveness of platforms with respect to the third option. Our results confirm a previous insight of the multi-sided

⁵⁷Results are available upon request.

literature: **normally, it is easier to launch a one-sided service**, and then recon-vert it into a platform. This is because a platform requires a great effort to break the chicken & egg problem at the launching phase.

We also find that, in comparison with a case without the third option, the adoption of platforms may be overestimated because the third option affects the overall adoption in a non-linear way. Depending on the degree of market differentiation, the effect of that alternative can be critical. Lastly, **markets highly differentiated, or markets where information flows slowly, are more predisposed to fail** even when the platforms have an advantage, as we found in previous sections.

6.9 Discussion and Conclusions

In this Chapter, we have addressed three questions. *How is platform adoption influenced by the spread of information among consumers? What does foster their adoption? Is it a matter of how users transmit the information?* In previous Chapters, we have observed that, if we want to keep the same theoretical models, first, we have to be able to relax their assumptions without increasing their complexity. In that sense, agent-based modeling is a potential solution, but another question has to be answered before, *Can price competition be implemented in agent-based models following a set of common rules in concordance with Game Theory and economic intuitions?*

We start this Chapter by providing an answer to this last question. **We develop an algorithm for agent-based models that simulates the behavior of price-competing companies.** We test the price-competition algorithm in several theoretical frameworks such as the Hotelling model, a vertical differentiation model or a two-sided market. In all of them, we prove the algorithm is capable of reaching the equilibria predicted by theory. We also prove that the algorithm works in cases that were not considered by theory, or in parameter regions where the theoretical model was not suitable to be analyzed. **These results open the door to implementing endogenous pricing in agent-based models.**

Once we prove that price competition can be implemented in agent-based models

following a set of common rules in concordance with Game Theory and economic intuitions, we can start answering the remaining questions. We first addressed the question on how platform adoption may be influenced by the spread of information. We extend the Hotelling's and Hagiu and Halaburda's models to consider a random network of consumers that become aware of the products by infection, and we prove that the insights on the differentiation still apply, but the way information spreads is relevant, and it modifies the optimal pricing. When companies spread information about their own products, the prices tend to be more volatile than when both agree on spreading information about their both common products. Additionally, we observe that highly differentiated markets are more prone to failures in launching than low differentiated ones. **This finding supports the idea of launching products on homogeneous market niches.**

Afterward, we have addressed the role of influencers in the spread of information. In this case, we consider the Hagiu and Halaburda's model, and we assume users are in random, preferential attachment and small-world networks. We prove that adoption is higher and faster when there are influencers. **Without influencers, the profits, the adoption, and the speed of adoption are much lower than the case with them.** We also show that the speed of adoption may be overestimated if we only assume a word-of-mouth process. We find that **prices are sensitive to influencers**, but that influence depends on which influence measure we consider. Lastly, an interesting result is that, in all the cases, independently of what influence measure we consider, profits are higher with influencers. They help in accelerating adoption and profits.

Then, we conclude by addressing how one-sided companies may influence the take-off phase of platforms. In this case, we extend the Hagiu and Halaburda's model by allowing the existence of a one-sided company that compete with platforms for users. We compare two cases. One in which the platforms are better valued than the one-sided company, and another one in which they are symmetric. We find that, if platforms cannot create a significantly large value, the one-sided company will be able to attract consumers, and the platform will fail. On the other hand, if platforms

can create a significantly large value, the one-sided company will not influence the adoption of platforms. Even when platforms create value, if it is not large enough, the one-sided may limit the adoption of platforms⁵⁸. In those cases, the only available instrument to avoid to fail is to reduce the price, a strong price competition or becoming a one-sided platform during the take-off. We also find that, in comparison with a case without the third option, the adoption of platforms may be overestimated because the third option affects the overall adoption in a non-linear way. Depending on the degree of market differentiation, the effect of that alternative can be critical. Therefore, we conclude that **launching a one-sided company is easier than launching a platform**. Nonetheless, if the platform creates a large added-value, its launching will be easy, but if it is a moderate added-value, either the platform is willing to keep a strong competition at the beginning, or it is better to become a one-sided platform.

With this evidence, we have answered the proposed research questions. Nonetheless, it may be other features that may foster the adoption of platforms or the spread of information that we have not considered. However, our results highlight that **it matters how users transmit the information**, and we have proved that faster transmissions increase the adoption. It is not desiderata of this Thesis to provide a comprehensive list of features that influence the adoption, but to point out that information flows are essential, but not the only ones, as we have shown with the third-option case.

⁵⁸This happens because the platforms have not strong network effects at the beginning. This result points out the trade-off of strengths between an emerging platform and a one-sided platform.

Chapter 7

Conclusions and Main Results

7.1 Conclusions

Internet-of-Things (IoT) is the new digital revolution and, in this new revolution, wearables are one of the most interesting and representative technologies. **These devices illustrate the main features of the new digital revolution: devices, platforms, and data.** Users buy a *device* to know more about their fitness, their health, or the daily activities. These devices are based on *platforms* that coordinate users with developers, advertisers, or other stakeholders that are interested in *users*. The interest in platforms is also skyrocketing because it does not matter which will be the successful technology, **the business model will be based on platforms**, see Nielsen (2014) or Parker et al. (2016) among others.

Platforms create value *by reducing transactions costs faced by multiple distinct economic agents that would benefit from coming together*, see Evans (2011). Digital platform markets are exciting to study but also, it quite complex to describe them because they are so unique that, in most of the cases, no data is available to analyze their impact, performance, or behavior. Many companies have enough data to address this issue. However, they are reluctant to share that data with third-party institutions because they fear that it will allow competitors to overtake the market by studying the strategies of the incumbent. In this situation, the only possible approach was to consider a theoretical perspective.

We have first analyzed the available data on fitness tracker market. **The most important insight we have found is that the fitness tracker market encompasses two sub-markets, one in which devices are sold to users, and another one in which developers provide services based on users' data.** However, both markets are intermediated by several platforms that compete with each other. **Therefore, fitness tracker markets are operating as multi-sided platforms.** This finding clearly points out that, to understand this market, we need to address the multi-sided market structure. However, the analysis of this market has also pointed out which features are especially relevant among fitness tracker companies. **We have observed that brand expansion (differentiation among platforms), compatibility among platforms, and especially price competition are cornerstone aspects of this market.** This preliminary study has drawn our attention towards a big set of questions that we can summarize in these bullet points:

- It is essential to understand multi-sided platforms so, What are multi-sided platforms? What is the current state of the literature on multi-sided platforms? What is already known, and what should we pay attention to?
- Prices, compatibility, and differentiation seem to play an essential role so, what are the main drivers of pricing? Why are platforms sharing their networks? What are the implications of commoditizing data?
- What does make the launching of platforms successful? How do platforms attract users over time? Is it homogeneous? Is it a matter of how information spread?

We have analyzed the literature on multi-sided markets, and we have shown that fitness tracker platforms have the necessary characteristics to be analyzed as multi-sided platforms. We have also observed that these markets have exclusive features that make their study different from other markets. Especially regarding pricing and costs, which leads us to question *How to properly price fitness trackers? Which are the*

main drivers of pricing? We have studied the main lines of research of this literature as well as the main conclusions, and we have seen that **asymmetric pricing is the norm**. We have observed that there is an ongoing discussion about how to properly price platforms at their launching to overcome the chicken & egg problem. Several proposals have been addressed in the literature, but there is not a clearly better one. But the evidence highlights that **platforms should set low initial prices to foster adoption among early-adopters**, and they should change those prices as the number of users on each side changes. However, there are open questions, *What does foster their adoption? Is it a matter of how users transmit the information?* We have also discussed which organization scheme is better, and we have highlighted that **there is no economic model that is always better**. Nonetheless, we have observed that some platforms were born as one-sided platforms, and only when they were mature enough, they adopted a multi-sided platform business model. However, currently, what we observe in new digital markets is that **platforms born as multi-sided markets** (see Facebook or JustEat for example). So, **it makes sense to analyze the wearable (or fitness tracker) market as a multi-sided market**. We have also observed that compatibility is not well addressed in the literature, which drives us to the next question, *what are the implications of compatibility in the market? What are the consequences of sharing network effects among platforms?* Global platforms such as Facebook or Google have created vibrant ecosystems full of users and developers that are generating huge amounts of data that they interchange. But, *to what extent the use of data in these networks influences our economic intuitions? Can we rely on our traditional insights? Or is this time different?* After the literature review, there are even more open questions, such as *What is the role of users expectations? Is it matter if users care about the device but not about the connecting with other people? What is the optimal pricing policy when launching a platform?* These questions are essential in the context of wearables and IoT markets. Nonetheless, the lack of works that address these issues is related to the lack of works that address these markets.

To complement the current research on multi-sided markets, we have laid out sev-

eral models that reproduce the fitness tracker markets. In the most simple case, we prove two insights. On the one hand, **users' expectations matter. The optimal pricing policy and profits heavily depend on the expectations** so, successful platforms have to invest time and resources to address their customers' expectations. On the other hand, **network effects can accelerate adoption, but they may cause a failure in launching**. In that sense, we have observed that launching a platform with an independent device could guarantee the take-off, but its adoption may be slower than a pure platform. We have also observed in a more complex model that **platforms have incentives to become compatible**. However, these incentives are not symmetric. In vertically differentiated frameworks, the follower has incentives to share its database with the leader. In this way, the differentiation is maximized, and both companies increase their profits. Nonetheless, other configurations of compatibility may drive the market to extreme cases of competition. These results highlight one essential issue. When platforms are differentiated by their number of customers, or by the quality of their products only, there are incentives to separate both markets. In that sense, **there is a risk of creating "monopolies of data" and "competitive markets of users"**.¹ We have modified this framework to consider another type of differentiation, and we find that **compatibility always reduces the competition**. This incentive to become compatible has risen a concern, *may it create incentives to deter entry?* We addressed this issue too, and we have found that new entrants threat the status quo of the incumbents, and therefore, incumbents have larger incentives to deter entry than in traditional markets or incompatible platform's markets. In that sense, **platforms have incentives to launch new brands because it may foreclose niche markets to entrants**, and it improves their position with respect to other competitors. This incentive to foreclose the market is increased when platforms become compatible with one another. **The steady increase in brands in the fitness tracker market since 2011 is clear evidence of this finding.**

¹These results have been published in Sanchez-Cartas, J.M., and Leon, G. (forthcoming): Data Sharing Agreements in Vertically Differentiated Two Sided Markets. International Journal of Economic Theory.

To prove that our previous conclusions about compatibility can be applied to any market, we have also developed a generalized model. In that framework, we prove that **compatibility increases the market power of the platforms involved**, and it may be in the interest of all the parties to create such agreements. We illustrate our findings with the evolution of compatibility networks in the fitness trackers market². We have also addressed the concern regarding the commoditization of data. *Is it improving competitiveness, or is it creating monopolies?* We have analyzed the prices on both sides, developers' and users', and we have found that developers' prices are based on the relative difference in data quality among providers, as traditional theory predicts. However, when analyzing users' side, we have found something interesting. The pricing depends on the relative strength of the network effects that users generate on developers' side. If those are weak, there is a possibility of a platform becoming a monopoly of data. However, if the network effects are relatively strong, the market will be competitive.

Lastly, we address the questions regarding the launching of platforms. We propose a theoretical dynamic model of three stages, and we find that **prices on the subsidized side can be lower than what static theory points out because of the necessity of attracting not only current consumers but also, future consumers**. These prices highlight two issues: **previous consumers increase prices for future ones, and predatory prices are harder to detect in these markets because of the current and future network effects. It is optimal to reduce prices more than in static models** on at least one side. However, the complexity of this model quickly increases, and its tractability is compromised. Additionally, we observe that this framework does not allow us to have a clear picture of how users make their adoption decisions because it assumes simultaneous decisions on all the stages. To try to address the complexity of the adoption process, we laid out a model with three agents. We test their adoption decisions in three scenarios, sequential decision, semi-sequential decision, and simultaneous decision. We find two results.

²These results have been published in Sanchez-Cartas, J.M., and Leon, G. (2017b): Shared networks and market power in two-sided markets. *Economics Bulletin*, vol. 37, no. 3, pp. 2173-2180.

The users' heterogeneity and the users' timing matter, and **coordination is easier to achieve when there are sequential decisions**. However, in reality, there are users who wait to see what others do. This feature imposes a limitation on the answers we can provide to the questions on launching/adoption of digital platforms. In a nutshell, we can partially answer the questions on the optimal pricing of these platforms, but we cannot answer *how do platforms attract users over time, or how is platform adoption influenced by the spread of information among consumers?* **With the previous models, we cannot answer those questions**. Relaxing some of their assumptions make them either intractable or not suitable to be addressed analytically. In that sense, a desideratum is a tool that allows us to keep the same framework, relax their assumptions, and avoid the increase in complexity. Therefore, to address adoption, we need to study the literature of diffusion of innovations. To narrow the scope of that literature, we only focus on those approaches that deal with individual decisions.

In other words, we analyze the suitability of multi-agent systems or agent-based models to address the study of the launching of digital multi-sided platforms. We have found that many agent-based models have adopted theoretical economic models as frameworks. However, those works only consider the equilibrium equations. Therefore, **previous works are constrained by the same set of assumptions than theoretical models, and the applicability of agent-based models is limited**. On the other hand, there are cases that address the adoption of innovations without considering those equilibrium equations, but they do not take into account the optimal behavior of companies. This is especially relevant because prices are essential in the adoption process, and companies are the ones that set them. Additionally, given the current state of the literature on diffusion/adoption of products, there is no way to address them properly. **No empirical or theoretical literature is available regarding the diffusion of innovation literature to simulate the launching of platforms, optimal prices, or competition**. We know that pricing matters, so we have considered a new question, *Can price competition be implemented in agent-based models following a set of common rules in concordance with Game Theory and*

economic intuitions? We also know that network effects may play an essential role as well as network topologies, so both of them have to be part of any model that pretends to simulate the adoption of digital platforms.

We develop an algorithm for agent-based models that simulates the behavior of price-competing companies. We test the price-competition algorithm in several theoretical frameworks such as the Hotelling model, a vertical differentiation model or a two-sided market. In all of them, **we prove the algorithm is capable of reaching the equilibria predicted by theory.** We also prove that the algorithm works in cases that were not considered by theory, and in parameter regions where theoretical models were not suitable to be analyzed. These results open the door to implementing endogenous pricing in agent-based models³. Then, we extend the Hotelling's and Hagiu and Halaburda's models to consider the flow of information throughout networks, and we prove that the insights on the differentiation still apply, but the way information spreads is relevant, and it modifies the optimal pricing. **When companies spread information about their own products only, the prices tend to be more volatile than when companies agree on spreading information about their own products and the competitors'.** Additionally, we observe that **highly differentiated markets are more prone to failures in launching than low differentiated ones.** This finding supports the idea of launching products on homogeneous market niches, and it answers the first question. The flow of information is essential in both, the pricing and the adoption⁴. Afterward, we have addressed the role of influencers in the spread of information. We prove that adoption is higher and faster when there are influencers. **Without influencers, the profits, the adoption, and the speed of adoption are much**

³This algorithm has been presented in Sanchez-Cartas, J.M. (2017): An agent-based algorithm for simulating markets with price competition. In: 23rd International Conference Computing in Economics and Finance. Society for Computational Economics, and an extended version has been published in Sanchez-Cartas, J.M. (2018): Agent-based models and industrial organization theory. A price-competition algorithm for agent-based models based on Game Theory. Complex Adaptive Systems Modeling, Vol. 6, no. 1, pp. 2. Springer.

⁴These results have been published in Sanchez-Cartas, J.M., and Leon, G. (2017a): On Simulating the Adoption of New Products in Markets with Rational Users and Companies. In: International Conference on Practical Applications of Agents and Multi-Agent Systems. CCIS 722, pp. 83-94. Springer.

lower than the case with them. We also show that the speed of adoption may be overestimated if we only assume a word-of-mouth process. We find that prices are sensitive to influencers, but that influence depends on which influence measure we consider. Lastly, an interesting result is that, in all the cases, independently of what influence measure we consider, profits are higher with influencers. They help in accelerating adoption and profits. Therefore, **the node heterogeneity also matters**⁵. Then, we conclude by addressing how one-sided platforms or third-options may influence the take-off phase of platforms. We compare two cases. One in which the platforms are better valued than the third option, and another one in which they are symmetric. We find that, if platforms cannot create a significantly large added value, the third option will be able to attract consumers, and the platform will fail. On the other hand, if platforms can create a significantly large added value, the third option will not influence the adoption of platforms. However, the interesting result is in the middle. **When platforms create a moderate added-value in comparison with one-sided platforms, competition is stronger than in any other case.** This happens because platforms have to overcome the chicken & egg problem and, at the same time, they have to mitigate the influence of one-sided platforms by competing. One way to mitigate their influence and to overcome the chicken & egg problem is to integrate one of the sides and become a one-sided platform. Nonetheless, the optimality of this decision depends on the exact influence of other one-sided platforms, which is difficult to predict because it is not linear.

We also find that, depending on the degree of market differentiation, the effect of the one-sided platform can be critical. We conclude by pointing out that **one-sided platforms are an important barrier that limits the launching of platforms.** In the beginning, multi-sided platforms are weaker than other business models.

⁵These results have been published in Sanchez-Cartas, J.M., and Leon, G. (2018): On Influencers and Their Impact on the Diffusion of Digital Platforms. In: International Conference on Practical Applications of Agents and Multi-Agent Systems. CCIS 887, pp. 210-222. Springer.

7.1.1 Limitations, and Future Steps

The scope of this Thesis is quite ambitious. Addressing the wearable (fitness tracker) market only with theoretical tools is neither easy nor enough. We have laid out the most relevant questions, and we have answered them. However, there are other questions that we did not consider. For example, we did not address the role of privacy, nor we made predictions on the future of this market. We did not address these questions because there is no available data to address them. If we want to study the role of privacy, the evolution of fitness trackers, or specific effects of compatibility agreements, we need data. Data that either is not available, or it does not exist yet. However, it may be argued that other features could be addressed with theoretical models, such as the role of privacy. Although we do not disagree with it, it is open to discussion what is the real impact of privacy on the user's decision-making. For example, it could be considered another dimension of differentiation that may be orthogonal to the vertical/horizontal dimensions. In that way, our conclusions will not change so much. Nonetheless, to the best of our knowledge, privacy has not been addressed in the Industrial Organization literature to the extent of providing evidence that supports that we should change the way we assume either users' or companies' behavior (utilities).

On the other hand, our theoretical results have proved to be useful to provide us with a clear answer to some questions. But with our models, we have also pointed out another problem in the literature on multi-sided markets. Every question tends to be solved with a different model, To what extent those results depend on the model assumed? Or are they general? In the case of compatibility, we prove the specific and the general conclusions. However, in other aspects, it is legitimate to feel that some results may depend on the chosen model. In that sense, an interesting line of research would be the robustness analysis of these results under more relaxed assumptions. This is also a potential future line of research in both, theoretical and empirical fields. Our literature review has shown that many questions remain open with respect to compatibility and the launching of these platforms, therefore,

expanding our models by relaxing their assumptions is a natural extension of this Thesis.

However, the most interesting part of the discussion is regarding the application of agent-based models. We have proved that we can use the proposed algorithm to simulate any theoretical model with price competition but also, that it is possible to simulate price competition in any agent-based model. This feature clearly opens the door to extend the use of this tool to other frameworks, such as the simulation of platform competition in cities (Uber vs Lyft), dynamic pricing schemes based on reported utilities, etc. However, we have only provided three examples of the power of this algorithm, and all of them are interrelated. They consider the same theoretical framework, and they address similar issues. This situation may generate doubts about our claiming that it can be applied to any other framework. Nonetheless, that is beyond the scope of this Thesis, but it is part of our future steps. In that sense, **this algorithm has opened the door to extend the use of agent-based models to multi-sided platform research** but also, the optimality of this tool allows us to consider this algorithm in the simulation of pricing in more realistic markets than those assumed in theoretical frameworks. For example, **it could be used to simulate the pricing of platforms like JustEat or Uber in real time.** Nonetheless, there are multiple paths that can be followed once we have a reliable tool for simulating pricing in any market. This is probably the best sub-product of this Thesis apart from its scientific contribution, and it opens us a big set of research opportunities in the future.

Lastly, in this Thesis, we have considered the fitness tracker market. Nonetheless, many of the models we have used so far have common characteristics with other IoT markets and digital markets. Therefore, some conclusions are valid in those markets too. However, it will be interesting to contrast these results with more rich data that is not available nowadays. **The theories that we have developed have to guide future empirical research.** Many of our claims, such as that compatibility increases market power should be contrasted with real data, and that is a natural extension of this Thesis. Nonetheless, we have to wait until that data becomes available. The

other natural extension is to **study to what extent the features that we have pointed out are present in other markets**. In this way, it would clarify the generality and the scope of the theories presented in this Thesis beyond the wearable markets.

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Appendix A

Appendix

A.1 Wearables

Although there is a constant increase in the functionalities of fitness trackers, there is a set of technologies that we can define as the basic ones. However, we have to be aware that the set we are about to point out may increase in the future.

- **Accelerometer**

This sensor measures orientation and the acceleration force. It can determine whether the device is horizontal or vertical, and whether it is moving or not. It is used to count steps, but its accuracy depends on the number of axes. Right now, the most common one is the three axes accelerometer.

- **GPS**

It is a very useful technology for sportsmen that are worried about their performance. It allows runners, walkers, cyclists, etc. to map their workout and their speed easily. GPS allows for a much more accurate measure of distances than the accelerometer and, in combination with it, they can track with great detail the routes.

- **EKG and optical heart-rate monitor**

There are two ways of measuring your heart-rate, the most accurate and expensive one is the EKG. It is used in hospitals and in chest straps. It requires

a pair of electrodes. The other option is used in the vast majority of fitness trackers with heart-rate monitoring. It is the optical sensor that measures your heart rate using a LED sensor. However, this technology has a problem. The technology and the measures differ from company to company.

- **Thermometer**

A simple thermometer can give valuable information about your body and your environment. For example, if your temperature raises but you are not doing any workout, maybe you might be getting sick. Also, it is very useful to control your temperature in extreme environments or under hardcore training sessions.

- **Ambient light sensor**

This technology is normally used to record measures of your workout routine, sleep quality, etc. Some high-quality devices use this technology to turn-on the “night mode” that are used by firefighters, policemen or soldiers. This sensor can consider the light spectrum that is not visible to the human eye, for example, the UV sensors are used to provide information about how much harmful UV radiation you are absorbing.

A.1.1 Design and Characteristic

To achieve a successful fitness tracker, we need to take into account human factors. In recent works, Motti and Caine (2014) and Lowens et al. (2015) point out that there is a set of human-centered principles “that are relevant to orient the design phase”. The design is a critical phase in these devices, and it covers not only how fashionable the device is but also, how it interacts with the user in his/her everyday life. In fact, this aspect is a critical point given that more than a half of US consumers who have owned a fitness tracker no longer use it, see Motti and Caine (2014) and Mobile (2016). The 20 “wearability” principles pointed out by Motti and Caine (2014) involve both hardware and software aspects of devices. They are the followings:

- Aesthetics: An attractive design

- Affordance: Intuitiveness of the device in aspects related to the physical interaction
- Comfort: A comfortable device is the one that is no longer sensed after some time wearing it
- Contextual-awareness: Designers have to be aware of the scenarios in which the wearable will be used
- Customization: It helps to create larger markets because the device will fit better the users' expectations
- Ease of Use: The device has to be simple and intuitive
- Ergonomics: It is related to the physical shape of the device
- Fashion: It affects the users' perception of the device
- Intuitiveness: It concerns the immediate understanding of how the interaction occurs
- Obtrusiveness: Devices have to be “transparent” in the sense of allowing free movement
- Overload: Humans are limited in the information they can process, information has to be delivered in small quantities
- Privacy: Users must to able to choose their desired level of privacy
- Reliability: It refers to the level of precision an effectiveness
- Resistance: The devices have to be robust enough to be used in the context they were designed
- Responsiveness: Users tend to be less patient when they are on the move, it is needed to ensure high responsiveness
- Satisfaction: It refers to the overall level of fulfillment of users emotionally

- Simplicity: The device has to respect principles of minimalist design
- Subtlety: It refers to how transparent the communication is
- User friendliness: Every user has to be able to use the device
- Wearability: It is a global concept that covers the physical shape of objects and their relationship with humans

Among those principles, some of them present strong correlations (positive -Affordance and comfort- or negative -customization and simplicity-). Nonetheless, this list is not exhaustive, other dimensions can be considered when designing, such as “safety” or battery life.

One important aspect in the design phase is, who is going to use the device? This is probably one of the main questions in the fitness tracker market right now as consequence of two tendencies.

- The convergence trend. This one is oriented towards mainstream markets, they try to make fashion fitness trackers but increasing tracking functionalities from time to time.
- The niche trend. This one is based on focusing more and more on functionalities related to specific markets (swimmers, alpinists, etc.)

The devices related to the convergence approach tend to rely on basic sensors. On the other hand, those devices related to the niche approach use cutting edge technology. For example, chest heart monitors use EKG sensors, and smartbands tend to adopt optical sensors that are cheaper but less accurate.

Although the design is essential in developing a successful wearable, this phase is usually developed by third companies. Many companies like Fitbit, Misfit or Basis (Intel’s wearable company) are making agreements with design studios like NewDealDesign or Swarovski.

Characteristics. Main Metrics and Legend

The measures of fitness trackers depend on what kind of fitness tracker we are talking about. Those related to the convergence approach tend to converge to the same set of measures (number of steps, sleep quality, calories burned, and so on). On the other hand, those related to the niche approach tend to look for more ways to give consumers valuable information about their workout. In this case, the set of measures involved depends on the sport considered (See Garmin VivoActive HR, Polar V800 or Mio VELO).

However, the number of metrics these devices consider is constantly changing because of the competition between companies. The first fitness tracker (Fitbit, 2009) only counted steps, but right now, the cheapest and simplest version of a fitness tracker also counts calories, distances, floors, etc. So, as time goes by, fitness trackers tend to incorporate more tracking technologies and functionalities, such as water-proof devices or heart-rate monitors. In the following Table, we can observe the current set of technologies used by the most relevant fitness trackers of the market.

- **WP:** Waterproof
- **Hit Resist.:** Hit Resistance
- **BAR:** Barometer
- **ACCEL:** Accelerometer
- **24/7:** Whether or not it works during all day
- **SM:** Sleep Monitoring
- **HM:** Heart Monitoring
- **CAL:** Calories Tracking
- **ALT:** Altimeter
- **Sport Recog.:** Sport Recognition

- **Notify.:** Notifications

Brand	Model	Price	WP	Hit Resist.	GPS	Battery	BAR	ACCCEL	24/7	Steeps	SM	HM	CAL	ALT	Sport Recog.	Notify.
Polar	V800	450	Yes	Yes	Yes	13-50 hours	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes
Polar	Loop	69.9	Yes	No	No	6 days	No	No	Yes	Yes	Yes	No	Yes	No	No	No
Polar	Loop 2	120	Yes	No	No	8 days	No	No	Yes	Yes	Yes	No	Yes	No	No	Yes
Polar	Loop Crystal	160	No	No	No	8 days	No	No	Yes	Yes	Yes	No	Yes	No	No	Yes
Polar	A360	200	Yes	No	No	2 weeks	No	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Garmin	Vivosmart HR+	220	Yes	Yes	Yes	5 days	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Garmin	Vivomove	170	Yes	No	No	1 year	No	Yes	Yes	Yes	Yes	No	No	No	No	No
Garmin	Vivoactive HR	270	Yes	Yes	Yes	8 days	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Garmin	Vivofit3	120	Yes	No	No	1 year	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No
Garmin	Vivoactive	250	Yes	Yes	Yes	3 weeks	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes
Garmin	Vivosmart HR	150	Yes	Yes	No	5 days	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Fitbit	Surge	250	No	No	Yes	7 days	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fitbit	Blaze	240	No	No	Yes	5 days	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fitbit	Charge HR 2	160	No	No	No	5 days	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fitbit	Charge HR	150	No	No	No	5 days	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fitbit	Alta	140	No	No	No	5 days	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes
Fitbit	Flex 2	100	Yes	No	No	5 days	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes
Fitbit	Flex	100	No	No	No	5 days	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No
Misfit	Ray	95	Yes	No	No	6 months	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes
Misfit	Shine 2	100	Yes	No	No	6 months	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes
Misfit	Shine 2 Swimmer's Ed.	114	Yes	No	No	6 months	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes

Misfit	Shine	67	Yes	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No	No
Misfit	Speedo Shine	76	Yes	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No	No
Misfit	Swarovski Activity Crystal	161	Yes	No	No	No	Yes	Yes	Yes	No	Yes	No	No	No
Misfit	Flash	30	No	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No	No
GOQi	Band	29	No	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No	Yes
Samsung	Gear Fit	135	No	No	No	Yes	No	Yes	Yes	Yes	Yes	No	No	Yes
Samsung	Gear Fit2	200	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Timex	Ironman One GPS+	200	Yes	No	Yes	No	No	No	No	No	No	No	No	Yes
LG	Lifeband Touch	100	No	No	No	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes
Xiaomi	Mi Band	15	No	Yes	No	No	Yes	Yes	Yes	No	Yes	No	No	Yes
Xiaomi	Mi Band 2	40	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	No	No	Yes
MyKronoz	ZeFit	59	No	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No	No
MyKronoz	ZeFit2	40	No	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No	Yes
MyKronoz	ZeCircle	60	No	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No	Yes
MyKronoz	ZeFit2 Pulse	80	No	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No	Yes
WiseWear	Several products	<345	No	No	No	No	Yes	Yes	Yes	No	Yes	No	No	Yes
Amigo	Amigo	NA	Yes	No	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No
Razer	Nabu	120	No	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No	Yes
Razer	Nabu X	60	No	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No	Yes
Moov	Moov Now	60	Yes	No	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No
Wellograph	Wellograph	100-300	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	No	No	No
Pivotal Living	Pivotal Living	12	No	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No	No
Jawbone	Up 2	120	No	No	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No
Jawbone	Up 3	180	No	No	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No

Jawbone	Up 4	150	No	No	No	7 days	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Withings	Pulse Ox	100	No	No	No	2 weeks	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Sony	SmartBand SWR10	100	Yes	No	No	5 days	No	No	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes
Sony	SmartBand Talk SWR30	159	No	No	No	3 days	No	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes
Sony	SmartBand Roxy SWR10	40	Yes	No	No	5 days	No	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes
Sony	SmartBand 2	130	Yes	No	No	5 days	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes
Under Armour	UA Band	180	Yes	No	No	5 days	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes
Mio	LINK	95	Yes	Yes	No	6-8 hours	No	No	No	No	Yes	Yes	No	No	No	No	No
Mio	VELO	120	Yes	Yes	No	8 hours	No	No	No	No	Yes	Yes	No	No	No	No	No
Mio	FUSE	120	Yes	Yes	No	6-7 days	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes
Mio	ALPHA 2	142	Yes	Yes	No	1 month	No	Yes	Yes	Yes	Yes	Yes	No	Yes	No	No	Yes
Basis	Peak	NA	Yes	Yes	No	4 days	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Runtastic	Orbit	80	Yes	No	No	5-6 days	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes
Adidas	Micoach Fit Smart	150	No	No	No	10 hours	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes
Atlas	Wristband2	200	Yes	No	No	5 days	No	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No
Huawei	TalkBand B3	170	Yes	No	No	3-4 days	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Huawei	TalkBand B2	90	No	No	No	6 days	No	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Huawei	TalkBand	50	No	No	No	6 days	No	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Huawei	Band	70	Yes	Yes	No	4 days	No	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes

A.2 Classification of Multi-sided Works

Multi-sided Works		Affeldt (2011)	Affeldt et al. (2013)	Alexandrov et al. (2011)	Amelio and Jullien (2012)	Ambrus and Argenziano (2004)
Type of Paper	Two-Sided	Yes	Yes	Yes	Yes	Yes
	One-Sided	No	Yes	Yes	No	No
	Policy	Not Applicable	Yes	No	Not Applicable	Not Applicable
Orientation	Theoretical	Yes	Yes	Yes	Yes	Yes
	Empirical	No	Yes	No	No	No
	Market-Maker	No	No	Yes	No	No
Evans' classification	Audience-Makers	No	Yes	No	No	No
	Demand Coordinators	Yes	Yes	No	Yes	Yes
	Memberships	Yes	Yes	No	Yes	Yes
Filistrucchi's classification	Usage	No	No	Yes	No	No
	Strategies	Yes	No	Yes	Yes	No
	Markets	No	Yes	No	No	Yes
Temporality	Static	Yes	Yes	Yes	Yes	Yes
	Dynamic	No	No	No	No	No
	Generic	No	Yes	Yes	Yes	Yes
Abstraction	Specific	Yes	No	No	No	No
	Singlehoming	Consumers	Yes	Yes	Yes	Yes
	Multihoming	Yes	No	No	No	No
Type of Competition	Monopoly Platf.	No	No	No	Yes	Yes
	Duopolist Platf.	Yes	Yes	No	Yes	Yes
	N Platforms	No	Yes	Yes	No	No
Ownership Structures	Two-Sided Platf.	Yes	Yes	Yes	Yes	Yes
	Others	No	Yes	Yes	No	No
	One Side	No	No	No	No	No
Differentiation	Two Sides	Yes	No	Yes	Yes	Yes
	Horizontal	Yes	Yes, Empirically	Yes	Yes	Yes
	Vertical	No	No	No	No	No
Type of Differentiation	Tying/Bundling	Yes	No	No	Yes	No
	Own-Side competition	No	No	No	No	No

Multi-sided Works		Anderson and Coate (2005)	Argentesi and Filistrucchi (2007)	Armstrong (2006)	Armstrong and Wright (2007)	Belleflamme and Toulemonde (2004)
Type of Paper	Two-Sided	Yes	Yes	Yes	Yes	Yes
	One-Sided	No	No	No	No	No
Orientation	Policy	No	Not Applicable	Not Applicable	No	Not Applicable
	Theoretical	Yes	No	Yes	Yes	Yes
	Empirical	No	Yes	No	No	No
Evans' classification	Market-Maker	No	No	No	Yes	Yes
	Audience-Makers	Yes	Yes	Yes	No	No
	Demand Coord.	No	No	Yes	Yes	No
Filistrucchi's classification	Membership	Yes	Yes	Yes	Yes	No
	Usage	No	No	No	Yes	Yes
	Strategies	No	No	No	Yes	Yes
Rysman's classification	Markets	Yes	Yes	Yes	No	No
	Static	Yes	No	Yes	Yes	No
	Dynamic	No	Yes	No	No	Yes
Abstraction	Generic	No	No	Yes	Yes	Yes
	Specific	TV channels	Newspapers	Yes	No	No
Behaviours	Singlehoming	Viewers	Yes	Yes	No	Yes
	Multihoming	Advertisers	No	Yes	Yes	No
	Monopoly Platf.	Yes	No	Yes	No	Yes
Type of Competition	Duopolist Platf.	Yes	No	Yes	Yes	Yes
	N Platforms	No	Yes	No	No	No
	Two-Sided Platf.	Yes	Yes	Yes	Yes	Yes
Ownership Structures	Others	Yes	Yes	No	No	Yes
	One Side	Yes	Yes	No	No	No
	Two Sides	No	No	Yes	Yes	No
Type of Differentiation	Horizontal	Yes	Yes	Yes	Yes	No
	Vertical	No	No	No	No	No
	Tying/Bundling	No	No	No	No	No
Own-Side competition		No	No	Yes	No	Yes

Multi-sided Works		Bessen (2006)	Schröder and Bitzer (2003)	Boffa and Filistrucchi (2014)	Bohli et al. (2009)	Böhme and Müller (2013)
Type of Paper	Two-Sided	No	No	Yes	No	Yes
	One-Sided	Yes	Yes	No	Yes	No
	Policy	No	No	No	Yes	No
Orientation	Theoretical	Yes	Yes	Yes	Yes	Yes
	Empirical	No	No	No	No	No
Evans' classification	Market-Maker	Not Applicable	Not Applicable	No	Not Applicable	No
	Audience-Makers	Not Applicable	Not Applicable	Yes	Not Applicable	No
	Demand Coordinators	Not Applicable	Not Applicable	No	Not Applicable	Yes
Filistrucchi's classification	Membership	Not Applicable	Not Applicable	Yes	Not Applicable	Yes
	Usage	Not Applicable	Not Applicable	No	Not Applicable	No
	Strategies	Not Applicable	Not Applicable	Yes	Not Applicable	No
Rysman's classification	Markets	Not Applicable	Not Applicable	No	Not Applicable	Yes
	Static	Yes	Yes	No	Not Applicable	Yes
	Dynamic	No	No	Yes	Not Applicable	No
Temporality	Generic	No	No	No	No	Yes
	Specific	Open source develop.	Operating Systems	TV channels	IoT	No
Behaviours	Singlehoming	Not Applicable	Not Applicable	Viewers	Not Applicable	Yes
	Multihoming	Not Applicable	Not Applicable	Advertisers	Not Applicable	Yes
	Monopoly Platf.	Not Applicable	Not Applicable	Yes	Not Applicable	Yes
Type of Competition	Duopolist Platf.	Not Applicable	Not Applicable	Yes	Not Applicable	Yes
	N Platforms	Not Applicable	Not Applicable	No	Not Applicable	No
	Two-Sided Platf.	No	No	Yes	Not Applicable	Yes
Ownership Structures	Others	Yes	Yes	Yes	Not Applicable	No
	One Side	Not Applicable	Yes	No	Not Applicable	No
	Two Sides	Not Applicable	No	Yes	Not Applicable	Yes
Differentiation	Horizontal	Yes	Yes	Yes	Not Applicable	Yes
	Vertical	No	Yes	Yes	Not Applicable	No
	Tying/Bundling	Yes	No	No	Not Applicable	No
Own-Side competition		Not Applicable	Not Applicable	Yes	Not Applicable	No

Multi-sided Works		Bolt and Tieman (2005)	Cabral (2011)	Caillaud and Jullien (2001)	Caillaud and Jullien (2003)	Carrillo et al. (2006)
Type of Paper	Two-Sided	Yes	Yes	Yes	Yes	Yes
	One-Sided	No	No	No	No	No
Orientation	Policy	Not Applicable	Not Applicable	Not Applicable	Not Applicable	Not Applicable
	Theoretical	Yes	Yes	Yes	Yes	Yes
Evans' classification	Empirical	No	No	No	No	No
	Market-Maker	Yes	No	Yes	Yes	No
Fillstrucchi's classification	Audience-Makers	No	No	No	No	No
	Demand Coordinators	No	Yes	No	No	Yes
Rysman's classification	Membership	No	Yes	No	Yes	Yes
	Usage	Yes	No	Yes	Yes	No
Temporality	Strategies	No	No	No	No	Yes
	Markets	Yes	Yes	Yes	Yes	No
Abstraction	Static	Yes	No	Yes	Yes	Yes
	Dynamic	No	Yes	No	No	No
Behaviours	Generic	No	Yes	No	No	Yes
	Specific	Credit Card	No	Internet Matching	Internet Matching	No
Type of Competition	Singlehoming	Not Applicable	Not Applicable	Yes	Yes	Yes
	Multihoming	Not Applicable	Not Applicable	Yes	Yes	Yes
Ownership Structures	Monopoly Platf.	Yes	Yes	Yes	No	No
	Duopolist Platf.	No	No	Yes	Yes	Yes
Differentiation	N Platforms	No	No	No	No	No
	Two-Sided Platf.	Yes	Yes	Yes	Yes	Yes
Type of Differentiation	Others	No	No	No	No	Yes
	One Side	No	No	No	No	No
Tying/Bundling	Two Sides	Yes	Yes	No	No	Yes
	Horizontal	Yes	Yes	Yes	Yes	Yes
Own-Side competition	Vertical	No	No	No	No	No
	Tying/Bundling	No	No	No	No	No
	Own-Side competition	No	Yes	No	No	No

Multi-sided Works		Chandra and Collard-Wexler (2009)	Chao and Dardenger (2010)	Choi (2010)	Doganoglu and Wright (2006)	Economides and Katsamakas (2006)
Type of Paper	Two-Sided	Yes	Yes	Yes	Yes	Yes
	One-Sided	No	No	No	Yes	Yes
	Policy	Not Applicable	No	Not Applicable	No	Not Applicable
Orientation	Theoretical	Yes	Yes	Yes	Yes	Yes
	Empirical	Yes	Yes	No	No	No
Evans' classification	Market-Maker	No	No	No	No	No
	Audience-Makers	Yes	No	No	No	No
	Demand Coord.	No	Yes	Yes	Yes	Yes
	Memberships	Yes	Yes	Yes	Yes	Yes
Filistrucchi's class.	Usage	No	No	No	No	No
	Strategies	Yes	Yes	Yes	Yes	Yes
Rysman's classification	Markets	No	No	No	No	No
	Static	Yes	Yes	Yes	Yes	Yes
Temporality	Dynamic	No	No	No	No	No
	Generic	No	Yes	No	Yes	No
Abstraction	Specific	Newspapers	No	Operating systems	No	Software
	Singlehoming	Yes	Not Applicable	Consumers	Yes	Yes
Behaviours	Multihoming	No	Not Applicable	Yes	Yes	No
	Monopoly Platf.	No	Yes	No	No	Yes
Type of Competition	Duopolist Platf.	Yes	No	Yes	Yes	Yes
	N Platforms	Yes, Empirically	No	No	No	No
Ownership Structures	Two-Sided Platf.	Yes	Yes	Yes	Yes	Yes
	Others	Yes	No	No	Yes	Yes
Differentiation	One Side	No	Yes	No	No	No
	Two Sides	Yes	No	Yes	Yes	No
Type of Differentiation	Horizontal	Yes	Yes	Yes	Yes	Yes
	Vertical	Yes	No	No	No	No
Tying/Bundling Own-Side competition		No	Yes	Yes	No	No
		No	No	No	No	No

Multi-sided Markets		Evans et al. (2008)	Economides and Tåg (2012)	Evans (2003)	Evans (2002)	Evans (2011)
Type of Paper	Two-Sided	Not Applicable	Yes	Not Applicable	Not Applicable	Not Applicable
	One-Sided	Not Applicable	No	Not Applicable	Not Applicable	Not Applicable
	Policy	Yes	Not Applicable	Yes	Yes	Yes
Orientation	Theoretical	Yes	Yes	Yes	Yes	Yes
	Empirical	Yes	No	Yes	Yes	Yes
Evans' classification	Market-Maker	Not Applicable	No	Not Applicable	Not Applicable	Not Applicable
	Audience-Makers	Not Applicable	No	Not Applicable	Not Applicable	Not Applicable
	Demand Coordinators	Not Applicable	Yes	Not Applicable	Not Applicable	Not Applicable
Filistrucchi's classification	Membership	Not Applicable	Yes	Not Applicable	Not Applicable	Not Applicable
	Usage	Not Applicable	No	Not Applicable	Not Applicable	Not Applicable
	Strategies	Not Applicable	Yes	Not Applicable	Not Applicable	Not Applicable
Rysman's classification	Markets	Not Applicable	No	Not Applicable	Not Applicable	Not Applicable
	Static	Not Applicable	Yes	Not Applicable	Not Applicable	Not Applicable
	Dynamic	Not Applicable	No	Not Applicable	Not Applicable	Not Applicable
Temporality	Generic	Yes	No	Yes	Yes	Yes
	Specific	No	Net Neutrality	No	No	No
	Singlehoming	Not Applicable	Consumers	Not Applicable	Not Applicable	Not Applicable
Behaviours	Multihoming	Not Applicable	Providers	Not Applicable	Not Applicable	Not Applicable
	Monopoly Platf.	Not Applicable	Yes	Not Applicable	Not Applicable	Not Applicable
	Duopolist Platf.	Not Applicable	Yes	Not Applicable	Not Applicable	Not Applicable
Type of Competition	N Platforms	Not Applicable	No	Not Applicable	Not Applicable	Not Applicable
	Two-Sided Platf.	Not Applicable	Yes	Not Applicable	Not Applicable	Not Applicable
	Others	Not Applicable	Yes	Not Applicable	Not Applicable	Not Applicable
Ownership Structures	One Side	Not Applicable	No	Not Applicable	Not Applicable	Not Applicable
	Two Sides	Not Applicable	Yes	Not Applicable	Not Applicable	Not Applicable
	Horizontal	Not Applicable	Yes	Not Applicable	Not Applicable	Not Applicable
Type of Differentiation	Vertical	Not Applicable	No	Not Applicable	Not Applicable	Not Applicable
	Tying/Bundling	Not Applicable	No	Not Applicable	Not Applicable	Not Applicable
	Own-Side competition	Not Applicable	No	Not Applicable	Not Applicable	Not Applicable

Multi-sided Works		Evans and Noel (2008)	Evans and Schmalensee (2005)	Evans and Schmalensee (2010)	Evans and Schmalensee (2013)	Farhi and Hagiu (2008)
Type of Paper	Two-Sided	Yes	Yes	Yes	Yes	Yes
	One-Sided	No	No	Yes	No	Yes
	Policy	Yes	Yes	Yes	Yes	No
Orientation	Theoretical	Yes	Yes	Yes	Yes	Yes
	Empirical	Yes	Yes	No	Yes	No
Evans' classification	Market-Maker	Not Applicable	Not Applicable	No	Not Applicable	No
	Audience-Makers	Not Applicable	Not Applicable	Yes	Not Applicable	No
Flistruchi's classification	Demand Coordinators	Not Applicable	Not Applicable	No	Not Applicable	Yes
	Memberships	Not Applicable	Not Applicable	Yes	Not Applicable	Yes
	Usage	Not Applicable	Not Applicable	No	Not Applicable	No
Rysman's classification	Strategies	Not Applicable	Not Applicable	Yes	Not Applicable	No
	Markets	Not Applicable	Not Applicable	No	Not Applicable	Yes
Temporality	Static	Yes	Not Applicable	No	Not Applicable	No
	Dynamic	No	Not Applicable	Yes	Not Applicable	Yes
	Generic	Yes	Yes	No	Yes	Yes
Abstraction	Specific	No	Yes	Yes	Yes	No
	Singlehoming	Not Applicable	Not Applicable	Not Applicable	Not Applicable	Yes
Behaviours	Multihoming	Not Applicable	Not Applicable	Not Applicable	Not Applicable	No
	Monopoly Platf.	Not Applicable	Not Applicable	Yes	Not Applicable	No
Type of Competition	Duopolist Platf.	Not Applicable	Not Applicable	No	Not Applicable	Yes
	N Platforms	Not Applicable	Not Applicable	No	Not Applicable	No
Ownership Structures	Two-Sided Platf.	Yes	Not Applicable	Yes	Not Applicable	Yes
	Others	Yes	Not Applicable	No	Not Applicable	No
	One Side	Not Applicable	Not Applicable	No	Not Applicable	No
Differentiation	Two Sides	Not Applicable	Not Applicable	Yes	Not Applicable	Yes
	Horizontal	Not Applicable	Not Applicable	Yes	Not Applicable	Yes
Type of Differentiation	Vertical	Not Applicable	Not Applicable	No	Not Applicable	No
	Tying/Bundling	Not Applicable	Not Applicable	No	Not Applicable	Yes
Own-Side competition		Not Applicable	Not Applicable	Yes	Not Applicable	No

Multi-sided Works		Jezioriski (2014)	Filistrucchi (2008)	Filistrucchi et al. (2012a)	Filistrucchi et al. (2014)	Filistrucchi and Klein (2013)
Type of Paper	Two-Sided	Yes	Yes	Yes	Not Applicable	Yes
	One-Sided	No	No	No	Not Applicable	No
	Policy	No	Yes	Yes	Yes	No
Orientation	Theoretical	No	Yes	Yes	Yes	Yes
	Empirical	Yes	Yes	Yes	Yes	Yes
Evans' classification	Market-Maker	No	Not Applicable	Not Applicable	Not Applicable	No
	Audience-Makers	Yes	Not Applicable	Not Applicable	Not Applicable	Yes
	Demand Coordinators	No	Not Applicable	Not Applicable	Not Applicable	No
Filistrucchi's classification	Membership	Yes	Not Applicable	Not Applicable	Not Applicable	Yes
	Usage	No	Not Applicable	Not Applicable	Not Applicable	No
	Strategies	No	Not Applicable	Not Applicable	Not Applicable	No
Rysman's classification	Markets	Yes	Not Applicable	Not Applicable	Not Applicable	Yes
	Static	No	Yes	Not Applicable	Yes	Yes
	Dynamic	Yes	No	Not Applicable	No	No
Temporality	Generic	No	Yes	Yes	Yes	Yes
	Specific	Radio industry	No	No	No	Newspapers
Behaviours	Singlehoming	Listeners	Not Applicable	Not Applicable	Not Applicable	Readers
	Multihoming	Advertisers	Not Applicable	Not Applicable	Not Applicable	Advertisers
	Monopoly Platf.	No	Not Applicable	Not Applicable	Not Applicable	Yes
Type of Competition	Duopolist Platf.	No	Not Applicable	Not Applicable	Not Applicable	Yes
	N Platforms	Yes	Not Applicable	Not Applicable	Not Applicable	Yes
	Two-Sided Platf.	Yes	Yes	Not Applicable	Not Applicable	Yes
Ownership Structures	Others	Yes	No	Not Applicable	Not Applicable	No
	One Side	No	Not Applicable	Not Applicable	Not Applicable	No
	Two Sides	Yes	Not Applicable	Not Applicable	Not Applicable	Yes
Type of Differentiation	Horizontal	Yes	Not Applicable	Not Applicable	Not Applicable	Yes
	Vertical	Yes	Not Applicable	Not Applicable	Not Applicable	No
	Tying/Bundling	No	Not Applicable	Not Applicable	Not Applicable	No
Own-Side competition		Yes	Not Applicable	Not Applicable	Not Applicable	No

Multi-sided Works		Filistrucchi et al. (2012b)	Gabszewicz and Wauthy (2004)	Goos et al. (2011)	Hagiü (2004)	Hagiü (2006)
Type of Paper	Two-Sided	Yes	Yes	Yes	Yes	Yes
	One-Sided	No	No	No	No	No
	Policy	No	No	No	Not Applicable	Not Applicable
Orientation	Theoretical	No	Yes	Yes	Yes	Yes
	Empirical	Yes	No	No	No	No
Evans' classification	Market-Maker	No	No	Yes	No	No
	Audience-Makers	Yes	No	No	No	No
	Demand Coordinators	No	Yes	No	Yes	Yes
Filistrucchi's classification	Membership	Yes	Yes	Yes	Yes	Yes
	Usage	No	No	No	No	No
	Strategies	No	No	No	No	No
Rysman's classification	Markets	Yes	Yes	Yes	Yes	Yes
	Static	Yes	Yes	Yes	Yes	Yes
	Dynamic	No	No	No	Yes	Yes
Temporality	Generic	No	No	Yes	No	No
	Specific	Newspapers	Exhibition Centers	No	Software	Software
Behaviours	Singlehoming	Readers	Yes	Not Applicable	Consumers	Yes
	Multihoming	Advertisers	Yes	Not Applicable	Developers	Yes
	Monopoly Platf.	No	Yes	Yes	Yes	Yes
Type of Competition	Duopolist Platf.	No	Yes	No	Yes	Yes
	N Platforms	Yes	No	No	No	No
	Two-Sided Platf.	Yes	Yes	Yes	Yes	Yes
Ownership Structures	Others	No	No	No	Yes	No
	One Side	No	No	No	No	Yes
	Two Sides	Yes	Yes	Yes	Yes	No
Type of Differentiation	Horizontal	Yes	Yes	Yes	Yes	Yes
	Vertical	No	Yes	Yes	Yes	No
Tying/Bundling		No	No	No	No	No
	Own-Side competition	No	No	Yes	Yes	No

Multi-sided Works		Hagi (2007)	Hagi and Halaburda (2014)	Hagi and Wright (2015)	Ivaldi et al. (2011)	Jeitschko and Tremblay (2014)
Type of Paper	Two-Sided	Yes	Yes	Yes	Yes	Yes
	One-Sided	Yes	No	No	Yes	No
	Policy	No	No	Not Applicable	No	No
Orientation	Theoretical	Yes	Yes	Yes	No	Yes
	Empirical	No	No	No	Yes	No
Evans' classification	Market-Maker	No	No	No	Yes	No
	Audience-Makers	No	No	No	No	No
	Demand Coordinators	Yes	Yes	Yes	No	Yes
Filistrucchi's classification	Membership	Yes	Yes	Yes	No	Yes
	Usage	Yes	No	Yes	Yes	No
Rysman's classification	Strategies	Yes	No	Yes	Yes	No
	Markets	No	Yes	No	No	Yes
Temporality	Static	Yes	Yes	Yes	Yes	Yes
	Dynamic	No	No	No	No	No
	Generic	Yes	No	Yes	No	Yes
Abstraction	Specific	No	Software	No	Airports	No
	Singlehoming	Not Applicable	Yes	Yes	Not Applicable	Yes
Behaviours	Multihoming	Not Applicable	Yes	No	Not Applicable	Yes
	Monopoly Platf.	Yes	Yes	No	Yes	Yes
Type of Competition	Duopolist Platf.	No	Yes	No	No	Yes
	N Platforms	No	No	Yes	Yes	No
Ownership Structures	Two-Sided Platf.	Yes	Yes	Yes	Yes	Yes
	Others	Yes	No	Yes	Yes	No
Differentiation	One Side	No	No	Yes	No	No
	Two Sides	Yes	Yes	No	Yes	Yes
Type of Differentiation	Horizontal	Yes	Yes	Yes	Yes	Yes
	Vertical	No	No	Yes	No	No
Tying/Bundling		No	No	No	No	No
Own-Side competition		Yes	No	Yes,	Yes	No

Multi-sided Works		Jullien (2005)	Kaiser and Wright (2006)	Bakos and Katsamakas (2008)	Kauffman and Wang (2001)	Kim et al. (2013)
Type of Paper	Two-Sided	Yes	Yes	Yes	No	Yes
	One-Sided	No	No	No	Yes	No
Orientation	Policy	Not Applicable	No	Not Applicable	Not Applicable	No
	Theoretical	Yes	Yes	Yes	No	No
Evans' classification	Empirical	No	Yes	No	Yes	Yes
	Market-Maker	Yes	No	No	Not Applicable	Yes
Filistrucchi's classification	Audience-Makers	No	Yes	No	Not Applicable	No
	Demand Coordinators	No	No	Yes	Not Applicable	No
Rysman's classification	Memberships	No	Yes	Yes	Not Applicable	No
	Usage	Yes	No	No	Not Applicable	Yes
Temporality	Strategies	No	No	No	Not Applicable	No
	Markets	Yes	Yes	Yes	Not Applicable	Yes
Abstraction	Static	Yes	Yes	Yes	No	No
	Dynamic	No	No	No	Yes	Yes
Behaviours	Generic	No	No	No	No	No
	Specific	Digital Industry	Magazines	Digital intermediaries	Online auctions	Online Daily deals
Type of Competition	Singlehoming	Yes	Yes	Not Applicable	Not Applicable	Yes
	Multihoming	No	No	Not Applicable	Not Applicable	Yes
Ownership Structures	Monopoly Platf.	Yes	No	Yes	Not Applicable	No
	Duopolist Platf.	Yes	Yes	No	Not Applicable	No
Differentiation	N Platforms	No	Yes	No	Not Applicable	No
	Two-Sided Platf.	Yes	Yes	Yes	Not Applicable	Yes
Type of Differentiation	Others	No	No	Yes	Not Applicable	No
	One Side	No	No	No	Not Applicable	No
Tying/Bundling	Two Sides	Yes	Yes	No	Not Applicable	Yes
	Horizontal	Yes	Yes	No	Not Applicable	Yes
Own-Side competition	Vertical	No	No	No	Not Applicable	No
	Tying/Bundling	Yes	No	No	Not Applicable	No
Own-Side competition	Own-Side competition	No	No	No	Not Applicable	No

Multi-Sided Works		Kind et al. (2008)	Kind et al. (2009)	Kind et al. (2010)	Kind et al. (2013)	Kind and Koethenburger (2018)
Type of Paper	Two-Sided	Yes	Yes	Yes	Yes	Yes
	One-Sided	No	No	No	No	Yes
	Policy	No	No	No	No	No
Orientation	Theoretical	Yes	Yes	Yes	Yes	Yes
	Empirical	No	No	No	No	No
Evans' classification	Market-Maker	No	No	No	No	No
	Audience-Makers	No	No	No	No	No
	Demand Coordinators	Yes	Yes	Yes	Yes	Yes
Filistrucchi's classification	Memberships	Yes	Yes	Yes	Yes	Yes
	Usage	No	No	No	No	No
	Strategies	No	No	No	No	No
Rysman's classification	Markets	Yes	Yes	Yes	Yes	Yes
	Static	Yes	Yes	Yes	Yes	Yes
	Dynamic	No	No	No	No	No
Temporality	Generic	Yes	Yes	Yes	Yes	Yes
	Specific	No	No	No	No	No
Abstraction	Singlehoming	Yes	Yes	Yes	Yes	Yes
	Multihoming	No	No	No	No	No
	Monopoly Platf.	Yes	Yes	Yes	No	Yes
Type of Competition	Duopolist Platf.	No	No	Yes	Yes	No
	N Platforms	No	No	No	No	No
	Two-Sided Platf.	Yes	Yes	Yes	Yes	Yes
Ownership Structures	Others	No	No	No	No	No
	One Side	No	No	No	Yes	No
	Two Sides	No	No	Yes	No	No
Type of Differentiation	Horizontal	No	No	Yes	Yes	No
	Vertical	No	No	Yes	No	No
	Tying/Bundling	No	No	No	No	No
Own-Side competition		Yes	Yes	Yes	Yes	Yes

Multi-sided Works		Krämer and Wiewiorra (2012)	Kumar et al. (2010)	Lee (2013)	Lerner and Tirole (2002)	Liu and Serfes (2013)
Type of Paper	Two-Sided	Yes	Yes	Yes	Not Applicable	Yes
	One-Sided	No	No	No	Not Applicable	No
Orientation	Policy	No	Not Applicable	Not Applicable	Yes	Yes
	Theoretical	Yes	No	Yes	Yes	Yes
Evans' classification	Empirical	No	Yes	Yes	No	No
	Market-Maker	No	Not Applicable	No	Not Applicable	No
Filistrucchi's classification	Audience-Makers	No	Not Applicable	No	Not Applicable	No
	Demand Coordinators	Yes	Not Applicable	Yes	Not Applicable	Yes
Rysman's classification	Membership	Yes	Not Applicable	No	Not Applicable	Yes
	Usage	No	Not Applicable	Yes, partially	Not Applicable	No
Temporality	Strategies	No	Not Applicable	Yes, Empirically	Not Applicable	No
	Markets	Yes	Not Applicable	Yes, theoretically	Not Applicable	Yes
Abstraction	Static	Yes	No	No	No	Yes
	Dynamic	No	Yes	Yes	Yes	No
Behaviours	Generic	No	No	No	No	Yes
	Specific	Net neutrality	Yahoo! Answer	Video Consoles	No	No
Type of Competition	Singlehoming	Not Applicable	Not Applicable	No	Not Applicable	Yes
	Multihoming	Not Applicable	Not Applicable	Yes	Not Applicable	Yes
Ownership Structures	Monopoly Platf.	Not Applicable	Not Applicable	No	Not Applicable	No
	Duopolist Platf.	Yes	Not Applicable	No	Not Applicable	Yes
Differentiation	N Platforms	No	Not Applicable	Yes	Not Applicable	No
	Two-Sided Platf.	Yes	Not Applicable	Yes	Not Applicable	Yes
Type of Differentiation	Others	Yes	Not Applicable	Yes	Not Applicable	No
	One Side	Yes	Not Applicable	No	Not Applicable	No
Tying/Bundling	Two Sides	No	Not Applicable	Yes	Not Applicable	Yes
	Horizontal	Yes	Not Applicable	Yes	Not Applicable	Yes
Own-Side competition	Vertical	No	Not Applicable	Yes	Not Applicable	No
		No	Not Applicable	No	Not Applicable	No
		No	Not Applicable	No	Not Applicable	No
		No	Not Applicable	No	Not Applicable	No

Multi-sided Works		Lam (2014)	Musacchio et al. (2009)	Njoroge et al. (2013)	Nocke et al. (2007)	OECD (2009)
Type of Paper	Two-Sided	Yes	Yes	Yes	Yes	Yes
	One-Sided	Yes	Yes	No	No	No
Orientation	Policy	Not Applicable	Not Applicable	Not Applicable	Not Applicable	Yes
	Theoretical	Yes	Yes	Yes	Yes	Yes
Evans' classification	Empirical	No	No	No	No	Yes
	Market-Maker	No	Yes	No	No	Not Applicable
Filistrucchi's classification	Audience-Makers	No	No	Yes	Yes	Not Applicable
	Demand Coordinators	Yes	No	No	No	Not Applicable
Rysman's classification	Memberships	Yes	No	Yes	Yes	Not Applicable
	Usage	No	Yes	No	No	Not Applicable
Temporality	Strategies	No	Yes	No	Yes	Not Applicable
	Markets	Yes	No	Yes	No	Not Applicable
Abstraction	Static	No	Yes	Yes	Yes	Not Applicable
	Dynamic	Yes	No	No	No	Not Applicable
Behaviours	Generic	Yes	No	No	Yes	Yes
	Specific	No	ISP - Net Neutrality	ISP - Net Neutrality	No	No
Type of Competition	Singlehoming	Yes	Consumers	Yes	Not Applicable	Not Applicable
	Multihoming	Yes	Providers	No	Not Applicable	Not Applicable
Ownership Structures	Monopoly Platf.	No	No	No	Yes	Not Applicable
	Duopolist Platf.	Yes	No	Yes	No	Not Applicable
Differentiation	N Platforms	No	Yes	No	No	Not Applicable
	Two-Sided Platf.	Yes	Yes	Yes	Yes	Not Applicable
Type of Differentiation	Others	No	Yes	Yes	Yes	Not Applicable
	One Side	No	Yes	No	No	Not Applicable
Type of Differentiation	Two Sides	Yes	No	Yes	Yes	Not Applicable
	Horizontal	Yes	No	Consumers	Yes	Not Applicable
Tying/Bundling	Vertical	No	Yes	Providers and platforms	No	Not Applicable
	Own-Side competition	No	No	Yes	No	Not Applicable
Own-Side competition		No	No	No	Yes	Not Applicable
		No	No	No	Yes	Not Applicable

Multi-sided Works		Parker and Van Alstyne (2005)	Reisinger (2004)	Rochet and Tirole (2003)	Rochet and Tirole (2006)	Rochet and Tirole (2008)
Type of Paper	Two-Sided	Yes	Yes	Yes	Yes	Yes
	One-Sided	No	No	No	No	No
Orientation	Policy	Not Applicable	Not Applicable	Not Applicable	Yes	Not Applicable
	Theoretical	Yes	Yes	Yes	Yes	Yes
Evans' classification	Empirical	No	No	No	No	No
	Market-Maker	Yes	No	Yes	Yes	Yes
Filistrucchi's classification	Audience-Makers	No	Yes	Yes	Yes	No
	Demand Coordinators	No	No	No	Yes	No
Rysman's classification	Memberships	No	Yes	Yes	Yes	No
	Usage	Yes	No	Yes	Yes	Yes
Temporality	Strategies	No	No	No	No	No
	Markets	Yes	Yes	Yes	Yes	Yes
Abstraction	Static	Yes	Yes	Yes	Yes	Yes
	Dynamic	No	No	No	No	No
Behaviours	Generic	Yes	No	No	Yes	No
	Specific	No	Advertising	Credit Card, Newspapers	No	Credit Card
Type of Competition	Singlehoming	Not Applicable	Yes	Sellers	Yes	No
	Multihoming	Not Applicable	No	Both sides	Yes	Yes
Ownership Structures	Monopoly Platf.	Yes	No	Yes	Yes	Yes
	Duopolist Platf.	No	Yes	Yes	Yes	Yes
Differentiation	N Platforms	No	No	No	No	No
	Two-Sided Platf.	Yes	Yes	Yes	Yes	Yes
Type of Differentiation	Others	No	Yes	Yes	Yes	Yes
	One Side	No	Yes	No	No	Yes
Type of Bundling	Two Sides	No	No	Yes	Yes	Yes
	Horizontal	Yes	Consumers	Yes	Yes	Yes
Own-Side competition	Vertical	No	No	No	No	No
	Tying/Bundling	No	No	No	No	Yes
Own-Side competition		No	No	No	No	No
		No	No	No	No	No

Multi-sided Works		Ruhmer (2010)	Rysman (2004)	Rysman (2007)	Rysman (2009)	Schiff (2003)
Type of Paper	Two-Sided	Yes	Yes	Yes	Not Applicable	Yes
	One-Sided	No	No	No	Not Applicable	No
	Policy	No	Not Applicable	Not Applicable	Yes	No
Orientation	Theoretical	Yes	No	No	Yes	Yes
	Empirical	No	Yes	Yes	No	No
Evans' classification	Market-Maker	No	No	Yes	Not Applicable	No
	Audience-Makers	No	Yes	No	Not Applicable	No
	Demand Coordinators	Yes	No	No	Not Applicable	Yes
Filistrucchi's classification	Membership	Yes	Yes	No	Not Applicable	No
	Usage	No	No	Yes	Not Applicable	Yes
Rysman's classification	Strategies	No	No	No	Not Applicable	No
	Markets	Yes	Yes	Yes	Not Applicable	Yes
Temporality	Static	Yes	Yes	Yes	Yes	Yes
	Dynamic	No	No	No	No	No
	Generic	Yes	No	No	Yes	Yes
Abstraction	Specific	No	Yellow Pages	Credit Card	No	No
	Singlehoming	Yes	Consumers	Yes	Not Applicable	Yes
Behaviours	Multihoming	No	Advertisers	Yes	Not Applicable	No
	Monopoly Platf.	Yes	No	No	Not Applicable	Yes
Type of Competition	Duopolist Platf.	Yes	No	No	Not Applicable	Yes
	N Platforms	No	Yes	Yes	Not Applicable	No
Ownership Structures	Two-Sided Platf.	Yes	Not Applicable	Yes	Not Applicable	Yes
	Others	Yes	Not Applicable	No	Not Applicable	No
	One Side	No	No	Yes	Not Applicable	No
Differentiation	Two Sides	Yes	Yes	No	Not Applicable	Yes
	Horizontal	Yes	Yes	Yes	Not Applicable	Yes
Type of Differentiation	Vertical	No	Yes	No	Not Applicable	No
	Tying/Bundling	No	No	No	Not Applicable	No
Own-Side competition		No	No	No	Not Applicable	No

Multi-sided Works		Song (2013)	Sun (2014)	Tremblay (2016)	van Damme et al. (2010)	Weisman and Kulick (2010)
Type of Paper	Two-Sided	Yes	Yes	Yes	Yes	Not Applicable
	One-Sided	Yes	No	No	No	Not Applicable
	Policy	Not Applicable	No	No	Yes	Yes
Orientation	Theoretical	No	Yes	Yes	Yes	Yes
	Empirical	Yes	No	No	Yes	No
Evans' classification	Market-Maker	No	No	No	Not Applicable	Not Applicable
	Audience-Makers	Yes	No	No	Not Applicable	Not Applicable
	Demand Coordinators	No	Yes	Yes	Not Applicable	Not Applicable
Filistrucchi's classification	Membership	Yes	Yes	Yes	Not Applicable	Not Applicable
	Usage	No	No	No	Not Applicable	Not Applicable
	Strategies	No	No	No	Not Applicable	Not Applicable
Rysman's classification	Markets	Yes	Yes	Yes	Not Applicable	Not Applicable
	Static	Yes	Yes	No	Not Applicable	Yes
	Dynamic	No	No	Yes	Not Applicable	No
Temporality	Generic	No	Yes	No	No	No
	Specific	TV Magazine	No	Software	Yes	Net Neutrality
	Singlehoming	Yes	Yes	Yes	Not Applicable	Not Applicable
Behaviours	Multihoming	Yes	Yes	Yes	Not Applicable	Not Applicable
	Monopoly Platf.	No	No	Yes	Not Applicable	Not Applicable
	Duopolist Platf.	No	Yes	Yes	Not Applicable	Not Applicable
Type of Competition	N Platforms	Yes	No	No	Not Applicable	Not Applicable
	Two-Sided Platf.	Yes	Yes	Yes	Not Applicable	Not Applicable
	Others	Yes	No	No	Not Applicable	Not Applicable
Ownership Structures	One Side	No	No	No	Not Applicable	Not Applicable
	Two Sides	Yes	Yes	Yes	Not Applicable	Not Applicable
	Horizontal	Yes	Yes	Yes	Not Applicable	Not Applicable
Type of Differentiation	Vertical	No	No	Yes	Not Applicable	Not Applicable
	Tying/Bundling	No	Yes	No	Not Applicable	Not Applicable
	Own-Side competition	No	No	No	Not Applicable	Not Applicable

Multi-sided Works		Weyl (2008)	Weyl (2010)	Weyl and White (2014)	Weyl and Fabinger (2009)
Type of Paper	Two-Sided	Yes	Yes	Yes	No
	One-Sided	No	No	No	Yes
	Policy	No	Not Applicable	Yes	No
Orientation	Theoretical	Yes	Yes	Yes	Yes
	Empirical	No	No	Yes	No
Evans' classification	Market-Maker	Yes	Yes	Not Applicable	Not Applicable
	Audience-Makers	No	Yes	Not Applicable	Not Applicable
	Demand Coordinators	No	Yes	Not Applicable	Not Applicable
Filistrucchi's classification	Memberships	No	No	Not Applicable	Not Applicable
	Usage	Yes	Yes	Not Applicable	Not Applicable
Rysman's classification	Strategies	Yes	No	Not Applicable	Not Applicable
	Markets	No	Yes	Not Applicable	Not Applicable
Temporality	Static	Yes	Yes	Yes	Yes
	Dynamic	No	No	Yes	No
	Generic	No	Yes	Yes	Yes
Abstraction	Specific	Credit Cards	No	No	No
	Singlehoming	Not Applicable	Not Applicable	Not Applicable	Not Applicable
Behaviours	Multihoming	Not Applicable	Not Applicable	Not Applicable	Not Applicable
	Monopoly Platf.	Yes	Yes	Not Applicable	Not Applicable
Type of Competition	Duopolist Platf.	No	No	Not Applicable	Not Applicable
	N Platforms	No	No	Not Applicable	Not Applicable
Ownership Structures	Two-Sided Platf.	Yes	Yes	Not Applicable	Not Applicable
	Others	Yes	No	Not Applicable	Not Applicable
Differentiation	One Side	No	No	Not Applicable	Not Applicable
	Two Sides	Yes	Yes	Not Applicable	Not Applicable
Type of Differentiation	Horizontal	Yes	Yes	Yes	Not Applicable
	Vertical	No	Yes	Not Applicable	Not Applicable
Tying/Bundling		No	No	Not Applicable	Not Applicable
	Own-Side competition	No	Yes	Not Applicable	Not Applicable

Multi-sided Works		White and Weyl (2016)	Wilbur (2008)	Wright (2004)
Type of Paper	Two-Sided	Yes	Yes	Not Applicable
	One-Sided	No	No	Not Applicable
	Policy	Not Applicable	Not Applicable	Yes
Orientation	Theoretical	Yes	No	Yes
	Empirical	No	Yes	No
Evans' classification	Market-Maker	No	No	Not Applicable
	Audience-Makers	No	Yes	Not Applicable
	Demand Coordinators	Yes	No	Not Applicable
Filistrucchi's classification	Membership	Yes	Yes	Not Applicable
	Usage	No	No	Not Applicable
	Strategies	No	No	Not Applicable
Rysman's classification	Markets	Yes	Yes	Not Applicable
	Static	Yes	Yes	Not Applicable
	Dynamic	Yes	No	Not Applicable
Temporality	Generic	Yes	No	Yes
	Specific	No	TV Market	No
	Singlehoming	Yes	Viewers	Not Applicable
Behaviours	Multihoming	Yes	Advertisers	Not Applicable
	Monopoly Platf.	No	No	Not Applicable
	Duopolist Platf.	Yes	No	Not Applicable
Type of Competition	N Platforms	Yes	Yes	Not Applicable
	Two-Sided Platf.	Yes	Yes	Not Applicable
	Others	Yes	No	Not Applicable
Ownership Structures	One Side	No	No	Not Applicable
	Two Sides	Yes	Yes	Not Applicable
	Horizontal	Yes	Yes	Not Applicable
Type of Differentiation	Vertical	Yes	No	Not Applicable
	Tying/Bundling	No	No	Not Applicable
	Own-Side competition	Yes	Yes	Not Applicable

A.3 Theoretical Modeling. Vertically Differentiated Framework

For simplicity's sake, we only consider the pure two-sided case throughout this Appendix. However, the way we solve this model is the same in the rest of the cases. Only the case with direct network effect and responsive beliefs is different, but we consider it separately.

A.3.1 Monopoly Model

We consider the utility function defined in Section 4.2 and derive the monopoly demands

$$\begin{aligned} U_i \geq 0; \theta \geq \frac{v}{m^e} &\rightarrow n(v, m^e) = 1 - \frac{v}{m^e} \\ \pi_i \geq 0; \delta \geq \frac{T}{n^e} &\rightarrow m(T, n^e) = 1 - \frac{T}{n^e} \end{aligned}$$

We replace these two expressions in the platforms profits function $\Pi = vn(v) + Tm(T)$. Then, we compute the two first-order conditions with respect to (v, T) :

$$v^*(m^e) = \frac{m^e}{2} \quad T^*(n^e) = \frac{n^e}{2}$$

We impose the rational expectations condition $n^* = n^e$; $m^* = m^e$ and we solve for the equilibrium prices and demands.

$$v^* = T^* = 1/4 \quad n^* = m^* = 1/2$$

A.3.2 Proof Proposition of “no responsive expectations”

Let's consider the two-sided demands:

$$n(v, m^e) = 1 - \frac{v}{m^e} \quad m(T, n^e) = 1 - \frac{T}{n^e}$$

We solve this system for $(n^e = n, m^e = m)$ and we obtain

$$n^2 - n(T - v + 1) + T = 0 \quad m^2 - m(v - T + 1) + v = 0$$

Solving the roots of those quadratic equations we have:

$$n = \frac{1+T-v}{2} \pm \sqrt{\frac{(-1-T+v)^2}{4} - T} \quad m = \frac{1+v-T}{2} \pm \sqrt{\frac{(-1-v+T)^2}{4} - v}$$

However, to rule out irrational results, the next conditions must hold

$$\frac{(-1-T+v)^2}{4} - T > 0 \quad \frac{(-1-v+T)^2}{4} - v > 0$$

Straightforward computation yields

$$v > 2\sqrt{T} + T + 1 \quad T > 2\sqrt{v} + v + 1$$

This is a contradiction because both conditions cannot be fulfilled at the same time.

This approach is not feasible in this model.

A.3.3 Monopoly Model. Direct Externalities and Responsive Expectations

In this case, we only consider the case on users' side because there is no change in how platform makes the price decision on sellers' side. Users' demand are

$$n(v, n^e) = 1 - \frac{v}{n^e}$$

We consider users are rational, so we solve the expression for $n^e = n$:

$$v(n, n) = n(1 - n)$$

This expression has two roots, so it may exist more than one n that satisfies the equilibrium condition for a given price. For instance, for any price v such that $0 < v < 1/4$, there are three network sizes consistent with this price:

$$n = 1/2 \pm \sqrt{\frac{1}{4} - v}, \quad n = 0$$

We need a rule to choose among the equilibria. In this sense, we follow (Belleflamme and Peitz, 2015, pag. 591), and we consider that the platform will choose the network size that maximizes its profits. We replace those expressions in the profits function $\Pi = vn(v) + Tm(T)$. Then, we compute the first-order conditions of the profit function with respect to (n, T) , and we obtain:

$$n^* = 2/3, \quad T^*(n^e) = \frac{n^e}{2}$$

Solving the system, we have:

$$v^* = n(1 - n) = 2/9 \quad T^* = n/2 = 1/3 \quad m^* = 1/2$$

A.3.4 Duopoly Model

Let's assume both sides singlehome and $n_1^e > n_2^e; m_1^e > m_2^e$. Following our definition of active agents, we consider two marginal agents: the one indifferent between both platforms; and the one indifferent between consuming the low-quality one and not consuming at all. If we consider these two marginal agents, it is straightforward to derive demands addressed to platforms:

$$U_1 \geq U_2; \theta = \frac{(v_1 - v_2)}{(m_1^e - m_2^e)} \rightarrow n_1(v_i, m_i^e) = 1 - \theta$$

$$U_2 \geq 0; \theta' \geq \frac{v_2}{m_2^e} \rightarrow n_2(v_i, m_i^e) = \theta - \theta'$$

Solving, we obtain:

$$n_1(v_i, m_i^e) = 1 - \frac{v_1 - v_2}{m_1^e - m_2^e} \quad n_2(v_i, m_i^e) = \frac{v_1 m_2^e - v_2 m_1^e}{(m_1^e - m_2^e) m_2^e}$$

Symmetrically:

$$m_1(T_i, n_i^e) = 1 - \frac{T_1 - T_2}{n_1^e - n_2^e} \quad m_2(T_i, n_i^e) = \frac{T_1 n_2^e - T_2 n_1^e}{(n_1^e - n_2^e) n_2^e}$$

To determine the price equilibrium, we replace those expressions in the profits functions $\Pi_i = v_i n_i + T_i m_i$. Then, we compute the first-order conditions of the profits functions with respect to (v_i, T_i) , and we obtain

$$v_1 = \frac{m_1^e - m_2^e + v_2}{2} \quad v_2 = \frac{v_1 m_2^e}{2m_1^e}$$

Solving the system we have:

$$v_1 = \frac{2m_1^e(m_1^e - m_2^e)}{4m_1^e - m_2^e} \quad v_2 = \frac{m_2^e(m_1^e - m_2^e)}{4m_1^e - m_2^e}$$

Symmetrically:

$$T_1 = \frac{2n_1^e(n_1^e - n_2^e)}{4n_1^e - n_2^e} \quad T_2 = \frac{n_2^e(n_1^e - n_2^e)}{4n_1^e - n_2^e}$$

If we replace these expressions in demands, we obtain:

$$n_1 = \frac{2m_1^e}{4m_1^e - m_2^e}; m_1 = \frac{2n_1^e}{4n_1^e - n_2^e} \quad n_2 = \frac{m_1^e}{4m_1^e - m_2^e}; m_2 = \frac{n_1^e}{4n_1^e - n_2^e}$$

If we impose the rational expectations condition $n_i^* = n_i = n_i^e; m_i^* = m_i = m_i^e$ and we solve the system of four equations, we have

$$n_1^* = m_1^* = 4/7 \quad n_2^* = m_2^* = 2/7 \quad v_1^* = T_1^* = 8/49 \quad v_2^* = T_2^* = 2/49$$

A.3.5 Duopoly Model. Direct Externalities and Responsive Beliefs

In this case, we only consider the case on users' side because there is no change in how platforms make the price decisions on sellers' side. Users' demands are:

$$n_1(v_i, n_i^e) = 1 - \frac{v_1 - v_2}{n_1^e - n_2^e} \quad n_2(v_i, n_i^e) = \frac{v_1 n_2^e - v_2 n_1^e}{n_2^e (n_1^e - n_2^e)}$$

If we consider that users are rational, we impose $n_1^e = n_1; n_2^e = n_2$:

$$v_1(n_1, n_2) = n_1(1 - n_1) - n_2^2 \quad v_2(n_2, n_1) = n_2(1 - n_1 - n_2)$$

We need a rule to choose among the equilibria. In this sense, we follow (Belleflamme and Peitz, 2015, pag. 591), and we consider that the platforms will choose the network size that maximizes their profits in the users' side, and they will choose the prices that maximize the profits in the sellers' side. We replace those expressions in the profits functions, $\Pi_i = v_i n_i + T_i m_i$. Then, we compute the first-order conditions of the profits functions with respect to (n_i, T_i) .

$$n_1 = \frac{1}{3} \pm \frac{1}{3} \sqrt{1 - 3n_2^2} \quad n_2 = \frac{1 - n_1}{3} (1 \pm 1)$$

We can consider four possible solutions. However, the only case that is in the interval $[0,1]$ is the following system:

$$n_1 = \frac{1}{3} + \frac{1}{3} \sqrt{1 - 3n_2^2} \quad n_2 = \frac{2(1 - n_1)}{3}$$

Solving the system we have:

$$n_1^* = 0.636 \quad n_2^* = 0.243 \text{ (or } n_2^* = 0)$$

We replace these values, and we have:

$$\begin{aligned} m_1^* &= 0.553 & T_1^* &= 0.217 & v_1^* &= 0.173 \\ m_2^* &= 0.276 & T_2^* &= 0.042 & v_2^* &= 0.03 \end{aligned}$$

The case with $n_2^* = 0$ leads to another interior equilibrium in which the platform 2 is active but is not participating in the market

A.3.6 Duopoly Model with Data Sharing Agreements

We only solve the two-sided case because the rest of cases are similar. In this case, the network size of any platform is given by the following expressions¹

$$n_i^{e,c} = n_i^e + \rho_{-i} n_{-i}^e; \quad m_i^{e,c} = m_i^e + \rho_{-i} m_{-i}^e$$

Therefore, the utility functions are

$$U_{i,u} = \theta m_i^{e,c} - v_i; \quad U_{i,s} = \delta n_i^{e,c} - T_i$$

Solving $U_i \geq 0$ and $U_i \geq U_{-i} \geq 0$, we have

$$\begin{aligned} n_1(v_i, m_i^e) &= 1 - \frac{v_1 - v_2}{(1 - \rho_1)m_1^e - (1 - \rho_2)m_2^e} & n_2(v_i, m_i^e) &= \frac{v_1(m_2^e + \rho_1 m_1^e) - v_2(m_1^e + \rho_2 m_2^e)}{(m_2^e + \rho_1 m_1^e)((1 - \rho_1)m_1^e - (1 - \rho_2)m_2^e)} \\ m_1(T_i, n_i^e) &= 1 - \frac{T_1 - T_2}{(1 - \rho_1)n_1^e - (1 - \rho_2)n_2^e} & m_2(T_i, n_i^e) &= \frac{T_1(n_2^e + \rho_1 n_1^e) - T_2(n_1^e + \rho_2 n_2^e)}{(n_2^e + \rho_1 n_1^e)((1 - \rho_1)n_1^e - (1 - \rho_2)n_2^e)} \end{aligned}$$

To determine the price equilibrium, we replace those expressions in the profits functions $\Pi_i = v_i n_i + T_i m_i$. Then, we compute the first-order conditions of the profits functions with respect to (v_i, T_i) . We impose the rational expectations condition $n_i^* = n_i = n_i^e; m_i^* = m_i = m_i^e$ and we solve the system of equations for prices and demands. Then, we can analyze some points to figure out how are the profits in comparison with the case without data sharing agreements.

¹The subscript $-i$ makes references to the “other company”.

Table A.21: Interior Equilibria. Vertically Differentiated Framework with Compatibility

Pure Two-Sided	$\pi_1 = \frac{8(1-2\rho_1+\rho_2)(2+\rho_2)^3}{(7-2\rho_1+4\rho_2)^3}$	$\pi_2 = \frac{2(1-2\rho_1+\rho_2)(2+\rho_2)^2(1+2\rho_1)}{(7-2\rho_1+4\rho_2)^3}$
Exogenous quality level	$\pi_1 = \frac{4s_1(2+\rho_2)^2(1-2\rho_1+\rho_2)}{(4s_1-s_2)(7-2\rho_1+4\rho_2)^2}$	$\pi_2 = \frac{2s_1(2+\rho_2)(1+2\rho_1)(1-2\rho_1+\rho_2)}{(4s_1-s_2)(7-2\rho_1+4\rho_2)^2}$
Direct network effects. Passive beliefs	$\pi_1 = \frac{4(1-2\rho_1+\rho_2)(2+\rho_2)^3}{1/2(7-2\rho_1+4\rho_2)^3}$	$\pi_2 = \frac{2(1-2\rho_1+\rho_2)(2+\rho_2)^2(1-2\rho_1)}{1/2(7-2\rho_1+4\rho_2)^3}$

Table A.22: Platforms' Payoff at Specific Points. Vertically Differentiated Framework with Compatibility

Platforms' payoffs $(\rho_1, \rho_2) = (1,1)$			
Puro Two-Sided	Exogenous Quality Level	Direct Network Effects	
$\pi_1 \approx 0$ $\pi_2 \approx 0$	$\pi_1(1, 0.5) = 0.1633$ $\pi_2(1, 0.5) = 0.0204$	Passive beliefs $\pi_1 = 0$ $\pi_2 = 0$	Responsive beliefs $\pi_1 \approx 0$ $\pi_2 \approx 0$
Platforms' payoffs $(\rho_1, \rho_2) = (0,0)$			
Puro Two-Sided	Exogenous Quality Level	Direct Network Effects	
$\pi_1 = 0.1866$ $\pi_2 = 0.0233$	$\pi_1 = 0.2566$ $\pi_2 = 0.0321$	Passive beliefs $\pi_1 = 0.1866$ $\pi_2 = 0.0233$	Responsive beliefs $\pi_1 = 0.23$ $\pi_2 = 0.02$
Platforms' payoffs $(\rho_1, \rho_2) = (1,0)$			
Puro Two-Sided	Exogenous Quality Level	Direct Network Effects	
$\pi_1 < 0$ $\pi_2 < 0$	$\pi_1 < 0$ $\pi_2 < 0$	Passive beliefs $\pi_1 < 0$ $\pi_2 > 0$	Responsive beliefs $\pi_1, \pi_2 \notin \mathbb{R}$
Platforms' payoffs $(\rho_1, \rho_2) = (0,1)$			
Puro Two-Sided	Exogenous Quality Level	Direct Network Effects	
$\pi_1 = 0.3246$ $\pi_2 = 0.0811$	$\pi_1 = 0.3333$ $\pi_2 = 0.0346$	Passive beliefs $\pi_1 = 0.3246$ $\pi_2 = 0.0271$	Responsive beliefs $\pi_1 = 0.341$ $\pi_2 = 0.0245$

Table A.23: Roots and Demands. Vertically Differentiated Framework with Compatibility. Direct Network Effects with Responsive Beliefs

Roots and demands	n_1	n_2
(+,+)	-0.3333	0
(+,-)	0.5972	0.268
(-,+)	-0.3333	0
(-,-)	-0.1762	0.7841

The Direct Network Effects with Responsive Beliefs Case

This case imposes an extra difficulty than the previous ones. Although it is analytically solvable, the equilibrium outcomes are far from intuitive (it fills more than 2 A4 pages²). However, the process is the same than before, we only have to take into account the small change in utilities of Section 4.3.1.

In this case, the equilibrium outcome in the sellers' side is the same than in the previous section, so the interesting point is to see what happens on the users' side. At equilibrium, users' demands are

$$n_1 = \frac{1 - n_2(\rho_1 + \rho_2)}{3} \pm \frac{1}{6} \sqrt{(2 - 2\rho_1 n_2 - 2\rho_2 n_2)^2 + 12(\rho_2 n_2 - n_2^2)}$$

$$n_2 = \frac{1}{3} \left(1 - n_1(1 + \rho_1) \pm \sqrt{1 + n_1(\rho_1 - 2 + n_1(1 - \rho_1 + \rho_1^2))} \right)$$

This system of equations has four solutions. Nonetheless, the correct solution depends on the pair (ρ_1, ρ_2) . For example, when $(\rho_1, \rho_2) = (1, 0)$, no solution is correct because there is no solution in the real numbers. However, when $(\rho_1, \rho_2) = (1, 1)$, only the solution with two positive roots is correct. An interesting case to analyze is $(\rho_1, \rho_2) = (0, 1)$. The graphs depicted in Table 4-2 seem to point out to the existence of two equilibria. But let's analyse how the demands in these two cases are. The 1st solution corresponds to the pair with two positive roots. The 2nd solution corresponds to the pair with a positive and a negative root, $(n_1, n_2) \mapsto (+, -)$. Let's analyze the four cases: Then, the immediate question is why profits are positive in the 2nd solution. The reason is that sellers consider that users will converge to the "correct"

²The computation of this case was made using Wolfram Mathematica 10.3. Code is available upon request.

equilibrium. That is, $(n_1, n_2) \mapsto (+, -)$. So, this case is not a real equilibrium because the number of users considered by sellers is not the same than the number of users in the platforms. That violates the rational expectations assumption. Then, the only correct solution is $(n_1, n_2) \mapsto (+, -)$.

A.4 List of Publications

Some parts of this Thesis have been published in peer-reviewed journal or conferences. In this Section, we highlight the scientific contribution of this Thesis in terms of the published material.

- Sanchez-Cartas, J.M., and Leon, G. (2017a): On Simulating the Adoption of New Products in Markets with Rational Users and Companies. In: International Conference on Practical Applications of Agents and Multi-Agent Systems. CCIS 722, pp. 83-94. Springer
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A.5 Algorithm Pseudo-Code

In this appendix, we provide the pseudo-code of the whole algorithm. It is divided into several procedures.

- The Sub-Algorithm 1 computes the situation of the market at any moment
- The Sub-Algorithm 2 provides a high-level vision of how the price competition is simulated. This sub-algorithm calls to procedure calls "DemandPrediction"
- The Sub-Sub-Algorithm 3 computes how each company considers that the change in prices will affect the market. During this procedure, three more procedures are called: an estimation of impact in utilities, an estimation of impact in demands, and the decision of platforms.
- The Sub-Sub-Algorithm 4 and the Sub-Sub-Algorithm 5 control the estimation of new utilities.
- The Sub-Algorithm 6 and the Sub-Sub-Algorithm 7 control the estimation of new demands.

- The Sub-Sub-Algorithm 8 controls indirect effects that some companies may cause on other platforms.
- The Sub-Sub-Algorithm 9 controls the final decision of companies with regard to prices.

Algorithm 1 Compute Static Situation of Market

```

1: procedure UTILITIES
2:   for Each Sides j do
3:     Users: Create UtilityVector  $\leftarrow \emptyset$ 
4:     for Users: Each Platform i do
5:       Compute  $\rightarrow$  users' utility in i minus Prices
6:       UtilityVector[i]  $\leftarrow$  i-utility
7:     end for
8:     Users: OptimalDecision = max(UtilityVector)
9:     if Users: OptimalDecision < 0 then
10:      OptimalDecision =  $\emptyset$ 
11:    end if
12:    Users w/ OptimalDecision  $\neq \emptyset$  : ChosenCompany  $\leftarrow$ 
      UtilityVector.index(OptimalDecision)
13:  end for
14: end procedure
15:
16: procedure DEMANDS
17:   for Each Sides j do
18:     Create DemandVector  $\leftarrow \emptyset$ 
19:     for Each Platform i do
20:       Demand-i = Count users w/ [ChosenCompany = i]
21:       DemandVector[i]  $\leftarrow$  Demand-i
22:     end for
23:   end for
24: end procedure
25:
26: procedure PROFITS
27:   for Each Platform i do
28:     for Each Sides j do
29:       Platforms: Profits  $\leftarrow$  Profits[j-1] + prices-i * DemandVector[i]
30:     end for
31:   end for
32: end procedure

```

Algorithm 2 Price Competition. High level vision

```
1: procedure PRELIMINARY ACTIONS
2:   for Each Sides j do
3:     Create  $\epsilon$  = change in prices
4:     Platforms: Create  $PricesUp \leftarrow Prices + \epsilon$ 
5:     Platforms: Create  $PricesDown \leftarrow Prices - \epsilon$ 
6:   end for
7: end procedure
8: procedure PREDICTION
9:    $Actions \leftarrow (PricesUp, PricesDown)$ 
10:  repeat
11:    DemandPrediction
12:  until number repeats = number platforms
13: end procedure
```

Algorithm 3 Price Competition. Companies address the consequences of their changes in prices

```

1: procedure DEMANDPREDICTION
2:   for ( doEach Sides j)
3:     for Each Actions x do
4:       ConsiderPlatf  $\leftarrow$  0
5:       change  $\leftarrow$  DemandVector[0]
6:       iteration  $\leftarrow$  0
7:       Users: Create PotentialUtilityVector  $\leftarrow$   $\emptyset$ 
8:       Users: Create will  $\leftarrow$  [none]
9:       Platforms: Create PotentialDemandVector  $\leftarrow$   $\emptyset$ 
10:      for Users: Each Platform i do
11:        Compute  $\rightarrow$  users' utility in i minus (Actions[x])
12:        PotentialUtilityVector[i]  $\leftarrow$  i-utility
13:      end for
14:      while change  $\geq$  0.01 do
15:        ControlChange  $\leftarrow$  Profits of Platform[ConsiderPlatf]
16:        Users: Create ComparionUtilityVector  $\leftarrow$   $\emptyset$ 
17:        procedure EVALUATION OF NEW UTILITIES
18:      end procedure
19:      procedure EVALUATION OF NEW UTILITIES. FEEDBACK LOOPS
CONTROL
20:      end procedure
21:      procedure GENERATION OF POTENTIAL DEMANDS
22:    end procedure
23:    if Indirect Network effects exists then
24:      procedure FEEDBACK LOOPS
25:    end procedure
26:    end if
27:    Platform[ConsiderPlatf]:
      (Actions[x]) * PotentialDemandVector[i] + PotentialProfits =
      PotentialDemandVector(Group2)[i] + prices-i(Group2) *
28:    procedure IMPACT FEEDBACK LOOPS ON OTHER PLATFORMS
29:    end procedure
30:    iteration = iteration + 1
31:    change = abs(ControlChange - PotentialProfits of platform[i])
32:  end while
33:  end for
34: end for
35: procedure DECISION MAKING.PLATFORM[ConsiderPlatf]
36: end procedure
37: ConsiderPlatf  $\leftarrow$  ConsiderPlatf + 1
38: if ConsiderPlatf = N then
39:   ConsiderPlatf  $\leftarrow$  0
40: end if
41: end procedure

```

Algorithm 4 Price Competition. Sub-Procedures(1/6). Utilities estimation

```
1: procedure EVALUATION OF NEW UTILITIES
2:   if iteration  $\leftarrow 0$  then
3:     if ConsiderPlatf  $\leftarrow 0$  then
4:       Users: ComparisonUtilityVector[0]  $\leftarrow$  PotentialUtilityVector[0]
5:       Users: ComparisonUtilityVector[1:N]  $\leftarrow$  UtilityVector[1:N]
6:     end if
7:     if ConsiderPlatf  $\neq 0$  and ConsiderPlatf  $\leq N-1$  then
8:       Users: ComparisonUtilityVector[0:i-1]  $\leftarrow$  UtilityVector[0:i-1]
9:       Users: ComparisonUtilityVector[i]  $\leftarrow$  PotentialUtilityVector[i]
10:      Users: ComparisonUtilityVector[i+1:N]  $\leftarrow$  UtilityVector[i+1:N]
11:    end if
12:    if ConsiderPlatf = N then
13:      Users: ComparisonUtilityVector[0:N-1]  $\leftarrow$  UtilityVector[0:N-1]
14:      Users: ComparisonUtilityVector[N]  $\leftarrow$  PotentialUtilityVector[N]
15:    end if
16:  end if
17: end procedure
```

Algorithm 5 Price Competition. Sub-Procedures(2/6). New utilities if externalities are present

```
1: procedure EVALUATION OF NEW UTILITIES. FEEDBACK LOOPS CONTROL
2:   if iteration  $\neq 0$  then
3:     if ConsiderPlatf = 0 then
4:       Users: ComparisonUtilityVector[0]  $\leftarrow$  PotentialUtilityVector[0]
5:       Users: ComparisonUtilityVector[1:N] = IteratedUtilityVector[1:N]
6:     end if
7:     if ConsiderPlatf  $\neq 0$  and ConsiderPlatf  $\leq N-1$  then
8:       Users: ComparisonUtilityVector[0:i-1]  $\leftarrow$  IteratedUtilityVector[0:i-1]
9:       Users: ComparisonUtilityVector[i]  $\leftarrow$  PotentialUtilityVector[i]
10:      Users: ComparisonUtilityVector[i+1:N]  $\leftarrow$  IteratedUtilityVector[i+1:N]
11:    end if
12:    if ConsiderPlatf = N then
13:      Users: ComparisonUtilityVector[0:N-1]  $\leftarrow$  IteratedUtilityVector[0:N-1]
14:      Users: ComparisonUtilityVector[N]  $\leftarrow$  PotentialUtilityVector[N]
15:    end if
16:  end if
17: end procedure
```

Algorithm 6 Price Competition. Sub-Procedures(3/6). Estimation of potential demands

```

1: procedure GENERATION OF POTENTIAL DEMANDS
2:   Users:  $PotentialOptimalDecision = \text{Max}(ComparisonUtilityVector)$ .
3:   if Users:  $PotentialOptimalDecision < 0$  then
4:      $PotentialOptimalDecision \leftarrow \emptyset$ 
5:   end if
6:   Users w/  $PotentialOptimalDecision \neq \emptyset$ :  $PotentialChosenCompany \leftarrow$ 
      $ComparisonUtilityVector.index(PotentialOptimalDecision)$ 
7:   for Each Platform  $i$  do
8:      $PotentialDemand-i = \text{Count users w/ } PotentialOptimalDecision = i$ 
9:      $PotentialDemandVector[i] \leftarrow PotentialDemand-i$ 
10:  end for
11: end procedure

```

Algorithm 7 Price Competition. Sub-Procedures(4/6). Estimation of potential demands if externalities are present

```

1: procedure FEEDBACKS LOOPS
2:   Users(Group2): Create  $PotentialUtilityVector(Group2) \leftarrow \emptyset$ 
3:   Users(Group2): Create  $will(Group2) \leftarrow [none]$ 
4:   for Users(Group2): Each Platform  $i$  do
5:     Compute  $\rightarrow$  users' utility w/  $NetworkEffects=Demand-i$ 
6:      $PotentialUtilityVector(Group2)[i] \leftarrow i\text{-utility}$ 
7:   end for
8:   Users(Group2)  $PotentialOptimalDecision =$ 
      $\max(PotentialUtilityVector(Group2))$ 
9:   if Users:  $PotentialOptimalDecision < 0$  then
10:     $PotentialOptimalDecision \leftarrow \emptyset$ 
11:  end if
12:  Users:  $PotentialChosenCompany \leftarrow PotentialUtilityVector(Group2)$ 
      $.index(PotentialOptimalDecision)$ 
13:  for Each Platform  $i$  do
14:     $PotentialDemand-i(Group2) = \text{Count Users(Group2) w/}$ 
      $[PotentialOptimalDecision = i]$ 
15:     $PotentialDemandVector(Group2)[i] \leftarrow Demand-i(Group2)$ 
16:  end for
17: end procedure

```

Algorithm 8 Price Competition. Sub-Procedures(5/6). Control for indirect effects on other companies

```

1: procedure IMPACT FEEDBACK LOOPS ON OTHER COMPANIES
2:   Users: Create PotentialUtilityVector  $\leftarrow \emptyset$ 
3:   Users: Create IteratedUtilityVector  $\leftarrow \emptyset$ 
4:   Users: Create will  $\leftarrow$  [none]
5:   Platforms: Create PotentialDemandVector  $\leftarrow \emptyset$ 
6:   for Users: Each Platform i do
7:     Compute  $\rightarrow$  users' utility in i minus (PricesUp or PricesDown) w/
       NetworkEffects=Demand-i(Group2)
8:     PotentialUtilityVector[i]  $\leftarrow$  i-utility
9:     Compute  $\rightarrow$  users' PotentialUtility in i minus Prices
10:    IteratedUtilityVector[i] i-PotentialUtility
11:  end for
12: end procedure

```

Algorithm 9 Price Competition. Sub-Procedures(6/6). Companies decision

```

1: procedure DECISION MAKING. PLATFORM[ConsiderPlatf]
2:   if PotentialProfits at (Actions[x]) > Profits & PotentialProfits at
     (Actions[x]) > PotentialProfits at (Actions[-x]) then
3:     Set Prices  $\leftarrow$  Actions[x]
4:   end if
5: end procedure

```

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