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05 TESIS DOCTORAL

INDUSTRIALES

TESIS DOCTORAL

ESSAYS ON FINANCIAL TECHNOLOGY AND SME FINANCE

A Tale of Two Effects of the Global Financial Crisis:
Financing SMEs and Innovative Financing

JULY 2020

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TESIS DOCTORAL
PARA LA OBTENCIÓN DEL
TÍTULO DE **DOCTOR**

POLITÉCNICA

UNIVERSIDAD POLITÉCNICA DE MADRID
ESCUELA TÉCNICA SUPERIOR DE INGENIEROS
INDUSTRIALES

Departamento de Ingeniería de Organización, Administración de
Empresas y Estadística

Programa de doctorado:
European Doctorate in Industrial Management

Essays on Financial Technology and SME Finance

A Tale of Two Effects of the Global Financial Crisis:

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TESIS DOCTORAL

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2020

This research was conducted within the framework of the “[European Doctorate in Industrial Management](#)”—EDIM—which is funded by The Education, Audiovisual and Culture Executive Agency (EACEA) of the European Commission under Erasmus Mundus Action 1 programmes.

Dedicated to my father, Saied, who taught me courage,

To my mother, Shayesteh, who taught me love,

To my brother, Reza, who taught me determination,

You have always been my greatest heroes.

“Everything you possess of skill, and wealth, and handicraft, wasn’t it first merely a thought and a quest?”

Rumi, Persian Poet

*“Muere lentamente
quien no voltea la mesa cuando está infeliz en el trabajo,
quien no arriesga lo cierto por lo incierto para ir detrás de un sueño,*

*Muere lentamente
quien no viaja,
quien no lee,
quien no oye música,
quien no encuentra gracia en si mismo.*

*Muere lentamente
quien destruye su amor propio,
quien no se deja ayudar.*

*Muere lentamente,
quien pasa los días quejándose de su mala suerte
o de la lluvia incesante.*

*Muere lentamente,
quien abandona un proyecto antes de iniciarlo,
no preguntando de un asunto que desconoce
o no respondiendo cuando le indagan sobre algo que sabe.*

*Evitemos la muerte en suaves cuotas,
recordando siempre que estar vivo exige un esfuerzo mucho mayor
que el simple hecho de respirar.
Solamente la ardiente paciencia hará que conquistemos
una espléndida felicidad.”*

Martha Medeiros, Brazilian Poet (Spanish Translation)

Acknowledgements

To have five years spent shaping this thesis flash before my eyes, and to pen an ode to those who made traversing this road enjoyable, is proving as surreal, as it is emotional. It has been a journey of learning, as great as any I have experienced. I owe this to many. First, I would like to thank my supervisors at UPM, Felipe Ruiz, and at KTH, Anders Broström and Ali Mohammadi. Their patience and unwavering support in directing my curiosity and musings into meaningful and grounded endeavors has been priceless. Felipe, thank you so much for facilitating the way for me to engage in exciting research in finance and our enriching, thought-provoking and enjoyable discussions. You have always been very supportive of my endeavors and ambitions along the way and I immensely appreciate that. Anders, you are a great advisor, thoughtful, patient, committed and unyieldingly supportive. Thank you for giving me, the freedom to explore my ideas, and great support in guiding them. Ali, you are as great a teacher as one can hope for, energetic, dedicated, pedagogical, and untiringly optimistic. I value your advice greatly, not merely professionally, but personally as well.

I would like to thank Gustavo Morales for his constant help and friendship, even going out of his way to make me feel welcome at UPM. That also goes for Isabel Herran who was devotedly helping me and others throughout the years. I would like to thank Hans Lööf for his invaluable help and for trusting me to deliver lectures or lead Masters' students. I would like to thank Andreas Stephan and Gustav Martinsson for valuable comments on my papers. I benefitted immensely from visiting, attending and engaging in seminars and courses at the Swedish House of Finance (SHoF) at Stockholm School of Economics for more than two years. I would particularly like to thank Per Strömberg, Ramin Baghai and Daniel Metzger at SHoF for fascinating conversations and courses on research in financial economics.

This journey was enriched enormously because it was shared with fellow Ph.D. students and colleagues, Hossein Zarei, Claudia Manca, Vikash Sinha, Andra Riandita, Marin Jovanovic, Luis Perez, Milan Jocevski, Yury Kucheev, Matthew Stogsdill, Simon Okwir, Richard Backteman, Shoaib Kazmi, Enes Ünal, Isaac Lemus, Emrah Karakaya, Julia Liljegren, Ingrid Ros, Yilsy Núñez, Christopher Roberts, Vardan Hovsepyan, Gregg Vanourek, Sarah Behnam, Sina Lessani, Ebru Susur, Maxim Miterev, Andres Ramirez, Anna Darmani, Hakan Karaosman, Monia Lougui, Felix Bracht, Serdar Temiz, Armaghan Chizayifard, Daniel Berlin, Oskar Törnblom and many others who have been supportive. Many friends and doctoral students at SHoF made my visit there memorable: Tolga Demir, Berenice Ramirez Hart, Viktor Thell, Alberto Allegrucci, Ivika Jäger, and Markus Ibert amongst others. Exceptional thanks go: Juanci, Nicolas, William, Lars, Dina, Tobias, Maria, Sahar, Sima, Emil, Emelie, Evgenia, Florian, Shardoob, Jamila, Eric, Jose, Simin, Mehdi, Ryan, Amaia, Elias, Ramón to name a few. I want to thank the other helpful staff of EDIM, the European Commission-funded fellowship I benefited from: Kristin Lohse, and Martina Sani, as well as the EDIM scientific committee, Joaquin Ordieres, Mats Engwall, Cali Nuur, and Paolo Trucco.

To say this journey started with the plane ride to Europe to start my PhD would be to turn a blind eye to those who inspired me to embark on it in the first place. That inspiration originates from my heroes, my phenomenal dad, Saied Saiedi, and my incredible mum, Shayesteh Jahanfar. I remember as a kid standing proud at your PhD graduation ceremonies. Like any son, I hope to make you proud. You laid all the groundwork and made my growth easier, with all your selfless sacrifices and love. My other eternal encourager, my dear brother, Reza Saiedi was standing next to me then. Brother, learning from your determination and your cheers for any progress of mine have given me immense strength. I drew invaluable inspiration from Pouya Zanganeh, revamped by our commitment to cap grad school with PhDs and Makmiller Pedroso, owing to our series of fortunate adventures during and after his PhD. Lastly, Hélène, you have made the difficult stretch down the finish line of this PhD, easy by your presence.

Stockholm, May 2020

Ed (Hamed) Saiedi

Disclaimer:

Some parts of this Ph.D. thesis have already been published as:

- Saiedi, Ed; Mohammadi, Ali; Broström, Anders; Shafi, Kourosh (2020);
Distrust in Banks & FinTech Participation: The Case of Peer-to-Peer Lending. Conditionally Accepted at *Entrepreneurship, Theory and Practice*.
- Saiedi, Ed; Broström, Anders; Ruiz López, Felipe (2020);
Global Drivers of Cryptocurrency Infrastructure Adoption. *Small Business Economics*.
Available online: <https://link.springer.com/article/10.1007%2Fs11187-019-00309-8>
- Saiedi, Ed (2020);
Turned Down in a Downturn? Real Effects of Not Securing Capital in the Global Financial Crisis.
Academy of Management Proceedings 2020 (1), 19793
- Saiedi, Ed (2019);
Essays in Financial Technology and SME Finance: A Tale of Two Effects of the Global Financial Crisis: Financing SMEs and Innovative Financing (*Doctoral Dissertation*).
Available online: <http://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-263146>

Abstract

The financial crisis of 2008-2009 took place exactly half a century after the publication of the seminal Modigliani and Miller (M&M) theorem, often called the capital structure irrelevance principle. This timing is curious since the crisis has highlighted the significance of deviations from assumptions of this theorem, i.e. the importance of corporate finance. A decade on, this thesis explores consequences of this unprecedented event by examining the determinants and effects of financiers' and firms' financing decisions, whose irrelevance is implied by the capital structure irrelevance principle.

The financial crisis has not only expanded our knowledge frontier on corporate financing, it has altered financing itself. A host of financial innovations have arisen in its wake, enabled by digital technologies, which reshape or remove the role of traditional intermediaries. By tracing the adoption of these technologies to the crisis, this thesis frames the crisis not merely as a source of value destruction, but also as a source of creative destruction. Specifically, this thesis aims to empirically investigate two overarching research questions:

- (1) What are the determinants and effects of financing decisions and outcomes for Small and Medium Enterprises, in the face of crisis-era contractions in lending?
- (2) What are the main drivers of the adoption of new financial technologies?

First, this thesis exploits two novel datasets, unique in enabling observation of SME applications for, and use of, various debt and equity instruments, to study determinants of financing choices and outcomes of European SMEs. It tests applicability of extant research to business cycle contractions and bank-based financial systems, and finds similar results. During the crisis, SMEs largely behave in accordance with the pecking-order theory. Innovative firms seek debt more, but innovativeness is only associated with successful search if SMEs are old or market-oriented, and not tech-intensive. Young firms with high investment needs in the crisis had difficulties obtaining debt, but were more likely than average to obtained equity.

Second, this thesis investigates effects of funding rejections on firm investments and performance, through matching successful and observably-similar unsuccessful capital-seeking Small and Medium Enterprises (SMEs). This approach to disentangling supply- from demand-side forces by exploiting application outcomes is novel and robust to substitution effects between sources of capital. The study finds evidence of firms' investments being hampered due to inability to access capital in the crisis. Whereas liquidity helps absorb this supply shock, rejection makes firms less prone to use liquidity for investments in the post-crisis period. Reduced investment plans following rejection are a primary channel through which firm performance is lowered. Results imply that capital substitutions were not adequate to shield SMEs from crisis-era distress to creditor balance sheets.

Third, this thesis sets out to explore what has boosted fintech's growth. In the case of peer-to-peer (P2P) lending, it highlights the role of consumers' distrust in banks. This study offers evidence that distrust in banks likely triggers individuals to supply funding toward crowdfunding and away from bank deposits. It highlights that a distrust mindset promotes questioning default choices and considering alternatives, and fosters comparisons focusing on dissimilarities. Findings suggest US states whose residents express greater distrust in banks are more likely to fund P2P loans and, conditional on funding, lend higher amounts. This relationship is more pronounced when funding small loans or borrowers with less banking access. **Forth**, this thesis empirically investigates drivers of the spread of infrastructure necessary to maintain and grow Bitcoin as a system (Bitcoin nodes) and infrastructure enabling the use of bitcoins for everyday economic transactions (Bitcoin merchants).

Specifically, it investigates the role of legal, criminal, financial and social determinants. Findings offer some support for the view that the adoption of cryptocurrency infrastructure is driven by perceived failings of traditional financial systems, in that the spread of Bitcoin infrastructure is associated with low trust in banks and the financial system among inhabitants of a region, and with the occurrence of inflation crises. Active support for Bitcoins is higher in locations with well-developed banking services. It lends support to the bitcoin adoption being partly driven by cryptocurrencies' usefulness in illicit trade.

Keywords: Financial Innovation, P2P Lending, Digital Currencies, Financial Technology, SME Finance, Global Financial Crisis, Corporate/Entrepreneurial Finance

Resumen

La crisis financiera de 2008-2009 tuvo lugar exactamente medio siglo después de la publicación del teorema seminal de Modigliani y Miller (M&M), a menudo llamado principio de irrelevancia de la estructura de capital. Este momento es curioso ya que la crisis ha resaltado la importancia de las desviaciones de los supuestos de este teorema, es decir, la importancia de las finanzas corporativas. Una década después, esta tesis explora las consecuencias de este evento sin precedentes al examinar los determinantes y los efectos de las decisiones financieras de los financieros y las empresas, cuya irrelevancia está implícita en el principio de irrelevancia de la estructura del capital.

La crisis financiera no solo ha ampliado nuestra frontera de conocimiento sobre el financiamiento corporativo, sino que también ha alterado el financiamiento. Una serie de innovaciones financieras han surgido a su paso, habilitadas por las tecnologías digitales, que remodelan o eliminan el papel de los intermediarios tradicionales. Al rastrear la adopción de estas tecnologías hasta la crisis, esta tesis enmarca la crisis no solo como una fuente de destrucción de valor, sino también como una fuente de destrucción creativa. Específicamente, esta tesis tiene como objetivo investigar dos preguntas:

- (1) ¿Cuáles son los determinantes y los efectos reales de las decisiones de financiación y los resultados para las pequeñas y medianas empresas (PYME), frente a las contracciones de la era de crisis en los préstamos?
- (2) ¿Cuáles son los principales motores de la adopción de nuevas tecnologías financieras?

En primer lugar, esta tesis explota dos conjuntos de datos novedosos, únicos para permitir la observación de las aplicaciones de las PYME y el uso de diversos instrumentos de deuda y capital, para estudiar los determinantes de las opciones de financiación y los resultados de las PYME europeas. Prueba la aplicabilidad de la investigación existente a las contracciones del ciclo económico y los sistemas financieros basados en bancos, y encuentra resultados similares. Durante la crisis, las PYME se comportan en gran medida de acuerdo con la teoría del orden jerárquico. Las empresas innovadoras buscan más deuda, pero la innovación solo se asocia con una búsqueda exitosa si las PYME son antiguas o están orientadas al mercado, y no son intensivas en tecnología. Las empresas jóvenes con altas necesidades de inversión en la crisis tuvieron dificultades para obtener deuda, pero tenían más probabilidades que el promedio de obtener capital.

En segundo lugar, esta tesis investiga los efectos de los rechazos de fondos en las inversiones y el rendimiento de las empresas, a través de la búsqueda de PYME exitosas y observables similares que no tuvieron éxito en la búsqueda de capital. Este enfoque para separar las fuerzas del lado de la oferta de la demanda al explotar los resultados de la aplicación es novedoso y robusto a los efectos de sustitución entre fuentes de capital. El estudio encuentra evidencia de que las inversiones de las empresas se ven obstaculizadas debido a la incapacidad de acceder al capital en la crisis. Mientras que la liquidez ayuda a absorber este shock de oferta, el rechazo hace que las empresas sean menos propensas a usar liquidez para inversiones en el período posterior a la crisis. Los planes de inversión reducidos después del rechazo son un canal principal a través del cual se reduce el rendimiento de la empresa. Los resultados implican que las sustituciones de capital no fueron adecuadas para proteger a las PYME de las dificultades de la era de la crisis en los balances de los acreedores.

En tercer lugar, esta tesis se propone explorar lo que ha impulsado el crecimiento de fintech. En el caso de los préstamos entre pares (P2P), destaca el papel de la desconfianza de los consumidores en los bancos. Este estudio

ofrece evidencia de que la desconfianza en los bancos probablemente provoca que las personas proporcionen fondos para el crowdfunding y lejos de los depósitos bancarios. Destaca que una mentalidad de desconfianza promueve cuestionar las opciones predeterminadas y considerar alternativas, y fomenta las comparaciones centradas en las diferencias. Los resultados sugieren que los estados de EE. UU. Cuyos residentes expresan una mayor desconfianza en los bancos tienen más probabilidades de financiar préstamos P2P y, condicionalmente a la financiación, otorgan montos más altos. Esta relación es más pronunciada cuando se financian préstamos pequeños o prestatarios con menos acceso bancario. En cuarto lugar, esta tesis investiga empíricamente los impulsores de la propagación de la infraestructura necesaria para mantener y hacer crecer Bitcoin como sistema (nodos de Bitcoin) e infraestructura que permite el uso de bitcoins para transacciones económicas cotidianas (comerciantes de Bitcoin). Específicamente, investiga el papel de los determinantes legales, penales, financieros y sociales. Los hallazgos ofrecen cierto apoyo para la opinión de que la adopción de la infraestructura de criptodivisas está impulsada por fallas percibidas de los sistemas financieros tradicionales, ya que la propagación de la infraestructura de Bitcoin está asociada con una baja confianza en los bancos y el sistema financiero entre los habitantes de una región, y con la ocurrencia de crisis inflacionarias. El soporte activo para Bitcoins es mayor en ubicaciones con servicios bancarios bien desarrollados. Presta apoyo a la adopción de bitcoins que se debe en parte a la utilidad de las criptodivisas en el comercio ilícito.

Palabras clave: Innovación financiera, Préstamos entre particulares, monedas digitales, tecnología financiera, finanzas para PYMEs, crisis financiera de 2008, finanzas corporativas/empresariales

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1 Introduction

The Global Financial Crisis (GFC), or the financial crisis of 2007-2009, triggered by unprecedented subprime mortgage losses in the United States, ushered in the greatest recession worldwide since the Great Depression of the 1930s. Brunnermeier & Sannikov (2014) show that when financial frictions exist, a large adverse shock can divert the economy away from its normal growth trajectory for a long but finite time. Sedláček & Sterk (2017) show that periods of financial distress could prevent high-growth potential start-ups from emerging. Barnichon, Matthes, & Ziegenbein (2018) show that a decade on from the crisis, United States GDP stood at 12 percentage points below what the level implied by its pre-crisis trend. This is not unique to the US; Europe and the United Kingdom's economies remain far below levels implied by their pre-crisis trends (Barnichon, Matthes, & Ziegenbein, 2019). Analyzing the aftermath of post-war financial crises in 24 OECD countries, Romer & Romer (2017) find similar results in that the GDP is typically about 9 percentage points lower five years after an extreme financial crisis. They find that the average decline in output linearly depends on the severity and persistence of the financial distress itself. Given the severity of the global financial crisis, persistence of its effects a decade on and the documented slow recovery may not be surprising. These studies paint a picture of significant value destruction having originated from the US subprime mortgage crisis into a global recession with long-lasting consequences (Mishkin, 2011). Half of this thesis explores the determinants and real effects of financing decisions and outcomes of Small and Medium Enterprises, which are the predominant form of enterprise (OECD, 2016), and may have been affected worse by the financial crisis (Amador & Nagengast, 2016; Balduzzi, Brancati, & Schiantarelli, 2018; Berg, 2018; Cingano, Manaresi, & Sette, 2016; De Jonghe, Dewachter, Mulier, Ongena, & Schepens, 2019).

The most obvious silver lining is that since the crisis, major steps have been taken towards financial stability. Stringent new banking regulations have increased capitalization and liquidity of the largest US dealer banks, and some weaknesses in market infrastructure and unsafe practices in securitization and derivatives markets have been fixed (Duffie, 2019). While the financial sector may be more resilient now, the Coronavirus (Covid-19) pandemic of 2020 has hit the real economy, causing arguably as much, if not more damage to households and firms, especially SMEs. If anything, drawing lessons from financing frictions for SMEs due to the global financial crisis is yet more significant given the Covid-19-induced economic crisis which may disproportionately affect SMEs.

Schumpeterian economics may hint at a less obvious silver lining of the crisis. The gale of creative destruction could be at work amidst the economic turmoil and value destruction brought forth by the global financial crisis. Innovation scholars have shown that a group of small firms that are responsive to new market opportunities and were in pursuit of more explorative strategies, have thrived in the aftermath of the financial crisis (Archibugi, Filippetti, & Frenz, 2013). Filippetti & Archibugi (2011) compare the post-crisis innovation investments of European firms and find that the competence and quality of human resources, specialization

in the high-technology sector and development of the financial system help firms offset the effect of the financial crisis on innovation investments.

Just as fascinating may be innovations within financing itself which have exponentially grown following the crisis (Arner, Barberis, & Buckley, 2016). Laeven, Levine, & Michalopoulos (2015) finds that economic growth and technological innovation stop unless financiers themselves innovate. Surveys of financial innovations however, show that a substantial portion of innovations in financing since the crisis, are initiated by non-intermediaries (Arner et al., 2016). Curiously, some recent financial innovations by startups and the open-source community have been aimed at reducing the degree of intermediation by banks and traditional financial intermediaries themselves. The drivers of growth of these financial technologies are the focus of the other half of this thesis. Significantly, less obvious consequences and perhaps silver linings of the crisis emerge. In particular, this thesis explores how the growth of these financial technologies may be rooted in the societal effects of the financial crisis, which together with technological opportunities, are contributing to emergence of a new era in financial innovation, termed fintech 3.0.

This doctoral thesis follows as below. Chapter 2 describes the two effects that the global financial crisis had on financing SMEs and innovative financing, which the thesis explores. Chapters 3 through 6 then describe the four studies on which this study rests. Each study contains its own literature review, research gap, theory and hypotheses, research design, data, methodology, results, limitations, discussions, and conclusions describing suggestions for future research. Finally, Chapter 7 concludes by framing the contributions of the thesis in perspective of research on the financial crises, and their role as a source of value, and creative, destruction.

2 A Tale of Two Effects of the GFC: Financing SMEs and Innovative

Finance

A decade has passed since events in mid-to-late September 2008 which economists have attributed to causing the US subprime mortgage to go global (Mishkin, 2011): the bankruptcy of Lehman Brothers (Sept 15), the collapse of AIG insurance firm and run on the Reserve Primary Fund in money markets (Sept 16), and struggles to pass the Troubled Asset Relief Plan in the US Congress (Sept 19 to Oct 3). As overvalued mortgage-backed securities lost their value, it was unclear which banks were exposed, resulting in banks being unwilling to lend to one another, resulting in a credit crunch which spread through the wider economy. The already globalized state of the banking system transmitted stresses in the banking system of the US and other countries exposed to US mortgages or structured products worldwide, either through liquidity crunches in international funding markets or the shock to foreign funding of various countries' banking systems, reducing credit supply (Aiyar, 2012). More recently, financial economists have shown that the loss in housing wealth (Mian and Sufi, 2010), a decrease in consumer credit (Mian, Rao, & Sufi, 2013), highly-levered households (Mian & Sufi, 2018) and

panics from the collapse of Lehman Brother (Mian & Sufi 2015) led to a consumption-driven recession, reducing global demand. Some economists hold both these factors responsible (Gertler & Gilchrist, 2018).

Regardless of whether a supply-side or a demand-side shock caused it or both, a decade on, the Global Financial Crisis has altered both the financial landscape and economists' knowledge of the effects of financial constraints.

This new financial landscape is characterized by a reduction of unsafe practices and presumptions of bailouts by taxpayer money, market infrastructure for securitization and notably more stringent bank capital requirements, e.g. Basel III, (Duffie, 2019) either raising the cost of bank capital (Baker & Wurgler, 2015), or reducing lending to firms (Fraisse, Lé, & Thesmar 2019), with subsequent implications for investment and growth in the economy. These represent significant strides to overhaul a pre-crisis financial system that was prone-to-fail (Duffie, 2019).

2.1 Effects on Financing SMEs & SME Innovations

“From its onset, the 2008 financial crisis has highlighted the importance of deviations from the M&M assumptions, i.e., the importance of corporate finance”

- Kashyap & Zingales (2010)

Our knowledge of the effects and determinants of financial constraints has been increasing since the financial crisis of 2007-2009. The observation that the biggest financial crisis since the Great Depression occurred exactly half-a-century after the publication of the Modigliani and Miller (M&M) propositions regarding the irrelevance of a firm's capital structure, is a curious one. Kashyap & Zingales (2010) find this to be an ironic timing given that the financial crisis firmly shows that capital structure matters and financial economists must not ignore frictions that M&M's propositions assume away in their seminal contribution to modeling and establishing the theoretical underpinnings of capital structure theory. Such frictions exist as the assumptions of the M&M theorem, namely the absence of bankruptcy costs, agency costs, taxes, asymmetric information and perfectly financial markets with competitive, frictionless markets with rational agents, do not hold in the real world. The pervasive and ill-guided use of the M&M theorem to deny the significance of corporate finance in finance and economics, has been consequential.

Before the crisis, many macroeconomics and a non-negligible share of financial economists were willing to treat the M&M propositions as a sound approximation of reality and had effectively ignored financial frictions. In light of the financial crisis, renewed attention has been given to exploring specific deviations from the M&M assumptions (alternatively called the capital structure irrelevance theorem), such as the effect of credit rationing (Banerjee & Duflo, 2013) or more generally financial constraints (Campello, Graham, & Harvey, 2010; Faulkender & Petersen, 2012). It is imperative to focus attention on the very decisions leading to capital structures of firms as well, especially on SMEs and innovative firms.

“The 2008 economic crisis has severely reduced the short-term willingness of firms to invest in innovation.”

- Archibugi et al. (2013)

More stringent bank capital requirements such as in Basel II and III raise the cost of capital for banks, as they increase the fixed costs of issuing loans for banks. This often leads to cutbacks for banks on small loans and loans to Small Medium Enterprises (SMEs) (Fraisie, Lé, & Thesmar, 2019), as they are often riskier and harder to continue issuing in bank capital re-adjustments required following the crisis.

Cowling, Liu, & Ledger (2012) find that external finance was more readily extended to larger and older firms throughout the recession, and that during the worst three-month period, all credit applications of 10% of the total stock of smaller firms were rejected. Even five years following the initial shock of the credit crunch to the economy, bank lending had yet not recovered especially for smaller firms.

In recent research Lee, Sameen, & Cowling (2015) investigate the effect of the crisis on innovative firms and show that amongst all SMEs, there is a structural effect which means that innovative firms find their access to financing more restricted. They find that while the worsening of general credit conditions resulting from the crisis has been more pronounced for non-innovative SMEs, absolute credit rationing has been more severe for innovative SMEs, who are disproportionately unlikely to be able to obtain finance from any source.

There is growing evidence that debt and bank financing is crucial to startups and to finance innovation (Robb & Robinson, 2012; Kerr & Nanda, 2015; Benfratello, Schiantarelli, & Sembenelli, 2008). Innovative SMEs are most likely to create new markets and drive the growth of an economy, following recessions (Lee et al., 2015). Long-run growth of economies is driven by innovation (Grossman & Helpman, 2011) and innovation expands the technological frontier facilitating future innovations (Aghion & Jaravel, 2015). Hence, for social welfare it is imperative to focus on the fate of innovative firms following a recession and that is why I have dedicated the first second of thesis to under- or un-explored financing issues of innovative SMEs.

While research from before the crisis had already shown that small innovative firms find it harder to access finance (Beck & Demircuc-Kunt, 2006; Schneider & Veugelers, 2010), such additional bank lending constraints for SMEs during and after the crisis (Cowling et al., 2012), our understanding that SMEs have differential access to credit given their innovativeness (Atanassov, 2015; Lee et al., 2015; Freel, 2007; Mina, Lahr, & Hughes, 2013), raises further questions:

1. How did SMEs' prospects of obtaining various financing sources during the crisis differ given various firm characteristics, including along the lines of size, age and particularly, innovativeness?
2. What are the real effects (on firm investments and performance) of impaired access to finance to SMEs, given that SMEs can substitute between sources of finance?

The following two chapters, deal with these two questions, addressing aspects of capital financing decisions relating to financial frictions that SME firms face. The third chapter deals with determinants of SME financing applications and outcomes, and the fourth chapter deals with outcomes of unsuccessful financing

applications. Viewed temporally, the third chapter explores what happens *prior or ex-ante* to the **financing outcome**, while the fourth chapter explores what happens *posterior or ex-post* to the **financing outcome**. The context of the research is during and after the financial crisis.

Insofar, I have laid out arguments how the financial crisis has changed the financial landscape and especially affected financing to SMEs generally and innovative SMEs in particular, meriting further research. A silver lining of the Global Financial Crisis for financial economists studying the effect of financing has been the plethora of insightful research surveys conducted during or after it, aimed at investigating how SMEs were affected given the crisis. In this thesis, I exploit two novel survey-linked databases that enquire as to the years 2007 to 2017 in Europe in relation to SMEs' financing and other activities. As described in the following section, these enable exploiting novel features of the surveys to shed light on the two aforementioned research questions, using techniques that address sample selection and confounding of supply and demand in financing, which are original contributions of this thesis to the literature.

While chapters 3 and 4 are dedicated to financing SMEs and innovations, chapters 5 and 6 are dedicated to innovative financing. The title of this chapter, "A Tale of Two Consequences of the Global Financial Crisis" references the dual foci of this doctoral dissertation.

2.2 Effects on Innovative Financing & FinTech

"Technological innovation and economic growth eventually stop unless financiers innovate"

- Laeven et al. (2015)

Recent research has shed light on the importance of financial innovation. Laeven et al. (2015) develop a Schumpeterian model of economic growth in which entrepreneurs gain profits by inventing superior goods and profit-maximizing financiers invent better methods for costly screening of entrepreneurs. Their model predicts that economic growth and technological innovation eventually stop unless financiers themselves innovate. They provide empirical evidence consistent with this prediction.

Philippon (2016) assesses the potential impact of financial technology and finds that financial services and the unit cost of financial intermediation has remained consistently and surprisingly expensive from 1886 to 2012. The Global Financial Crisis spurred great debate about the dark and bright sides of financial innovation (Beck, Chen, Lin, & Song, 2016). The *innovation-fragility view* attributed the crisis to under-regulated financial innovation preceding the crisis. This view holds that whether by untethered expansion in credit markets helping to feed the boom and eventual bust in housing prices (Brunnermeier, 2009), via banks' use of structured products to cloud investors' understandings of financial markets (Henderson & Pearson, 2011), by engineering securities marketed to be safe but fraught with neglected risks (Gennaioli, Shleifer, & Vishny, 2012) or by making financial crises potentially more severe (Gai, Kapadia, Millard, & Perez, 2008), there is a dark side to financial innovation that was at the root of the crisis. On the flip side, the traditional *innovation-growth view* holds that such innovations help improve the variety and quality of banks' services (Merton, 1992;

Berger, 2003), complete the market (Duffie & Rahi, 1995; Elul, 1995, Grinblatt & Longstaff, 2000), facilitate sharing risks (Allen & Gale, 1991; Nachman, Allen, & Gale, 1995), and ultimately yield greater allocative efficiency in financial markets (Houston, Lin, Lin, & Ma, 2010; Ross, 1976).

“Critical financial intermediaries failed, or were bailed out, or dramatically reduced their provision of liquidity and credit to the economy. In short, the core financial system ceased to perform its intended functions for the real economy at a reasonable level of effectiveness.”

- Duffie (2019)

Prior to the crisis, much of these financial innovations originated by banks and financial services firms, whether the introduction of exotic and compound options, ATMs, “back-office” and “front-office” IT banking technologies, securitization and tranching, structured products or high-frequency or algorithmic trading. This is evidenced by a pre-crisis all-encompassing review of financial innovations by notable economists (Frame & White, 2004), whom only include innovations originated by financial services firms in their classifications of financial innovations:

*“Financial innovations can be grouped as new products (e.g., adjustable-rate mortgages, exchange-traded index funds); new services (e.g., online securities trading, internet banking); new “production” processes (e.g., electronic record-keeping for securities, credit scoring); or new organizational forms (e.g., a new type of electronic exchange for trading securities, internet-only banks). Of course, if a new intermediate product or service is **created and used by financial-services firms**, it may then become part of a new financial production process.”*

- Frame & White (2004)

Now, empowered by computer and internet technologies, a host of financial innovations originating outside of traditional banks and designed to bypass financial intermediation by traditional financial institutions have emerged. Their *raison d'être* is often framed by their developers as dissatisfaction with both the costs of financial intermediation and a lack of trust in banks, big companies and institutions. Quotations by developers of financial technologies hint at this.

The blueprint for Bitcoins, the first block-chain based cryptocurrency enabling truly disintermediated financial transactions, authored by Nakamoto (2008) was published in October 2008, barely a month after the aforementioned events causing the financial crisis to go global. In the very first Bitcoin mined, its founder, Satoshi Nakamoto, embedded the message *“The Times 03/Jan/2009 Chancellor on brink of second bailout for banks”*, referring to the Times of London’s same-day headline and massive governmental bank renationalization and bailouts as a result of troubles in UK banks starting with the collapse of Northern Rock (Elliott & Duncan, 2009). Cohen (2017) documents that bitcoin emerged as part of the 99 percent movement – initiated by the Occupy Wall Street protests – and frustrations with banks that had become too big to fail.

There is a great amount of anecdotal evidence suggesting a great increase in adoption of other new financial instruments enabled through financial technology, such as peer-to-peer loans, as a result of societal

frustrations with banks and traditional financial institutions. Some of this anecdotal evidence precedes the financial crisis, in the development of new financial technologies. For example, describing the development of the world's peer-to-peer lending platform, Zopa, The UK's Sunday Times (2005) states “(Richard) Duvall's - Zopa's founder's - pitch is that Zopa is part of a new-age phenomenon, whereby people want more control of their lives and money as they lose faith in institutions and big companies”.

The burden of the costs of financial intermediation to society may have been felt most intimately following the Global Financial Crisis. There is great evidence that trust in institutions decreased by great proportions after the financial crisis (Stevenson & Wolfers, 2011).

Figure 2.1 shows the evolution in trust in financial institutions in the US from two distinct, but greatly matching social surveys, where a great drop is evident as a result of the financial crisis of 2007-2009. The novelty of this thesis is in arguing and empirically demonstrating that in an age of non-improving financial intermediation costs, and given societal dissatisfactions with how the Global Financial Crisis led to the greatest global recession period since World War II, a wave of new financial innovations **have originated outside of financial intermediaries, whose adoption has accelerated due to societal dissatisfaction with traditional financial intermediaries**. Such a realization formed a part of the impetus for investigating the role of trust in this thesis and two academic papers published and conditionally accepted at two Scopus Q1 journals by myself and co-authors (Saiedi, Broström, & Ruiz, 2020; Saiedi, Mohammadi, & Broström, 2017).

Figure 2.1. Lack of Trust in Banks (/and Financial Institutions) as measured by two independent US Social Surveys

“Everybody talks about the weather, but nobody ever does anything about it.”

- Charles D. Warner or his co-novelist, Mark Twain

“Everybody talks about financial innovation, but (almost) nobody empirically tests hypotheses about it.”

- Frame & White (2004)

Frame & White (2004) review the literature on financial innovation and find a relative dearth of empirical studies that would either specifically test hypotheses or provide quantitative analyses of financial innovation. Surveying the financial literature landscape, they only find two studies advancing and testing hypotheses concerning the economic and environmental conditions that encourage financial innovation. This indicates that literature in this area is especially lacking, given that the broader field of innovation is found to be the *“second largest empirical literature in the field of industrial organization”* (Cohen & Levin, 1989).

They also find that a great deal of the research attention to financial innovation focuses on the innovative idea itself. They state however, that **at least as important is the adoption and spread of an innovation**, in other words its diffusion, across an industry. Faster diffusion can translate to a higher societal return on the underlying investments in the innovation at hand.

Since the dawn of the new millennia, the pace of technological progress in financial services has accelerated (He et al., 2017). Figure 2.2 presents a timeline of technological innovations in the provision of financial services since the 13th century onwards. The marked acceleration of financial innovation at the turn of the millennia is evident from this timeline. This period is characterized by new payment tools such as mobile payments and digital wallets, as well as new service providers entering the financial services market, such as telecom, retail and internet providers (He et al., 2017). Notable innovations made since 2000 have been crowdfunding/peer-to-peer (P2P) lending, contactless payments, cryptocurrencies/blockchain, and mobile wallets.

The term “fintech” as an abbreviation and portmanteau of financial technology, originated in the early 21st century,¹ concurrent with the aforementioned acceleration in financial innovation. It has been defined in academia as *“Fintech is a new financial industry that applies technology to improve financial activities.”* (Schueffel, 2017). Meanwhile in 2018 its entry into the English lexicon was sealed by the Merriam-Webster dictionary, which defines it as *“products and companies that employ newly developed digital and online technologies in the banking and financial services industry.”* (Fintech, n.d.-a).

Arner et al. (2016) analyze the evolution of financial technologies during the past 150 years, starting from the laying of the transatlantic telegraph cable in 1866 which provided the infrastructure for financial

¹ While Oxford dictionary states the term originates as an early 21st century abbreviation of financial technology, it is found earlier -as far back as in 1971- in the names of various companies (Fintech, n.d.-b).

globalization. They divide these years into three eras: Fintech 1.0 - Analogue (1866-1967), Fintech 2.0 - Digitization (1967-2008) and Fintech 3.0 (2008-present). What differentiates Fintech 3.0 is in the provider of the financial services: Start-ups and technology firms have come to substitute banks as the primary providers of niche financial technologies to businesses, the public and to banks themselves.

These start-ups and technology firms were taking advantage of a number of factors arising from the 2007-2008 financial crisis, providing favorable conditions for their provision of financial services (Arner et al., 2016): (1) Post-crisis regulation increased the compliance duties and costs of banks and tightened credit provision. New requirements for banks to conduct stress tests and prepare recovery and resolution plans increased bank costs (Barberis, 2013). Increased regulatory capital for banks changed their capacity and incentives to originate risky loans (Buchak, Matvos, Piskorski, & Seru, 2018). (2) Two technological developments which delivered consumer interfaces and interoperability among services and applications, being the proliferation of smartphones and application programming interfaces (APIs). (3) The crisis caused many finance professionals to lose their jobs, leading to seeking of new ventures for their skills.

While Arner et al. (2016) state that in the latest fintech era, **providers** of financial services have been non-intermediaries, this thesis posits that some recent financial innovations by startups and the open-source community are aimed at reducing the degree of intermediation by banks and traditional financial intermediaries themselves. This subset of financial technologies are the focus of this subsection.

Two pioneering examples of financial innovations reducing the degree of financial intermediation are peer-to-peer lending –a form of crowdfunding-, and cryptocurrencies – a cryptographically-secured form of digital currency-. They were invented respectively in March 2005 by the founder of Zopa, Richard Duvall, and in September 2008 by the founder of bitcoin, Satoshi Nakamoto. The focus of this research is empirically investigating the adoption of these financial technologies. In doing so this thesis contributes to a nascent body of research that delves into exploring the adoption of financial technologies of, internet banking (Xue, Hitt, & Chen, 2011), fintech markets (Haddad & Hornuf, 2019), equity crowdfunding (Estrin, Gozman, & Khavul, 2018), debit cards (Higgins, 2018), and Initial Coin Offerings or ICOs (Masiak, Block, Masiak, Neuenkirch, & Pielen, 2019). This nascent body of research on fintech is experiencing a huge surge, owing to a few factors and developments explained below.

The technological nature of fintech, as part of the information revolution of the 21st century, enables recording and storing vast amounts of data, in real-time and more granular detail than previously possible, on digital interactions, communications, transactions and their outcomes. Such data can grow so large, varied and complex to constitute Big Data, for which specialized data-processing applications are required. Big Data is characterized by high volume, velocity and variety, and requires tailored analytical methods and technology for its transformation into value (De Mauro, Greco, & Grimaldi, 2015).

Such large data sets represent a dramatic expansion in both the quantity and quality of data on economic activity. These can be used to offer researchers more insight into the “black box” of markets, firms and households, by providing important statistics on the behavior of agents such as search and information production, communication, decision-making and microlevel transactions. Better data can also help sharpen examination of existing theories and models which were previously difficult to test (Einav & Levin, 2014).

While these represent the potential contribution of large data sets to help inform economic behavior, economic theory can also play a vital role in the analysis of new data sets with complex structures. Organizing and researching such large data sets (or even deciding which variables to construct) can be difficult without a simplifying conceptual framework, and this is where economic models offer guidance (Einav & Levin, 2014).

A greater share of papers in economics over the past decade make use of newly available large-scale administrative or private sector data (Einav & Levin, 2014). Many fintech startups have embraced the use of open-source coding and application-programming interfaces (APIs) to provide their data to the public. These constitute fertile groundwork for testing economic theory in this vibrant and radically-innovating sector. I have attempted to use such sources in carrying out research work in Chapters 5 and 6.

Chapters 5 and 6 are dedicated to filling the very gap of empirically investigating the adoption of innovative financing. The focus is on adoption of a newer class of financial innovations, powered by financial technology and originating outside of financial intermediaries, seemingly spurred on by the global financial crisis. Chapter 5 advances empirical tests on the role of a (lack of) trust in banks and financial institutions on the growth of P2P lending technologies, and on what determines such lack of trust. Chapter 6 is the first study to provide global empirical evidence for economic and environmental factors driving cryptocurrencies. This research sheds light on the bright and dark sides of financial technology originating outside of financial intermediaries as well. Chapters 5 and 6 details the theoretical background, research design, results, implications and contributions of these studies in detail, under the heading of “Innovative financing”.

Figure 2.2. The Accelerated Pace of Technological Progress in Financial Services (reprinted with permission from the International Monetary Fund and He et al., 2017; graphic created from following sources: Arner et al., 2017; Quinn and Roberds, 2009; World Economic Forum, 2015)

3 Determinants of SME Financing Choices and Outcomes in the GFC

During the financial crises of 2007-2009, many firms faced worsening credit conditions. In particular, smaller and younger firms have been reported to have struggled to obtain credit during this period (Cowling et al., 2012; Fraisse et al., 2019). In this chapter, I draw on two novel survey datasets that allow us to examine the financing situation for European small- and medium-sized enterprises (SMEs) in the crisis given the mix of capital sources SMEs can substitute for credit, and to compare these patterns to that of the post-crisis period. I particularly evaluate financing decisions and outcomes of European SMEs against predictions of the pecking order theory, prevalent in assessing SME decisions (e.g. Cosh, Cumming, & Hughes, 2009). Two interrelated questions are explored. Firstly, what are the characteristics of SMEs that seek external capital, and what drives the request for capital from the different external financing instruments: Bank loans, credit lines, venture capitalists and angel investors, trade credit partners, among others? Second, what factors lead to acceptance or rejection of applications for external finance? In analysing these questions, this study explores differences between younger and older SMEs, and conduct a more in-depth analysis of how different types of innovation-related assets and activities are associated with firms' financing decisions and outcomes. The fate of young and innovative firms in the crisis is of particular interest, since such firms face greater information asymmetries, hindering access to finance (James R. Brown, Martinsson, & Petersen, 2012; Serrasqueiro & Nunes, 2012).

3.1 An Introduction to Effects of GFC on SME Financing

The global financial crisis has been characterized by restricted access of SMEs to debt. Cowling et al. (2012) find that external finance was more readily extended to larger and older firms throughout the recession, and that during the worst three-month period, all credit applications of 10% of the total stock of smaller firms were rejected. Even five years following the initial shock of the credit crunch to the economy, bank lending had yet not recovered especially for smaller firms. Sedláček and Sterk (2017) show that periods of financial distress could prevent high-growth potential start-ups from emerging. Deloof & Vanacker (2018) find that startups formed during the crisis use less debt and are less likely to survive, even accounting for their creditworthiness. Still, bank debt was the primary source of startup financing during the crisis. Fraisse, Lé, and Thesmar (2019) find that more stringent bank capital requirements following the crisis led to cutbacks on small loans and loans to SMEs, since they are often riskier and harder to continue issuing during bank capital re-adjustments. The bank lending shock (see e.g. Brunnermeier, 2009), as well as the general credit shock (see e.g. Gorton, 2010) to firms during the crisis, elevated the external finance premium – termed by Bernanke & Gertler (1989) to mean the additional cost of external funding over internal funding - during the financial crisis (Mark Gertler & Gilchrist, 2018).

3.1.1 Effects on innovative SMEs

Credit contractions due to the crisis may have hit innovative SMEs worse. Lee, Sameen, and Cowling (2015) find that while the worsening of general credit conditions post-crisis has been more pronounced for non-innovative SMEs, absolute credit rationing has been more severe for innovative SMEs, who are disproportionately unlikely to be able to obtain finance from any source. Bartz & Winkler (2016) also show that more entrepreneurial firms with a broader market orientation experience slower growth in crisis times than less entrepreneurial ventures. Davidsson & Gordon (2016) find that nascent entrepreneurs of high-tech startups are more likely to terminate their involvement in the aftermath of the crisis. Archibugi, Filippetti, & Frenz (2013) find that amongst innovative firms those with explorative, rather than exploitative, strategies coped better with the crisis.

3.1.2 Effects by age of SMEs

Some of the studies on the real effects of credit shocks during the crisis, have investigated whether these effects vary by firm age, given that young firms have a shorter track record and possibly a lower ability to substitute for credit cutbacks (Guler, Mariathasan, Mulier, & Okatan, 2019). The presented evidence indicates that banks did not disproportionately reduce lending to young firms (Cingano et al., 2016; De Jonghe et al., 2019). Notwithstanding, these studies have divergent evidence on firms' real effects. Whereas Cingano et al. (2016) and Balduzzi, Brancati, & Schiantarelli (2018) uncover greater reductions on investments for younger Italian firms, De Jonghe et al. (2019) find equal reductions across the age distribution for Belgian firms.

3.1.3 Ability of SMEs to substitute for bank debt

The contraction of bank debt during the crisis could cause SMEs to seek out more of other types of financing and substitute equity for their financing needs. Recent studies have shown that during the recession firms substituted for bank loans by issuing new equity (Dwenger, Fossen, and Simmler, 2018) or increasing trade payables (Fraisie, Lé, and Thesmar, 2019), grants or informal finance (Casey and O'Toole, 2014). While small firms would be expected to have a lower ability to offset reduced bank lending with alternative financing (M. Gertler & Gilchrist, 1994), in an extensive survey of real effects of credit supply shocks, Guler et al. (2019) do not find the evidence to always corroborate this.

Given this background, this chapter sets out to study debt versus equity financing decisions and financing outcomes of SMEs and entrepreneurial firms during the crisis, and their determinants.

3.2 Research Gap

Many previous studies have focused on market-based financial systems of the US or the UK (for an exception on high-growth Belgian firms, see Vanacker & Manigart, 2010). Comparative studies point to

divergent corporate financing implications for continental European and Anglo-Saxon economies given their differing (i) financial systems of bank- or market-based (e.g. Beck & Levine, 2002), (ii) legal origin of civil- or common-law (e.g. La Porta, Lopez-de-Silanes, & Shleifer, 2008), (iii) closely- (family-) or widely-held ownership structures (e.g. Faccio & Lang, 2002) or (iv) semi-formal or informal economy (e.g. Artavanis, Morse, & Tsoutsoura, 2016). These differences can result in divergent financing decisions, or more importantly outcomes, for the more bank-dependent relationship-based financing of continental European SMEs, especially during contractions to corporate credit in Europe due to the sovereign debt crisis (Ivashina & Scharfstein, 2010; Becker & Ivashina, 2018). There is a need for analysis on SME financing during the crisis extending extant scholarly literature where the researcher can observe the financing decisions and outcomes of SMEs from a broad set of European economies. The study in this chapter is able to do so.

Secondly, whereas extant work is limited to observing outcomes, or applications to only one particular financier (e.g. Andrieu, Staglianò, & van der Zwan, 2018; Duchin, Ozbas, & Sensoy, 2010) or bundles all external finance providers together (Cowling et al., 2012), there is a need for a study that can observe SME applications and outcomes for various debt and equity instruments. Such a study can help mitigate sample selection biases affecting many other studies on capital choices and outcomes, as done herein.

3.3 Theory and Hypotheses

3.3.1 Theoretical Background

Studies focusing on determinants of capital structure have proliferated during the past decades. Numerous studies test for the pecking-order theory (Shyam-Sunder & Myers, 1999), the pecking order theory accounting for debt capacity (M. L. Lemmon & Zender, 2010), the debt trade-off theory, whether static (Bradley et al, 1984; Kraus & Litzenberger, 1973) or dynamic (e.g. by Kane, Marcus, & McDonald, 1984; Brennan & Schwartz, 1984; Fischer, Heinkel, v Zechner, 1989; Hennessy & Whited, 2005; Leary & Roberts, 2005; DeAngelo, DeAngelo, & Whited, 2011) or other dynamic capital structure models (e.g. by Strebulaev & Whited, 2011; Strebulaev, 2013).

Frank & Goyal (2007) comprehensively review these extant theories and the related evidence and identify various important empirical **stylized facts**. Namely, they find great differences among firms along dimensions of their size (i.e. small or large) or public or private status. Developing stylized facts are crucial to our understanding of capital structure, which is at the core of corporate finance. In the words of (Frank & Goyal, 2007), capital structure stylized facts are “*empirical generalizations that appear to be robust and are particularly important for an understanding of actual leverage [and capital structures]*”. However, they find that none of the currently available models seem able to simultaneously account for all these stylized facts.

Nevertheless, many financial economists hold that the *“pecking order theory is an excellent first-order descriptor of corporate financing behavior”* (Shyam-Sunder & Myers, 1999). However, in examination of this theory for a larger cross-section of US firms, Frank & Goyal (2003) find the greatest support for the pecking order theory among large firms, which face the least severe adverse selection problems due to greater transparency via better equity analyst coverage. Even among large firms, support for pecking theory is waning over time.

3.3.2 *Pecking Order Theory & SMEs*

A great deal of corporate finance literature deals with how debt financing and equity financing (bank loans versus venture capital) have different implications for entrepreneurs (Schmidt, 2003; Ueda, 2004). Theoretically speaking, entrepreneurs may prefer securing financing through taking out debt to maintain full control rights over their firms (Berger & Udell, 1998). On the other hand, economic theory suggests that entrepreneurs prefer to smooth risk by securing equity financing and avoiding the need to meet fixed payments on debts, if the firm does not do well.

A stream of research resulting from seminal studies such as by Myers & Majluf (1984), have led to the derivation of a standard pecking order (PO) theory of capital, stating that in equilibrium, firms prefer to finance new projects with internal cash flows primarily, and then, if necessary, thereafter seek outside debt financing and finally seek external equity capital. This ordered preference may be rearranged by the fact that external suppliers of capital (e.g. venture capital firms), could potentially add value to their investee firms. This ordering, stems from various financing frictions, including adverse selection, agency conflicts and taxes. Importantly, agency problem cause raising funds externally to be more expensive than internally, which is termed the “external finance” premium by (Bernanke & Gertler, 1989). How these financing frictions lead to a pecking order of preferred financing for firms, forms the basis of optimal capital structure theory. Much of the frictions creating this pecking order, arise due to asymmetric information between firms (i.e. managers acting for existing shareholders) and new investors (whether debt or equity financiers). To explain this in summary, firms use sources of financing whose value is as insensitive to information asymmetry as possible, as firms incur costs (e.g. monitoring, signaling) to mitigate information asymmetry. Such minimization of information-sensitivity leads to firms preferring internal funds over external finance, and debt over equity.

Given that stylized facts vary with respect to firm size, it seems prudent to ensure the extent to which prominent theories of capital structure, such as the PO theory, apply to SMEs. Capital structure studies, reviewed in detail by Frank & Goyal (2007), rarely focus on SMEs or entrepreneurial firms solely. A notable early endeavor in this direction for SMEs has been by Cosh, Cumming, & Hughes (2009), who find evidence supporting the pecking order theory for UK SMEs and entrepreneurial firms. It is important to ensure that such findings can be replicated using independent datasets drawn for various

countries and other timeframes. The data choice and empirical methodology of this chapter is formulated in order to carry out this endeavor.

All models and theories of capital structure, such as the pecking-order or trade-off theory, deal with firms financing decisions in the face of financing frictions. It is plausibly difficult to make inferences about firm decisions, from studying firms' observed leverage or capital structure alone. A more direct way would be to observe the actual financing decisions of firms and see if these theories hold up. Most of the capital structure studies in the literature proxy for the financing choices and decisions firms make by studying determinants of firm leverage. However, firm leverage is an outcome of financing decisions and does not shed light as to firms' financing decisions resulting in rejections by financiers. Hence, it is important to observe the seeking stage of financing, to better account for financial decisions of firms. One important contribution in this endeavor is through the work of Cosh, Cumming, & Hughes (2009), who account for the non-randomness in SMEs decision to seek external finance, as they can observe which UK SMEs sought financing instruments and which obtained it. They find that their data supports the traditional pecking-order theory of capital.

3.3.3 Implications of PO Theory for Seeking and Obtaining Financing

As suggested by the traditional pecking order theory (Myers & Majluf, 1984), since entrepreneurs hold information that investors do not have, existing informational asymmetries cause their cost of financing to be lower by using internal profits than obtaining external capital. Along the lines of this reasoning, this chapter first explores if European SMEs and entrepreneurial firms prefer to finance new projects with their own profits prior to seeking external capital. The expectation is that as firms' profits compared to costs and investment needs increase, and as profit margins increase, the likelihood of seeking external finance reduces. Contingent on seeking external finance, it is furthermore posited that firms with greater profits are more likely to obtain the external finance sought.

Pecking-order reasoning furthermore suggest that external equity financing is costlier than debt financing to entrepreneurs. This is since equity financing involves dilution of the entrepreneur's ownership interest in the firm, and offers of equity financing signal low quality, given that investors expect entrepreneurs to have information that outside investors do not have (Myers and Majluf 1984). Hence, entrepreneurs would prefer to finance their projects with debt prior to equity. The expectation, hence, is that among firms applying for outside financing, firms with greater profits margins, and firms with greater investments over profits, are likely to seek debt financing prior to equity financing.

Dwenger et al. (2018) show that firms during the crisis partially offset reduced credit supply, by resorting to alternative sources of financing. Given the various sources of financing which are at the disposal of firms (short-term and long-term bank debt, debt securities, venture capital and private equity,

etc.), and the crisis-era contraction of bank debt, it is natural to expect that firms partially obtained their desired funding, however not in the form they preferred. Obviously, receiving some of the funding sought is a better outcome than being shut out of the capital market entirely. However various sources of capital are far from perfect substitutes and may impose different constraints on firms. The expectation is that firms having less favorable prospects would face more constraints in securing their desired type of capital. Therefore, firms with higher investment needs compared to profits, should have more difficulty obtaining their desired source of financing. Hence, the expectation would be that firms with higher investment needs relative to their profits, would have more difficulty obtaining debt rather than equity financing. This is motivated by equity financiers being able to share in all the upsides of returns to the firm's investments and profits, whereas debt financiers would face limited upsides to returns of the investments and profits, but all the downsides of not receiving their loan principle and accrued interest back.

One would expect that depending on the ability of financiers to mitigate information asymmetries, different firm characteristics would matter differently to various types of financiers. A great number of studies have found venture capitalists to be more skilled than bank managers at selecting investment firms, and provide more value to their investee firms (Ueda, 2004). These studies espouse a comparative advantage for venture capital funds in mitigating information asymmetry and agency problems, compared to banks. Hence, VCs would be more likely to finance higher risk businesses where potential returns are higher.

3.3.4 Innovation and Outside Capital for SMEs

In the previous sections, I explained that the financial crisis particularly affected firms' innovative activities. While the pecking order theory is an implication of asymmetric information between firms and new investors due to costs to mitigate information asymmetry, these costs are decidedly higher for innovative firms. Innovation is marked by greater information asymmetry and the costs to firms of mitigating this asymmetry, such as relinquishing intellectual capital in the form of patents for firms, can be too great for these firms to expend to fulfill their financing needs.

When a firm exhibits greater informational asymmetries, its cost of seeking and obtaining external capital are higher. The literature indicates that for younger and more innovative firms, these costs are more pronounced (e.g. see (Brown, Martinsson, & Petersen, 2012; Noe & Rebello, 1996). Entrepreneurial firms will only be willing to expend these greater costs if they are truly more innovative. More innovative firms believe that their new projects can earn income at an internal rate of return higher than the after-tax cost of external capital, compared to their less innovative peers. Hence, I examine how firms' behavior regarding financing needs is related to the innovativeness of a firm, as measured by whether the firm developed an innovative product during the past three years. I expect greater innovativeness of firms to

increase its willingness to seek external capital. I also investigate whether seeking and obtaining external finance is related to the organization of R&D, and to the nature of firms' innovation activities as proxied by their use of different types of IPR (applications for patenting, copyright claims and registering industrial designs and trademarks).

Expanding on the framework of Cosh et al. (2009), this chapter explores relationships between firms' innovation activities and their behavior regarding outside capital. In doing so, this work is closely aligning with Mina, Lahr and Hughes (2013) who analyze the demand and supply of external finance for 3,095 middle-market US and UK SMEs and investigate the link between financial constraints and innovation investments. This study differs from theirs in its focus on financing decisions and, again, in analysing firms not active in market-based economies.

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Registering industrial design is hypothesized to lead to success in obtaining financing, as strong industrial design has been found to be related to higher corporate financial performance (Gemser & Leenders, 2001; Hertenstein, Platt, & Veryzer, 2005). Extant research on copyright protection has examined two contradictory effects on social welfare; that it will decrease welfare loss stemming from under-protection or would increase it as a result of underutilization, only finding empirical support for the former (Novos & Waldman, 1984). The expectation would be that firms would only benefit from the protection copyrights afford and this will have a positive effect on seeking and obtaining external finance.

Riahi-Belkaoui (2003) hypothesises using the resource-based and stakeholder views of the firms and finds that US firms' intellectual capital as measured by registered trademarks are associated with higher return on assets based on net value added. Sandner & Block (2011) find trademarks positively affect firms' market value, while Block, De Vries, Schumann, & Sandner (2014) find that the number and breadth of applications for trademarks have an inverted U-shaped relationship with start-up valuations, as the value

of trademarks decreases with firm development stage. SMEs are seen to trademark for three distinct reasons of protection, marketing and relationship exchanges (Jörn H. Block, Fisch, Hahn, & Sandner, 2015), and the resultant expectation would be that each of these reasons will result in increases in seeking and obtaining financial instruments.

While Balasubramanian & Sivadasan (2011) find that patent stock increases increase firm size, scope and skill and capital intensity, the relationship between patenting activity and financing outcomes may be less straightforward. While patents with high importance, as measured by their citations, have been found to increase stock market valuations (B. H. Hall, Jaffe, & Trajtenberg, 2005) and broader patent scopes are associated with increased firm value by VCs (Lerner, 1994), patenting may not have a similarly positive effect on creditor decisions, as it does for equity providers. Liu & Wong (2011) use a real options model to argue that while intellectual capital can limit a firms' debt capacity owing to its low liquidation value, it can also increase that capacity as it positively affects earnings. They find the former effect dominates and the granting of patents to increases firm leverage. Meanwhile, firms encounter a trade-off between patenting and thereby disclosing their innovations, and secrecy (B. Hall, Helmers, Rogers, & Sena, 2014). Banks as intermediators of private credit, hold private information regarding firms, and applications for patenting publicly reveal that private information. Saidi & Zaldokas (2017) find that increased innovation disclosure resulted in lower cost of debt for firms, as it empowers them to switch lenders. Patents are applied for first, then disclosed and granted.² It is possible that each stage has a separate effect on financiers' decisions. While patent granting are likely to protect a firms' intellectual property, patent applications and disclosure may be viewed as foregoing trade secrets, which are often valued as more effective by firms than patents (B. Hall et al., 2014).

Since a firms' inputs into the innovation process can affect its innovation outputs, either in the contemporaneous year or with a lag, the primary regressions will only consider innovation outputs. Evaluating the quality of innovation inputs, such as quality of R&D and intellectual property acquisitions of a firm, by company outsiders requires a greater level of expertise than evaluating the quality of innovation outputs, such as patents, where metrics such as patent citations and patent litigation inform financiers to the value of innovations. Thus, innovation inputs suffer from greater information asymmetry than innovation outputs. For some types of financing instruments, the expectation would be that financiers would have the abilities to screen and assess inputs to innovation processes. In particular, this concerns financing from Venture Capital (VC) and Private Equity (PE) firms, as well as public funding providers.

² Patent public disclosure may precede patent granting, e.g. as the American Inventor's Protection Act mandated in the US.

3.4 Research Design and Data

3.4.1 *Research Framework*

Empirical evaluation of firms' preferences regarding capital is a challenging task, in that it is very difficult to separate demand from supply. In an important step towards addressing this challenge, Cosh et al. (2009) employed survey data on 2,520 UK SMEs in 1996-7 which allowed to directly observe firms' attempts to acquire different sources of outside capital, as well as their success in this regard. Specifically, the study investigates factors that affect rejection rates of SMEs in applications for external finance, taking into account non-randomness and self-selection biases associated with the types of firms seeking outside capital. Their analyses support the standard pecking order theory of capital.

A related recent study has reported a similar pattern to be found among start-ups in the US. Robb & Robinson (2012) analyse the longitudinal database of US early-stage firms created through the Kauffman Firm Survey to study the capital choices that entrepreneurs make in the early stages of operation. For startups included in their study, 81.5% had losses or less than \$10,000 in annual profit, meaning that internal cash flows, the first preference in the pecking order theory of capital, are virtually unavailable to them. The authors find that early stage firms, rely to a much greater extent on external debt sources, such as bank financing and less extensively on funds from friends and family. Their study indicates that even at the very early stages of firm formation and in the absence of meaningful internal profits, external debt is greatly sought after by new firms.

Following Cosh et al. (2009), the analysis of the current study focuses on two variables describing firms' current balance between profits and costs (Profit Margin) and between profits and investments (Capital Expenditure / Profit), respectively. Summarizing the arguments above, Profit Margin is expected to be negatively related to the likelihood of seeking finance, and positively related to the likelihood of obtaining finance (conditional on seeking it). This relationship is expected to be stronger for debt financing than for equity financing. Capital Expenditure/Profit is expected to increase the likelihood of seeking external finance and reduce the likelihood of a firm obtaining its preferred form of financing.

3.4.2 *Control Variables*

In testing the outlined hypotheses and the relationships between innovation and financing decisions, this study controls for a number of potentially important factors. First, it controls for industry idiosyncrasy in financing by including two sets of controls; one for the various sectors and one for technological subsectors³ within which the firms operate. Firms in high-tech industries are generally more likely to be

³ There are 11 sectors or industry codes that we control for, which are at the NACE CLIO classification level. These are separate from technological subsector categories following Pavitt (1999), categorizing NACE 3-digit industry subsectors into economies of scale, traditional, specialized and high-tech manufacturing. These were designed to be independent classifiers (Altomonte & Aquilante, 2012).

innovative, and have higher asset intangibility (Kortum & Lerner, 2000), which in turn are accompanied by greater information asymmetry and agency costs (P. A. Gompers & Lerner, 2004). Traditional manufacturing industries, as they are subject to less informational asymmetry for financiers and hence, would be expected to have a lower cost of access to finance.

Finally, this research also controls for a host of other factors, including, capital expenditures, insider ownership (particularly CEO ownership), debt levels relative to assets prior to seeking external finance, technological subsector, as well as the country the firm resides in.

3.4.3 Surveys to Study SME Financing Applications

Investigating determinants and effects of SME financing applications to various sources of financing, given the non-randomness in seeking financing, requires knowledge of firms' applications to all financiers. Financial economists have relied on single-bank (e.g. Berg, 2018) and or multiple-bank (e.g. Balduzzi et al., 2018) information sources in order to learn about effects of loan rejections. Information regarding all sources of financing of firms are yet rarer, as a single-source that would record all firm applications for financing, as far as the author knows, does not exist. In lieu of this, surveys of firms' financing applications can fill this gap. With European Commission funding since the financial crisis, two such surveys have been carried out across various European countries, which are utilized in this thesis: Bruegel's EFIGE and the ECB's SAFE.

Frank & Goyal (2007) find that the survey approach to studying capital structure remains rare in corporate finance, with the exception of Graham & Harvey (2001), Bancel & Mittoo (2004), and Brounen, Jong, & Koedijk (2004). They describe the advantages of survey approaches over large-sample studies prevalent in the literature to be the ability to ask qualitative questions, and over natural experiments and clinical studies, which typically use small samples, as the ability to use moderately large sample sizes. They describe criticisms of survey approaches to be that it measures beliefs rather than actions.

A contribution of this thesis is in the use of two extensive surveys which ask managers about actual financing decisions made (i.e. applications and their outcomes) rather than beliefs about access to financing. These are the European Commission's EFIGE and the European Central Banks' SAFE surveys of 14,000 and 124,000 firms respectively. In this way, this thesis adds to the dearth of literature using surveys to study capital structure, and partially overcomes the criticism of survey-studies measuring beliefs rather than actions, while matching the sample size of extant large-sample studies.

In this study, I exploit being able to observe applications for financing in the EFIGE and SAFE surveys and their outcomes, via a two-stage Heckman selection model. There is clearly a selection in obtaining external financing and debt or equity financing, in that obtaining financing is contingent on

having sought it. The Heckman selection model accounts for this sample selections, and provides better estimates of the determinants for external financing.

By including various innovative characteristics of firms as firm-level determinants in the two-stage Heckman selection model, I explore the role of these characteristics in being granted the financing sought. I broadly categorize these into inputs into the innovation process of R&D intensity and R&D Acquisitions, and outputs of the innovation process, namely patent applications, industrial designs, trademarks and copyrights.

EFIGE: Cross-sectional Survey of European SMEs during GFC

EFIGE, the primary dataset employed for this study is created from a subset of answers to a cross-sectional cross-country survey held for ~14,759 primarily Small-Medium Enterprises (SMEs) across seven European countries, namely France, Germany, Italy, Spain, Hungary, Austria and the UK.⁴ The survey was carried out in early 2010 and information is collected for the last available accounting year of 2009, while certain questions cover the years of 2007-2009 and the behavior of firms during the financial crisis. The data has the big advantage that responses from each firm is matched with fourteen years of balance sheet and income statement data (from 2000-2014) from the database Amadeus. However, given that the Amadeus database misses more financial information for smaller firms, a non-substantial number of firms miss financial information for 2008 and 2009, which are used in the analysis. Hence, this chapter restricts the database to 8,994 firms for which financial information exists.

In the EFIGE survey, one can observe whether a firm seeks for external finance, and whether it obtains it, and what type of financing it obtains (i.e. bank financing, VC and PE financing, public funds, securities, tax incentives, and other methods). Aside from for external debt, one does not however, observe whether each firm that seeks external financing, sought which of the above-mentioned types of financing. This limitation implies that the researcher can hypothesize regarding SME's preference for internal and external financing, and debt over other sources of external financing. However, the researcher cannot observe firms' order of preferences among the non-debt financing instruments.

Results are reported for the entire sample, as well as two subsamples of firms defined as younger SMEs and older SMEs. This sample split is motivated by the potential differences in need for external financing, and by potential survivorship bias of older firms being those that survived. In this analysis, 'younger firms' are defined as firms in the sample that are less than 20 years old at the time of the survey. Resultantly, the sample is of 3,735 younger, and 5,259 older European SMEs. This is similar to what Cosh et al. (2009) do.⁵

⁴ Due to limited financial information on Austrian firms, they are dropped from the analysis.

⁵ Their cut-off is 17 years instead of 20 in our sample.

Table 3.1 provides a summary of explanatory and control variables used in this econometric analysis. Since having obtained external financing (a dependent variable of ours) in the year preceding the 2010 survey (i.e. in 2009) for a firm would increase its total assets in that year, in order to prevent having the obtained external financing show up in both sides of the regression (left-hand and right-hand side), this study lags balance sheet items used in the regression by using total assets and long-term debt/assets for 2008, which is the year prior to the year in which the survey inquires on financing.

Table 3.1 shows statistics from the firms' income statements, consisting of profits and profit margins, as well as cash flow information calculated from income statement and balance sheet items. In particular, capital expenditures is calculated as the increase in tangible fixed assets in 2009 over 2008, plus the depreciation charge applied to these assets in 2009.⁶ The 2009 income statement and capital expenditures are used for this analysis, because when applying for finance, firms will be asked to present their most recent quarterly income and cash flow statement figures, alongside corresponding projected future predictions. Since seeking and obtaining external capital do not have a simultaneous impact on profitability, turnover or profit margin concurrently in the year they are carried through, endogeneity is not a concern. That is with the exception of capital expenditures in which for cash constrained firms, concurrent capital expenditures may be endogenous to obtaining external capital (Cosh et al., 2009). While Cosh et al. (2009) do not find this to be a major issue for their study, one must be cautious as sample firms in EFIGE are surveyed regarding finances during the Great Recession and capital constraints can be a legitimate concern.⁷ In the analysis, this study does not simultaneously consider current and past values of income and cash flow statement item as they are highly correlated over time.

SAFE: Longitudinal Survey of European SMEs during and after GFC

SAFE has been carried out twice per year by the European Central Bank since 2009, and is still ongoing. Firms in 38 European countries are surveyed every 6 months on their financing. As not all questions are asked every 6 months, the sample is restricted to firms for which the variables of interest are available.

A key feature of the SAFE survey, from the present analysis' point of view, is that just as the EFIGE survey, it contains direct questions about firms' attempts and success or failure in obtaining outside capital. It also contains questions on ownership, which are potentially important determinants of financing decisions and outcomes. However, the SAFE data also has particular limitations, in that it is less broad

⁶ Nearly 10% of firms were missing 2009 tangible fixed asset values. Since they accounted for many firms of specific countries with low filtered sample sizes (e.g. German firms) and the survey asks respondents whether firms sought financing in 2008-2009 (potentially two years in the sample), the capital expenditure for 2008 was calculated instead of for 2009 and deemed not to affect the results. Much the same pattern existed with profits and profit margins, and the same solution was employed. All results are robust to eliminating firms with no values for 2009 from the sample.

⁷ A simple test finds that for firms with negative profit margins and cash flows in the preceding three years, the ratio of firms that obtain financing is not smaller than for the other firms.

and it has not been possible, for the purpose of this analysis, to match the survey data to actual financial data. Instead, analysis has to be based on indicator variables for whether key financial figures (Turnover, Profit, Leverage, Fixed Investment) increased (+), decreased (-) or remained largely unchanged (base alternative). These are coded following recurring survey questions on changes in these figures. Similar questions were asked for e.g. the growth outlook of the firm (increase turnover, decrease turnover, or maintain turnover) and the credit worthiness (improved, deteriorated, remained unchanged). A further limitation is that while the survey does ask about different forms of debt finance separately, it does not contain sufficient information about equity financing to allow us to replicate the breakdowns by debt and equity performed in the main analysis. The summary statistics for the variables to be used in this analysis are outlined in Table 3.2.

Table 3.1. EFIGE Variable Definitions and Summary Statistics (Observations: 8989; Period: 2008)

Variable Name	Definition	Mean	Median	Std. Dev.	Min	Max
<i>Dependent Variables</i>						
Ext. Finance Sought	A dummy=1 if firm sought external financing in 2009	0.52	1.0	0.50	0	1
Ext. Finance Obtained	A dummy=1 if firm obtained financing in 2009	0.23	0.0	0.42	0	1
Debt Sought	A dummy=1 if firm sought any type of debt security in 2009	0.16	0.0	0.37	0	1
Debt Obtained	A dummy=1 if firm obtained any type of debt security in 2009	0.11	0.0	0.31	0	1
Equity Sought	A dummy=1 if firm sought any type of equity security in 2009	0.39	0.0	0.49	0	1
Equity Obtained	A dummy=1 if obtained any type of equity security in 2009	0.10	0.0	0.29	0	1
Equity (non-VC/PE) Obtained	A dummy=1 if firm obtained equity (non-VC/PE) in 2009	0.04	0.0	0.18	0	1
VC & PE Obtained	A dummy=1 if firm obtained VC or Private Equity in 2009	0.01	0.0	0.08	0	1
Short-Term Debt Obtained	A dummy=1 if firm obtained short-term bank credit in 2009	0.10	0.0	0.30	0	1
Mid-to-Long-Term Debt Obtained	A dummy=1 if obtained mid-to-long-term bank credit in 2009	0.17	0.0	0.38	0	1
Securities Obtained	A dummy=1 if obtained short/mid/long-term securities in 2009	0.00	0.0	0.06	0	1
Public Funds Obtained	A dummy=1 if firm obtained public funds in 2009	0.02	0.0	0.14	0	1
Tax Incentives Obtained	A dummy=1 if firm obtained tax incentives in 2009	0.01	0.0	0.10	0	1
<i>Independent Variables</i>						
<i>Firm Financial Characteristics</i>						
Turnover	Natural logarithm of a firm's total turnover in 1000s of euros in 2009	8.25	8.07	1.39	3	15.2
Capital Expenditures/Profits ⁸	Natural logarithm of capital expenditures over profits in 2009	3.48	0.79	4.7	0.41	25.3
Profit Margin	Ratio of operating income (=EBIT) over turnover in 2009	0.04	0.025	.05	0	0.2
Long-Term Debt/Assets	Total long-term Debt over Assets (lagged; i.e. from 2008)	0.18	0.12	0.33	0	17.6
Total Assets	Natural logarithm of total assets (in 1000s of euros; from 2008)	8.21	8.02	4.72	0	16.1
<i>Innovation Activities</i>						
Innovation	A dummy=1 if firm developed a new product in 2007-2009	0.49	0.0	0.50	0	1
Patent Application	A dummy = 1 if firm applied for a patent during 2007-2009	0.14	0.0	0.34	0	1
Industrial Design	A dummy = 1 if firm registered industrial design in 2007-2009	0.08	0.0	0.26	0	1
Trademark	A dummy=1 if firm registered a trademark in 2007-2009	0.14	0.0	0.35	0	1
Claim Copyright	A dummy=1 if firm claimed copyright in 2007-2009	0.04	0.0	0.19	0	1
R&D Intensity	Average percentage of turnover invested in R&D in 2007-2009	3.5	1	7.42	0	100
R&D Outsourcing	A dummy=1 if R&D acquired from external sources in group during 2007-09	0.13	0.0	0.34	0	1
<i>Firm Profile</i>						
Industry Dependence on External Financing	A dummy=1 if firms rated their industry as a 4 or 5 on a 1-5 scale of ext. finance dependence	0.30	0.0	0.46	0	1
Growth Objectives	A dummy=1 if firm plans to use external financing to expand scale of production	0.07	0.0	0.25	0	1
<i>Technological Subsector</i>						
Economy of Scale Mfg.	Dummy=1 if firm is an economy-of-scale manufacturing firm	0.26	0	0.44	0	1
High-Tech Mfg.	Dummy=1 if firm is a high-tech manufacturing firm	0.04	0	0.19	0	1
Specialized Mfg.	Dummy=1 if firm is a specialized manufacturing firm	0.18	0	0.39	0	1
Traditional Mfg.	Dummy=1 if firm is a traditional manufacturing firm	0.52	0	0.50	0	1

⁸ The Inverse Hyperbolic Sine Function is used to scale profits, profit margins and capital expenditures/profits, as recommended by Burbidge, Magee, & Robb (1988) and Pence (2006).

Table 3.2. SAFE Sample Summary Statistics (Observations = 31,837; Period: 2009 to 2017)

VARIABLES	Mean	Median	S.D.	Min	Max	VARIABLES	Mean	Median	S.D.	Min	Max
<i>Dependant Variables</i>						Debt/Assets +	0.16	0.16	0.37	0	1
External Finance Applied	0.44	0.44	0.50	0	1	Debt/Assets -	0.27	0.27	0.44	0	1
External Finance Obtained	0.34	0.34	0.47	0	1	<i>Fixed Investment</i>					
Trade Credit Applied	0.17	0.17	0.37	0	1	Fixed Investment +	0.25	0.25	0.43	0	1
Trade Credit Obtained	0.98	0.98	0.15	0	1	Fixed Investment -	0.12	0.12	0.33	0	1
Bank Loan Applied	0.21	0.21	0.41	0	1	<i>Turnover Categories</i>					
Bank Loan Obtained	0.97	0.97	0.18	0	1	500k-1m Euros	0.13	0.13	0.34	0	1
Credit Line Applied	0.21	0.21	0.41	0	1	1-2m Euros	0.13	0.13	0.34	0	1
Credit Line Obtained	0.97	0.97	0.18	0	1	2-10m Euros	0.27	0.27	0.44	0	1
Other External Finance Applied	0.12	0.12	0.33	0	1	10-50m Euros	0.19	0.19	0.39	0	1
Other External Finance Obtained	0.99	0.99	0.12	0	1	>50m Euros	0.04	0.04	0.19	0	1
Venture Capital or Angel Investing Obtained	0.00	0.00	0.05	0	1	<i>Firm Age</i>					
<i>Independent Variables</i>						2-5 years	0.04	0.04	0.19	0	1
Firm Makes Own Financing Choices	0.87	0.87	0.34	0	1	5-10 years	0.12	0.12	0.32	0	1
Innovation	0.36	0.36	0.48	0	1	>10 years	0.84	0.84	0.37	0	1
<i>Turnover</i>						<i>Employee Size</i>					
Turnover +	0.43	0.43	0.50	0	1	10-49 Employees	0.32	0.32	0.47	0	1
Turnover -	0.23	0.23	0.42	0	1	50-249 Employees	0.30	0.30	0.46	0	1
<i>Profit</i>						<i>Firm Ownership</i>					
Profit +	0.33	0.33	0.47	0	1	Angel or VC Ownership	0.01	0.01	0.08	0	1
Profit -	0.32	0.32	0.47	0	1	Public Firm	0.02	0.02	0.13	0	1
(Table Continued on Opposite Side)						Family/Entrepreneur Ownership	0.49	0.49	0.50	0	1
						Other Firm Ownership	0.12	0.12	0.33	0	1
						<i>Credit Worthiness</i>					
						Credit Worthiness +	0.27	0.27	0.44	0	1
						Credit Worthiness -	0.08	0.08	0.27	0	1
						<i>Growth Outlook</i>					
						Growth Outlook +	0.35	0.35	0.48	0	1
						Growth Outlook -	0.20	0.20	0.40	0	1

NOTE: + or –s in the table above represent increases or decreases of the variables quantities. Since the alternative is the variable quantity staying constant, averages of those values can be calculated by inference.

3.5 Methodology: Heckman Probit Models

This study examines the effect of firm-level characteristics on financiers' decisions by modelling these decisions as a function of firm-characteristics and controlling for the industry, technological subcategory and country in which the firm primarily operates. It models the decision to grant financing to a firm by a dummy variable for obtaining financing, O_{it} , as

$$O_{it} = \beta_1 X_{it} + \beta_2 Y_{i(t-1)} + \beta_3 + e_{it} \quad (1)$$

where X_{it} is a set of exogenous observable characteristics of the firm, $Y_{i(t-1)}$ is a set of lagged balance sheet variables,⁹ $\beta = \{\beta_1, \beta_2, \beta_3\}$ is a vector of parameters to be estimated and e_{it} is an error term. Assuming that the firm's propensity to seek financing is represented by

$$S_{it}^* = \beta_4 X_{it} + \beta_5 Y_{i(t-1)} + \gamma Z_{it} + \eta_{it} \quad (2)$$

$$S_{it} = 1 \text{ if } S_{it}^* > 0 \text{ \& } S_{it} = 0 \text{ if } S_{it}^* < 0$$

where S_{it} is a dummy variable equal to 1 if the firm seeks that type of financing and 0 otherwise, S_{it}^* is an unobserved and latent variable, Z_{it} , is an exclusion criterion driving the decision to seek financing (but not the outcome of such attempts), β_1, β_2 and γ are vectors of parameters to be estimated and η_{it} is an error term.

If the errors e_{it} and η_{it} are correlated, estimations of β using OLS would be subject to selection bias. Hence, the empirical setup corrects for the self-selection of firms that apply for finance using Heckman's (1979) two-stage sample selection correction procedure. The study estimates expected financing success conditional on the firm applying for financing as

$$E(O_{it}|S_{it} = 1) = \beta_1 X_{it} + \beta_2 Y_{i(t-1)} + \beta_3 + E(\eta_{it}|S_{it} = 1).$$

The Industry Dependence on External Finance is used as an exclusion criterion in the two-stage analysis, since it affects the decision to apply for finance, but should not independently affect the decision of financiers to grant finance to firms. This is used in analyses of both datasets, EFIGE and SAFE utilized in the survey. In addition, for the EFIGE analysis following Cosh et al. (2009), growth objectives are used as an additional exclusion criteria, as they should increase a firm's likelihood of seeking financing, but is a qualitative variable (not readily quantifiable by financiers) that bears little to no influence on their ability to secure finance.

⁹ Namely leverage and total assets. If these variables were not lagged, the financing obtained would appear on both the right and left-hand side of the equation, leading to simultaneity bias in estimations.

The study first tests the determinants of the decision to seek external finance in subsection 3.6.1, by regressing that decision onto various income and cash flow statement items and firm characteristics in the first step of the Heckman Probit model. Subsection 3.6.2. investigates the determinants of obtaining external finance, taking into account sample selection bias issues in that only firms that had sought finance would be expected to obtain it, as the second step in the Heckman Probit model.

3.6 Results

3.6.1 *What Are the Determinants of Application for External Finance?*

This section is devoted to determining financial information and firm and industry characteristics that drive the decision to apply for external finance. Table 3.3 reports three models of multivariate regression results, models (1) to (3). Each model consists of two steps, which respectively regress applications for external finance (seeking) and success in obtaining external finance, to the various explanatory and control variables described previously. In the first step of models (1) to (3), a Probit estimator is utilized since the dependent variable takes on binary values of 0 or 1. This subsection only deals with step 1, meaning the determinants of seeking finance, of the presented tables. Model (1) is a regression run on the sample of all SME firms in the sample. Model (2) is run for those SMEs that are classified as younger firms, due to their age being lower than 20 years.¹⁰ Model (3) shows results for SME firms older than 20 years. It must be noted that especially for model (3), survivorship bias is a real issue since older firms are those that have survived.

Throughout models (1) to (3), it is found that firms that seek external finance tend to have higher leverage (with leverage having a diminishing effect on external finance applications), and are less likely to come from traditional manufacturing subsectors.¹¹ Industry dependence on external finance is strongly associated with the likelihood of seeking external finance themselves. The inclusion of this parameter serves as an exclusion restriction in the selection equation (step 1).¹²

This study also finds two important differences between the two sub-samples of models (2) and (3). First, model (2) indicates that younger SMEs seek outside financing much more when their profit margins are low. Significantly, a one standard deviation decrease in profit margins will make younger firms ~3.9% more likely to seek external finance. This is in agreement with the expectations presented in subsection 3.3.3 above, and imply that firms prefer to finance projects using internal cash flows before seeking outside external financing. For older firms, such a relationship cannot be inferred from the results. Firms'

¹⁰ This is quite consistent with Cosh, Cumming and Hughes (2009).

¹¹ This last part is not seen in Table 3.3 as coefficients of technological subsector indicators are not shown for brevity.

¹² The Rho parameters, being the correlation between the error terms in the selection model and the error term in the outcome model, in Table 3.3 is estimated to be significantly different from 0 for Models 1 to 3, suggesting the presence of non-random selection and confirming the need for the selection model.

reliance on external finance for investments, as measured by their Capital Expenditure/Profit, is for neither group found to be associated with their likelihood of seeking external finance.

A second difference between older and younger firms is that for the latter group, innovation output is associated with greater likelihood of seeking outside capital. A firm that has produced an innovative product in 2007-2009 is ~17% more likely to seek external finance. This does suggest that more innovative younger firms are more willing to bear the external finance premium. This holds even during the crisis, when the external finance premium is elevated (Mark Gertler & Gilchrist, 2018). No corresponding relationships are found for older firms. Further examination (Table 3.4 and Table 3.5) suggest that the main difference between younger and older innovative firms is that the latter group is not particularly keen on applying for equity financing. Of the various forms of IPR, it is mainly trademark activity that is found to be associated with firms' capital-seeking behavior.

Table 3.4 and Table 3.5 enable a side-by-side comparison of access to external debt financing and to equity financing, respectively. As in Table 3.3, the models are run for all SMEs, a subset of younger SME firms as well as older SME firms. For debt financing, both older and younger firms behave in line with expectations developed in subsection 3.3.3, and with pecking-order theory. As seen in model (1) in Table 3.4 and Table 3.5, higher capital expenditures over profits is associated with more applications for debt, but with lower applications for equity financing. This is consistent with the expectation that entrepreneurs needing to finance their projects, seek debt prior to equity in order to retain their ownership. These findings are consistent with findings of Cosh et al. (2009), except that they do not find statistical significance for the negative coefficient of capital expenditures over profits for equity applications, as this study does. Indeed, this statistically-significant negative sign in Table 3.5 is somewhat surprising. It would seem that firms' interest in obtaining equity financing is not, for this sample, primarily driven by needs to finance new investments.

The two groups of younger and older firms -models (2) and (3) in Table 3.4- exhibit different drivers in seeking outside capital, however, in that whereas younger firms' appetite for debt is associated with lower profit margins, for older firms it seems that it is the need to finance capital expenditures that drives applications for further debt. The estimates reported in Table 3.5 shows that firms of any age are more likely to apply for equity financing when their profit margins run low, which is in line with the expectations.

3.6.2 What Are the Determinants of Obtaining External Finance?

Step 2 of models (1) to (3) of Table 3.3 show the probability of obtaining external finance, considering the selection bias in that only applying firms can obtain finance. Estimates on Profit margin are only significant for younger SMEs, implying that more profitable firms are more likely to obtain finance.

Further, as seen in model (1) in Table 3.4, higher capital expenditures over profits is associated with more difficulty in attaining debt. A comparison with model (1) in Table 3.5, indicates that higher capital expenditure over profits is positively associated with securing equity. This matches the expectation in subsection 3.3 that firms with high investment needs over profits, would have more difficulty obtaining their desired source of financing, meaning debt, compared to equity. These findings would seem to imply that firms with high investment needs during the crisis had difficulties in obtaining outside capital in the form of debt, and may have had to resort to equity financing. Breaking firms into younger and older SMEs in models (2) and (3) of Table 3.4, show that these difficulties with attaining debt financing is driven by younger firms with high investment needs.

Similarly, firms with higher profit margins are more likely to obtain equity financing (Table 3.5) but not more likely to obtain debt financing. These could be understood as equity financiers granting equity as they can share in the upside to firms' profits, while debt financiers have a limited upside from firms' profitability (see subsection 3.3.3).

Table 3.3 indicates that especially younger firms that engage in product innovation, face difficulties in securing external finance by being 4.6% less likely to obtain financing conditional on applying.¹³ This result does not remain, however, when breaking down financing into debt and equity (Table 3.4 and Table 3.5). In fact, the results for Model (3) of Table 3.4 suggests that for older firms, innovation is positively associated with success in obtaining debt financing – at least for non-patenting innovative firms. Older firms who claim a copyright, on the other hand, are considerably more successful in obtaining debt financing.

Table 3.6Table 3.7Table 3.8 respectively show firm-level determinants of financing decisions of SMEs broken down by type of financing instrument rather than by firm age. Hence, these tables included the entire sample of SMEs (similar to model 1 of prior tables). Table 3.6 in particular, breaks down debt into short-term debt (model 1), medium and long-term debt (models 2 and 3), and debt securities (model 4). A comparison of Table 3.3 and models (1), (2) and (4) in Table 3.6, indicates that among various forms of debt financing, results in Table 3.3 were driven by financiers of medium-to-long-term (MLT) bank debt. This is because most of firms' debt applications are for MLT bank debt. That patent applications are negatively associated with obtaining medium-to-long-term bank debt (Table 3.6; model 2), could be explained by bankers' private information being a substitute for the public disclosure of patenting activities, in line with findings of Saidi & Zaldokas (2017).

¹³ This is calculated using the conditional marginal effect as the probability of rejection for a young innovative firm given applying.

Table 3.3. Regression Analysis of External Finance Sought and Obtained

Firm-Specific Factors	Model (1)		Model (2)		Model (3)	
	All SMEs		Younger SMEs (<20 years)		Older SMEs (> 20 years)	
	External Finance Applied	External Finance Obtained	External Finance Applied	External Finance Obtained	External Finance Applied	External Finance Obtained
Turnover	0.00 (0.02)	-0.00 (0.03)	-0.02 (0.04)	-0.00 (0.04)	0.00 (0.03)	-0.00 (0.03)
Capital Expenditure/Profit	0.00 (0.00)	0.02*** (0.00)	0.00 (0.01)	0.02*** (0.01)	0.00 (0.00)	0.02*** (0.00)
Profit Margin	-0.00 (0.00)	-0.01 (0.02)	-0.79*** (0.27)	0.57* (0.30)	-0.00 (0.00)	-0.01 (0.02)
Long Term Debt/Assets	0.90*** (0.12)	-0.25* (0.13)	0.72*** (0.17)	-0.05 (0.19)	1.66*** (0.25)	-0.77*** (0.27)
(Long Term Debt/Assets) ²	-0.37*** (0.07)	0.11 (0.10)	-0.26*** (0.09)	-0.00 (0.10)	-1.37*** (0.31)	0.72** (0.33)
Total Assets	-0.01 (0.02)	-0.01 (0.03)	0.00 (0.04)	-0.01 (0.04)	-0.00 (0.03)	-0.01 (0.03)
Innovation	0.10*** (0.03)	-0.04 (0.03)	0.17*** (0.05)	-0.12** (0.05)	0.05 (0.04)	0.03 (0.04)
Patent Application	-0.04 (0.05)	0.02 (0.05)	0.07 (0.08)	-0.02 (0.08)	-0.11* (0.06)	0.05 (0.07)
Industrial Design	0.04 (0.06)	0.00 (0.07)	-0.10 (0.11)	0.10 (0.12)	0.12 (0.08)	-0.06 (0.08)
Trademark	0.21*** (0.05)	-0.03 (0.05)	0.22*** (0.08)	0.03 (0.08)	0.20*** (0.06)	-0.08 (0.06)
Claim Copyright	-0.15* (0.08)	0.05 (0.09)	-0.04 (0.16)	0.18 (0.17)	-0.19* (0.10)	-0.01 (0.12)
Industry Dependence on Ext. Finance	0.56*** (0.03)		0.60*** (0.05)		0.52*** (0.04)	
Industry, Tech. sector, Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Rho	-0.99*** (0.01)		-0.99*** (0.01)		-0.98*** (0.01)	
Log-likelihood	-8138.0		-3406.7		-4692.3	
Observations	8994		3735		5259	

Note: *, ** and *** indicate that the estimator's p-value is respectively less than 0.1, 0.05 and 0.01. All standard errors are clustered at the firm level. Test of independent equations for Heckman Probit:

(1) $\chi^2 = 681.7^{***}$, (2) $\chi^2 = 273.8^{***}$, (3) $\chi^2 = 408.7^{***}$

Table 3.4. Regression Analysis of Debt Sought and Obtained

Firm-Specific Factors	Model (1)		Model (2)		Model (3)	
	All SMEs		Younger SMEs (<20 years)		Older SMEs (> 20 years)	
	Debt Applied	Debt Obtained	Debt Applied	Debt Obtained	Debt Applied	Debt Obtained
Turnover	-0.07** (0.03)	0.20*** (0.06)	-0.06 (0.04)	0.22** (0.09)	-0.09** (0.04)	0.24*** (0.08)
Capital Expenditure/Profit	0.02*** (0.00)	-0.02** (0.01)	0.01 (0.01)	-0.04*** (0.01)	0.02*** (0.00)	-0.01 (0.01)
Profit Margin	-0.11 (0.11)	0.28 (0.37)	-1.81*** (0.61)	-1.06 (1.41)	-0.03 (0.08)	0.43 (0.82)
Long Term Debt/Assets	0.91*** (0.16)	-0.11 (0.41)	0.76*** (0.22)	-0.10 (0.73)	1.14*** (0.28)	0.47 (0.71)
(Long Term Debt/Assets) ²	-0.48*** (0.14)	0.33 (0.45)	-0.39** (0.17)	0.49 (1.00)	-0.68** (0.32)	-0.33 (0.88)
Total Assets	0.04 (0.03)	-0.12** (0.06)	0.06 (0.04)	-0.01 (0.08)	0.06 (0.04)	-0.26*** (0.09)
Innovation	0.12*** (0.04)	0.13* (0.08)	0.15*** (0.06)	0.05 (0.11)	0.10** (0.05)	0.26** (0.11)
Patent Application	-0.03 (0.06)	-0.31*** (0.11)	-0.04 (0.09)	-0.25 (0.17)	-0.03 (0.07)	-0.32** (0.16)
Industrial Design	0.12* (0.07)	0.10 (0.16)	0.05 (0.12)	-0.12 (0.26)	0.18* (0.09)	0.14 (0.20)
Trademark	0.13** (0.05)	0.20* (0.10)	0.14* (0.08)	0.26 (0.16)	0.12* (0.07)	0.15 (0.14)
Claim Copyright	0.01 (0.11)	0.44 (0.28)	0.10 (0.19)	-0.04 (0.41)	-0.05 (0.13)	1.14** (0.49)
Industry Dependence on Ext. Finance	0.56*** (0.04)		0.54*** (0.05)		0.56*** (0.05)	
Growth Objective	0.56*** (0.06)		0.44*** (0.10)		0.64*** (0.08)	
Industry, Tech. sector, Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Rho	-0.78*** (0.12)		-0.88*** (0.11)		-0.69** (0.18)	
Log-likelihood	-4326.9		-1928.6		-2354.3	
Observations	8994		3735		5259	

Note: *, ** and *** indicate that the estimator's p-value is respectively less than 0.1, 0.05 and 0.01. All standard errors are clustered at the firm level. Test of independent equations for Heckman Probit:

(1) $\chi^2 = 17.9^{***}$, (2) $\chi^2 = 9.4^{***}$, (3) $\chi^2 = 7.4^{***}$

Table 3.5. Regression Analysis of Equity Sought and Obtained

Firm-Specific Factors	Model (1)		Model (2)		Model (3)	
	All SMEs		Younger SMEs (<20 years)		Older SMEs (> 20 years)	
	Equity Applied	Equity Obtained	Equity Applied	Equity Obtained	Equity Applied	Equity Obtained
Turnover	0.03 (0.02)	-0.03 (0.03)	0.02 (0.04)	-0.02 (0.05)	0.04 (0.03)	-0.04 (0.04)
Capital Expenditure/Profit	-0.01*** (0.00)	0.03*** (0.00)	-0.01** (0.01)	0.03*** (0.01)	-0.01** (0.00)	0.03*** (0.01)
Profit Margin	-1.45*** (0.31)	1.21*** (0.40)	-1.66*** (0.48)	1.54** (0.66)	-1.22*** (0.40)	0.91* (0.52)
Long Term Debt/Assets	0.51*** (0.11)	-0.11 (0.21)	0.46*** (0.16)	0.54 (0.44)	1.00*** (0.24)	-0.73** (0.30)
(Long Term Debt/Assets) ²	-0.21*** (0.07)	-0.07 (0.25)	-0.16** (0.07)	-1.30** (0.64)	-0.96*** (0.32)	0.95** (0.37)
Total Assets	-0.01 (0.02)	0.01 (0.03)	-0.01 (0.04)	0.01 (0.05)	-0.02 (0.03)	0.03 (0.04)
Innovation	0.06** (0.03)	-0.01 (0.04)	0.10** (0.05)	-0.04 (0.06)	0.03 (0.04)	0.02 (0.05)
Patent Application	-0.00 (0.05)	0.03 (0.06)	0.06 (0.07)	0.01 (0.10)	-0.05 (0.06)	0.05 (0.07)
Industrial Design	-0.01 (0.06)	0.03 (0.07)	-0.04 (0.10)	-0.04 (0.13)	0.01 (0.07)	0.08 (0.09)
Trademark	0.11** (0.04)	-0.02 (0.05)	0.08 (0.07)	0.12 (0.09)	0.13** (0.05)	-0.09 (0.07)
Claim Copyright	-0.12 (0.08)	0.13 (0.10)	-0.02 (0.15)	0.26 (0.19)	-0.15 (0.10)	0.08 (0.12)
Industry Dependence on Ext. Finance	1.04* (0.55)		1.28 (0.89)		1.34* (0.71)	
Growth Objective	1.03*** (0.06)		1.08*** (0.09)		0.99*** (0.07)	
Industry, Tech. sector, Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Rho	-0.93*** (0.02)		-0.90*** (0.05)		-0.94*** (0.02)	
Log-likelihood	-7166.6		-3015.9		-4112.2	
Observations	8994		3735		5259	

Note: *, ** and *** indicate that the estimator's p-value is respectively less than 0.1, 0.05 and 0.01. All standard errors are clustered at the firm level. Test of independent equations for Heckman Probit:

(1) $\chi^2 = 256.3^{**}$, (2) $\chi^2 = 94.2^{***}$, (3) $\chi^2 = 161.5^{***}$

Table 3.6. Regression Analysis of SME's Debt Financing Instruments Sought and Obtained

	Model (1)		Model (2)		Model (3)		(Model 4)	
Firm-Specific Factors	Short-Term (ST) Bank Debt		Medium-to-Long-Term (MLT) Bank Debt				Debt Securities	
	Debt Applied	ST Debt Obtained	Debt Applied	MLT Debt Obtained	Debt Applied	MLT Debt Obtained	Debt Applied	Securities Obtained
Turnover	-0.07** (0.03)	0.01 (0.05)	-0.07** (0.03)	0.04 (0.04)	-0.07** (0.03)	0.04 (0.04)	-0.07** (0.03)	-0.05 (0.16)
Capital Expenditure/Profit	0.02*** (0.00)	-0.00 (0.01)	0.02*** (0.00)	-0.00 (0.01)	0.02*** (0.00)	-0.00 (0.01)	0.02*** (0.00)	0.04 (0.03)
Profit Margin	-0.11 (0.11)	-0.89 (0.72)	-0.13 (0.11)	0.21 (0.27)	-0.14 (0.11)	0.25 (0.33)	-0.11 (0.11)	0.16 (0.55)
Long Term Debt/Assets	0.91*** (0.16)	-1.10** (0.45)	0.90*** (0.16)	-0.08 (0.26)	0.92*** (0.16)	-0.08 (0.26)	0.91*** (0.16)	0.88 (2.09)
(Long Term Debt/Assets) ²	-0.48*** (0.14)	1.22** (0.56)	-0.48*** (0.14)	0.16 (0.21)	-0.49*** (0.14)	0.16 (0.21)	-0.48*** (0.14)	-1.09 (1.92)
Total Assets	0.04 (0.03)	0.00 (0.06)	0.05* (0.03)	-0.02 (0.04)	0.05* (0.03)	-0.02 (0.04)	0.05 (0.03)	0.03 (0.19)
Innovation	0.12*** (0.04)	0.08 (0.07)	0.11*** (0.04)	-0.04 (0.06)			0.12*** (0.04)	0.89* (0.51)
Patent Application	-0.03 (0.06)	-0.04 (0.11)	-0.03 (0.06)	-0.24*** (0.09)			-0.03 (0.06)	0.18 (0.34)
Industrial Design	0.13* (0.07)	-0.05 (0.14)	0.13* (0.07)	-0.12 (0.12)			0.12* (0.07)	0.27 (0.44)
Trademark	0.13** (0.05)	-0.04 (0.10)	0.13** (0.05)	0.04 (0.08)			0.13** (0.05)	0.65 (0.42)
Claim Copyright	0.01 (0.11)	0.01 (0.23)	-0.00 (0.11)	0.42** (0.20)			0.01 (0.11)	-43.41 (.)
R&D Intensity					0.01** (0.00)	-0.00 (0.00)		
R&D Outsourcing					0.12** (0.05)	-0.13 (0.08)		
Industry Dependence on Ext. Fin.	0.54*** (0.04)		0.49*** (0.04)		0.49*** (0.04)		0.54*** (0.04)	
Growth Objective	0.59*** (0.06)		0.68*** (0.05)		0.69*** (0.05)		0.59*** (0.06)	
Industry, Tech. sector, Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rho	-0.43** (0.17)		-0.96*** (0.03)		-0.97*** (0.03)		-0.80 (0.4)	
Log-likelihood	-4387.3		-4434.2		-4448.8		-3551.9	
Observations	8994		8994		8994		8994	

Note: *, ** and *** indicate that the estimator's p-value is respectively less than 0.1, 0.05 and 0.01. All standard errors are clustered at the firm level. Test of independent equations for Heckman Probit: (1) $\chi^2 = 4.51^{**}$, (2) $\chi^2 = 78.6^{***}$, (3) $\chi^2 = 81.6^{***}$, (4) $\chi^2 = 3.8^*$

Table 3.7. Regression Analysis of SME's Equity Financing Instruments Sought and Obtained

Firm-Specific Factors	Model (1)		Model (2)		Model (3)	
	Equity (non-VC or PE)		Venture Capital or Private Equity			
	Equity Applied	Equity Obtained	Equity Applied	VC/PE Obtained	Equity Applied	VC/PE Obtained
Turnover	0.05** (0.02)	-0.09** (0.04)	0.05** (0.02)	-0.05 (0.09)	0.05** (0.02)	-0.02 (0.09)
Capital Expenditure/Profit	-0.01** (0.00)	0.03*** (0.01)	-0.01** (0.00)	0.03*** (0.01)	-0.01** (0.00)	0.03*** (0.01)
Profit Margin	-0.00 (0.00)	-0.03 (0.24)	-0.00 (0.00)	0.01 (0.05)	-0.00 (0.00)	0.01 (0.05)
Long Term Debt/Assets	0.51*** (0.11)	0.35 (0.31)	0.51*** (0.11)	0.40 (0.37)	0.52*** (0.11)	0.35 (0.35)
(Long Term Debt/Assets) ²	-0.22*** (0.07)	-0.20 (0.36)	-0.22*** (0.07)	-0.02 (0.15)	-0.22*** (0.07)	0.01 (0.15)
Total Assets	-0.04* (0.02)	0.11*** (0.04)	-0.04* (0.02)	0.09 (0.09)	-0.04 (0.02)	0.10 (0.09)
Innovation	0.06* (0.03)	0.10* (0.05)	0.05* (0.03)	0.18 (0.12)		
Patent Application	-0.01 (0.05)	-0.06 (0.08)	-0.01 (0.05)	0.16 (0.15)		
Industrial Design	-0.02 (0.06)	0.15 (0.10)	-0.02 (0.06)	0.10 (0.18)		
Trademark	0.11** (0.04)	-0.07 (0.07)	0.11** (0.04)	-0.11 (0.15)		
Claim Copyright	-0.11 (0.08)	0.06 (0.14)	-0.11 (0.08)	0.21 (0.24)		
R&D Intensity					-0.00 (0.00)	0.01** (0.01)
R&D Outsourcing					0.07* (0.04)	-0.17 (0.16)
Industry Dependence on Ext. Fin.	0.30*** (0.03)		0.31*** (0.03)		0.31*** (0.03)	
Growth Objective	1.01*** (0.06)		1.00*** (0.06)		1.00*** (0.06)	
Ind., Tech sector, Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Rho	-0.81*** (0.03)		-0.61*** (0.10)		-0.42*** (0.08)	
Log-likelihood	-6607.9		-5906.5		-5614.6	
Observations	8994		8994		8994	

Note: *, ** and *** indicate that the estimator's p-value is respectively less than 0.1, 0.05 and 0.01. All standard errors are clustered at the firm level. Test of independent equations for Heckman Probit:

(1) $\chi^2 = 114.5***$, (2) $\chi^2 = 13.0***$, (3) $\chi^2 = 12.9***$

Table 3.8. Regression Analysis of SME's Public Funding or Other Instruments Sought and Obtained

	Model (1)		Model (2)		Model (3)		Model (4)	
Firm-Specific Factors	Public Funds				Tax Incentives			
	Ext. Fin. Applied	Public Funds Obtained	Ext. Fin. Applied	Public Funds Obtained	Ext. Fin. Applied	Tax Incent. Obtained	Ext. Fin. Applied	Tax Incent. Obtained
Turnover	-0.03 (0.02)	-0.09* (0.05)	-0.03 (0.02)	-0.08* (0.05)	-0.03 (0.02)	0.11 (0.08)	-0.03 (0.02)	0.13 (0.08)
Capital Expenditure/Profit	-0.01*** (0.00)	0.02** (0.01)	-0.01*** (0.00)	0.01* (0.01)	-0.01*** (0.00)	0.02** (0.01)	-0.01*** (0.00)	0.02** (0.01)
Profit Margin	-2.47*** (0.31)	0.92 (0.82)	-2.46*** (0.31)	0.83 (0.82)	-2.52*** (0.31)	0.91 (1.09)	-2.51*** (0.31)	0.98 (1.08)
Long Term Debt/Assets	0.98*** (0.12)	0.44 (0.46)	1.01*** (0.12)	0.45 (0.47)	1.00*** (0.12)	0.33 (0.64)	1.02*** (0.12)	0.29 (0.65)
(Long Term Debt/Assets) ²	-0.38*** (0.07)	-0.61 (0.62)	-0.40*** (0.07)	-0.66 (0.64)	-0.38*** (0.07)	-0.57 (0.86)	-0.40*** (0.07)	-0.61 (0.88)
Total Assets	0.04* (0.02)	0.05 (0.05)	0.05** (0.02)	0.05 (0.05)	0.05* (0.02)	-0.07 (0.08)	0.05** (0.02)	-0.07 (0.08)
Innovation	0.13*** (0.03)	0.14* (0.07)			0.13*** (0.03)	0.26*** (0.10)		
Patent Application	-0.02 (0.05)	-0.01 (0.11)			-0.02 (0.05)	0.03 (0.12)		
Industrial Design	0.01 (0.06)	0.23* (0.12)			0.02 (0.06)	0.05 (0.15)		
Trademark	0.23*** (0.05)	-0.04 (0.10)			0.22*** (0.05)	0.23** (0.11)		
Claim Copyright	-0.15* (0.08)	-0.20 (0.21)			-0.15* (0.08)	-0.12 (0.24)		
R&D Intensity			0.00 (0.00)	0.01** (0.00)			0.00 (0.00)	0.02*** (0.00)
R&D Outsourcing			0.19*** (0.04)	0.16* (0.09)			0.19*** (0.04)	0.14 (0.11)
Ind. Dependence on Ext. Fin.	1.02 (0.66)		1.04 (0.66)		1.15* (0.67)		1.18* (0.67)	
Growth Objective	6.96 (1322.52)		6.97 (1151.50)		6.84 (961.50)		6.89 (898.34)	
Ind., Tech sector, Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rho	-0.63*** (0.04)		-0.63*** (0.04)		-0.43*** (0.06)		-0.42*** (0.07)	
Log-likelihood	-5989.8		-6003.9		-5767.9		-5782.0	
Observations	8994		8994		8994		8994	

Note: *, ** and *** indicate that the estimator's p-value is respectively less than 0.1, 0.05 and 0.01. All standard errors are clustered at the firm level. Test of independent equations for Heckman Probit:

(1) $\chi^2 = 87.5^{***}$, (2) $\chi^2 = 87.8^{***}$, (3) $\chi^2 = 20.7^{***}$, (4) $\chi^2 = 21.5^{***}$

For forms of financing where the financier typically is expected to assess the firm more closely (MLT bank debt, VC or PE investments, Public Funding or Tax Incentives), this study additionally investigates innovation input variables. Results from models (2) and (3) of Table 3.6 suggest that neither innovation output (Innovation) nor input (R&D Intensity, R&D Outsourcing) affect banks' decision about debt financing. Models (2) and (3) of Table 3.7 seems to show that VCs and PEs respond to inputs rather than to output, in that they are more likely to finance firms with high R&D intensities, and are not found to base their financing on specific innovative outputs such as product innovation or patenting. This likely speaks to their superior ability to value innovation inputs rather than outputs, due to their better screening and monitoring skills (Kaplan & Strömberg, 2001; Keuschnigg & Nielsen, 2004; Ueda, 2004). In doing so, VCs fund riskier firms and those with greater growth objectives (P. Gompers & Lerner, 2001), which is in line with expectations developed in subsection 3.3.

In Table 3.8, this study explores how funding from public sources and governments function in relation to innovation activities. The results suggest that innovation input measures have greater importance than innovation outputs for public funding, indicating that public funding is tailored to R&D intensive firms.

3.6.3 Generalizability of Results Across Geographies and Time

In the main analysis, this research investigates a sample of firms surveyed at one point in time about their financial decisions and outcomes during the later phase of the global financial crisis. In order to assess to what extent the findings reflect particular circumstances of that time, this study needs to compare to an analysis of a non-crisis period which, similar to the main analysis, investigates both applications and outcomes of SMEs for a broad range of external finance. However, the only two studies with these characteristics that the author is aware of (Cosh et al., 2009; Robb & Robinson, 2012) may not be entirely comparable to the main analysis, since their findings relate to SMEs in the UK and US.

As pointed out in a rich literature on financial systems, the Anglo-Saxon settings may have partly different properties than that of other developed economies such as those in Continental Europe (T. Beck, Demirguc-Kunt, & Levine, 2010). In particular, the market-based Anglo-Saxon economies feature greater investor protection than in Continental Europe, allow for more efficient capital allocation to firms and, owing to institutional differences, may receive a greater supply of entrepreneurial capital of various forms than peer firms. English- or common law countries have been found to limit expropriation by corporate insiders and provide stronger shareholder and creditor rights protection, resulting in larger and deeper capital markets (La Porta, Lopez-de-Silanes, Shleifer, & Vishny, 1997a, 1998). SMEs in Continental Europe have to rely on banks to a much larger extent. These continental differences may also imply divergences in the relative importance of debt versus equity for European SMEs in their financing choices.

In view of these concerns, this study conducts an analysis of its own, drawing on data from SAFE. The primary analysis method is by running econometric regressions pooling all firms in different surveying rounds, but controlling for country, major industry classification and surveying round using fixed effects, and clustering the results at the level of the firm. This study uses a similar methodology as in the main analysis, in that a Heckman Probit estimator is used to correct for self-selection of firms into applications for various sources of financing.

Table 3.9 reports the results for the analysis corresponding to that of Table 3.3. For the full sample, it is found that firms experiencing a decrease in profits are more likely to apply for external finance. Such firms are, however, less likely than the average firm to succeed in obtaining sought after finance. This pattern is in line with expectations developed in subsection 3.3.3. In breaking down the sample by firm age, the pattern can however only be confirmed for older firms. This finding contrasts that of Table 3.3 of the main analysis, where younger firms were found to conform to expectations, and older firms were not.¹⁴

Congruent with results of Table 3.3, the level of fixed investments (in Table 3.3: capital expenditure / profit) is overall positively related to firms' potential to obtain external finance. But an interesting deviation is found when further investigating whether it is possible to replicate results reported in Table 3.4 – that debt finance was actually more difficult to obtain for firms (specifically: younger firms) with high investments. Table A.1 in 7.2Appendix A breaks down results for the post-crisis period by the three main forms of debt financing, revealing a pattern that when investments increase, firms are more – not less – likely to obtain debt financing that they have applied for. Cingano, Manaresi, & Sette (2016) and Balduzzi, Brancati, & Schiantarelli (2018) found that the credit supply shock had a larger deteriorating effect on investments of younger firms. The results that younger firms with higher investment needs during the crisis were disproportionately rejected in their credit applications, shows their particular vulnerability of younger firms in that not only do young firms seem to fare worse when not obtaining finance, they are more likely to not obtain financing and their desired source of financing.

Estimates on Innovation conform to expectations and to results in Table 2, in that innovation is generally positively associated with seeking external finance. This study does, however, find interesting differences between the two sets of results in the break downs by firm age. Whereas innovation was negatively associated with obtaining external finance (specifically: debt finance) only for younger firms in the results on the crisis period, in the post-crisis data this study finds a corresponding pattern only for older firms.¹⁵

¹⁴ We must note that break-downs by firm age are not entirely comparable; whereas the EFIGE survey reveals firms as being either younger or older than 20 years, the SAFE survey provides the category “>10 years” for older firms.

¹⁵ Further investigation, reported in Table A1 in the Appendix, confirms that these results hold for different forms of debt financing; thereby we can confirm that the differences between the two sets of analysis reflect differences in the behavior of providers of debt financing during and after the crisis.

Table 3.9. Firm-Level Determinants of SME, Entrepreneurial & Nascent Firms' Financing Decisions (SAFE Analysis)

	Model (1)		Model (2)		Model (3)	
	All SMEs		Younger SMEs		Older SMEs	
Firm-Specific Factors	External Finance Applied	External Finance Obtained	External Finance Applied	External Finance Obtained	External Finance Applied	External Finance Obtained
Turnover						
Turnover +	0.131*** (0.02)	-0.030 (0.04)	0.163*** (0.05)	-0.030 (0.13)	0.129*** (0.02)	-0.029 (0.05)
Turnover -	0.039 (0.02)	-0.060 (0.04)	0.018 (0.06)	-0.037 (0.10)	0.043* (0.03)	-0.068* (0.04)
Fixed Investments						
Fixed Investment +	0.090*** (0.02)	0.112*** (0.04)	0.0489 (0.05)	-0.035 (0.08)	0.098*** (0.02)	0.133*** (0.05)
Fixed Investment -	0.073*** (0.03)	-0.129*** (0.04)	-0.027 (0.07)	-0.080 (0.10)	0.088*** (0.03)	-0.136*** (0.04)
Profit						
Profit +	-0.0229 (0.02)	-0.000 (0.03)	-0.061 (0.05)	0.023 (0.09)	-0.0165 (0.02)	-0.007 (0.04)
Profit -	0.106*** (0.02)	-0.115*** (0.04)	0.120** (0.06)	-0.0585 (0.11)	0.106*** (0.02)	-0.118*** (0.04)
Debt/Assets						
Debt/Assets +	0.389*** (0.02)	-0.196*** (0.06)	0.339*** (0.05)	-0.0233 (0.21)	0.401*** (0.02)	-0.223*** (0.07)
Debt/Assets -	0.136*** (0.02)	-0.0278 (0.04)	0.146*** (0.05)	0.0581 (0.10)	0.135*** (0.02)	-0.036 (0.04)
Angel or VC Ownership	0.108 (0.09)	-0.110 (0.15)	0.181 (0.21)	0.280 (0.31)	0.0637 (0.10)	-0.204 (0.16)
Public Firm	-0.127* (0.07)	0.0700 (0.14)	-0.392** (0.19)	-0.532 (0.33)	-0.104 (0.07)	0.131 (0.15)
Family/Entrepreneur Ownership	0.075*** (0.02)	0.0321 (0.03)	0.077* (0.05)	0.017 (0.08)	0.072*** (0.02)	0.038 (0.04)
Other Firm Ownership	0.004 (0.03)	0.104** (0.05)	0.229*** (0.07)	0.056 (0.15)	-0.045 (0.04)	0.136** (0.06)
Credit History						
Credit History +	0.239*** (0.02)	0.0447 (0.05)	0.310*** (0.04)	0.268** (0.13)	0.222*** (0.02)	0.007 (0.06)
Credit History -	0.423*** (0.03)	-0.485*** (0.06)	0.341*** (0.07)	-0.333 (0.27)	0.438*** (0.03)	-0.508*** (0.07)

Innovation	0.115*** (0.02)	-0.092*** (0.03)	0.144*** (0.04)	-0.021 (0.11)	0.109*** (0.02)	-0.101*** (0.03)
Firm Makes Own Financing Choices	0.237*** (0.03)	-0.0622 (0.06)	0.238*** (0.07)	-0.014 (0.16)	0.230*** (0.03)	-0.0740 (0.07)
Age						
Reference: <2 years						
2-5 years	-0.041 (0.10)	0.151 (0.15)	-0.0268 (0.10)	0.116 (0.15)		
5-10 years	-0.020 (0.10)	0.202 (0.14)	0.000 (0.10)	0.191 (0.14)		
>10 years	-0.080 (0.09)	0.312** (0.14)				
Growth Outlook						
Growth Outlook +	0.100*** (0.02)		0.108** (0.05)		0.094*** (0.02)	
Growth Outlook -	0.041* (0.02)		0.132** (0.06)		0.024 (0.02)	
Industry-Specific Factor						
Industry Dependence on External Financing	2.049*** (0.64)		1.551 (2.09)		2.043*** (0.70)	
Turnover Size Controls	Yes	Yes	Yes	Yes	Yes	Yes
Employees Size Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Round (Biennial) FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,837		5,117		26,720	

Note: *, ** and *** indicate that the estimator's p-value is respectively less than 0.1, 0.05 and 0.01. All standard errors are clustered at the firm level. Turnover size controls are for turnover size categories of <€500k, between €500k and €1m, between €1m and €2m, between €2m and €10m, between €10m and €50m, and above €50m. Employee size controls are for employee categories of up to 10 employees, between 10 and 49 employees and 50 to 249 employees. These control for firm size, above which the effect of changes in financial statement items on our dependent variables of interest are reported herein.

3.7 Limitations

One of the limitations in this chapter is in the absence of matched financial statements in the SAFE survey, the second survey employed. Instead indicators are used for increases or decreases in key financial statement items. This data is matched at the ECB (Bańkowska, Osiewicz, & Pérez-Duarte, 2015; Ferrando & Mulier, 2015), however access is only granted to EU citizens who visit the ECB. Financial statement values, could help account for determinants of financing better than indicators and allow for more thorough investigation of whether during crises determinants of financing varies or not.

Another potential limitation relates generally to use of surveys. Survey research has a long history in economics, even if economists' use of information gathered in certain kinds of questionnaire surveys has been mostly indirect, in that the economist does not typically organize collection of this information (Boulier & Goldfarb, 1998). The extensive use of the US' Survey of Consumer Finances in economics research is one prominent example. While this thesis relies extensively on survey data, there are subject to potential errors. The most obvious would be measurement error, while other potential biases exist such as nonresponse, sampling and coverage errors (Ponto, 2015). The rigorous methodologies of the EFIGE and SAFE surveys (Altomonte & Aquilante, 2012; European Central Bank, 2019b) assuage worries about sampling, nonresponse and coverage errors. However, measurement error pertains to whether the survey questions accurately reflect the topic of inquiry and to what extent, questionnaires and interviews are able to evoke truthful answers. Notwithstanding, the questions utilized from the SAFE and EFIGE survey pertain to which financiers, firms applied to for capital and so are inquires on facts, rather than subjective or attitude questions.

3.8 Conclusions

A complete understanding of the effects of the financial crisis of 2007-2009 on firms, not only investigates the real effects of not obtaining credit,¹⁶ but also of how firms' prospects of obtaining various sources of capital (and especially, their desired capital) differed given firm characteristics. To this end, this study investigates access to finance for SMEs in Europe during the crisis, and compares it similar investigations for a post-2009 period. This comparison of crisis-era frictions in obtaining capital with more tranquil times can be enlightening, to clarify how much of these frictions represents temporal shifts in financiers' decisions during the crisis.

Exploiting data which allows direct observation of firms' application for different forms of outside capital, as well as the outcome of any such attempts, this chapter has taken steps in ascertaining that the traditional pecking order theory of capital holds for the sample of firms in non-market-based economies, analysed determinants of

¹⁶ As carried out by a plethora of studies surveyed by Guler et al. (2019).

success in applying for outside capital, and explored the role of innovation activities in shaping both types of decisions.

The results suggest that firms with lower profits in relation to total costs and/or investment needs are more likely to seek external finance. The results also suggest that firms generally prefer to finance their immediate investment needs through debt financing prior to equity financing. These patterns are consistent with the well-established pecking-order theory. However, it also finds interesting differences between firm age groups. Whereas clear indications of a preference for internal finance over external finance could only be traced for younger firms (< 20 years), the preference for debt over equity was found to be most accentuated among older firms. A possible interpretation is that older firms are better able to increase their debts in precautionary moves, for fear banks would restrict access in the future (Campello et al., 2010). Owing to their longer credit history and more established banking relationships, older firms may have been better able to draw down on credit lines existing at crisis-time (prior commitments by banks to lend to corporations at pre-agreed rates and up to pre-agreed limits), consistent with observations of Ivashina & Scharfstein (2010) during the crisis.

In further analysis, it is confirmed that firms with greater profit margins are more likely to be successful in attempts to obtain external financing. This study also find that debt financiers are less willing to provide funds to firms that signal project quality by allocating internal funds to projects, than equity providers are willing to do. It may be concluded that SMEs with high investments needs have had difficulties obtaining debt financing, but are more likely than the average firm to be successful if applying for equity financing. While the latter pattern is found also in the investigation of post-crisis data, it would seem that the difficulty of younger firms with high investment needs to obtain debt financing during the crisis may reflect temporal behavioral deviation on behalf of lenders, and by banks in particular (De Haas & Van Horen, 2013a; Ivashina & Scharfstein, 2010b). During the crisis firms with existing credit lines drew down on pre-agreed limits (Ivashina & Scharfstein, 2010b) and banks reduced lending to firms they did not have substantial lending experience with (De Haas & Van Horen, 2013b). These crisis-specific occurrences would have favoured older SMEs.

A final set of results concerns innovation activities. It is found that in general, innovative firms were more likely than non-innovative firms to be seeking external finance. This is primarily, however, true for debt-based forms of financing; only among the younger innovative firms, an enhanced appetite for equity financing is observed. Relating to the supply of outside capital, innovation is not found to have univocally strengthened financiers' willingness to engage with a firm. However, older firms and firms whose innovation are market-oriented rather than technology-oriented (as indicated by them being protected by copyrights and trademarks rather than by patents) seem to have been able to successfully utilize innovation activities in strengthening their bids for outside capital in the form of debt. Comparisons with the data on the post-crisis period suggests a somewhat different pattern, where innovation is positively associated with success in obtaining outside financing only for younger firms. A possible interpretation is that in the crisis, banks and other lending institutions had a reduced appetite for

risk (Chodorow-Reich, 2014). The combined uncertainty and information asymmetries associated with younger firms and technological innovation during the crisis may have made it temporarily more difficult for young innovative firms to secure debt financing. It is interesting to note that venture capital and private equity actors, and providers of public funding instruments are found to have attached positive weight to innovation input including during the crisis. Thereby, they would seem to have complemented other actors on the markets for capital in a potentially valuable way.

The study's results offer insights into firms' conditions for financing new investments, and to bridge shortfalls in financial resources caused by negative demand shocks during a period of enhanced economic uncertainty. This study is able to utilize panel data covering the post-crisis period to assess to what extent the results on European SMEs' preferences regarding external vs. internal finance are to be understood as specific to the crisis period. However, no corresponding analysis could be performed for the potentially different roles of debt and equity financing, and for the role of innovation activities in the financing decisions of firms and financiers. In order to achieve such tests, further work would need to construct and analyse data of similar richness to the EFIGE survey for a post-crisis period. Further work is also called upon to try to further disentangle firms' preferences from financiers' preferences, e.g. to address the potential limitation of the current study's data that firms may not apply for a type of funding if they anticipate negative outcomes. In this anticipated line of future work, the current study represents but one step towards better understanding of how different types of financing serves different types of needs for small and medium-sized firms.

4 Effects of SME Financing Outcomes in the GFC

What were the real effects of impaired access to capital during the 2008-2009 financial crisis? Corporate investment fell sharply following the onset of the crisis (Duchin, Ozbas, & Sensoy 2010, Campello, Graham, & Harvey 2010). Reviewing the literature, Kahle & Stulz (2013) state that theories of impaired access to capital dominate explanations of how subprime mortgage losses resulted in the worst recession since the Great Depression. However, performing various tests to speak to these theories and competing theories, such as a collateral channel or balance sheet multiplier effect (see Brunnermeier & Oehmke, 2013), or the demand-shock theory, they only find support for the demand-shock theory. The demand shock theory explains that the loss to housing wealth (Mian & Sufi, 2010), a decrease in consumer credit (Mian et al., 2013), and the panic resulting from the collapse of Lehman Brothers, triggered a shock to demand which led to a reduction in firm's desired investments and their demand for funding to finance investments. Mian and Sufi (2015) in effect state that while the collapse of Lehman Brothers exacerbated economic weakness, it should not be seen as a primary cause of the demand-shock. More recently, Gertler & Gilchrist (2018) find that financial distress in balance sheets of both households and banks were responsible for the fall in corporate investment. Clearly, there is yet substantial debate as to the role of demand- and supply-side factors, leaving the academic field open for evidence that can disentangle the two and strengthen the literature.

4.1 Introduction

Disentangling whether shocks to consumption-driven demand or to capital supply caused a reduction in firm investments requires data where researchers can observe corporate demand for capital and resultant supply, encompassing all the capital sources which firms can substitute for. There is a scarcity of such datasets. For example, Berg (2018) and Balduzzi et al. (2018) respectively exploit loan-level data from a single- or multiple banks to document investment declines for rejected firms. These papers would miss accounting for the alternative funding sources firms used to substitute for bank credit contractions during the crisis. This is highlighted given that recent studies have shown that during the recession firms substituted for bank loans by reducing dividends, issuing new equity (Dwenger, Fossen, & Simmler, 2018) or public debt (Becker & Ivashina, 2018), and increasing trade payables (Fraisie, Lé, & Thesmar, 2019), grants or informal finance (Casey & O'Toole, 2014).

Why is it important to answer what effect financing constraints had during the recession, as opposed to other periods? The reason is that if it is true that supply-side shocks aggravated the crisis, then the "external finance" premium, described in subsection 3.3.2, is elevated in financial crises (Gertler & Gilchrist 2018). This happens as balance sheet constraints often hit both households, whom determine demand for firms, and financial institutions, which finance firms. New macroeconomic models have been updated since the financial crisis to model the economy in boom times, as though it had frictionless financial markets, but with negative disturbances moving it to regions where balance sheet constraints of banks and households are binding. Models incorporating household

balance sheet constraints are developed in seminal contributions from Mian, Rao, & Sufi (2013) and Mian & Sufi (2014), as well as other notable studies by (Eggertsson & Krugman, 2012; Guerrieri & Lorenzoni, 2017; Justiniano, Primiceri, & Tambalotti, 2010). Models which incorporated credit constraints on banks were Gertler & Kiyotaki (2010), He & Krishnamurthy (2013; Brunnermeier & Sannikov (2014).

It is imperative that micro-econometric studies are carried out which can effectively tease out supply and demand effects when studying firm financial constraints at such a crucial time of crisis where binding bank and household balance sheet constraints may bear greater adverse effects on real effects for firms. Such binding constraints may necessitate firms to incorporate alternate strategies in the face of financial constraints they face. It is vital to empirically study effects on investments of financial constraints during the recession, and effects of these in the years following a crisis, using effective econometric identification tools. This necessity formed the motivation for the undertaking which led to this chapter.

In this chapter, I exploit a unique crisis-era setting where corporate financing applications and outcomes are observable, and isolate the real effects of impaired access to capital. To this end, I utilize a novel matching mechanism between successful and comparable rejected capital-seeking firms in a way that is robust to substitution effects between various capital sources. This study relies on a multi-faceted survey of small and medium enterprises (SMEs) in Europe during the crisis, matched to financials covering nearly 15,000 unique firms from 2001-2014. To isolate the effects of supply-side constraints, the sample is restricted to firms whom all had a demand for external financing in 2009 (i.e. have sought capital). Employing coarsened exact matching (CEM) between capital-seeking firms obtaining desired external finance and comparable capital-seeking firms that do not, the empirical setup effectively disentangles capital supply and demand by keeping demand constant but allowing capital supply to vary between matched firms. Matching along various outcome-relevant determinants, observable due to the breadth of the survey, provides an estimate for the counterfactual real effects of capital impairments during the crisis.

4.2 Literature Review

Campello et al. (2010) use a matching technique similar to this study, on firms who “only differ” in their CFOs assessment of the degree to which they can access credit. Duchin et al. (2010) use a difference-in-difference approach where they compare firm investments before and after the onset of the crises as a function of internal financing resources (net debt and cash reserves), dependence on external finance, and external financial constraints. The paper that comes closest to this study due to observing applications of SMEs for financing is Berg (2018), who exploits a regression discontinuity approach using a lender cut-off rule generating plausibly exogenous variation in the supply of credit. He finds that firms’ precautionary savings motives can aggravate real effects. He finds that low-liquidity firms with rejected loan applicants increase cash holdings and cut non-cash assets in excess of the requested bank loan amount. As a result, investment and employment decline substantially for these firms.

In turn high-liquidity firms decrease their cash holdings and absorb the credit supply shock without changing their investment, asset growth and employment. He plausibly attributes the underlying mechanism to firms updating their beliefs about the availability of future financing following rejections, and hence leading to increases in firm's targeted level of precautionary savings.

4.3 Research Gaps

This chapter is novel in a number of ways. Firstly, the identification strategy rests on matching on a broad set of outcome-relevant determinants isolating supply effects during the crisis. Secondly, the non-specificity of the survey to a capital type, makes this study robust to substitution effects. Substitution effects could be particularly aggravated in the financial crisis since bank balance sheets were especially weak and at the heart of the crisis. Most studies on real effects of crisis-era capital impairments are focused on bank credit supply shocks, understandably as the bulk of external financing comes from bank loans in all countries (Qian and Strahan, 2007). Often such studies are focused on single-bank (i.e. relationship-bank) firm-level or loan-level data (e.g. Berg, 2018), which cannot account for substitutions between banks¹⁷. While such data is by itself uninformative for all sources of capital firms can substitute for, these studies perform robustness tests using other debt or equity balance sheet information to account for substitution effects. On the other hand, this study is able to more directly account for substitution effects.

Thirdly, a great deal of studies exploring the real effects of credit constraints during the 2008-2009 financial crisis, do not observe whether firms actually applied for financing during the crisis as this study does, and subsequent outcomes. They do however use surveys of corporate perceptions of access to credit (Campello, Graham, and Harvey, 2010), or exploit variations in bank health without loan application data (Balduzzi, Brancati, and Schiantarelli, 2018; Bentolila, Jansen, and Jiménez, 2018; Popov and Rocholl, 2018, Duchin, Ozbas, and Sensoy, 2010), variations in long term debt maturity (Almeida et al., 2009) or other balance sheet items to isolate supply-side effects on real outcomes for firms. Exceptions are (Acharya, Eisert, Eufinger, & Hirsch, 2018) and (Chodorow-Reich, 2014) who utilize syndicated loans¹⁸. However, syndicated loans are often only used by the largest and most bank-dependent firms and results may not be generalizable to most firms in the economy, which are SMEs. In fact, private sector employment declined by 30% more at small firms than larger firms following the Lehman Bankruptcy (Chodorow-Reich, 2014). Hence, this study can observe actual financing applications for a more representative sample of firms in the economy than studies using syndicated loan data.

¹⁷ Exceptions include studies using multiple-bank data (e.g. Acharya et al., 2018) which do not account for other forms of credit or equity firms can substitute for.

¹⁸ Also while (Cingano et al., 2016) use outstanding loan exposure of banks to firms to quantify extent of lending relationships, these do not reveal crisis-era financing applications or demand.

Fourthly, the breadth of the survey during the financial crisis, linked to a long time-horizon of financials, allows to provide various additional tests to explore heterogeneity in firm outcomes following capital constraints.

Finally, most ex-ante studies on real effects of supply contractions during the financial crisis focus on real outcomes of investments and employment (e.g. Chodorow-Reich, 2014; Gertler and Gilchrist, 2018). While corporate investments can be sensitive to liquidity or financial shocks, these do not necessarily affect short-run production which in turn affects firm performance (Cingano, Manaresi, and Sette, 2016). Hence, a remaining question is to what extent do reductions in firm investments due to capital supply contractions reduce firm performance?¹⁹ My matching method and the survey utilized allow me to investigate the effect of hampered investments due to rejection on firm performance.

4.4 Research Design

Estimating the real effects of financial constraints during the financial crisis is complicated by the difficulty of distinguishing between the demand and supply for capital. Recent financial research has made strides in revealing real effects of capital impairments using quasi-causal identification methods that distinguish between capital supply and demand. Most of these studies are focused on bank credit supply shocks, understandably as the bulk of external financing comes from bank loans in all countries (Mayer, 1990; Qian & Strahan, 2007). While the early literature on credit rationing originating from Stiglitz & Weiss (1981) had spurred broader research on real effects of financial constraints (Fazzari, Hubbard, Petersen, Blinder, & Poterba, 1988; Lamon, 1997; Rauh, 2006), this literature has seen a renewed awareness following the 2008-2009 financial crisis specifically investigating the crisis, namely Campello et al. (2010), Almeida et al. (2009), Duchin et al. (2010), Balduzzi et al. (2018). Most of these studies do not observe actual firm applications for financing during the crisis as this study does, and use survey questions on access to credit (Campello et al., 2010), assumptions on supply-side effects of the crisis preceding the demand-side effects (Duchin et al., 2010), or exploit variations in bank health (Acharya et al., 2018; Balduzzi et al., 2018; Bentolila et al., 2018; Chodorow-Reich, 2014; Cingano et al., 2016; Popov & Rocholl, 2018), long term debt maturity (Almeida et al., 2009) or other balance sheet items to isolate supply-side effects on real outcomes for firms.

In this chapter, I take advantage of the ability to observe whether firms during the crisis applied for financing or not, and whether contingent on applying they received it, using a novel matching mechanism, to isolate the real effects of impaired access to capital. This observation, a unique feature of the surveys employed, was exploited for chapter 3 of the thesis as well. Hence, both chapters use different econometric methods (Coarsened Exact Matching in this chapter, and Heckman two-stage sample selection for chapter 3), while exploiting observation of

¹⁹ Most studies on the crisis have looked at the effect of a credit shock on employment (Bentolila, Jansen, and Jiménez, 2018; Balduzzi, Brancati, and Schiantarelli, 2018). A few recent studies have looked at the effect of credit supply contractions to value added (Cingano, Manaresi, and Sette, 2016), firm productivity (Manaresi and Pierri, 2017) or survival (Farinha, Spaliara, and Tsoukas, 2019). However, the author is not aware of any studies explicitly exploring the effect of reduced investments due to capital supply contractions on firm performance -in its most commonly-defined sense-, of firm profitability or return on assets.

the two stages of seeking and obtaining financing. Additionally, this study focuses on all external finance, not just on credit.

Exploiting the EFIGE survey used in Chapter 3, of 14,000 manufacturing firms carried out during the crisis and their matched financials, I utilize matching between capital-seeking firms obtaining external finance and capital-seeking firms that do not, in order to provide a novel means to distinguish between supply and demand, to investigate the effects of financing rejections on firm investments and performance.

4.5 Data

The European Commission's EFIGE (European Firms in a Global Economy) database is employed for the analysis. EFIGE is based on a survey of nearly 15,000 manufacturing firms in seven European countries. These are primarily SMEs, but include nearly 5% large firms²⁰. The survey provides detailed quantitative and qualitative information on a broad range of information related to firm structure, financing, investment, innovation, R&D, internationalization, market and pricing. As the survey has been conducted in early 2010, information is mostly collected as a cross-section for the last available accounting year of 2008, although some questions cover the period 2007-09 and/or the behaviour of firms during the crisis. EFIGE is fully comparable across countries, and stratified by sector, region and firm size (Altomonte and Aquilante, 2012). Firm respondents are matched with fourteen years of balance sheet and income statement data from Amadeus for these firms (from 2001-2014), forming a panel of 14,759 unique firms and 206,626 firm-year observations. Table 4.1 shows the definition of variables from the resulting database used in this study.

The event of interest is the outcome of the application for external capital. This is obtained from responses to the follow-up survey question, asked only of firms who had *"recurred to external financing"*, on whether they *"increased the total amount of external financing (i.e. access to financial funds not generated internally) during the last year (i.e. 2009)?"* Other studies have used these external financing questions in their analyses²¹. Crucially, this study does not inquire as to the magnitude of financing demanded or obtained. Table 4.2 shows the distribution of firms in need of external financing.

To construct the sample, I first restrict the data to all firms whom had a demand for external finance during the crisis. These are identified by those responding positively to the survey question of whether they applied to external financing. Secondly, I require that all firm-year observations have non-missing values for the key income statement item of operating income. Thirdly, I drop firms that are inactive in 2010 and firms that do not have any values for their income statement and balance sheet in any year from 2011 to 2014, so the post-survey data is truly

²⁰ Total assets larger than €43 million in 2009, classified as a large firm as per the EU's definition; see https://ec.europa.eu/growth/smes/business-friendly-environment/sme-definition_en.

²¹ e.g. by (Altomonte, Gamba, Mancusi, & Vezzulli, 2016) to study how firms finance exports or Mahmoudi (2014) to study credit rationing.

informative for firms. This effectively restricts the sample to firms surviving past 2010, necessitating survival analysis (described below).

Fourthly, similar to (M. Lemmon & Roberts, 2010), I create averages of all firm financial statement items for 2006-2008 and 2009-2011, the 3-year period before and after 2009, i.e. the year the survey enquires about, and restrict the analysis to firms with non-missing 3-year average values for sales, total liabilities, operating income cash flow, tangible or intangible fixed assets. This helps create a balanced time frame around 2009.

Finally, I drop any firms that do not have any values for their income statement and balance sheets for the pre-survey-year period of 2006-2008, so the pre-survey data is similarly informative for firms. The final sample comprises of 4,313 firms, for which I use observations from 2006-2014, since financials prior to 2006 are not of interest. All continuous firm-level financial variables are winsorized 0.5% in each tail to lessen the impact of outliers. Table 4.3 describes summary statistics for the unmatched sample.

One immediate concern of the sample selection is survivorship bias. To address this concern, prior to restricting firms to those surviving beyond 2010, a survival analysis is performed to explore the effect of rejection on external financing in 2009 on survival of firms through to 2010 using survey follow-up recordings of firm status in 2010 (see Appendix B, Table B.1). This analysis is performed on the unrestricted sample of capital-seeking firms (i.e. after the first step above). No statistically significant effect of rejection on survival in 2010 is found, indicating that restricting the sample to firms surviving beyond 2010, would not adversely down-weight effects of rejection on investments in my post event sample.

Table 4.1. Variable Definitions

Variable Name	Definition
Ext. Finance Sought	A dummy=1 if firm replied yes to “Did your firm recur to external financing in 2008-2009? By external financing, we mean funds not generated internally (not self-financing)”
Rejection	A dummy=1 if firm replied no to the follow-up question “Has the firm increased the total amount of external financing (i.e. access to financial funds not generated internally) during the last year (i.e. 2009)?”
Log (Sales)	Natural log of a firm’s total turnover (i.e. revenue) in 1,000s of euros.
Size	Natural log of a firm’s total assets in 1,000s of euros
PPE Investments	Annual Change in Tangible Fixed Assets/Lagged Total Assets
Intangible Investments	Annual Change in Intangible Fixed Assets/Lagged Total Assets
ROA	Ratio of operating income (=EBIT) over lagged total assets
Sales growth	Annual Change in Sales/Lagged Sales
Leverage	(Current + Noncurrent Liabilities)/Total Assets
Altman’s Z’-score	A Z-score for private firms following Altman and Hotchkiss (2006)
Firm Size	Natural logarithm of total assets (in 1,000s of euros)
Cash Flow	A standardized measure of Cash Flow/Lagged Total Assets
Asset Tangibility	Tangible Fixed Assets/Fixed Assets
Current Ratio	= Current Assets/Current Liabilities
Public	=1 if a firm is public
Distress Indicator	A dummy =1 if in a year either i) the firm’s EBITDA is less than it’s reported interest paid for the prior 2 years, or ii) EBITDA is lower than 80% of its interest paid in the past year.
Pre-2009 Investments	Average PPE or Intangible Investments over 2006-2008
R&D Intensity	Average percentage of turnover invested in R&D in 2007-2009
Asset Turnover	= Sales/Total Assets
Active in 2014	= 1 if firm is active in 2014 (reorganizations and acquired firms are coded as active)
Reduced investment in 2009	=1 if firm reduced its PPE or Intangible Investments in 2009
Economies of Scale Industries	=1 if firm’s NACE code of firm (3-digits) would classify it as an “Economy of Scale” manufacturing firm according to Pavitt (1999)
Traditional Industries	=1 if firm’s NACE code of firm (3-digits) would classify it as an “Traditional” manufacturing firm according to Pavitt (1999)
Specialized Industries	=1 if firm’s NACE code of firm (3-digits) would classify it as an “Specialized” manufacturing firm according to Pavitt (1999)
High-Tech Industries	=1 if firm’s NACE code of firm (3-digits) would classify it as an “High-Tech” manufacturing firm according to Pavitt (1999)
Employees	No. of Firm Employees
Operating Income	Total operating revenues (Net sales + Other operating revenues+ Stock variations). The figures do not include VAT.
Fixed Assets	Total amount (after depreciation) of non-current assets (Intangible assets + Tangible assets + Other fixed assets).
Tangible Fixed Assets	All tangible assets such as buildings, machinery, etc.
Intangible Fixed Assets	All intangible assets such as formation expenses, research expenses, goodwill, development expenses and all other expenses with a long term effect
Other Fixed Assets	All other fixed assets such as long term investments, shares and participations, pension funds etc.

Table 4.2. Distribution of firms' external financing demand and supply

Applied for External Financing?		
	Number	Percentage of Total
Yes	6,344	43.0%
No	7,856	53.2%
Do not know/Did not answer	556	3.8%
Total	14,759	100.0%

Raised External Financing?		
	Number	Percentage of Applicants
Yes	2,692	42.4%
No	3,636	57.3%
Do not know/Did not answer	16	0.3%
Total	6,344	100.0%

Table 4.3. Data Summary Statistics

Values correspond to years 2006 through 2011 for the unmatched and matched samples.

	Unmatched Sample (No. of Firms = 4,313)					Matched Sample (No. of Firms = 1,894)				
	Mean	SD	25 th Pctl.	Median	75 th Pctl.	Mean	SD	25 th Pctl.	Median	75 th Pctl.
Dependent Variables:										
Gross PPE (%)	6.66	12.01	1.04	3.10	7.48	5.90	8.85	1.29	3.07	6.74
Gross FA (%)	7.10	13.24	0.96	3.30	8.27	6.18	9.72	1.18	3.18	7.37
Net PPE (%)	2.01	11.24	-2.32	-0.45	2.40	1.67	8.39	-1.87	-0.33	2.09
ROA	0.05	0.25	0.01	0.04	0.08	0.05	0.08	0.02	0.04	0.07
Active in 2010	1.00	0.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00	1.00
Active in 2014	0.90	0.29	1.00	1.00	1.00	0.90	0.29	1.00	1.00	1.00
Independent Variables:										
Sales Growth	0.05	0.32	-0.10	0.03	0.16	0.04	0.25	-0.09	0.04	0.16
Cash Flow	0.06	0.09	0.02	0.06	0.10	0.06	0.07	0.03	0.05	0.09
Distress Indicator	0.23	0.42	0.00	0.00	0.00	0.21	0.41	0.00	0.00	0.00
Altman's Z'-Score	2.24	0.88	1.65	2.15	2.76	2.23	0.77	1.69	2.15	2.70
Sales	8.25	1.34	7.39	8.07	8.90	8.20	1.05	7.51	8.10	8.73
Current ratio	1.59	1.21	1.02	1.30	1.79	1.61	1.13	1.05	1.33	1.81
Liquidity ratio	1.11	1.42	0.62	0.88	1.28	1.13	1.54	0.65	0.89	1.29
Current asset reduction	-0.02	0.30	-0.12	-0.00	0.11	-0.01	0.20	-0.11	0.00	0.10
Reduced investment plans in 2009	0.47	0.50	0.00	0.00	1.00	0.47	0.50	0.00	0.00	1.00
<i>Firm Age in 2010:</i>										
< 6 Years	0.06	0.24	0.00	0.00	0.00	0.04	0.19	0.00	0.00	0.00
6-20 Years	0.38	0.48	0.00	0.00	1.00	0.37	0.48	0.00	0.00	1.00
> 20 Years	0.56	0.50	0.00	1.00	1.00	0.60	0.49	0.00	1.00	1.00
<i>Main Growth Obstacles:</i>										
Financial Constraints	0.41	0.49	0.00	0.00	1.00	0.41	0.49	0.00	0.00	1.00
Labour Market Regulation	0.29	0.45	0.00	0.00	1.00	0.31	0.46	0.00	0.00	1.00
Legislative or Bureaucratic Restrictions	0.30	0.46	0.00	0.00	1.00	0.31	0.46	0.00	0.00	1.00
Lack of Management and/or Organizational Resources	0.18	0.39	0.00	0.00	0.00	0.19	0.39	0.00	0.00	0.00
Lack of Demand	0.55	0.50	0.00	1.00	1.00	0.58	0.49	0.00	1.00	1.00
Other SME Characteristics:										
Employees	70.88	357.51	15.00	24.00	45.00	45.82	190.11	15.00	23.50	39.00
Sales (€m)	13.44	43.45	1.61	3.21	7.30	8.37	27.02	1.82	3.30	6.16

Operating Income (€m)	0.48	2.60	0.02	0.10	0.30	0.30	1.66	0.03	0.11	0.25
Fixed Assets (€m)	4.66	16.88	0.30	0.84	2.49	2.69	11.62	0.31	0.76	1.84
Tangible Fixed Assets (€m)	3.25	10.65	0.21	0.63	2.00	1.95	7.22	0.21	0.58	1.53
Intangible Fixed Assets (€m)	0.32	1.54	0.00	0.02	0.12	0.17	0.92	0.00	0.02	0.09
Current Assets (€m)	7.39	23.82	0.85	1.81	4.41	4.79	15.77	1.02	1.91	3.81
Current Liabilities (€m)	5.55	17.22	0.59	1.33	3.36	3.59	11.15	0.69	1.38	2.83
Leverage	0.69	0.23	0.54	0.70	0.84	0.69	0.22	0.55	0.71	0.85

4.6 Methodology

This section describes the empirical strategy by explaining the matching strategy, how the main dependent variable of investments is measured and the exact empirical specifications.

4.6.1 Matching Procedure

In order to control for observable differences between comparable successful and unsuccessful firms in external financing applications, I use a matching procedure on my sample of firms all of whom applied for external financing in 2009. This enables distinguishing between supply-side and demand-side effects and isolating effects of impaired access to capital by exploiting supply heterogeneity. To this end, the control group are capital-seeking firms who obtained financing in 2009 -the event date- and the treated group are comparable capital-seeking firms who did not obtain it in 2009 (i.e. were rejected)²². The matching is done with the aim of identifying firms that are observably similar along pre-event investment-relevant dimensions, in such a way as to impose the least functional-form assumptions on the data. Notably, matching procedures have been used in the corporate finance literature to measure investment differences between public or private firms (e.g. Asker et al., 2015), or unrated and speculative grade firms (e.g. Lemmon and Roberts, 2010).

The matching dimensions I employ follows the most stringent match performed by Asker et al. (2015) who use size and industry as their baseline match, and add leverage, sales growth, ROA and cash as the most stringent dimensions they match on for robustness purposes. I additionally match on firm creditworthiness, proxied for by creating yearly Altman Z'-scores for firms in my sample following Altman and Hotchkiss (2006), using available balance sheet and income statement information²³. This matching is done on average of financials for three-years prior to the event date (similar to Lemmon and Roberts, 2010). Differences in sector structure across the treatment and control groups may raise a concern that the control group would not be an appropriate counterfactual. To alleviate this concern, as per Cerqueiro et al. (2016), I perform exact matching on sector. To ensure matched firms are not different in investment levels, I also match on PPE Investments prior to the event date. This teases out prior differences in PPE investments, which could be endogenous to the financiers' decision to extend financing.

²² Assignment of treatment to *rejection*, as opposed to success, in obtaining financing is a choice made to align with (Berg, 2018), who similarly focuses on the real effects of getting *rejected*.

²³ Altman's Z-score is used extensively in corporate finance literature as a proxy for credit-worthiness of firms (see Lemmon and Roberts, 2010; Mohsni and Otchere, 2014). The Z'-score is put forth by Altman and Hotchkiss (2006) especially devised for private firms, and is equal to $0.717 \times X1 + 0.847 \times X2 + 3.107 \times X3 + 0.42 \times X4 + 0.998 \times X5$, where X1, X2, X3 and X5 are respectively measures of firm liquidity, retained earnings, operating income, and sales, standardized by total assets, and X4 is book value of equity, standardized by total equity.

Table 4.4 provides pairwise comparisons of sample means both prior to matching and after matching, for the treated and control groups. Beyond the exact matching performed on the eleven sectors of manufacturing firms in the data, I employ a coarsened exact matching (CEM) algorithm to match on PPE investments, firm size (or log of assets), ROA, leverage and sales growth.

A key practical difference of CEM lies in the data processing order; whereas propensity score matching (PSM) requires ex-ante determination of the size of the matched control sample and ensures balance ex-post, CEM performs balancing ex ante (Iacus, King, and Porro, 2012; Aggarwal and Hsu, 2014). It does this via “coarsening” a set of observed variables, exact matching on the coarsened data, performing data “pruning” so that matching strata have at minimum a control and treatment observation, before running estimations. CEM also has the advantage of effectively matching with replacement, meaning one observation can be used more than once as a control or a treated firm. This can allow for better matches, less bias, has lower data requirements and is not sensitive to the order in which treatments observations are matched, albeit at the expense of precision (Rosenbaum, 1995; Roberts and Whited, 2013). In corporate finance applications, matching with replacement is preferred (Roberts and Whited, 2013). Iacus et al. (2011) note that CEM constitutes part of a broad class of methods called “monotonic imbalance bounding” or MIB, having beneficial statistical characteristics, such as more balance and estimates of causal quantity of interest having lower root mean square errors, compared to “equal percent bias reducing” (EPBR) models (Rubin, 1976) such as PSM. MIB eliminates many assumptions needed for unbiased estimates of treatment effects and outperforms EPBR in most situations (see Iacus et al., 2011, 2012). I follow the Stata CEM software implementation described in detail by Blackwell et al. (2009).

Sales growth proxies for investment opportunities, which is the most widely used measure in the investment literature for private firms (e.g. Asker et al., 2015; Bloom et al., 2007; Michaely and Roberts, 2012). Prior to matching, control firms have higher *leverage* and *assets* and lower *ROAs* (Return on Assets). The employed CEM procedure reduces these differences, so that the t-tests show insignificant differences in the matched sample. Differences in means of other dimensions likely to affect rejection in external finance applications or investment levels (*Altman’s Z’-score*, *sales*, *cash flow*, *asset tangibility*, *public* status and technological class) of firms are also shown to become insignificant at the 5% level for treated and control groups. All matching variables are measured prior to the treatment in 2009 to ensure matching covariates are unaffected by the treatment itself. Following a guideline by Heckman et al. (1998) through ensuring that there are no significant differences along a rich set of variables related to the treatment (financing rejection) and outcomes (investment primarily and ROA secondarily), I attempt to absorb all outcome relevant heterogeneity with observable measures, to help identify the treatment. The final matched sample contains 1,894 firms, consisting of 1,018 treated or rejected firms and 876 control firms. Table 4.3 describes summary statistics for the matched sample.

Table 4.4. Pre-Rejection Pairwise T-test Comparisons for Treated and Control Groups

Means are averaged over years 2006 to 2008, three years prior to the rejection of financing application. The symbols ***, ** and * mean that the reported difference in means are significant, respectively, at the 0.1, 1 and 5 percent level.

	Unmatched Sample (4,313 Firms)			Matched Sample (1,894 Firms)		
	Control	Treated	Diff.	Control	Treated	Diff.
No. of Firms:	1,884	2,429		876	1,018	
Financial/Investment Characteristics:						
PPE Investments (%)	9.67	8.35	1.33***	6.67	6.34	0.33
Intangible Investments (%)	-0.06	0.00	-0.06	-0.03	-0.07	0.04
Size	8.14	8.07	0.08	8.07	8.01	0.06
Sales growth	0.12	0.11	0.01	0.08	0.08	0.00
ROA	0.10	0.11	-0.01***	0.10	0.10	-0.00
Leverage	0.71	0.68	0.03***	0.70	0.69	0.01
Altman's Z-score	2.26	2.43	-0.17***	2.31	2.38	-0.07
Sales	8.35	8.32	0.03	8.30	8.24	0.06
Cash Flow	0.08	0.08	-0.01**	0.07	0.07	-0.00
Asset Tangibility	0.28	0.26	0.02***	0.25	0.24	0.01
Public	0.01	0.01	-0.00	0.01	0.01	0.00
Firm Age:						
< 6 Years	0.07	0.06	0.01	0.03	0.04	-0.00
6-20 Years	0.38	0.37	0.01	0.37	0.37	0.00
> 20 Years	0.55	0.57	-0.02	0.59	0.59	0.00
Technological Class:						
Economies of Scale Industries	0.238	0.241	-0.00	0.215	0.208	0.01
Traditional Industries	0.534	0.566	-0.03*	0.601	0.627	-0.03
Specialized Industries	0.196	0.156	0.04***	0.164	0.143	0.02
High-Tech Industries	0.032	0.037	-0.01	0.020	0.023	-0.00

4.6.2 Measures of Investment

I measure investment following Asker et al. (2015) where Gross investment, is defined as the annual increase in net fixed assets recorded on the balance sheet plus depreciation scaled by lagged total assets. To the extent in which accounting depreciation rates and schedules can be somewhat arbitrary, gross investment captures a firm's investment decisions better. I measure three categories of investments, one of gross tangible or *PPE* (property, plant and equipment) *investments*, one of *gross fixed assets (Gross FA)*

which includes intangible fixed assets as well, and one of *Net PPE*, which does not add back depreciation²⁴. Intangible fixed assets include research expenses, formation expenses, goodwill, development expenses and all other expenses with a long term effect. For detailed definitions of these and other variables, see Table 4.1.

4.6.3 Empirical Specification

I follow the investment regression model used by Asker et al. (2015) who compare investment behaviour of observably similar private and public firms conditioning for investment opportunities, with my treatment variable being rejection in external financing application. While their conditional model uses Ordinary Least Squares (OLS) given their matched firms are either private or public, I am able to include firm fixed effects to control for unobserved time-invariant heterogeneity at the firm level. Crucially, regressions are once run as a panel model with firm fixed effects and once as an OLS model with averaged financials for pre- and post-2009. Equation (3) presents the firm fixed effects model:

$$Inv_{it} = \alpha Rejection_i \times Post_t + \beta Sales\ growth_{it} + \delta ROA_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (3)$$

where i and t are indices for firms and fiscal years, respectively. Inv_{it} is an investment measure, standardized by lagged total assets, being either Gross PPE Investments (*Gross PPE*), Gross Fixed Asset (*Gross FA*) or Net PPE Investments (*Net PPE*), *Rejection* is a dummy for whether the applying firm was unsuccessful in obtaining external financing, and ROA is defined as operating income standardized by lagged total assets²⁵. Firm fixed effects, μ_i , remove unobserved time-invariant firm-level heterogeneity and year fixed effects, η_t , control for common trends. Controlling for firm and year fixed effects, the estimator for the interaction variable of *Rejection* $\times$ *Post* would capture changes in investments due to financing rejection. I estimate the effects of *rejection* on post-rejection *investments* for time periods of three- and two-years following the rejection event. So the firm-year observations for the panel model once run from 2006 to 2011 and once from 2006 to 2010.

²⁴ *Gross PPE* is a gross investment measure, because depreciation is added back to the annual change in tangible fixed assets, before being scaled by lagged assets. Gross investments is advantageous over capital expenditure since firms can also grow their assets by purchasing other firms' existing assets through acquisitions. Firms can also sell their tangible fixed assets, so the PPE investments measure can be negative. (Denis & Sibilkov, 2010) drop firm-year observations with negative Capital Expenditures, and we follow their methodology since we are interested in predicting effect of rejection on actual investments of firms, not on their occasional asset divestitures or write-downs. This drops fewer than 7.5% of firm-year observations in our sample, but for robustness we also explore results including all firm-year observations. (Asker et al., 2015) also drop 15% of private firms whose data violates basic accounting identities.

²⁵ Asker et al. (2015) explain that prior research shows that investment opportunities are not sufficient in predicting investment and that ROA is positively correlated with investment, and hence justify conditioning on ROA as well. I follow their specification, while there is debate as to whether ROA captures financing constraints or not (see Kaplan and Zingales, 1997).

Since owing to missing SME financials in certain years a small percentage of firm-year observations may drop out in panel models, the following OLS model is run with averaged financials for pre- and post-2009 to provide greater robustness to the main analysis:

$$Inv_{i,t} = \alpha Rejection_i + \beta Sales\ growth_{i,t} + \delta ROA_{i,t-1} + Inv_{i,t-1} + \varphi_j + \gamma_{c(i)} + \varepsilon_{it} \quad (4)$$

where j and $c(i)$ used as indices for sectors and firm-headquarter countries, and $t-1$ and t instead correspond to a pre-2009 time period (corresponding to three-year averages²⁶) or a post-2009 time period (corresponding to two- or three-year averages). In equation 4, $Inv_{i,t-1}$ controls for pre-2009 investment levels of each firm, proxying for firm-specific time-invariant investment propensity independent of the rejection event. Sector dummies, φ_j , remove unobserved industry-level heterogeneity and country dummies, $\gamma_{c(i)}$, remove unobserved country-level variations in investments.

Finally, I use ROA to measure for firm performance. To measure effects of external financing rejection on ROA, I control for *sales growth* and additionally control for *leverage*, *sales*, and lagged ROAs, as per the corporate finance literature (Delis, Kokas, and Ongena, 2017; Hauser, 2018; Adams, Almeida, and Ferreira, 2005). Particular attention is paid to the effect of *reduced investment plans* in 2009 due to rejection, derived from a survey question, on firm performance. Panel model regressions estimating ROA are run similar to the main investment estimation Equation (3). However, since the effects of rejection on firm performance due to lowered investments is thought to manifest itself over a longer period from the rejection date, for this model, firm-year observations run from 2006 to 2014.

4.7 Results

4.7.1 Effects of Rejection on Investments

In Table 4.5, I present the estimation results. The baseline model, as specified in equation (3), estimates the effect of rejection on annual investments. All columns use the baseline model. Estimates of the effect of rejection on future investments remain significant and negative. The magnitude of the estimates show that rejection from the external financing application, results in a 0.8 and 1.4 reduction in the *Gross PPE* measure, respectively 3- and 2-years after 2009, which are equivalent to a 12.6% and 22.1% decline respectively relative to the pre-2009 treated subsample investment mean (which is 6.34 as per Table 4.4). These estimates are statistically significant at the 5% level for the 3-year effects and 1% level for the 2-year effects. The proxy for investment opportunities, *sales growth*, and *ROA* are statistically significant at 1% in most regressions and positive, as expected. Columns 2 and 4 regress *Gross Fixed Assets* instead, and

²⁶ Averaging financial items over 3- or 4-year periods is common in corporate finance literature. While Lemmon and Roberts (2010) average financials over 4- years, I average over 3- and 2-years as it this is deemed most appropriate for SMEs in the sample.

show estimates slightly higher in magnitude of approximately 0.9 and 1.5 respectively. This shows robustness of the main result to inclusion of intangible fixed assets in the dependent variable, and suggests intangible capital may be hampered as well due to the rejection. Columns 3 and 6 regress *Net PPE* and find similar effects, indicating that the main result is not sensitive to adding back the depreciation item to changes in tangible fixed assets.

For robustness in the Appendix Table B.2, a number of additional controls are added to the baseline model, which are used by Lemmon and Roberts (2010) to control for a range of investment policies such as *cash flow*, *log of sales*, an indicator variable measuring whether a firm is *distressed* or not²⁷. While not shown, these regressions are robust to substituting for this threshold distress variable with *Altman's Z'-score*, a continuous measure for creditworthiness and cost of bankruptcy of firms. The estimate magnitude and significance of the effect of rejection slightly increase, while the *cash flow* and *sales* variables become positive and significant, accounting for the effects of short term liquidity and firm size respectively on driving investments. For robustness, Table B.3 includes firm-year observations with negative capital expenditures (fewer than 7.5% of observations) when estimating equation (3). These were dropped in the main analyses following the methodology of (Denis & Sibilkov, 2010). While negative in magnitude, results are not significant for the 3-year period post-2009, but are significant at 1% for 2-years following 2009. The associated R-squared noticeably drops for these specifications (from 28% to 25% for the 3-year effect, and from 32% to 28% for the 2-year effect), meaning the model cannot account for as large of the variations, when including occasional asset divestitures or write-downs.

Consistently estimates are greater in magnitude for the 2-year post-2009 event window. This suggests a more immediate effect of rejection on investments, which indicates that rejection from external financing applications in 2009 acted like a true shock. These effects are for inability to obtain financing just for one year, at the height of the financial crisis. Given that the EFIGE survey does not follow up on firms' financing applications in subsequent years, these effects may act as lower-bounds to persistent real effects of rejection on firm investments.

For additional robustness, Table 4.6 shows the results of estimating Equation (4) by running a cross-sectional analysis in which t and $t-1$, are respectively the pre- and post-event 3-year periods of 2006-2008 and 2009-2011 (or 2009-2010). Columns 1 to 3 capture average effects in a balanced time horizon of three years before and after the event. Since firm fixed effects cannot be included, the pre-2009 level of the investment measure being estimated, controls for firm-specific time-invariant investment propensity. The results of this model are shown in Table 4.6. Table 4.6 increases confidence in reliability of estimates via averaging over three years and reduces the effects of missing yearly observations, volatility and outliers

²⁷ Lemmon and Roberts (2010) term “kitchen-sink” specification for models with many controls, yielding more conservative estimates in terms of magnitude and statistical significance.

in income statement items during the post-event period, such as *ROA* or *sales growth* on any firm's predicted investment level in the model.

The magnitude of the treatment variable of *rejection* is within the confidence interval of the estimation in Table 4.5. For the 3-year post-2009 effects, the significance is at 10% in regressing gross investments in columns 1 and 2, and 5% for *Net PPE*. Similarly, the magnitude for the two year post-2009 effects are greater and significant at 1%. The baseline regression robust to inclusion of additional controls used by Lemmon and Roberts (2010), as can be seen in Appendix Table B.4. While not shown, all the main results hold using operating income before depreciation, for *ROA* in the regressions.

4.7.2 *Cushioning Effect of Liquidity*

To test whether liquidity can cushion some of the negative effects of external financing rejection on investments, I add an interaction term of pre-2009 firm liquidity -*Current Ratio*- times the *post* indicator, to the model in Equation (3). Table 4.7 shows the results of these regression. As before, columns 1 to 3 (or columns 4 to 6) respectively measures effects up to 3-years (or 2-years) after the rejection. While as in Table 4.5, rejection reduces investments post-2009, the interaction of *current ratio* with *post* is positive and statistically significant at 1% in all regressions. Pre-2009 liquidity does increase investments after the financing application, regardless of the outcome. The coefficient is also economically significant: A one standard deviation increase in pre-2009 *Current ratio*, increases post-rejection *Gross PPE* by 10% (or 12%) of its mean pre-2009 value 3-years (or 2-years) following rejection. Results for 2-years after rejection are robust to substituting *Liquidity ratio* for *Current ratio* (see Appendix B, Table B.5).

While results demonstrate that pre-application liquidity increases post-financing investments, an open question is how this tendency varies for rejected versus funded firms. To test this I interaction the double-interaction in Table 4.7 with the rejection dummy. Table 4.8 presents the results. The coefficient of the resulting triple-interaction is negative and statistically significant at the 5% or 10%-level in most specifications. The economic magnitude suggests that rejection reduces the cushioning effect of pre-application liquidity by 12.5%. This means while pre-application liquidity increases post-financing investments, rejection lowers this tendency. This could be explained by rejection during the crisis increasing the marginal benefit of maintaining liquidity for firms. These results are consistent with literature highlighting a higher marginal benefit of cash holdings for firms following financial crises (Bliss, Cheng, and Denis, 2015; Pinkowitz, Stulz, and Williamson, 2013; Song and Lee, 2012). These findings are also consistent with findings of (Berg, 2018) that loan rejection decreases a firm's belief about the availability of future financing and thus, increases their targeted level of precautionary savings.

Firms cushion the effects of rejection on investment by reducing their pre-application current assets (i.e. inventories, receivables and cash and marketable securities). They do this by selling inventories,

collecting their receivables or using their cash and marketable securities. When reducing their current assets, firms have two options: They can either use them to pay out current liabilities or use them for investments in fixed assets. One would expect rejected firms with low working capital (i.e. current assets – current liabilities; equivalent to firms with low *Liquidity ratios*) to use current asset drawdowns more for the former (i.e. paying out current liabilities) and less for investments than rejected high-liquidity firms, and vice-versa for high working capital firms. I investigate this in Table 4.9, by interacting *Liquidity ratio* with *rejection* with *current asset reductions* (i.e. reductions in current assets in 3-year post- and pre-2009 periods, standardized by total assets) in regressing investment measures. This table uses an OLS regression, since *current asset reductions* is a cross-sectional variable. The triple-interaction term is positive and statistically significant at 10% in most specifications, which supports the assertions: Rejected high-liquidity firms that cut their current assets, invest more than rejected low-liquidity firms that cut their current assets by an equal amount. By inference, low liquidity firms would be more likely to use cuts in current assets for paying their current liabilities.

Table 4.5. Effects of Financing Rejection on Investments

This table reports the results of estimating investment Equation (3). Models are fixed effects models and their associated R-squared are reported. Data are from Amadeus and EFIGE for the period 2006 to 2011 for columns 1 to 3, and for the period 2006 to 2010 for columns 4 to 6. Firm-year observations with negative capital expenditures are excluded. Standard errors, clustered at the firm level, are reported in parentheses. The symbols ***, ** and * mean that the reported coefficients are statistically different from zero, respectively, at the 1, 5 and 10 percent level.

<i>Inv. measure:</i>	3-years post-2009 effects			2-years post-2009 effects		
	Gross PPE	Gross FA	Net PPE	Gross PPE	Gross FA	Net PPE
	(1)	(2)	(3)	(4)	(5)	(6)
Rejection x Post	-0.815** (0.400)	-0.877** (0.427)	-0.794** (0.386)	-1.380*** (0.477)	-1.462*** (0.503)	-1.376*** (0.458)
Sales Growth	1.322** (0.487)	1.630*** (0.561)	0.496 (0.469)	1.359** (0.628)	1.669** (0.713)	0.564 (0.605)
ROA	6.727*** (1.659)	6.635*** (1.863)	7.720*** (1.660)	7.982*** (2.166)	7.741*** (2.428)	8.612*** (2.138)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	9,853	9,853	9,853	8,359	8,359	8,359
R-Squared	28%	26%	24%	32%	30%	28%

Table 4.6. Average Effects of Financing Rejection on Investments

This table reports the results of estimating investment Equation (4). All models are OLS models and their associated R-squared are reported. Data are from Amadeus and EFIGE for the period 2006 to 2011 for columns 1 to 3, and for the period 2006 to 2010 for the columns 4 to 6. The Pre-2009 Investments variable is calculated by averaging for PPE investments in 2006 to 2008, and the other variables are averaged over the subsequent 3-years for columns 1 to 3, or 2 years columns 4 to 6. Standard errors, clustered at the firm level, are reported in parentheses. The symbols ***, ** and * mean that the reported coefficients are statistically different from zero, respectively, at the 1, 5 and 10 percent level.

<i>Inv. measure:</i>	Average 3 years post-2009			Average 2 years post-2009		
	Gross PPE	Gross FA	Net PPE	Gross PPE	Gross FA	Net PPE
	(1)	(2)	(3)	(5)	(6)	(7)
Rejection	-0.521*	-0.588*	-0.543**	-1.272***	-1.295***	-1.244***
	(0.285)	(0.308)	(0.267)	(0.375)	(0.402)	(0.343)
Sales growth	5.850***	5.392***	4.038***	5.584***	5.237***	3.516***
	(1.052)	(1.104)	(0.988)	(1.295)	(1.416)	(1.205)
ROA	5.396***	5.046**	8.756***	6.990***	5.929**	11.063***
	(1.898)	(2.019)	(1.978)	(2.265)	(2.708)	(2.271)
Pre-2009 investments	0.079***	0.083***	-0.019	0.081**	0.100***	-0.023
	(0.025)	(0.031)	(0.027)	(0.032)	(0.038)	(0.028)
Constant	3.261***	4.652***	-0.400	5.472***	5.438***	1.414
	(1.098)	(1.250)	(0.491)	(0.890)	(1.058)	(0.892)
Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	1,894	1,894	1,894	1,715	1,715	1,695
R-Squared	8%	6%	5%	6%	5%	4%

Table 4.7. Cushioning Effect of Liquidity on Investments

All models are fixed effects models and their associated R-squared are reported. Data are from Amadeus and EFIGE for the period 2006 to 2011 for columns 1 to 5, and for the period 2006 to 2010 for column 6. Firm-year observations with negative capital expenditures are excluded. Standard errors, clustered at the firm level, are reported in parentheses. The symbols ***, ** and * mean that the reported coefficients are statistically different from zero, respectively, at the 1, 5 and 10 percent level.

	3-years post-2009 effects			2-years post-2009 effects		
	Gross PPE	Gross FA	Net PPE	Gross PPE	Gross FA	Net PPE
	(1)	(2)	(3)	(4)	(5)	(6)
Current ratio x post	0.721*** (0.207)	0.785*** (0.218)	0.689*** (0.203)	0.821*** (0.219)	0.825*** (0.234)	0.790*** (0.222)
Rejection x post	-0.877** (0.398)	-0.945** (0.425)	-0.854** (0.384)	-1.458*** (0.476)	-1.541*** (0.503)	-1.451*** (0.457)
Sales growth	1.223** (0.486)	1.522*** (0.561)	0.402 (0.469)	1.240** (0.625)	1.549** (0.710)	0.450 (0.603)
ROA	7.235*** (1.666)	7.189*** (1.874)	8.206*** (1.663)	8.592*** (2.181)	8.354*** (2.445)	9.200*** (2.147)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,853	9,853	9,853	8,359	8,359	8,359
R-Squared	28%	26%	24%	32%	30%	28%

Table 4.8. Effect of Rejection on Cushioning Effect of Liquidity on Investments

All models are fixed effects models and their associated R-squared are reported. Data are from Amadeus and EFIGE for the period 2006 to 2011 for columns 1 to 5, and for the period 2006 to 2010 for column 6. Firm-year observations with negative capital expenditures are excluded. Standard errors, clustered at the firm level, are reported in parentheses. The symbols ***, ** and * mean that the reported coefficients are statistically different from zero, respectively, at the 1, 5 and 10 percent level.

	3-years post-2009 effects			2-years post-2009 effects		
	Gross PPE	Gross FA	Net PPE	Gross PPE	Gross FA	Net PPE
	(1)	(2)	(3)	(4)	(5)	(6)
Current ratio x post x rejection	-0.809*	-0.934**	-0.646	-1.108**	-0.932	-0.938*
	(0.434)	(0.455)	(0.420)	(0.547)	(0.578)	(0.529)
Current ratio x post	1.306***	1.417***	1.182***	1.584***	1.467***	1.436***
	(0.346)	(0.363)	(0.335)	(0.496)	(0.522)	(0.470)
Rejection x post	0.716	0.885	0.480	0.200	-0.146	-0.048
	(0.834)	(0.868)	(0.810)	(1.016)	(1.056)	(0.975)
Sales growth	1.784***	1.767***	0.991**	1.232**	1.543**	0.443
	(0.461)	(0.524)	(0.452)	(0.624)	(0.710)	(0.601)
ROA	7.132***	6.891***	8.335***	8.714***	8.456***	9.302***
	(1.584)	(1.844)	(1.597)	(2.178)	(2.441)	(2.145)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,853	9,853	9,853	8,359	8,359	8,359
R-Squared	25%	24%	21%	32%	30%	28%

Table 4.9. Liquidity Sensitivity of Allocation of Pre-2009 Current Assets to Investments

All models are OLS models and their associated R-squared are reported. Data are from Amadeus and EFIGE for the period 2006 to 2011. The *Liquidity ratio* and *Pre-2009 investments* are calculated by averaging for 2006 to 2008, and the other variables are averaged over the subsequent 3-years, i.e. 2009 to 2011 (columns 1 to 3) or 2-years, i.e. 2009-2010. Standard errors, clustered at the firm level, are reported in parentheses. The symbols ***, ** and * mean that the reported coefficients are statistically different from zero, respectively, at the 1, 5 and 10 percent level.

	Average 3 years post-2009			Average 2 years post-2009		
	Gross PPE	Gross FA	Net PPE	Gross PPE	Gross FA	Net PPE
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity ratio x rejection x current asset reductions	3.233 (2.147)	4.074* (2.385)	3.132* (1.854)	5.522* (2.835)	6.072* (3.137)	4.661* (2.603)
Liquidity ratio x rejection	-0.951** (0.410)	-0.940** (0.460)	-0.812** (0.380)	-0.837 (0.521)	-0.823 (0.582)	-0.755 (0.487)
Liquidity ratio x current asset reductions	-1.918 (1.830)	-2.643 (2.069)	-1.683 (1.557)	-4.347* (2.477)	-4.615* (2.790)	-3.361 (2.261)
Rejection x current asset reductions	-4.133 (2.541)	-3.926 (2.797)	-2.910 (2.285)	-5.056 (3.337)	-4.497 (3.679)	-3.141 (3.129)
Liquidity ratio	0.745* (0.392)	0.700 (0.442)	0.662* (0.363)	0.611 (0.497)	0.550 (0.555)	0.590 (0.462)
Rejection	0.429 (0.527)	0.334 (0.580)	0.211 (0.508)	-0.385 (0.669)	-0.426 (0.705)	-0.562 (0.644)
Current asset reductions	1.567 (2.023)	1.610 (2.262)	0.664 (1.755)	2.764 (2.652)	2.774 (3.021)	1.758 (2.401)
Sales growth	5.049*** (1.081)	4.975*** (1.201)	3.162*** (1.010)	4.936*** (1.430)	4.728*** (1.559)	3.001** (1.342)
ROA	5.810*** (2.011)	5.120** (2.263)	9.322*** (1.967)	5.941** (2.348)	5.112* (2.792)	11.039*** (2.427)
Pre-2009 Investments	0.075*** (0.025)	0.081** (0.032)	-0.051* (0.028)	0.079** (0.032)	0.098** (0.038)	-0.030 (0.037)
Constant	3.270*** (0.782)	3.870*** (0.621)	-0.289 (0.771)	3.753*** (0.715)	4.573*** (0.759)	-0.073 (0.704)
Sector & Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,894	1,894	1,894	1,711	1,715	1,711
R-Squared	8%	7%	7%	7%	6%	6%

4.7.3 Effects of Rejection on Firm Performance

As described in the empirical specification, measurement of firm performance is carried out by regressing ROA on *lagged ROA, sales, firm size, leverage, asset turnover, R&D intensity, pre-2009 PPE investments*, as well as *firm age*, which the corporate finance literature has found to be relevant. Column 1 in Table 4.10 describes the results of a panel specification. No statistically significant effect of rejection in external financing applications in 2009 is found on firm ROA. However, column 2 in Table 4.10 interacts *rejection* $\times$ *post* with an indicator variable for firms that actually reduced their planned PPE investments in 2009 and shows that while the effect of rejection on average on ROA may not be statistically significant in column 1, firms that reduced their planned PPE investments and were rejected fared worse than those that were not rejected and reduced their planned PPE investments. Results are robust to measuring ROA as net income over total assets. This shows that the effect on firm performance is through a lower investment channel.

Firms face various growth obstacles in their operations and development. If investments are impaired for capital-seeking rejected firms, then the effect of reduced investments on performance must be larger for firms for which financial constraints are the main obstacle to growth. Hence, in columns 3 and 4 of Table 4.10, I utilize answers to an EFIGE survey question on “*Indicate the main factors preventing the growth of your firm*”, and split the sample of firms responding to this, to those mentioning “financial constraints” as a response and those that do not²⁸. Such perceptions of financial constraints as an obstacle have been found to be good proxies for actual financing constraints (Ferrando and Mulier, 2015) and have been to investigate real effects of financial constraints (e.g. Campello, Graham, and Harvey, 2010). Indeed, financially-constrained rejected firms that reduced their investments in 2009, experienced greater reductions to their firm performance (the triple interaction is negative and significant only for firms specifying financial constraints as a main growth impediment. Findings in this section indicate that firm performance was hit worse for firms that reduced their investments following rejection and who were most financially-constrained. These results verify that the identification method used is able to identify real effects of capital constraints during the 2008-2009 recession.

²⁸ Survey conductors would code factors which respondents would mention into six categories of “*financial constraints, labour market regulations, legislative or bureaucratic restrictions, lack of management and/or organisational resources, lack of demand, or other*”. Multiple answers were possible. Please note the sample size is reduced because responses from 519 Spanish firms were not available.

Table 4.10. Effect of External Finance Rejection on ROA

All regressions are fixed effect models and their associated R-squared values are reported. . Data are from Amadeus and EFIGE for the period 2006 to 2014 for all regressions. Standard errors, clustered at the firm level, are reported in parentheses. The symbols ***, ** and * mean that the reported coefficients are statistically different from zero, respectively, at the 1, 5 and 10 percent level.

	All Firms	All Firms	Sample Split on Financial Constraint Perception	
			Main Factor	Not Main Factor
	(1)	(2)	(3)	(4)
Rejection x post	0.000 (0.004)	0.011** (0.005)	0.023** (0.011)	0.006 (0.008)
Reduced investment plans x rejection x post		-0.018** (0.007)	-0.024* (0.014)	-0.011 (0.011)
Reduced investment plans x post		0.007 (0.006)	0.012 (0.012)	0.002 (0.010)
Sales Growth	0.094*** (0.012)	0.081*** (0.006)	0.077*** (0.011)	0.090*** (0.011)
Leverage	-0.185*** (0.048)	-0.227*** (0.041)	-0.242*** (0.029)	-0.230** (0.095)
Sales	-0.017 (0.017)	-0.002 (0.010)	0.002 (0.009)	-0.022 (0.023)
ROA(t-1)	0.200** (0.093)	0.114*** (0.043)	0.106** (0.042)	0.097 (0.093)
Firm FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	13,356	11,772	3,615	5,047
R-Squared	45%	48%	56%	41%

4.8 Limitations

While this chapter contributes to the literature on real effects of the financial crisis, unique in its ability to observe actual financing applications in a way that is robust to substitution effects between various sources of capital, the identification rests on a matching approach on a broad set of observable firm characteristics. The main limitation with matching approaches is that it is unlikely to fully solve the endogeneity problem since it relies on the ability observe all outcome-relevant determinants (Roberts and Whited 2013). The choice of this method was driven by the breadth of the EFIGE survey allowing observation of a large set of outcome-relevant determinants and the ability to disentangle supply and demand that it afforded during the financial crisis, which is a period of heightened capital impairments. Another limitation of this study is shared with other studies of SME finance in the extensiveness of

available SME accounting data. This resulted in the requirement to limit the sample size rather extensively.

A more substantial limitation relates to the inability to observe subsequent applications for financing by firms. Future research could utilize recurring surveys of access to finance matched with financials to shed light on dynamic effects of capital impairments. Follow-up surveys with higher quality data could be devised and exploited shedding light on whether various sources of finance are substitutes or complements, where unanswered questions remain in the realm of corporate finance (Cumming, Johan, and Zhang 2018).

Another potential limitation relates generally to use of surveys. Survey research has a long history in economics, even if economists' use of information gathered in certain kinds of questionnaire surveys has been mostly indirect, in that the economist does not typically organize collection of this information (Boulier & Goldfarb, 1998). The extensive use of the US' Survey of Consumer Finances in economics research is one prominent example. While this thesis relies extensively on survey data, there are subject to potential errors. The most obvious would be measurement error, while other potential biases exist such as nonresponse, sampling and coverage errors (Ponto, 2015). The rigorous methodologies of the EFIGE and SAFE surveys (Altomonte & Aquilante, 2012; European Central Bank, 2019b) assuage worries about sampling, nonresponse and coverage errors. However, measurement error pertains to whether the survey questions accurately reflect the topic of inquiry and to what extent, questionnaires and interviews are able to evoke truthful answers. Notwithstanding, the questions utilized from the SAFE and EFIGE survey pertain to which financiers, firms applied to for capital and so are inquires on facts, rather than subjective or attitude questions. The main methodology of studies in chapters 3 and 4 rely on these facts, so measurement error concerns should not bias results. In the few instances where research uses parameters such as perception of firms in regards to how financially constrained they are, I have been careful to phrase and analyze these as perceived traits.

4.9 Conclusions

Employing coarsened exact matching (CEM) between capital-seeking firms obtaining external finance and capital-seeking firms that do not, the empirical setup in this study aims at disentangling supply-side from demand-side forces. By matching along various outcome-relevant determinants, observable due to the breadth of the survey, it provides an estimate for the counterfactual real effects of investments and it crucially does so at a time of capital impairments during the 2008-2009 financial crisis.

I find evidence consistent with hampered investment effects due to impairments in access to capital during the crisis, however only uncover effects for tangible investments and not intangible investments. I find that liquidity enables firms to absorb capital supply shocks and invest more post-rejection. However,

rejection lowers this tendency in an economically meaningful way. These findings can be explained by rejection during the crisis increasing the marginal benefit of maintaining liquidity for firms, consistent with recent literature showing increased cash holding for firms following financial crises (Bliss, Cheng, and Denis, 2015; Pinkowitz, Stulz, and Williamson, 2013; Song and Lee, 2012). By tracing the increase in firms' marginal benefit of liquidity to actual rejections in financing applications during a recession, I complement this nascent literature.

I find rejected firms which reduced their investment plans following rejection performed worse than those that did not. This effect is greater for firms perceiving themselves to be financially constrained. These findings show that reduced investments following rejections are one of the channels in which firm performance is lowered following inability to attain financing.

While studies on real effects of crisis-era supply-constraints have explored the effect of credit impairments, firms are able to substitute for credit. Indeed recent research shows that firms substituted for credit impairments during the financial crisis by reducing dividends, issuing new equity (Dwenger, Fossen, and Simmler 2018) or public debt (Becker and Ivashina 2018), and increasing trade payables (Fraisie, Lé, and Thesmar 2019), grants or informal finance (Casey and O'Toole 2014). The setting of this study is unique in its ability to observe crisis-era applications for all external financing in a way that is robust to substitution effects between various sources of capital. It confirms that capital impairments and supply-side frictions during the financial crisis mattered for investments. The findings imply that capital substitutions during the recession were not adequate to help SMEs avert the credit crunch of 2008-2009 which particularly weakened bank balance sheets.

5 Distrust in Banks and Participation in P2P Lending

Crowdfunding is an alternative means of finance for individuals, including entrepreneurs, and it is organized in several models that are still evolving: reward-based crowdfunding; equity-based crowdfunding; donation-based crowdfunding; P2P lending; and initial coin offering. However, P2P lending is distinct from other models by matching a multitude of lenders with borrowers who are posting loans through an online platform. A 2019 study from the Cambridge Center for Alternative Finance reported that P2P consumer lending comprised the most widespread form of alternative finance in Europe. This model accounted for 41% of all volume (excluding P2P business lending, with 13.8% of the market share) and almost doubled in one year, from €697 million in 2016 to €1.392 billion in 2017.²⁹

By expanding funding opportunities, crowdfunding offers the promise of democratizing access to funding for many entrepreneurs (Bruton, Khavul, Siegel, & Wright, 2015), especially underprivileged ones and those in underfunded regions (Sorenson, Assenova, Li, Boada, & Fleming, 2016). In addition to obtaining financing from crowds, individuals organizing crowdfunding campaigns harness benefits ranging from market validation of their business ideas to launching new ventures and creating new jobs (Belleflamme, Lambert, & Schwienbacher, 2014; Block, Colombo, Cumming, & Vismara, 2018). However, successfully attracting funding from a large crowd requires understanding what drives their contributions (McKenny, Allison, Ketchen, Short, & Ireland, 2017). This question lies at the core of crowdfunding's sustained growth as an alternative arrangement, hailed by policy makers who seek ways to grow the entrepreneurial ecosystem as a means of revitalizing their economies and creating jobs.

This chapter examines distrust in traditional financial institutions as a factor behind the rise of crowdfunding. More specifically, it assesses whether distrust in banks and other financial institutions boosts P2P lending contributions. This context is chosen for several reasons. First, P2P lending is the most widespread form of crowdfunding,³⁰ and banks and P2P lenders perform similar functions, as both extend debt financing to consumers. P2P lending is facilitated by online platforms that connect investors with borrowers, or peers, without relying on banks to expose lenders to a portfolio of unsecured loans with repayments typically made monthly. Second, trust is a crucial component in banking (Zucker, 1986; Thakor & Merton 2018). However, in the wake of the recent financial crisis of 2008-2009, trust in banks has nosedived (Sapienza & Zingales, 2012; see also Guiso, 2010; Mosch & Prast, 2008; Knell & Stix, 2015), a phenomenon that has been linked to predatory lending methods directed at vulnerable communities (Agrawal, Amromin, Ben-David, Chomsisengphet, & Evanoff, 2014), breaching banks'

²⁹ https://www.jbs.cam.ac.uk/fileadmin/user_upload/research/centres/alternative-finance/downloads/2019-05-4th-european-alternative-finance-benchmarking-industry-report-shifting-paradigms.pdf

³⁰ Cambridge Center for Alternative Finance (CCAF) (2019 report): https://www.jbs.cam.ac.uk/fileadmin/user_upload/research/centres/alternative-finance/downloads/2019-05-4th-european-alternative-finance-benchmarking-industry-report-shifting-paradigms.pdf

obligations to protect consumers. A survey from the Edelman trust barometer on U.S. financial services and banking industries in 2012 indicates that consumers' distrust in banks exceeded that expressed toward any other industry. Against the backdrop of financial institutions falling out of favor, popular media have touted P2P lending as a strong contender for the consumer lending market.

This chapter provides an introduction to peer-to-peer lending (subsection 5.1), then describes the literature of research related to the research (subsection 5.2). The subsections follow with discussing the research gap (subsection 5.3), hypothesis development (subsection 5.4), employed research design and methodology (subsections 5.5 and 5.6), data (subsection 5.7) utilized, while subsections 5.8 to 5.10 respectively lay out the results, limitations and discussion and conclusions for the study.

5.1 Introduction

In July 2004, Robert Duvall's business pitch was met with the backing of the same Venture Capitalists³¹ who had formerly funded eBay and its German spinoff.³² Launching in March 2005, Zopa became the world's first online peer-to-peer lending platform, allowing lenders to directly lend to borrowers and cut out banks' financial intermediary role. Over the following decade, Zopa facilitated nearly £2 billion worth of loans on its platform. The five largest platforms for online consumer lending worldwide³³ are generating loans at a rate of \$10 billion a year. According to Ziegler et al. (2017), in 2016 there has been nearly \$21.1 billion of P2P consumer lending in the US. To place this in context, according to the Federal Reserve,³⁴ in 2016 there was \$228.1 billion outstanding consumer credit flows from traditional finance providers, meaning P2P marketplace consumer credit equaled 9.3% of US traditional consumer lending. Given the \$3.6 trillion of US consumer debt outstanding, this nascent sector has a potential to grow much larger, and likely will, given that the sector is doubling its lending at a pace of roughly every nine months (Economist, 2015). Industry analysts partially attribute this growth to P2P platforms' better customer satisfaction due to quicker response times, faster loan approval and funding.

Peer-to-peer lending online enables individual lenders to pool funds to lend to individual borrowers requesting loans. Individuals post a description of their borrowing application and their profile on an internet platform and individuals or institutional lenders can then browse and invest in loans through the platform.

P2P loans have been termed non-intermediated credit (Thakor & Merton, 2018; Thakor, 2019), or disintermediated loans (Balyuk, 2016; Morse, 2015), and as disintermediating financial markets (Lin, Prabhala, & Viswanathan, 2013). Morse (2015) explains that P2P does indeed disintermediate an asset

³¹ Benchmark Capital and Wellington Partners, respectively

³² Alonde.de, acquired by eBay in 1999

³³ Lending Club, Prosper, SoFi, Zopa and RateSetter

³⁴ See <https://www.federalreserve.gov/releases/g19/current/default.htm>

class of consumer loans, and removes a layer of financial intermediation. P2P lending platforms primarily serve as facilitators (or have a consignment role, as per terminology of Rubinstein & Wolinsky, 1987), making money by closing and servicing loans. An investor in a P2P platform, takes part in the underwriting of loans via the choice to fund a loan or not, and the ability to track if a loan reaches a threshold for being underwritten, and hence the lending function is not intermediated by a third-party.

P2P lending is enabled through employing a series of technologies facilitating digitization and widening of the lender/borrower base of the lending process (of unsecured loans). The digitization of financial records of consumers and individuals, the declining cost of information gathering and the sharing of information on credit activity of individuals, has enabled credit rating agencies to monitor the creditworthiness of individuals faster and at a lower cost (Economist, 2015). In turn, lowering of the cost of accessing credit information on individuals by credit rating agencies, standardization of information on potential loan applicants and the ease of matching borrowers with lenders, have reduced the screening-cost required in the lending process (Agrawal, Catalini, & Goldfarb, 2015; Shafi, 2016). By bearing these lowered costs for access to credit information on individuals, P2P lending platforms have emerged as a low-cost way for individuals to screen and lend to other individual investors. As an example, banks spend roughly 7% of value of a loan on administration, while this figure is just 2.7% for Lending Club (Economist, 2015). P2P platforms have also enabled smaller financial transactions to receive broad participation with limited downside risk for each investor, and consequently lessening the need for ex-post monitoring of loans compared to bank loans which tend not to be dispersed across many investors (Agrawal et al., 2015; Gorton & Winton, 2003).

5.2 Literature Review

5.2.1 *On Participation in Financial Markets*

Numerous studies have studied the determinants of participation in traditional financial markets. For example numerous studies have documented the effect of various individual and societal characteristics on participation in the stock market, such as financial awareness and literacy (Almenberg & Dreber, 2015; van Rooij, Lusardi, & Alessie, 2011; Guiso & Jappelli, 2005; Christiansen, Joensen, & Rangvid 2008), stock market return experience (Malmendier & Nagel, 2011), IQ (Grinblatt, Keloharju, & Linnainmaa, 2016), gambling attitudes (Barberis, Huang, & Thaler, 2016), genetics (Barnea, Cronqvist, & Siegel, 2010), optimism (Puri & Robinson, 2007), ability to understand investments (Graham, Harvey, & Huang, 2009; Christelis, Jappelli, & Padula, 2010), cognitive ability (Benjamin, Brown, & Shapiro, 2013), internet adoption (Bogan, 2008), political activism (Bonaparte & Kumar, 2013), political orientation (Kaustia & Torstila, 2011) and social interactions (Hong, Kubik, & Stein, 2004; Brown et al., 2016; Bönke and Filipiak, 2012).

While there is a **well-established literature** focused on the determinants of **participation in traditional financial markets**, the study of the determinants of participation in **alternative financial markets** is still a **nascent field** (for exceptions see: Boudreau, Jeppesen, Reichstein, & Rullani, 2015; Daskalakis & Yue, 2017). For the case of participation in traditional financial markets, the **central role of trust** is well documented (Georgarakos & Pasini, 2011; Guiso, Sapienza, & Zingales, 2004, 2008).

As the Nobel laureate Kenneth Arrow emphasized: “*Virtually every commercial transaction has within itself an element of trust, certainly any transaction conducted over a period of time* (Arrow, 1972)”.

Trust facilitates exchanges that may end up being mutually beneficial. Gambetta (2000) defines trust as the expectation that another person or institution will perform actions that are beneficial, or at minimum not harmful, to us regardless of our capacity to monitor those actions. In a financial transaction, trust would be defined following the social capital literature, as a subjective belief about the probability that a potential trading partner will act honestly (Bottazzi, Rin, & Hellmann, 2016). While trust is the fundamental backbone of all trade and investment, it is particularly important in financial markets, where people give away their money in exchange for promises. These promises only find worth through the existence of trust (Sapienza & Zingales, 2012).

Trust enables a widening of economic transactions by empowering people to not be restricted to familiar relationships (e.g. friends, family members) where trust is anchored in experience and first-hand knowledge about particular people (Fukuyama, 1995; Yamagishi & Yamagishi, 1994).

Research in information systems has emphasized that the role of trust is accentuated for on-line transactions (Brynjolfsson & Smith, 2000). Specifically, this literature has paid considerable attention to the role of trust in gaining traction for new on-line markets such as B2C e-commerce (Gefen, Karahanna, & Straub, 2003; Pavlou, Liang, & Xue, 2007), and online auction platforms (Ba & Pavlou, 2002; Angelika Dimoka, Hong, & Pavlou, 2012).

The online setting of fintech merits investigation of the role of trust in fintech markets, which is a mission chapters 5 and 6 contribute to.

5.2.2 *On Role of Trust in Financial Markets*

Fundamentally, trust may capture differences in the subjective probability of being cheated and hence, trust increases risk tolerance (Guiso, Sapienza, & Zingales, 2008). Also, as evidenced by experimental trust games, trust decisions involve costs of trust betrayal (Bohnet & Zeckhauser, 2004; Bohnet et al., 2008), and individuals with a higher *ex-ante* cost of betrayal demonstrate less trusting behaviors.

Hoffman et al. (2009) investigate the role of trust on the long-run development of credit markets in France since 1740 to 1899. They find that while trust is critical to explain aggregate fluctuations in

financial outcomes (e.g. in financial crises stemming from loss of confidence), and in individual financial success and failure, it is an intermediate variable that from a generational perspective (over a generational timescale) evolves rather quickly in response to shocks to the demand for credit.

Guiso et al. (2008) study the effect of general trust (i.e. trust to others) on participation in the stock market. In the decision to participate in the stock market, investors factor in the risk of being cheated. The perception of this risk is a function of the objective characteristics of the stocks and the subjective characteristics of the decision-maker. They find that less trusting individuals are less likely to invest in the stock market, and conditional on investing, they will invest less. They go on to show that while lack of trust always reduces stock market participation, the strength of this effect increases with increases in the fixed costs of participation in the stock market. In addition, they find that those who hold more trust towards their own bank official or broker as a financial advisor, are more likely to buy stocks and conditional on buying stocks, invest a larger share of their wealth into stocks. They test for the possibility that trust may simply be a proxy for risk aversion in that trust would increase risk tolerance and resultantly increase participation, however they present evidence that this is not the case.

Their findings, corroborated by those of Gennaioli et al. (2015) who study the role of trust in money managers on investors' portfolio management, speak to the pervasiveness of the effects of trust in portfolio allocation.

Giannetti & Wang (2016) study the effect of corporate fraud in a state on household's stock market participation in that state. They find that households react to corporate fraud in a state, by decreasing holdings in fraudulent and non-fraudulent firms, whether they held stocks in fraudulent firms or not. Exploiting the exogenous variation in fraud revelation due to the demise of Arthur Andersen, they find that states with more Arthur Andersen clients experience a greater decrease in equity holdings. They provide evidence that this effect is likely caused by a lack of trust in the stock market. Using yearly surveys on confidence in big business in US states from 1981 to 2009, they demonstrate that fraud revelation in a state is associated with a drop in trust in big firms for the state's households. They go on to explore channels and mechanisms through which trust may affect individual's stock market participation decisions. Their results are consistent with the effect of fraud on trust depending on betrayal costs rather than changes in risk aversion.

Bottazzi et al. (2016) find that bilateral trust between European countries positively predicts venture capital firms' investment decisions, but is negatively correlated with successful exits.

Simultaneous to the research leading up to this thesis, a few studies have looked at the role of general trust in emerging financial technologies. Shafi (2016) investigates the underlying behavioral and rational reasons for the decline of P2P loan value with distance, and includes a test of the positive interacting

effect of general trust with distance on lending in the UK P2P loan market. Rau (2017) analyzes country-level determinants of crowdfunding volume on over 1,300 platforms worldwide, and finds little evidence for the role of general trust or other social factors.

While these papers explore the role of general trust in emerging financial technologies, the role of distrust in banks and traditional financial institutions is not studied within alternative financial markets.

5.2.3 *On Distrust in Banks and Financial Institutions*

Trust in institutions is impersonal, i.e., individuals who trust institutions believe that the collective entities that describe institutions are perceived to be legitimate, technically competent, and able to fulfil their assigned duties and obligations efficiently.³⁵ Distrust in banks represents consumers' reluctance to put themselves in a vulnerable position with respect to banks because they perceive banks to be incapable, exhibit opportunistic behavior, violate or breach obligations, act against consumers' interests, or even intentionally take advantage of consumers (Kramer, 1999; Lewicki, McAllister, & Bies, 1998; Sitkin & Roth, 1993).

A few surveys have assessed the U.S. general public's trust in banks. Sapienza and Zingales (2012) find that only 27% of Americans trust financial institutions. Gallup polls in 2012 also indicate that less than 30% of Europeans trusted banks or other financial institutions, below the median of 55% in a sample of 135 countries.³⁶ Overall, in the wake of the financial crisis of 2008-2009, several economists expressed concerns about a "trust crisis" in banking (Sapienza & Zingales, 2012; see also Guiso et al., 2009; Mosch & Prast, 2008; Knell & Stix, 2015; see single-country evidence on trust in banks: for the U.S., Sapienza & Zingales, 2012; for Spain, Carbo-Valverde, Maqui Lopez & Rodríguez-Fernández, 2013; for the Netherlands, Jansen, Mosch, & van der Cruysen, 2015; and for Austria, Knell & Stix, 2015). Understanding the factors associated with trust in financial institutions is important to policymakers because distrust in banks can undermine financial stability by increasing the likelihood of bank runs (Guiso, 2010) or influencing the public's decisions about how to save (Stix, 2013).

What drives distrust in banks? Guiso (2010) uses several surveys to suggest that fraud, such as the Madoff case, which received heavy media attention, may be a reason for the collapse of trust in U.S. banks. Stevenson and Wolfers (2011) study trust in public institutions across business cycles in the U.S. and document how trust in several institutions, including banks, decreased during the Great Recession. Their study associates this development with rising unemployment, suggesting that trust fluctuations

³⁵ The concept of trust in institutions should not be confused with institutional trust, which refers to trust judgment based on laws, regulations, guarantees, or other social (impersonal) structures that enable people to feel assured about their expectations of the other party's future behavior in transactions. While in the latter, the basis of trust formation comprises institutional safeguards and arrangements, in the former, the object of trust is institutions.

³⁶ <https://news.gallup.com/poll/162602/european-countries-lead-world-distrust-banks.aspx>

entail cyclical responses. Knell and Stix (2015) use Austrian survey data to find that the extension of deposit insurance coverage and the lack of bank collapses had a cushioning effect on trust in banks. Van der Cruijssen, de Haan and Jansen (2016) survey Dutch households and find respondents' personal adverse financial crisis experiences reduce their trust in banks. The financial crisis brought to light banks' pervasive opportunistic behaviors (Guiso 2010). Banks failed to act in investors' best interests. For instance, an important factor that precipitated the financial crisis was financial institutions' moral hazard in loan securitization, as they had limited skin in the game (Keys, Mukherjee, Seru, & Vig, 2010).

Trust in financial institutions, including banks, is necessary for financial markets to function efficiently. Such trust has played a historically deep-rooted role in the emergence of banking, especially in relation to banks' safekeeping and depository functions (Zucker, 1986; Thakor & Merton, 2018). Consistent with this observation, distrust in banks reduces ownership of savings deposits (but drives cash preferences) (Stix, 2011; see also Coupe, 2011, for similar evidence on "money under the mattress"). Trust in financial institutions influences individuals and countries' participation in the stock market, as well as the composition of investors' portfolios (Guiso, Sapienza, & Zingales, 2008). Guiso et al. (2013) find that less trust in banks makes it more likely that borrowers strategically default on their mortgage debts. This study suggests and investigates another consequence of distrust in banks: inflows into P2P lending.

5.2.4 On Decision-Making by P2P Lenders or Crowdlenders

Scholars have examined how crowds make lending decisions and the consequences for listed loans' funding outcomes (for a review, see Morse, 2015). Information asymmetries and moral hazards are two challenges facing crowds when screening loans. To overcome resulting adverse selection issues, crowds can use quality signals and information disclosures (Iyer, Khwaja, Luttmer, & Shue, 2016). Miller (2015) exploits a change in the amount of information visible to lenders and finds that access to more borrower credit information improves lenders' decisions by eliciting reduced default rates among high-risk borrowers – on average, by 17 percentage points. Besides hard information, lenders seem to consider soft information, such as a description of a loan's purpose (an explanation for a poor credit grade that is voluntary and a typically unverifiable disclosure) (Michels, 2012), identity claims, or judgments about the attraction or trustworthiness of faces from profile pictures. Information on what other investors do (information cascades) can also attract more funding (Zhang & Liu, 2012; Herzenstein et al., 2011). Researchers also have identified several signals generated directly from borrowers or indirectly from social connections, such as endorsements associated with bidding on friends' loan listings (Freedman & Jin, 2017). Kawai, Onishi, and Uetake (2014) find that borrowers can signal low default risk by posting low reserve interest rates. Having friends with high credit ratings helps prospective borrowers increase

the chances of successfully securing funding, lowering interest rates and resulting in fewer defaults (Lin, Prabhala, & Viswanathan, 2013).

Related literature has also tied local availability of credit to lending outcomes. Ramcharan and Crowe (2013) find that borrowers facing declines in home prices in their geographical locations during the recent housing crisis procured funding with higher interest rates compared with those of otherwise-matched borrowers. Butler, Cornaggia, and Gurun (2016) find that borrowers residing in areas with good access to bank finance request loans with lower interest rates – an effect that is more pronounced for borrowers seeking risky or small loans. Thus, both lenders and borrowers’ geographical locations influence their decisions beyond evidence on home bias (Lin & Viswanathan, 2016), which describes a tendency for lenders to prefer funding geographically proximate borrowers. Tang (2019) uses a shock to bank credit supply to find that P2P lending substitutes banks when serving infra-marginal borrowers and complements them for small loans. Overall, this study contributes to the growing interest among scholars who study the link between banks and P2P lending, with a special emphasis on the supply side of market (lenders).

5.2.5 On Crowdfunders’ Motivation

Scholars have investigated the question of what motivates backers’ participation in crowdfunding.³⁷ Backers could be motivated extrinsically or intrinsically to participate. Extrinsic motivation describes external factors that encourage backers to contribute in hopes of earning money, avoiding punishment, or complying with social norms (Deci & Ryan, 2010). In the context of crowdfunding, examples of extrinsic motivation could include receipt of tangible rewards for campaigns that involve pre-purchasing a product (Cholakova & Clarysse, 2015) or the collection of interest payments. Pierrakis and Collins (2013) surveyed P2P lenders and showed that financial returns are lenders’ most important motivation. Additionally, backers might pursue direct reciprocity (Colombo, Franzoni, & Rossi-Lamastra, 2015) or recognition from others (Bretschneider & Leimeister, 2017).

A range of intrinsic motivations is enumerated for crowdfunders. Backers might act pro-socially (Giudici, Guerini, & Rossi-Lamastra, 2018) and enjoy helping others realize certain projects’ success (Cholakova & Clarysse, 2015), especially when they like, sympathize, or identify with the cause or the campaign’s goals (Boudreau, Jeppesen, Reichstein, & Rullani, 2018). Backers also might want to belong to a community (Gerber & Hui, 2013), to be liked, or to have good standing and be well-regarded by others. Finally, Daskalakis and Yue (2017) surveyed crowdfunders in Germany, Spain, and Poland about their motivations and report that “interest and excitement” is ranked as the second most important motivation, following financial returns as the number one reason to participate in P2P lending. Demir,

³⁷ For the motivation of entrepreneurs who choose crowdfunding as their preferred source of financing, see references cited in Table 1 in Moritz and Block (2016).

Mohammadi, and Shafi (2019) find that sensation seeking is a motivating factor behind the decision to lend on Prosper.com. The research examines whether distrust in banks constitutes a relevant driver of P2P lending.

5.2.6 On Information Processing Under Distrust

Information-processing strategies differ under a distrust mindset compared with a trust mindset (for a review, see Mayo, 2015). Trust appears to be the default state of mind; thus, people in situations with a trust mindset typically rely on routine information-processing strategies and on uncritical acceptance of default positions. Routine strategies are decision frames that, more or less, are executed effortlessly (e.g., the decision maker provides a flimsy initial response based on heuristics) and are typically found to be the most useful in normal or well-known environments (Schul & Peri 2015). Thus, routine strategies are more likely to be activated by default (Schul, Mayo, & Burnstein, 2008) because situations, people, and institutions are as they appear on the surface (i.e., they can be taken at face value), and careful and critical processing is unnecessary. Conversely, a state of distrust indicates that something in the environment is amiss or potentially misleading, fostering the use of non-routine information-processing strategies that involve close scrutiny and careful consideration of alternatives to one's initial default choices (e.g., Kleiman, Sher, Elster, & Mayo, 2015; Mayer & Mussweiler, 2011; Mayo, Alfasi, & Schwarz, 2014; Schul et al., 2004, 2008). Extant research has highlighted specific patterns of thought and action patterns that these information-processing strategies generate under trust and distrust mindsets (Schul, Mayo, & Burnstein, 2004).

Under distrust, individuals engage in questioning their default positions (Mayer & Mussweiler, 2011; Posten & Mussweiler, 2013; Schul et al., 2008). For example, Mayo, Alfasi, and Schwarz (2014) suggest that individuals under a distrust mindset tend to use disconfirmatory hypothesis testing, which allows for falsification of their initial hypotheses. Under distrust, individuals consider events from multiple perspectives and interpret information in multiple frames (Schul, Burnstein, & Bardi, 1996), apply and activate multiple information categories (Friesen & Sinclair, 2011), encode incoming information as if it is both true and false (Schul et al., 1996), increase the chances of arriving at creative solutions to problem-solving tasks (Mayer & Mussweiler, 2011), attentively look for unusual contingencies (Schul et al., 2008), and rely less on stereotypes in favor of individuating information (Posten & Mussweiler, 2013). In sum, the distrust mindset promotes critically assessing default positions and fosters consideration of alternative responses and interpretations.

The stream of literature that focused on the distrust mindset has examined further how decisions are made while considering alternatives, finding that the distrust mindset fosters dissimilarity-focus comparisons (Posten & Mussweiler, 2013). To elaborate, it is helpful to note that one characteristic of all judgments is their essential relativity. When judging other objects or people, we tend to compare them

with comparison standards that are easily accessible (Dunning & Hayes, 1996; Gilbert, Giesler, & Morris, 1995; Mussweiler, Ruter, & Epstude, 2003). In comparison judgments, scholars have identified two patterns, depending on whether the invoked focus of the judgment in a given situation concerns similar or dissimilar aspects of the comparison standards. Dissimilarity-focused comparisons involve contrasting the target away from the standard, whereas similarity-focused comparisons direct attention toward similarities between the target and standard by selectively activating dimensions of interest that are consistent with such assimilation (Mussweiler, 2001, 2003). Posten and Mussweiler (2013) find that a (dis-)similarity-focus is more likely to be used under (dis-)trust. Overall, extant literature on the distrust mindset offers concrete information-processing mechanisms that can help us understand what dimensions of alternatives individuals are likely to rely on for comparison tasks.

5.3 Research Gap

This thesis consists of the first study to empirically investigate the role of trust in banks and financial institutions in peer-to-peer (P2P) lending.

This chapter suggests that distrust in an established industrial structure can pave the way for the emergence of substitute digitized structures (i.e. P2P lending). This view is partially and indirectly substantiated by evidence from a large number of studies that document a significant increase in distrust in established financial institutions over time (Stevenson & Wolfers, 2011; Birth, 2014; Corso, 2009; Guiso, 2012; Sapienza & Zingales, 2012; Bennett & Kottasz, 2012; Gritten, 2011). But this explanation for the emergence of crowdfunding has not been subject to direct empirical investigation.

Subsequent to this study's academic presentations,³⁸ a prominent theoretical study of trust in lending for banks and P2P platforms (Thakor & Merton, 2018) has emerged. Just as this contribution enriches the literature and highlight the significance of trust in online lending, this thesis is the first to focus on the role of trust in banks on the motivations of contributors (i.e. on the supply) in P2P lending markets. This is important for the crowdfunding literature, since considerably less is known about the motivations of the supply side in crowdfunding campaigns, i.e. the "crowd". This chapter adds to the literature empirically studying motivations of crowdfunders by highlighting the importance of distrust in banks, in funder allocations to alternative versus traditional financial markets. It also contributes to the emerging literature on how fintech interacts with banks.

³⁸ The first formal submission of this paper was on March 2017 to the Second Annual Conference on Alternative Finance at the Cambridge Centre for Alternative Finance (CCAF). The first formal presentation of this paper was at 5th Crowdfunding Symposium Berlin in October 6, 2017, preceding the first version of following papers, on July 2018 and November 2017, respectively.

5.4 Hypotheses Development

This study proposes that distrust in banks can motivate contributions to P2P lending. The core argument is based on how the distrust mindset cognitively attunes people toward carefully considering alternatives (Kleiman et al., 2015; Schul et al., 2004). In the case of distrust in banks, whatever its underlying source, its consequence is a thought process that increases the salience of relevant alternative possibilities, including P2P lending, which competes directly with banks in its lending function, albeit with some operational differences. P2P opens direct access to the asset class of consumer loans to individual lenders who are wary of banks' motivations, intentions, or past opportunistic behaviors. P2P lending removes the need for banks, as a financial intermediary, to hold deposits and offer loans on their balance sheets. Evidence suggests that borrowers substitute between P2P loans and local bank finance. Butler et al. (2016) find that borrowers benefiting from better access to bank financing seek loans with lower interest rates on P2P lending markets. Additionally, Tang (2019) examines a regulatory change that led to banks tightening their lending criteria, thereby affecting local credit markets. She finds that some borrowers who otherwise would have been served by banks turned to P2P platforms. While these studies highlight potential demand-induced substitution between P2P lending platforms and banks, this study hypothesizes that distrust in banks is associated with contributions to P2P lending away from banks:

Hypothesis 1: *Greater distrust in banks is associated with higher participation in funding P2P loans.*

This chapter next suggests that distrust in banks increases the flow to P2P loans particularly when the loans are related to marginal borrowers, defined as borrowers seeking small loans and those with less access to banks. To support this argument, this chapter draws on extant literature that suggests that the distrust mindset tends to focus on dissimilarities when making comparisons (Posten and Mussweiler, 2013). Accordingly, those with distrust in banks selectively tend to activate and seek information that highlights dissimilarities between P2P lending and traditional banks. Besides considering P2P lending, the mindset of distrust in banks triggers comparing and contrasting features of P2P lending with those of traditional banks. Two observable (and testable) dimensions that can be of interest concerning contrast-based comparison judgments are highlighted: (i) how P2P can reach under-served customers and (ii) how P2P can serve small loans.

This chapter proposes that P2P lenders differ from traditional banks in terms of how they can cost-effectively reach under-served and infra-marginal lenders. P2P lending platforms benefit from lower search costs to match borrowers with lenders in the following ways: P2P platforms benefit from technology advances that facilitate credit scoring of prospective borrowers, servicing, monitoring, and

credit-history reporting of loan performances.³⁹ P2P lending platforms create searchable databases of borrowers for all lenders without the need for relationship lending. P2P lenders have digitized most operations (including loan-origination processes), and as such, they do not need investment in a network of physical branch distributions. In fact, P2P lending platforms have made inroads into regions that are under-served by banks (Havrylchyk Mariotto, Rahim, & Verdier, 2019), as high bank-branch density appears to deter the entry and expansion of P2P lending. In sum, this study hypothesizes that those with distrust in banks who consider P2P lending as an alternative option likely pay attention to this important dissimilarity in accessibility to under-served borrower segments in their comparisons:

Hypothesis 2: *The less accessible banks are for a borrower, the stronger the association between distrust in banks and participation in funding P2P loans.*

Second, this research proposes that P2P lenders differ from traditional banks in terms of the lower bound of loan sizes they can offer. In addition to lower search costs (explained in the previous paragraph), P2P lending platforms also offer reduced transaction costs involving bargaining, policing, or obtaining verified creditworthiness data in transactions. For instance, platforms provide a standard contract and enforcement that make negotiations unnecessary and obviate the need for individual collections activity. P2P lenders also automate the loan-origination process (Buchak, Matvos, Piskorski, & Seru, 2018; Fuster, Plosser, Schnabl, & Vickery, 2018), lowering the fees associated with loan applications and approval. The decrease in costs makes it economical for lenders to provide smaller loans (on which less information is available), especially when existing options are not suitable or available. Tang (2019) finds that small borrowers are the most likely to benefit from the expansion of P2P lending. Thus, P2P platforms can serve customers whose loan sizes are perhaps too small for traditional banks. In sum, this study hypothesizes that those with distrust in banks consider P2P lending as an alternative option likely pay attention to dissimilarities in the loan sizes that P2P lenders can offer:

Hypothesis 3: *The lower the loan size, the stronger the association between distrust in banks and participation in funding P2P loans.*

5.5 Research Design

In the spirit of Angrist and Pischke (2008)'s book and ultimate companion to graduate students in economics, entitled *Mostly Harmless Economics*, this subsection starts with discussing the ideal experiment and then describing new fintech data opportunities exploited in order to study this research question, as well as remaining limitations in data, for strong causal inference.

³⁹ Credit decisions typically are based on big data, predictive algorithms, and machine learning techniques with a wide range of data points, including non-traditional data sources such as information from social media (Jagtiani and Lemieux, 2018).

The overarching research question is “*whether and to what degree, people allocate their money and investments, to peer-to-peer financial technology, given reductions in trust (or increases in distrust) in traditional financial intermediaries*”. The ideal experiment would possess the following key features: (1) Precise measurements of investors’ trust levels at an adequate frequency (general trust, trust in traditional financial intermediaries, and to peer-to-peer financial technologies), (2) Preferably a rapid change/shock in the trust to financial intermediaries and not to others, which does not confound other variables of importance. (3) Information about financial investment possibilities and subsequent decisions of a representative (large enough) portion of the population, (4) Knowledge about investors’ financial literacy, technological savviness, and all variables which can affect the allocation decision besides trust.

Trust is a sentiment that is difficult to measure. Economists have often measured trust based on responses to surveys on attitudes towards others and particular institutions (Aghion, Algan, Cahuc, & Shleifer, 2010; Guiso et al., 2004; Knack & Keefer, 1997; La Porta, Lopez-de-Silanes, Shleifer, & Vishny, 1997b; Stevenson & Wolfers, 2011). Most studies use a close variant of this survey question to assess general trust, popularized by the various social surveys conducted regularly for decades worldwide (e.g. World Values Surveys, European Values Study, Eurobarometer, General Social Survey, Life in Transition Surveys): “*Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people?*”. To assess trust in institutions, the phrasing often changes to “*To what extent [on a scale of 1 to 5] do you trust the following institutions [or the people running them]? Government, banks, foreign firms, [etc.]*”. Economic studies most often aggregate these measures at the country or region level, to measure prevailing societal trusting sentiments.

Knack & Keefer (1997) provide empirical evidence for the validity of such aggregated measures, finding that they are strikingly correlated across regions and countries with the percentage of wallets that were ‘lost’ and subsequently returned intact in a field experiment in the US and various European countries. When used on a region or country level, values for trust are consistent with case study and anecdotal evidence on trust (Zak & Knack, 2001). This measure, while likely picking up trustworthiness at the level of the individual, when aggregated up to the country or region level (as performed in this study), can form a useful measure of societal trust (Glaeser, Laibson, Scheinkman, & Soutter, 2000).

A rapid change in financial trust, without a change in confounders, would be beneficial for the ideal research design to be able to exploit the shock. Giannetti & Wang (2016) exploit the demise of Arthur Andersen in the Enron scandal to find that states with more Arthur Andersen clients experience a greater household decrease in stock holdings. They show that corporate scandals reduce trust in big business, and hence attribute the decreased stock market participation in reductions in trust in the stock market. This is not a direct regression of individual’s investments in the stock market given their rapid decline in

trust in big business, but goes some ways to use a shock to information reliability of firms' financial accounts to study changes in stock market investments.

Ideally, a researcher could measure trust of investors in P2P platforms both to banks and to P2P platforms. However while surveys of P2P lenders have been carried out (e.g. Pierrakis & Collins, 2013), I am unaware of any surveys inquiring on financial trust.

In view of these limitations, and in keeping with the vetted and standard economic measurement, the best alternative until such direct surveys exist, is to proxy for individual's trust to banks at a regional level, and to exploit region-level variation in trust levels, in assessing contributions of individual investors on P2P platforms. While the reliability of these measures depends on their representativeness at the chosen geographic level (state-level in US analysis in this chapter), additional tests of external validity, construct validity, exclusion of outliers and additional analyses are carried out in herein to increase confidence in inferences.

The research hinges on rich and granular data obtained on Prosper.com (the most prominent P2P lending platform in the US in the late 2010s), on all loans between 2005 and 2012, concerning all P2P lenders' loan bids and loan parts (i.e. successful loan bids) to P2P borrowers' loans. This is an example of fintech data that allows for researching investors' and the crowds' decisions with more granularity than possible before. Researchers have used this very platform's data to investigate the effect of home bias (Lin & Viswanathan, 2015), heterogeneous risk aversion given wealth (Paravisini, Rappoport, & Ravina, 2017), trustworthiness (Duarte, Siegel, & Young, 2012), beauty (Ravina, 2008), creditworthiness assessments (Iyer, Khwaja, Luttmer, & Shue, 2016; Lin et al., 2013), sensation-seeking (Demir, Mohammadi, & Shafi, 2019) and rational herding (Zhang & Liu, 2012) on investor's decisions.

Given this data, the research design involves regressing state-level aggregates of P2P lenders' loan bids (or loan parts) on state-level trust levels, controlling for loan characteristics using loan fixed effects, and state-level heterogeneity using state-level covariates of relevance. This chapter expands on this in detail.

5.6 Methodology

This study exploits geographical variation in participation in peer-to-peer loans and distrust in banks to test the theoretical predications. The analysis is conducted at the level of U.S. states and loans. For each loan, 40 observations exist corresponding to the number of U.S. states in the GSS survey. Thus, all bids (pertaining to a listing) from lenders in a state are aggregated into one observation. This is repeated for all states and listings. This leads to 7,275,560 ($40 \times 181,889$) observations from 181,889 listings.

Denoting lender states by i , peer-to-peer loans by j , and time by t , the main regression specification is as follows:

$$\mathbf{P2P\ Participation}_{ij} = \beta_1 \times \mathbf{Distrust\ in\ Bank}_{it} + \gamma \mathbf{X}_{it} + \alpha \mathbf{Y}_{ij} + \mathbf{l}j + \epsilon_{ij} \quad (5)$$

The explanatory variable of interest is the state-averaged level of distrust in banks. The main dependent variable is the log of the total amount of bids into a given loan listing by bidders from each state (*Participation Amount*). Alternatively, this study uses *Participation Indicator* to measure the likelihood of participating in P2P loans. This study also tests if conditional on participation in a P2P loan (*Participation Indicator*=1), the participation amount increases with distrust in banks. The vector $\mathbf{X}_{it}$ includes controls for state-level economic and demographic characteristics that may affect participation level in peer-to-peer markets. The vector $\mathbf{Y}_{ij}$ includes *Lending Distance*, which varies across the bidder's state (i), and loans (j). The data are unlikely to capture all sources of heterogeneity. Participation can be driven by factors on both the demand and supply sides. On the demand side, borrowers' characteristics also can affect lenders' participation. This study includes loan fixed effects ($\mathbf{l}j$) that control for unobserved demand-side heterogeneity by calculating within-loan estimates (Wooldridge, 2010). As the loans are usually open for a short period of time (between seven and 14 days), it is less likely for demand-side characteristics to vary across time for each loan. Having variation at the state level allows one to separate the effect of trust in banks from economic shocks, which operate at the national level (e.g., the interest rate that the Federal Reserve sets). To isolate the *Distrust in Banks* effect from other supply-side characteristics,⁴⁰ an extensive list of economic and demographic characteristics ($\mathbf{X}_{it}$) are controlled for that may affect the state level of participation in peer-to-peer markets and can be correlated with *Distrust in Banks*. Standard errors are also clustered for each listing.

5.7 Data

5.7.1 Data on US Study on P2P Lending on Prosper.com

Peer-to-Peer Lending Data

The sample comprises all bids made on Prosper.com from February 5, 2006 (the day that the marketplace was opened to the public), to October 19, 2008.⁴¹ The sample contains data on 181,889 listings and 5,973,771 bids. Given that the unit of analysis considers listing-state bidding possibilities,⁴² the data is

⁴⁰ As the survey data in our sample are related to only two years (2006 and 2008), we are not able to include state fixed effects. However, including a rich set of control variables at the state level should capture supply-side heterogeneities across different states. In additional analyses, we used a longer period (2006-2012) and included the state of lender fixed effect.

⁴¹ By the end of our sample period, USD \$444 million had been bid on Prosper.com, of which USD \$288 million became successful bids, i.e., USD \$288 million was lent out to borrowers.

⁴² The choice of level of analyses at state is due to data availability concerning bidders' location. More granular data than on bidders' states of residence is not available.

transformed, yielding 7,275,560 observations. Below, this chapter explains why the main analyses is restricted to a sample of bids on listings until October 19, 2008.

First, between October 19, 2008 and July 13, 2009, Prosper.com temporarily was shut down,⁴³ and Prosper suspended new lending to register with the Securities and Exchange Commission (SEC). Prior to this hiatus, lenders from all states were allowed to participate in loans, but afterward, due to the SEC's requirement that Prosper obtain each state's approval for lending to comply with state-mandated investor-protection regulations, readmission of lenders from various states into Prosper's lending market was staggered. After the shutdown, given the gradual nature of Prosper's ability to obtain operating licenses in various U.S. states, total bidding amounts increased, but as of the end of 2011, they had not yet reached their heights prior to the closure. Numerous other published studies using Prosper's database also limited their samples to those prior to this hiatus (e.g., Butler et al., 2016; Duarte et al., 2012; Freedman & Jin, 2008; Lin et al., 2013; Lin & Viswanathan, 2015; Zhang & Liu, 2012).

Second, as the market has grown, institutional investors have begun to engage in P2P lending (Lin, Sias, & Wei, 2017; Mohammadi & Shafi, 2017). Lin et al. (2017) show that institutional investors invested less than 5% of all investments in Prosper.com prior to the shutdown in October 2008, but this grew after the shutdown ended and peaked in 2012. As this study focuses on determinants of participation of individuals (and not institutions) within the P2P online market, the chosen period for the sample is suitable for analysis.

Finally, limiting the sample to prior to October 2008 helps us avoid confounding factors associated with the U.S. financial crisis, which exacerbated economic outcomes in late 2008.

Dependent variables

The main dependent variable is the total amount of bids (in dollar) into each loan listing by bidders from each state (*Participation Amount*). This variable is natural log-transformed, and measures participation in funding P2P loans. The average of this variable is \$58.1, i.e., citizens in a given state, on average, invested \$58.1 on listings. Alternatively, this study uses a dummy variable equal to one if at least one bidder from a state (regardless of the amount) participates in a loan, and zero otherwise (*Participation Indicator*). This alternative variable assesses the likelihood of participating in P2P loans. The average of this variable is 18.4%, i.e., a listing, on average, is backed by citizens from 18.4% of U.S. states. This study also tests whether, conditional on participation in a P2P loan (*Participation Indicator*=1), the total amount increases with distrust in banks. The average of this variable is equal to \$315.5.⁴⁴

⁴³ Solely between April 28 and May 9, 2008 and only from the State of California was lending allowed during this hiatus.

⁴⁴ One concern with this aggregated amount is that we are not able to differentiate between investments that originate from just a few bidders and those from a large number of bidders. Thus, in robustness checks, we also include number of bids per capita (bids per capita) and the number of unique bidders per capita (bidders per capita)

Distrust in Banks

The data originates from the General Social Survey (GSS), obtained from the U.S. National Opinion Research Council (NORC) at the University of Chicago, which biennially surveys nearly 2,500 individuals regarding their level of confidence in various institutions. This survey was conducted from 1975 to 2016 and contains information on respondents' location, income, age, gender, race, education, political orientation, and religion (in certain years). I, and co-authors, obtained confidential geo-identifiers for respondents to this survey, which also contain state-of-residence data.⁴⁵ The survey asks: "As far as the people running these institutions (namely banks and financial institutions) are concerned, would you say you have a great deal of confidence, only some confidence, or hardly any confidence at all in them?" Possible answers to the institutional-confidence questions were (a) a great deal, (b) only some, (c) hardly any, or (d) don't know. This study defines a respondent distrust-in-banks dummy variable as being equal to 1 if the response was (c) and 0 if the response was (a) or (b); it excludes those responding with (d).⁴⁶ Such an approach has been used by others including Aghion et al. (2010). By averaging the dummy variable across respondents residing in a state, this study obtains the average level of prevailing *distrust in banks* sentiment in that state.⁴⁷

Being limited by the P2P data time frame, this study utilizes trust data in the 2006 and 2008 survey waves. For 2007, it utilizes average values corresponding to 2006 and 2008.⁴⁸ Not all 50 U.S. states, plus D.C., are surveyed in each biennial survey wave. All states that are included in both the 2006 and 2008 surveys are included, which totaled 40 states. Figure 5.1Figure 5.2 show the geographical distribution of distrust in banks for each state in the sample. The lowest levels of distrust in banks is in Kentucky (0%), Connecticut (7.1%), Wyoming (9.0%), Wisconsin (9.3%), and Indiana (9.9%). The five states exhibiting the highest levels of distrust in banks are Delaware (75%), the District of Columbia (37.5%), New Mexico (32.3%), Iowa (26.1%), and Arizona (27.4%).⁴⁹ For robustness checks, the distrust in bank variable is winsorized at 5% to ensure that outliers (e.g., Kentucky and Delaware) do not drive results. The results are robust and available upon request.

as alternative dependent variables. The results show that distrust in banks is associated with a larger number of bidders and bids. Results are available upon request.

⁴⁵ The authors signed a non-disclosure agreement with the NORC.

⁴⁶ Less than 1.5% of respondents answered (d) don't know (1.1% in 2006 and 1.4 % in 2008).

⁴⁷ Survey-based, state-level trust variables have been taken to be representative in prior studies in economics (e.g. Aghion et al. 2010; Giannetti and Wang, 2016).

⁴⁸ We repeated our analysis by excluding 2007 and the results are very similar and are available upon request. We also assumed that the distrust variable did not change in one year, so we replace the distrust variable for 2007 with values from 2006. Again, the results are very similar and available upon request.

⁴⁹ The extreme values in Kentucky and Delaware can be attributed to the small number of respondents in the survey because changing one answer will have a significant effect on distrust in bank. To verify robustness, we defined a lower limit of 20 to and 50 respondents per state as a minimum cut-off for survey respondents. This also led to exclusion of outlier states Kentucky and Delaware. The results are highly similar and available upon request. Finally, we created a three (two)-year trailing average of three (two) waves of surveys. Again, the results are very similar and are available upon request.

Figure 5.1. Distrust in Banks in 2008

Figure 5.2. Distrust in Banks in 2006

Control Variables

An extensive list of additional state-related (of lenders) variables is collected to control for possible confounding factors, including technological development, economic conditions, demographics, and access to banking.

To ensure that distrust in banks is not merely capturing a general component of distrust, this study also includes the variable *Trust in Others* in specifications. To build this variable, the study uses data from another question from the same survey, phrased as follows: “Do you think most people can be trusted?” Possible answers are (a) Most people can be trusted, (b) You can’t be too careful, (c) It depends, or (d) I don’t know. The *Trust in Others* variable is constructed as a share of state residents responding (a) Most people can be trusted (those who responded (d) I don’t know, are excluded). Furthermore, *Distrust in Government* is included to capture a general dimension of anti-establishment distrust. Possible answers to the trust in government question were (a) a great deal, (b) only some, (c) hardly any, or (d) don’t know. The *Distrust in Government* variable is constructed as a share of state residents responding (c) hardly any to the question of trust in the U.S. federal government (those who responded (d) don’t know, are excluded).

Prior literature has shown that geographical distance plays an important role in P2P lending behavior (Lin & Viswanathan, 2016). Thus, this study includes a variable that measures the geographical distance between the borrower and lender. To control for a state’s general economic condition, this study includes annual gross domestic product (GDP) growth and GDP per capita. It also controls for population, population density, and each state’s working-age population. Another set of controls is used to capture tech-savviness among each state’s residents, namely level of Internet use at home, percentage of science and engineering graduate study enrollments, and per capita cyber-crime perpetrators.

This study additionally controls for P2P demand in the borrower’s state to separate the direct relationship between distrust in banks and P2P lending from increases in local demand for P2P funding. It also controls for financial literacy as an explanatory factor distinct from lenders’ distrust in banks. It adds a control for entrepreneurial activities within a state by including a variable to capture the per-capita annual change in net total number of firms in a state compared with the prior year. Furthermore, the regression controls for banking density to capture to what extent lending on P2P platforms is driven by scarcity of banking services or investment advice. Finally, several variables are included to capture states’ demographic characteristics: religion (Protestant, Jewish), race (White, Hispanic), political views (Republicans), and gender (Male). Table C.1 provides variable descriptions and data sources (correlation table). Table 5.1 summarizes descriptive statistics of all variables included in the main analysis.⁵⁰

⁵⁰ To maintain brevity, summary statistics on the rest of the variables included in the following sections are reported in Appendices 3 and 4.

Table 5.1. Data Summary Statistics (N = 7,275,560)

Variable Name	Mean	SD	Median	Min	Max
<i>Dependent variables</i>					
Participation Indicator	0.184	0.387	0.000	0.000	1.000
Participation Amount	58.066	316.810	0.000	0.000	33056.020
<i>State Trust Measures</i>					
Distrust in banks	0.195	0.134	0.176	0.000	0.750
<i>Lister or Listing Characteristics</i>					
Borrower Banking Density	0.311	0.078	0.305	0.191	0.677
Listing Size (log)	8.606	0.847	8.517	6.908	10.127
High Risk Listings	0.793	0.405	1.000	0.000	1.000
Debt to income ratio	0.415	1.140	0.220	0.000	10.010
Home Ownership	0.377	0.485	0.000	0.000	1.000
<i>Control variables</i>					
Trust in others	0.407	0.156	0.400	0.000	0.778
Distrust in government	0.419	0.124	0.412	0.000	0.789
Lending distance (log)	7.127	1.346	7.335	0.000	9.015
Internet access	0.674	0.063	0.683	0.521	0.790
GDP per capita	49.511	20.235	44.900	30.500	168.200
GDP growth	0.039	0.033	0.036	-0.043	0.190
Population	7146038	6937427	5412337	522667	36604337
State P2P demand	1.050	0.480	0.977	0.000	7.308
Financial literacy	3.001	0.107	3.017	2.750	3.276
New firms	0.071	0.438	0.055	-0.887	1.629
Science & Engineering specialization	0.179	0.048	0.179	0.061	0.324
Cybercriminality	0.421	0.201	0.455	0.112	0.907
Banking density	0.350	0.077	0.351	0.191	0.554
Population density	0.170	0.564	0.049	0.002	3.672
Working age population	0.531	0.013	0.530	0.503	0.568
Male	0.491	0.006	0.491	0.472	0.509
White	0.798	0.134	0.832	0.294	0.965
Hispanic	0.105	0.100	0.074	0.011	0.452
Republican	0.441	0.116	0.440	0.034	0.666
Protestant	0.527	0.131	0.517	0.269	0.758
Jewish	0.015	0.018	0.009	0.001	0.085

5.7.2 Data on UK P2P Loans

The database on UK peer-to-peer lending is obtained from the Open Data Institute. This comprehensive database of UK peer-to-peer lending from October 2010 to May 2013 was collected using data from the three largest P2P platforms in the UK, namely Zopa Funding Circle and RateSetter. P2P lending was first

originated in the UK, with the launch of Zopa to the public in 2005. Zopa initially focused on personal lending. Funding Circle was established in August 2010 and was one of the first firms in the world to allow individuals to lend to companies (Pierrakis & Collins, 2013). It holds the greatest market share in the UK for P2P business lending. RateSetter launched in 2010. These platforms received a boost in funding by the UK government, through the British Finance Partnership and the British Business Bank in the past years, increasing their legitimacy. In Zopa and RateSetter, by design investors cannot make investments based on the geographic location of the borrower (Bholat & Atz, 2016).

The data comprises details of 13,924,547 loan parts (i.e. individual loan contracts), totaling 59,851 individual loans amounting to £378 million in loan value, including information on the geographic distribution (i.e. districts or 12 UK regions of residence) of lenders and borrowers.

All of the trust data employed are obtained from the European Bank for Reconstruction and Development's Life in Transition Survey (LiTS) II, which surveyed 1504 household heads in Britain in late 2010.⁵¹ This survey is particularly suitable for this study, as it was conducted in late 2010, coinciding with the start of the period in which the peer-to-peer loans originate in the UK. Trust data is limited to 11 of UK's 12 regions, as the survey excluded Northern Ireland. Figure 5.3Figure 5.4 show the distribution of both peer-to-peer lending in these three platforms from 2010 to 2013 and distrust (lack of) trust in banks in 2010.

⁵¹ As part of surveying 39,000 households in 34 countries. This survey does not include trust variables for Northern Ireland. Hence loanparts originating from Northern Ireland are dropped from P2P loans in this study. References to UK regions, hereinafter, exclude Northern Ireland for this reason.

Figure 5.3. UK Regional Variation of Total Lending Per Capita from October 2010 to May 2013

Figure 5.4. UK Regional Variation of Distrust in Banks and Financial System (intervals in the legend express ratios)

5.8 Results

The main analysis focuses on associations between distrust in banks and participation in P2P lending. Table 5.2 reports estimates based on specification (1), which includes control variables and loan-fixed effects, with the level of analysis at listing–state of bidder.⁵²

Model 1 of Table 5.2 is a linear probability model, in which the dependent variable is a dichotomous variable indicating whether a bidder from a state has participated in bidding for a listing or not. The coefficient on distrust in banks is positive and statistically significant (0.034, $p < 0.001$). One standard-deviation increase in distrust in banks (roughly the distance in surveyed distrust from California to New Mexico) is associated with a 0.4 percent increase in probability of participation in P2P listings. Similar results are found using a logistic regression (Table 5.2, Model 2).

⁵² In our main analysis, we included all bids and listings regardless of whether they are successful. We followed this methodology to include all people who committed to participating because bids on Prosper.com were irrevocable. The success of bids is determined in an auction. In robustness checks, we include only successful bids, i.e., only those that turned into loans to borrowers by reaching the minimum loan-funding threshold. The results are similar to those in Table 2 and confirm that distrust in banks is associated with higher participation in P2P loans.

Models 3 and 4 of Table 5.2 use OLS specifications to predict *Participation Amount* as a dependent variable. The coefficient of the distrust in banks variable (0.275, $p < 0.001$) suggests that greater distrust in banks is associated with higher amounts of participation by bidders, in support of Hypothesis 1. The coefficient implies that one standard-deviation increase in distrust in banks is associated with a 3.7-percentage-point increase in the amount of money invested in a loan. In Model 4 of Table 5.2, this study restricts the analysis to states that participate in bidding on P2P loans and exclude zero-participation amounts. Thus, the number of observations is reduced to 1,272,927. This is the intensive margin of participation in P2P loan listings. The positive and significant magnitude (0.211, $p < 0.001$) of distrust in banks is consistent with expectations. Overall, based on results from Models 1-4, distrust in banks is associated with a higher probability of participation and a higher dollar amount of participation in funding P2P loans.

Beyond the main results described above, this study first notes that “trust in others” is correlated positively with participation in P2P lending across all models. To understand the magnitude of the effect of distrust in bank on participation, this study compares its effect with “trust in others.” The effect size of “distrust in bank” relative to “trust in others” in Models 1 and 3 is 59.6% and 116%, respectively. Appendix 5 shows the marginal effect of one unit change in “distrust in bank”, “trust in others,” and “distrust in government.” Second, “lending distance” is correlated negatively with participation in P2P lending across all models. This is in line with prior literature on “home bias” in P2P lending markets (Lin & Viswanathan, 2016). Third, and interestingly, “banking density” is correlated negatively with participation in P2P lending across all models. Finally, “financial literacy” negatively affects participation amount.⁵³

⁵³ This can indicate that greater financial literacy increases diversification across various P2P loans, e.g., smaller amounts for each loan or participation in other alternative assets not observed in our sample.

Table 5.2. Determinant of Participation in P2P Loans

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
	Participation Indicator		Participation Amount ^a			
Distrust in Banks	0.034*** (0.001)	0.169*** (0.012)	0.275*** (0.006)	0.211*** (0.010)	0.307*** (0.015)	1.129*** (0.032)
Distrust in Banks x Borrower Bank Density					-0.100* (0.042)	
Distrust in Banks x Listing Size						-0.099*** (0.004)
Trust in others	0.057*** (0.001)	0.866*** (0.015)	0.237*** (0.006)	0.041*** (0.008)	0.237*** (0.006)	0.238*** (0.006)
Distrust in government	0.002** (0.001)	0.038*** (0.008)	0.027*** (0.004)	-0.027*** (0.007)	0.027*** (0.004)	0.025*** (0.004)
Lending distance (log)	-0.003*** (0.000)	-0.002** (0.001)	-0.021*** (0.000)	-0.008*** (0.000)	-0.021*** (0.000)	-0.021*** (0.000)
Internet access	0.117*** (0.005)	3.141*** (0.045)	0.868*** (0.024)	2.714*** (0.032)	0.868*** (0.024)	0.872*** (0.024)
GDP per capita (log)	0.048*** (0.001)	0.268*** (0.012)	0.235*** (0.005)	0.181*** (0.009)	0.235*** (0.005)	0.236*** (0.005)
GDP growth	-0.099*** (0.006)	-0.736*** (0.049)	-0.366*** (0.031)	1.224*** (0.040)	-0.366*** (0.031)	-0.364*** (0.031)
Population (log)	0.087*** (0.000)	0.646*** (0.002)	0.508*** (0.002)	0.605*** (0.002)	0.508*** (0.002)	0.508*** (0.002)
P2P loan demand	0.016*** (0.000)	0.077*** (0.002)	0.089*** (0.001)	0.153*** (0.002)	0.089*** (0.001)	0.089*** (0.001)
Financial literacy	-0.046*** (0.002)	-0.401*** (0.017)	-0.293*** (0.007)	-0.188*** (0.011)	-0.293*** (0.007)	-0.292*** (0.007)
New firm creation density	0.018*** (0.000)	0.072*** (0.005)	0.059*** (0.002)	-0.041*** (0.004)	0.059*** (0.002)	0.057*** (0.002)
Science & Engineering specialization	0.173*** (0.003)	0.385*** (0.029)	1.110*** (0.014)	0.443*** (0.021)	1.110*** (0.014)	1.108*** (0.014)
Cybercriminality	0.034*** (0.001)	0.133*** (0.016)	0.209*** (0.005)	0.099*** (0.007)	0.209*** (0.005)	0.208*** (0.005)
Banking density	-0.238*** (0.002)	-1.307*** (0.022)	-1.202*** (0.012)	-0.455*** (0.018)	-1.202*** (0.012)	-1.206*** (0.012)
Population density	-0.010*** (0.001)	-0.074*** (0.006)	0.011*** (0.003)	0.092*** (0.004)	0.011*** (0.003)	0.010*** (0.003)
Working age population	-0.751*** (0.015)	-7.835*** (0.138)	-2.348*** (0.071)	1.557*** (0.111)	-2.346*** (0.071)	-2.364*** (0.071)
Male	3.671*** (0.038)	2.163*** (0.347)	23.195*** (0.174)	8.721*** (0.283)	23.193*** (0.174)	23.157*** (0.174)
White	-0.031*** (0.001)	-0.791*** (0.010)	-0.089*** (0.005)	-0.338*** (0.009)	-0.089*** (0.005)	-0.089*** (0.005)
Hispanic	0.031*** (0.002)	0.686*** (0.015)	0.390*** (0.009)	1.202*** (0.013)	0.390*** (0.009)	0.392*** (0.009)
Republican	-0.221*** (0.001)	-1.431*** (0.014)	-1.075*** (0.007)	-0.716*** (0.011)	-1.075*** (0.007)	-1.074*** (0.007)
Protestant	0.154*** (0.002)	0.943*** (0.018)	0.835*** (0.009)	0.420*** (0.016)	0.835*** (0.009)	0.837*** (0.009)
Jewish	2.143*** (0.015)	4.346*** (0.117)	10.264*** (0.068)	-0.098 (0.086)	10.264*** (0.068)	10.269*** (0.068)
Listing FE	Yes	Yes	Yes	Yes	Yes	Yes
Specification	OLS	Logit	OLS	OLS	OLS	OLS
Observations	7275560	7275560	7275560	1272927	7275560	7275560
Adjusted R-squared	0.467		0.537	0.537	0.537	0.537
Number of Listings	181889	181889	181889	110772	181889	181889

Clustered standard errors are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level. ^a This variable is in natural logarithm.

5.8.1 *Heterogeneity of Effects*

This subsection tests Hypothesis 2 (the less accessible banks are for a borrower, the stronger the association between distrust in banks and participation in funding P2P loans) and Hypothesis 3 (the lower the loan size, the stronger the association between distrust in banks and participation in funding P2P loans). Model 3 in Table 5.2 forms the baseline regression for testing cross-sectional variations in the effect of distrust in banks on participation in P2P loans. In Model 5 of Table 5.2, the coefficient of interaction term (distrust in banks and borrower bank density) is negative and statistically significant ($\beta = -0.100$, $p < 0.05$). The coefficient implies that at the average value of distrust in banks (0.195), a change in borrower bank density equivalent to that from its maximum value (0.677) to its minimum value (0.191) corresponds to a 20.3% increase in the effect of distrust in banks on participation in P2P loans. This implies that the lower the bank density in a borrower's state (worse local access to financing), the larger the effect of lenders' distrust in banks on participation in P2P loans. This study graphically plots the marginal effects corresponding to Model 5 in Appendix C, Figure C.2. The results provide empirical evidence that supports Hypothesis 2.

This chapter then tests Hypothesis 3. In Model 6 of Table 5.2, the coefficient of the interaction term (distrust in banks and loan size) is negative and statistically significant ($\beta = -0.099$, $p < 0.001$). The coefficient implies that at the average value of distrust in banks (0.195), changes in loan size from its maximum value (10.127) to its minimum value (6.908) corresponds to a 252.1% increase in the effect of distrust in banks on participation in P2P loans. This implies that the smaller the loan, the larger the effect of distrust in banks on P2P loan participation. The marginal effects corresponding to Model 6 are geographically plotted in Appendix C, Figure C.2. The results provide empirical evidence that supports Hypothesis 3.

5.8.2 *Additional Analyses and Robustness Check*

This section investigates the main variable's construct's validity, endogeneity issues, alternative explanations, and the findings' generalizability in a different setting (external validity).

Construct Validity

The main independent variable (distrust in banks) is extracted from the GSS survey. The construct's validity can be a concern, as this measure might be noisy and not merely capture distrust in banks. To alleviate this concern, additional analysis is conducted.⁵⁴

⁵⁴ This study also checks how much our variable (distrust in banks) overlaps with the Gallup Analytics surveys on "Confidence in Institutions," which examines a random sample of approximately 1,000 individuals across the U.S. Appendix 7 shows distrust in

This study investigates whether events related to banks and financial institutions determine distrust in banks. *Construct validity* refers to what extent a measure reflects the theoretical construct (Cronbach & Meehl, 1955) – in this case, distrust in banks. Distrust originates from breaches to expectations of the trustee’s goodwill or technical competence (A Dimoka, 2010; Mcknight & Chervany, 2001). Consequently, events such as bank fraud, in which expectations of banks’ benevolence are not met (Guiso, 2010), or bank failures, in which expectations, *vis-a-vis* banks’ competence, are damaged, should engender societal distrust in banks and other financial institutions. To test the validity of the survey-based construct of distrust in banks, this study tests the effect of such events on it.

Using an extensive database of all cases of fraud committed by listed financial firms and commercial bank failures in the U.S. from 1978-2012, this study investigates whether distrust in banks in states is associated with the revelation of financial institution frauds and banking failures.⁵⁵

This chapter proxies for the severity of bank failures in a state using the FDIC’s estimation of losses of failed banks, and for the severity of frauds using the log of monetary penalties imposed by regulators on firms and employees, or the log of duration of prison sentences served by convicted employees. To control for the size of each state’s banking system, this study standardizes the failure measures by dividing them by total commercial bank domestic deposits in states. This study lags the bank failure and financial firm fraud measures by one period to determine their effect on engendering distrust in banks. Appendix C (Figure C.5) shows annual U.S. totals on these measures beside the distrust variable over this period.

Table 5.3 presents regression results for the analyses. In Model 1, distrust in banks is regressed on the frequency of bank failures in a state. The coefficient is positive and statistically significant ($\beta=0.068$, $p<0.05$). A standard-deviation increase in exposure to bank failures in a state corresponds to 1.5% in additional distrust in banks. In Model 2 of Table 5.3, this study uses the first proxy for the severity of financial firm fraud, comprising penalties on firms and employees. The coefficient is positive and statistically significant ($\beta=0.011$, $p<0.01$). A standard-deviation (\$161 million) increase in such penalties from the mean of \$8 million to \$173 million is associated with a 14.1% increase in the distrust variable. In Model 4, I proxy for the severity of bank failures using FDIC-estimated losses, resulting in a positive and statistically significant coefficient ($\beta=0.75$, $p<0.05$). A one-standard-deviation rise in such losses increases distrust in banks by 1.1%. This result holds when I include both measures of financial firm fraud’s severity and bank failure, as Model 5 demonstrates. Model 6 uses an alternative measure of fraud severity – convicted executives or employees’ prison sentences. The results ($\beta=0.010$, $p<0.05$)

banks from both surveys (GSS and Gallup) across time. Measures derived from the surveys are highly correlated (92.5%). This shows that both surveys (which are conducted independent of each other) measure the same construct and, thus, can increase our construct validity.

⁵⁵ Appendix 8 (Figure A4) depicts the distrust variable, along with the number of FDIC-insured commercial bank failures and fraud cases over this period, encompassing 3,472 bank failures and 153 fraud cases.

show that events related to banks and financial institutions determine distrust in banks (fraud and failures). Fraud's economic impact on distrust in banks seems to be larger than bank failures' impact on distrust in banks.

Table 5.3. Determinant of Distrust in Banks

	(1)	(2)	(3)	(4)	(5)	(6)
	Distrust in Banks					
Bank Failures	0.068*		0.065*			
	(0.030)		(0.030)			
FDIC Est. Losses of Bank Failures				0.748*	0.720*	0.723*
				(0.297)	(0.303)	(0.301)
Penalties for Financial Firm Frauds		0.011**	0.010*		0.010**	
		(0.004)	(0.004)		(0.004)	
Frauds' Prison Sentences						0.010*
						(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	1978-2012	1978-2012	1978-2012	1978-2012	1978-2012	1978-2012
Observations	810	810	810	810	810	810
Adjusted R-squared	0.444	0.440	0.446	0.441	0.444	0.442

Notes: All regressions include all controls: Trust in others, Distrust in Government, Age, Years of Education, Male, High Income, White, Hispanic, Republican, Protestant, Jewish, Employed, GDP Growth. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level. The level of analyses is state-year.

Endogeneity issues

Biased estimates of the main coefficient can relate to two sources of unobserved heterogeneity: demand and supply side factors. I control for unobserved heterogeneity from the demand side by including listing fixed effects. To attenuate concerns about supply-side heterogeneity, I included an extensive list of economic and demographic characteristics that may affect the regional level of participation in peer-to-peer markets. While this reduces concerns over unobserved supply-side heterogeneity, it is not able to address the issue completely. In this subsection, I address this issue in a few steps.

First, I use a longer time period from 2006 to 2012 (the main analyses only went through October 2008).⁵⁶ This longer period (due to greater variations in distrust) allows us to improve the identification strategy. I repeat all analyses on the new sample (Table 4, Models 1 and 2). The results remain similar to the main findings.

⁵⁶ This is not ideal, as many changes occurred at Prosper.com after the October 2008 hiatus.

Second, I include the state's (of the lender) fixed effects in the model, allowing us to reduce concerns about time-invariant heterogeneities across states (Table 5.4, Models 3 and 4). Again, the results support the main hypotheses.

Third, this study uses an instrumental variable approach to alleviate endogeneity concerns. In the previous section, it is shown that at the state level, fraud committed by listed financial firms and commercial bank failures are correlated positively with distrust in banks. The authors argue that while these variables are correlated with distrust in banks (relevance criteria), they are not correlated strongly with unobserved state-level characteristics (exclusion restriction). The exclusion restriction is more valid for fraud that listed financial firms committed. The decision to commit fraud is made by a handful of individuals working in financial institutions and is less likely to affect general state-level economic and demographic characteristics.⁵⁷ To implement this method, this study uses a two-stage instrumental variable approach at the state-listing level (Table 5.4, Models 5, 6, and 7). In the first stage, this study estimates distrust in banks by including fraud that listed financial firms committed, commercial bank failures, and all control variables (Model 5). Cragg-Donald Wald F-statistics of the first-stage regression (1400) is larger than the critical value of 10. This indicates that the instrumental variables are not weak (Stock & Yogo, 2005). The R-squared of the first stage is also 0.651. The preceding statistics reassure us about the relevance and validity of the instrumental variables. In the second stage, this study use estimated distrust in banks (from the first stage) and repeat Models 1 and 3 from Table 5.2 (Table 5.4, Models 2, 3, and 5). The results support the hypothesis that distrust in banks is associated with greater participation in funding P2P loans.

Alternative explanations

A possible concern is that results are driven by a common time pattern of the growth of P2P lending and distrust in banks (e.g., due to the U.S. financial crisis of 2008-2009). The financial crisis also impacted interest rates strongly. This is especially alarming, as the sample includes observations from 2008 (the sample ends on October 19, 2008). To alleviate this concern, this study restricts the analysis to 2006 only, as well as to 2006 and 2007. This should alleviate the concern, as Lehman Brothers collapsed in September 2008, which is “generally considered to be the epicenter of the financial collapse” (Mark Gertler & Gilchrist, 2018). The interest rates that the Federal Reserve set also were quite stable during 2006 and 2007. The results (Table 5) demonstrate support for the hypothesis that distrust in banks is associated with greater participation in funding P2P loans.

⁵⁷ Guiso (2010) shows that both in Europe and in the U.S., exposure to fraud is associated with distrust in banks.

Table 5.4. Determinant of Participation in P2P Loans Using time period 2006-2012.

	(1) Participation Indicator	(2) Participation Amount ^a	(3) Participation Indicator	(4) Participation Amount ^a	(5) Distrust in banks First stage	(6) Participation Indicator Second Stage	(7) Participation Amount Second Stage
Distrust in Banks	0.090*** (0.001)	0.598*** (0.006)	0.075*** (0.002)	0.446*** (0.009)		0.315*** (0.007)	1.190*** (0.031)
FDIC Est. Losses of Bank Failures (t-1)					0.520*** (0.003)		
Financial Institution Frauds' Prison Sentences (log) (t-1)					0.010*** (0.000)		
Control	YES	YES	YES	YES	YES	YES	YES
Listing FE	YES	YES	YES	YES	YES	YES	YES
State FE	NO	NO	YES	YES	NO	NO	NO
Observations	8214309	8214309	8214309	8214309	8214309	8214309	8214309
Adjusted R-squared	0.505	0.575	0.510	0.587	0.651	0.140	0.200
Number of Listings	232645	232645	232645	232645	232645	232645	232645

Notes: Model 1 and Model 2 replicates the results of main models in Table 2. In model 3 and 4 we include state of borrower fixed effect. Model 5 reports the first stage of the instrumental variable model. Model 6 and 7 shows the second stage of instrumental variable models. All regressions include all controls including Trust in others, Distrust in government, Lending distance, Internet access, GDP per capita, GDP growth, population, P2P Demand, Financial literacy, New firms, Science & Engineering specialization, Cybercriminality, banking density, Population density, Working age population, Male, White, Hispanic, Republican, Protestant, Jewish. Clustered standard errors are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level.

^a This variable is in natural logarithm.

Table 5.5. Determinant of Participation in P2P Loans limiting period to only 2006 & 2007 and only 2006.

	(1)	(2)	(3)	(4)	(5)	(6)
	Participation Indicator		Participation Amount ^a			
Time period	2006 & 2007	2006	2006&2007	2006	2006&2007	2006
Distrust in Banks	0.101*** (0.002)	0.236*** (0.004)	0.676*** (0.009)	1.424*** (0.018)	0.427*** (0.017)	0.660*** (0.042)
Controls	YES	YES	YES	YES	YES	YES
Listing FE	YES	YES	YES	YES	YES	YES
Observations	4,364,360	1,291,920	4,364,360	1,291,920	751,930	183,287
Adjusted R-squared	0.4583413	0.3984585	0.5252584	0.4500271	0.5234091	0.4513701
Number of Listings	109,109	32,298	109,109	32,298	104,101	30,614

Notes: All regressions include all controls including Trust in others, Distrust in government, Lending distance, Internet access, GDP per capita, GDP growth, population, P2P Demand, Financial literacy, New firms, Science & Engineering specialization, Cybercriminality, banking density, Population density, Working age population, Male, White, Hispanic, Republican, Protestant, Jewish. Clustered standard errors are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level. Model 5 and 6 is conditional on participation (participation indicator=1).

^a This variable is in natural logarithm.

Furthermore, as the specification relies on state-level variations, events that operate on the national level are less likely to bias the findings, as the variations will be similar for all states. For example, as mentioned earlier, the Federal Reserve sets interest rates at the national level; thus, changes in interest rates are less likely to explain the results. This study also includes several economic characteristics at the state-year level (e.g., annual GDP growth and GDP per capita) as control variables, allowing to separate the effect of distrust in banks from general economic factors (i.e., the financial crisis and interest rates). Finally, the entire 2008 round of the GSS survey, which measures distrust in banks, was carried out before Lehman Brothers' collapse; 98% of interviews were carried out between April and August 2008.

Types of distrust

Distrust in banks, as a driver of participation in P2P lending, can be related to sources of distrust. On one hand, a fear of losing money invested by banks, and on the other, a more general and ideologically oriented distrust in banks as institutions. Depending on which source is the more important driver, the results' implications clearly differ. If fear of losing money is the prevalent driver of resource allocation, banks and states' actions to alleviate such concerns could be expected to impact participation in P2P lending directly. Alternatively, if ideologically oriented types of distrust in banks drive the results, adopting P2P lending reflects motives other than strictly financial considerations.

To investigate the mechanism underlying fear of losing money, this study examines whether increased participation in P2P lending (that seemingly is associated with distrust in banks) can be associated with loss-aversion behavior. This study argues that if distrust in banks is driven by a fear of losing money, lenders should be less-inclined to invest in riskier loans, which have a greater chance of default, thereby providing lenders with a higher probability of losing their money.⁵⁸ The riskiness of the loan and borrowers is measured using three different variables, following Iyer et al. (2016) and Lin and Viswanathan (2016). First, by including a dummy variable, *High-Risk Listing*, representing listings by borrowers with credit categories of C or lower (i.e., D, E, and HR). Credit categories are assigned based on credit-score information, which Prosper.com sources from Experian. Second, by including the borrower's debt-to-income ratio. Finally, by considering whether the borrower is a homeowner. Borrowers with higher debt-to-income ratios have a higher probability of default, but borrowers who are homeowners are considered less risky, as their home can be used to recover the loan.

Table 5.6 reports the results from introducing interactions between distrust in banks and the risk variables. In Model 1, this study interacts distrust in banks with the dummy variable *High-Risk Listings*. The result shows that the effect of distrust in banks on participation in P2P loans is larger for borrowers

⁵⁸ For example, Iyer et al. (2016) show that the default rate is 14.7% in the lowest risk-category level (AA) and reaches 51.6% in the highest credit-category level (HR). In addition, in case of default, lenders lose only 9% of their principals in credit category AA, but lose 38.5% of their principals in credit category HR.

with higher risks (worse credit ratings). The empirical regression cannot include credit categories separately in the specification, as they are correlated perfectly with listing fixed effects. Model 2 (3) shows that the effect of distrust in banks on participation in P2P loans is larger (smaller) for borrowers with higher debt-to-income ratios (homeownership). Generally, the results show that the effect of distrust in banks on participation in P2P loans is larger for riskier loans and borrowers. These results suggest that the form of distrust in banks that is driven by fear of losing money seemingly would not be the main driver of participation among crowdfunders with greater distrust in banks.

Table 5.6. Heterogeneity of participation in P2P Loans based on riskiness of loans and borrowers

	(1)	(2)	(3)
	Participation Amount_a		
Distrust in Banks x High-Risk Listings	0.547*** (0.010)		
Distrust in Banks x Debt to income ratio		0.043*** (0.002)	
Distrust in Banks x Borrower Homeownership			-0.208*** (0.007)
Distrust in Banks	-0.144*** (0.011)	0.260*** (0.006)	0.358*** (0.006)
Controls	Yes	Yes	Yes
Listing FEs	Yes	Yes	Yes
Observations	7 275 560	7 275 560	7 275 560
Adjusted R-squared	0.538 181	0.537	0.537
Number of Listings	889.00	181 889.00	181 889.00

Notes: All regressions include all controls including Trust in others, Distrust in government, Lending distance, Internet access, GDP per capita, GDP growth, population, P2P Demand, Financial literacy, New firms, Science & Engineering specialization, Cybercriminality, banking density, Population density, Working age population, Male, White, Hispanic, Republican, Protestant, Jewish. Clustered standard errors are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level.

This variable is in natural logarithm.

External validity

Another concern is whether the result is only valid for Prosper.com context and the institutional environment in the U.S. For further robustness, this chapter repeat all analyses using a sample of all P2P loans active between 2010 and 2013 in the United Kingdom and measure distrust in banks from the European Bank for Reconstruction and Development's Life in Transition Survey (LiTS) II. Details on the data and variables are explained in Panel D of Appendix 9. Generally, the results (0 C, Table 0.) are similar to those of Table 5.2 and show that increases in distrust in banks are correlated positively with the likelihood and level of participation in P2P loans. Using different surveys and samples increases

confidence in the main findings' external validity. This also allows us to rule out some secular time-trend issues in the U.S. that probably are not present in the U.K. sample and time period.

Effect of Distrust in Banks on Bank Deposits

The theoretical argument was that individuals with higher distrust in banks are likely to allocate a portion of their assets to alternative assets (e.g., crowdfunding) instead of holding them with banks. Thus, this study should observe that distrust in banks also will decrease assets held with banks. While this hypothesis is not new and has been reported in previous studies (Sapienza & Zingales, 2012; Guiso, 2010), the analyses is repeated by regressing the aggregated deposits of each single-state bank on the distrust in banks variable. Thus, the level of analysis is at a single-state bank-year. Bank deposits and banks' balance sheets are extracted from the Federal Deposit Insurance Corporation's (FDIC) branch-level data. The sample includes the 2001-2016 period. Appendix [10](#) reports the results (the definitions of all variables and their summary statistics are provided in Panel A of Appendices 3 and 4). The sign and magnitude of the distrust in banks variable in Models 1 and 2 (Model 3) indicate that increases in distrust in banks decrease (increase) deposits (other liabilities) in single-state banks.

5.9 Limitations

While part of the novelty of this study is on utilizing new fintech data sources, there are yet data limitations. One limitation relates to the length of time-series of such data. Owing to their nascency, less than a decade of non-interrupted fintech data exist. For example, Prosper.com underwent two hiatuses during its operation in 2008, which caused us to limit the analysis to prior to the crisis.

Another potential limitation relates generally to use of social variables from surveys. Subsection 3.7 described the potential biases when using survey data of measurement, nonresponse, sampling and coverage errors (Ponto, 2015). The rigorous methodologies of the GSS and LiTS surveys (EBRD, 2006; T. W. Smith, 2018) lessen the latter three of these errors. However, measurement error pertains to whether the survey questions accurately reflect the topic of inquiry and to what extent, questionnaires and interviews evoke truthful answers. The utilized questions in these surveys regarding individuals' trust in institutions are subjective attitude questions. Bertrand & Mullainathan (2001) find that when a subjective variable measure is used as an independent variable (such as in this chapter), measurement error is reduced if year or survey fixed effects are used. However, the remaining part of measurement error is correlation with individual characteristics which remains. While the main independent variable of distrust in banks can be correlated with individual characteristics, similar to Giannetti & Wang (2016), distrust in other institutions and general trust levels are controlled for, to diminish this measurement error.

5.10 Discussion and Conclusion

This study leverages insights from the literature on the distrust mindset to argue that distrust in banks boosts the use of P2P lending. This study uses data from Prosper.com and find that residents of states with higher levels of distrust in banks are more likely to participate in P2P loans and allocate greater sums toward P2P loans. Given prior findings on negative correlations between distrust in banks and bank deposits (Sapienza & Zingales, 2012), the findings imply that distrust in banks drives the adoption of peer-to-peer lending as an alternative to banks. Additionally, the relationship between distrust in banks and inflow to P2P lending is stronger for borrowers who seek small loans and who live in areas that provide relatively lower access to bank branches.

This study discusses the potential origins of distrust in banks in the context of the study. Distrust in banks can reflect two sets of distinctive judgments. The first concerns the expectation that a generic bank will fail to repay depositors and violate its commitments. This situation represents heightened fears that investors or depositors will lose all or part of their money, e.g., due to the possibility of bank failure. Such pessimistic perceptions were especially widespread during the recent financial crisis after Lehman Brothers collapsed in 2008. The second source of distrust concerns a diffused belief that actors at financial institutions (e.g., brokers, bankers, financial advisors, etc.) may act opportunistically and take advantage of their investors. For instance, bank managers might charge non-transparent commissions, hide relevant information, commit fraud, misuse funds, or undertake risky and speculative investment bets that benefit themselves at the cost of customers and investors. This second source of distrust in banks can take the form of social or ideological perspectives. In fact, protest movements such as Occupy Wall Street in 2011, partially were motivated by such negative sentiment toward banks, as evidenced by the publication of a book titled *Occupy Finance*, which the group “Occupy Wall Street Alternative Banking Group” distributed to discuss misconduct in the financial industry leading up to the financial crisis and the ways in which the financial industry skirted prosecution.⁵⁹ This study presented some preliminary and indirect evidence in the investigated context that favors ideologically oriented distrust in banks over distrust in banks’ abilities to live up to their direct obligations toward their clientele. In particular, this study finds that the relationship between distrust in banks and P2P participation is stronger for high-risk and high-default borrowers. This evidence likely weakens the idea that P2P lenders primarily are concerned with a fear of losing money when distrusting banks (Had this been the case, the effect of distrust in banks would be expected to correlate with a preference for low risk borrowers).

Another discussion point from this study relates to the role of generalized trust (trust in strangers) and inflows to P2P lending. Prior research has reported a positive relationship between generalized trust

⁵⁹ http://altbanking.net/projects/our_book/

and several financial and economic outcomes, including economic performance (Knack & Keefer, 1997; Neira, Vázquez, & Portela, 2009), flow of trade (Guiso, Sapienza, & Zingales, 2009), and equity capital investments (Colombo & Shafi, 2016). Van der Cruysen, Doll, & van Hoenselaar (2019) find that trust in other people has a statistically and economically significant positive effect on participation in a wide range of peer platform markets, where goods or services are exchanged between peers through online platforms. This study finds similar evidence investigating a particular type of such markets, i.e. loan-based crowdfunding models. Generalized trust appears to lubricate economic activity in the form of sharing financial resources, particularly substituting for heavy reliance on informal borrowing or more established ways of accessing financial services.

This study makes two theoretical contributions. This study contributes to extant research that explore P2P lenders' motivations (Shafi & Mohammadi, 2019; Demir et al., 2019). Crowdfunding literature has highlighted both intrinsic and extrinsic motivations, including earlier access to innovative products and ideas, making an impact, sympathy, a desire to help others, feeling good about oneself, recognition from others, image promotion and social reputation, and sensation seeking (Boudreau et al., 2018; Colombo et al., 2015; Demir et al., 2019; Cholakova & Clarysse, 2015; Galak, Small, & Stephen, 2011). It is able to offer a new motivation and further delineate the moderating conditions associated with this new motivation by choosing a crowdfunding type that offers (lending) functions like those of banks and by employing geographic variations on expressed distrust in banks. The broader contribution to extant literature on investors in crowdfunding draws on theories first developed in social psychology about information processing under the distrust mindset (Mayo, 2015). Moreover, it applies these theories to observational data instead of laboratory experiments, which frequently have been used to develop and test such theories, with certain methodological caveats, including limited room for external validity assessments.

This study also contributes to an emerging stream of literature interested in the relationship between technology and financial intermediaries (Balyuk, 2019; Chava, Paradkar, & Zhang, 2017; Cole, Cumming, & Taylor, 2019; Fuster et al., 2019; Navaretti, Calzolari, Mansilla-Fernandez, & Pozzolo, 2018). In particular, this study adds to the conversation about the advantages of firms that exploit financial technology (fintech firms) over incumbents – whether P2P lending is a substitute for or complement to bank lending. Whereas most studies focus on the substitute role between banks and fintech lenders from the demand side (Buchak et al., 2018; de Roure, Pelizzon, & Thakor, 2018; Tang, 2019; Wolfe & Yoo, 2017), this research examines the supply side, which new theoretical papers, such as Thakor and Merton (2018), are beginning to develop further.

The findings have several practical implications, including for policy makers concerned with seed and early-stage gaps in markets for entrepreneurial finance, as well as for individuals such as entrepreneurs

who aim to succeed in fundraising. With this growth in the volume of crowdfunding transactions during the past decade, scholars initially focused on examining demand-driven factors – such as campaign characteristics, the product, and the management team – which all correlate with campaign success. Subsequently, scholars have investigated crowdfunders’ motivations as another important growth driver. One overlooked impetus for crowdfunders’ contributions is negative sentiments toward established institutions. Such distrust-in-bank motivated contributions have specially the potential to address gaps in funding from current institutions (e.g., limited access to bank branches). Note that policy makers are concerned with negative effects associated with distrust in the banking sector, including financial instability and bank runs, lower demand for financial products, and investors’ adverse portfolio choices, discounting of advice, and reduced reliance on financial intermediaries when making financial decisions. Accordingly, policy makers might pursue regulatory interventions and oversight, but these concerns might be overstated, as distrust in banks may have helped with the emergence of alternatives (especially when these alternatives fill a market gap and have not yet suffered from major failures). Whereas failures to maintain consumer trust may have adverse impacts on incumbents (e.g., banks), they can lend an advantage to new and emerging fintech competitors. Therefore, policy makers can heed this evidence, which provides a dynamic perspective on disruption.

This study contains certain limitations that offer opportunities for future research. First, while this study used two different samples in different countries, the identification strategy remains malleable to unobserved heterogeneity. While the authors cannot exogenously manipulate levels of distrust in banks to study contributions to crowdfunding, several analyses were performed to increase the findings’ reliability. Future research can examine the effect of institutional differences on the presented results despite efforts utilized herein in using samples from two countries. Additionally, authors have assumed that P2P lenders in the sample share the same beliefs about trust in banks as the average person living in that state at the time of survey measurements. Furthermore, future research can investigate whether the results presented in this study can be extended to other forms of crowdfunding. Such analyses also would require identifying corresponding institutions that provide services similar to those of different crowdfunding forms.

We conclude this study by highlighting the role of negative trust sentiment toward banks in propelling P2P lending’ growth. Whereas distrust in financial institutions traditionally is viewed as detrimental for financial stability, we propose a silver lining: Distrust in banks fuels growth of P2P lenders, which increases the diversity of available funding options, especially in dimensions that are dissimilar to banks. By embracing new developments for fintech lenders, we hope that this study inspires further research into factors that propel this new industry.

6 Adoption of Cryptocurrency Infrastructure

Cryptocurrencies are proliferating. A decade on since their dawn with the invention of Bitcoin, the value of all cryptocurrencies reached \$0.25 trillion. To put that in perspective, there is \$1.7 trillion USD and \$1.4 trillion Euros in circulation today (European Central Bank, 2019a; U.S. Federal Reserve Board, 2019). As of November 2019, bitcoin is the world's sixth largest currency in circulation.⁶⁰ The average daily trading of cryptocurrencies has surpassed 1% of trading in foreign exchange markets, the world's largest market by trading volume.⁶¹ Bitcoin transactions and unique accounts alone have grown at nearly 60% per annum over the past five years. In short, cryptocurrencies are being adopted rapidly and broadly. While theoretical papers are emerging discussing why cryptocurrencies, or digital currencies in general, may be adopted by individuals or businesses (e.g. Cohen, 2017; Dierksmeier & Seele, 2018; Dodgson et al. 2015), there is a scarcity of global empirical studies on drivers of their adoption.

The emergence of cryptocurrencies has often been viewed as driven by the opportunity for radical innovation and entrepreneurship in financial solutions as created through the spread of new internet-based technology (Iyidogan, 2018; Teo, 2015). However, recent studies have emphasized that in order to understand the historical growth and future prospect of fintech innovation, we must also understand the nature of the needs addressed by such innovations (B. Cohen, 2017; Huang, Meoli, & Vismara, 2019; Saiedi et al., 2017). The development and spread of technology is in this sense a prerequisite – but not a sufficient factor – for the spread of cryptocurrencies. In this chapter, we focus on socio-economic and institutional factors related to potential drivers for interest in cryptocurrency development. Thereby, we seek to offer a novel and broader account for the growth of this type of financial technology.

We explore drivers behind the global uptake of digital infrastructure enabling the use of the most prominent digital currency to date; Bitcoin (spelled with capital B when referring to the system, and with lower-case b when referring to the unit of account, in keeping with convention in the computer science literature.) We consider infrastructure necessary for Bitcoin's blockchain information dissemination and transaction verification, *Bitnodes*, as well as infrastructure necessary for the adoption of bitcoin as a means of payment in regular retail. We believe these types of *Bitcoin infrastructure*⁶² to provide an informative lens and context for exploring the drivers behind the recent growth of the cryptocurrency. In particular, we believe that that by studying patterns of adoption of these two different types of infrastructure, we obtain complimentary perspectives of the drivers behind the growth of Bitcoin as a system.

⁶⁰ <https://howmuch.net/articles/how-much-currencies-are-worth>

⁶¹ In October 2019, daily trading in all cryptocurrencies varied between \$41.7B and \$15.63B (source: <https://coinmarketcap.com/charts/>), whereas daily trading in global foreign exchange was approximately \$6.6T in April 2019 (Bank of International Settlements, 2019).

⁶² A review of these two types of technical infrastructure and their role for bitcoin as a currency is provided in the Appendix.

We chose to focus on Bitcoin since it is presently the most well-known and wide-spread cryptocurrency.⁶³ Most cryptocurrencies are recorded as clones or as variations of the Bitcoin technology (e.g. Litecoin), build their blockchain as a fork of the Bitcoin blockchain (e.g. Bitcoin cash) or on nearly identical transaction ledgers (Gandal and Halaburda 2014; Wang, Bellavitis, DaSilva 2019). Bitcoin has the highest cryptocurrency trading volume, constitutes more than half of cryptocurrencies' market capitalization, provides much-needed liquidity to other cryptocurrencies and enables a secondary market for the cryptocurrency ecosystem to thrive on. Bitcoin's decade-long dominating position is demonstrated by it being the only cryptocurrency whose price has causality effects on alternative cryptocurrencies or *altcoins*⁶⁴ (Svetlana et al. 2017).

Bitcoin has also been shown to play an important role for the emergence of new digital entrepreneurial ecosystems, consisting of Initial Coin Offering (ICO) issuers, payment processors, exchanges, wallets, financial services, mining hardware, and developers (Sameeh, 2018). Bitcoin, or emulations of Bitcoin, play a central role in this development. For example, the first ICO was carried out in July 2013 by Mastercoin, a cryptocurrency built on the Bitcoin blockchain (Shin 2017). The central role of bitcoin is illustrated by the findings of Masiak et al. (2019), who find that shocks in bitcoin prices positively influence ether - the cryptocurrency underlying most ICOs' blockchain platforms - but not vice versa. In this light, the development of Bitcoin infrastructure might be expected to play a role in enabling the expansion of digital financing and entrepreneurship rapidly emerging through cryptocurrencies.

This chapter starts with an introduction to cryptocurrencies, and their infrastructure, a literature review on adoption of bitcoins, the research gap, theoretical framework, research design, data and methodology for this study, and ends with results, discussions and conclusions.

6.1 Introduction

6.1.1 *On Cryptocurrencies & their Infrastructure*

In October 2008, anonymous developer(s) Satoshi Nakamoto posted a whitepaper entitled "Bitcoin: A Peer-to-Peer Electronic Cash System" (Nakamoto, 2008) to a cryptography mailing list, describing the

⁶³ See <https://www.blockchain.com/en/charts/n-transactions-total?timespan=all> for bitcoin transactions and <https://www.quandl.com/data/BCHAIN/NADDU-Bitcoin-Number-of-Unique-Bitcoin-Addresses-Used> for unique accounts.

⁶⁴ Bitcoin constitutes ~20-35% of all cryptocurrency trading volumes, and litecoin or bitcoin cash, which utilize Bitcoin's blockchain, are respectively the 4th and 7th largest cryptocurrency by volume as of January 3, 2019 (coinmarketcap.com/charts). Wei (2018) calculates Amihud-illiquidity ratios for 456 cryptocurrencies, listing Bitcoin as the most liquid. Hu *et al.* (2018) document average daily and monthly bitcoin price cross-correlation of respectively 0.174 and 0.21 with all altcoins with market values exceeding \$1M. Bitcoin's price cross-correlation with ether, litecoin and monero was 0.88 (Fisch 2019), 0.43 and 0.43 (Hu, Parlour, and Rajan 2018) respectively. ICO-bitcoin correlations have increased since January 2018's cryptocurrency price peaks (Fatás & Weder, 2019).

protocol for the first decentralized cryptocurrency, bitcoin.⁶⁵ Nakamoto launched the implemented protocol on the Bitcoin software and created the Bitcoin network on January 3, 2009 by sending the first bitcoin transaction to Hal Finney, inventor of the reusable proof-of-work system, a precursor to the decentralized (or peer-to-peer) proof-of-work system used by Bitcoin itself.⁶⁶ Hal Finney, like many inventors of bitcoin predecessors, such as b-money (Wei Dai) and bitgold (Nick Szabo), was a “cypherpunk” -activists advocating for the use of privacy-enhancing technologies and cryptography as a means to realizing socio-political change-. The bitcoin protocol provided the first distributed network of trust which crucially does not rely on a centralized intermediary for validation of authenticity and ownership. Instead, transactions are irreversibly recorded on a blockchain (i.e. a growing list of cryptographically-linked records).

The Bitcoin protocol laid the groundwork for all decentralized cryptocurrencies to emerge, altogether amounting to a total market capitalization of \$218B as of October 2018, as well as a fast-growing market of initial coin offerings (ICOs), which raised \$21.6B in 2018.

Computer scientists and digital entrepreneurs have hailed Bitcoin for more than its mere role in enabling secure digital payments, but for their ability to produce a decentralized record of nearly anything (Böhme, Christin, Edelman, & Moore, 2015). The rationale for this is presented by Marc Andreessen (2014), cofounder of the first widely-used internet browser:

*“Bitcoin gives us, for the first time, a way for one Internet user to transfer a unique piece of digital property to another Internet user, such that the transfer is guaranteed to be safe and secure, everyone knows that the transfer has taken place, and nobody can challenge the legitimacy of the transfer. . . . All these are exchanged through a distributed network of trust that does not require or rely upon a central intermediary like a bank or broker. What kinds of digital property might be transferred in this way? Think about **digital signatures, digital contracts, digital keys** (to physical locks, or to online lockers), **digital ownership of physical assets** such as cars and houses, **digital stocks and bonds** . . . and **digital money**.”*

These digital entrepreneurs are continuously developing numerous applications for digital property transfers, with the digital currency ecosystem constantly evolving. For example, subsequent to Andreessen’s assertion, in 2015, the Ethereum blockchain was invented which made digital contracts (without the need for third parties, called **smart contracts**) able to be embedded with programs that can solve any reasonable computation problem.⁶⁷

⁶⁵ In keeping with spelling in the computer science literature, capital-B is used to refer to the Bitcoin system and a lower case-B is used to refer to the bitcoin unit of account. Grammar rules override this adopted convention.

⁶⁶ Paper II, on adoption of cryptocurrency infrastructure, was first published on the Social Science Research Network exactly ten years after January 3, 2009, as a tribute to this technology’s decennial.

⁶⁷ Such a blockchain is called a Turing-complete blockchain.

By now, a vast digital entrepreneurial ecosystem has sprung up in the wake of the introduction of these digital currencies. The digital currency entrepreneurial ecosystem now consists of Initial Coin Offering issuers, payment processors, exchanges, wallets, financial services, mining hardware, and developers, and engages a growing number of technology firms.

6.1.2 On Digital Entrepreneurial Systems and Digital Infrastructure

Digital entrepreneurial ecosystems have two foundational pillars of digital users and infrastructure (Sussan & Acs, 2017) and infrastructures facilitating connectivity, e.g. digital infrastructure, are found to particularly enhance startup activity (Audretsch, Heger, & Veith, 2015). Digital infrastructures enable innovation (Henfridsson & Bygstad, 2013; Sussan & Acs, 2017), anchor open entrepreneurship (Ingram, Bogusz, and Morisse, 2018), allow for FinTech platforms to grow (Yermack, 2018), and create decentralized work organizations (Tilson, Lyytinen, & Sørensen, 2010).

Recent literature has emphasized the need to integrate the economic, social, and cultural elements when studying entrepreneurial ecosystems (Spigel, 2017). Not much is known about the digital infrastructure underpinning the vast emerging digital currency ecosystem. Learning about this digital infrastructure can shed light on the ecosystem as a whole. In addition, as a uniquely decentralized, yet rapidly growing, phenomenon, understanding the factors behind its growth may require more extensive research than centralized systems, owing to information sources being more dispersed.

The emergence of cryptocurrencies has been viewed as driven by the opportunity for radical entrepreneurship and innovation in financial solutions as created through the spread of new web-based technologies (Teo, 2015; Iyidogan, 2019). However, recent studies have emphasized that in order to understand the historical growth and future prospect of fintech innovation, one must also understand the needs which are addressed by such innovations (Cohen, 2017; Saiedi, Mohammadi, & Broström, 2017; Huang, Moeli, & Vismara, 2019). The development and spread of technology is in this sense a prerequisite – but not a sufficient factor - for the spread of cryptocurrencies. Hence, understanding the socio-economic and institutional drivers of the adoption of the digital currency ecosystem can reveal the least and most favorable conditions for this ecosystem to thrive on. Understanding these have implications for monetary authorities, developers and entrepreneurs engaged in this ecosystem, including technology firms, financial institutions and e-commerce payment system providers.

In doing so, I focus on the drivers behind the emergence of infrastructure enabling the use of bitcoins. Bitcoin is the most wide-spread and well-known cryptocurrency. Most cryptocurrencies are recorded as clones or as variations of the Bitcoin technology (e.g. Litecoin), build their blockchain as a fork of the Bitcoin blockchain (e.g. Bitcoin cash) or on nearly identical transaction ledgers (Gandal & Halaburda, 2014; Wang, Bellavitis, & DaSilva, 2019).

6.2 Literature Review

Böhme et al. (2015) review the economics, technology and governance of Bitcoins in their early years. They note that early use of Bitcoin was dedicated to the online sale of narcotics and gambling transfers. They state that its adoption moved into use for consumer payments and for buy-and-hold purposes. Foley, Karlsen, & Putniņš (2018) estimate that 25% of all Bitcoin users and 44% of transactions are in illegal activity (illicit drug, prescription drugs, weapons, etc.). They used three methods to identify addresses involved in illegal activity, namely matching Bitcoin seizures by law enforcement agencies, transactions in wallets of illegal dark-net marketplaces and users identified in dark-net forums. Athey et al. (2016) find that 55% of transactions are carried out by individuals, 17% relate to gambling, 14% relate to Bitcoin exchanges, 5% relate to mining and 3% are related to contraband. They find that most of the holdings are by long-term transactors (mostly long-term investors) and that frequent transactors (mostly speculators and currency-users) are not growing. They estimate that the short-term and one-time user base of Bitcoins (mostly experimenters and adventurers) are growing. By scraping Bitcointalk.org, where a small percentage of bloggers may self-report their country of residence, they find that privacy concerns, illicit activity, technological savviness and trusted exchanges affect adoption. Ermakova et al. (2017) carry out a survey of Bitcoin experts to identify drivers of its adoptions, finding that its use is driven by a desire for anonymity, security and leaving out intermediaries, globalized use, flexibility in use, and lack of central control. While these studies paint a picture of Bitcoin adoption, none carries out a global empirical exploration on the determinants of this digital currency's growth.

Henry et al. (2018) and Schuh & Shy (2016) use consumer consumption surveys in Canada and the US respectively to study the users of bitcoins themselves. Yermack (2018) uses Bitcoin client downloads to study the spread of cryptocurrencies in Africa. Sadhya and Sadhya (2018) use archival data to study barriers to the adoption of bitcoin's blockchain technology.

6.3 Research Gap

While recent studies have shed light on determinants of FinTech startup activity or fundraising using cryptocurrencies (Fisch, 2019; Haddad & Hornuf, 2019; Huang et al., 2019), there are, as of yet, no empirical studies exploring determinants of adoption of the infrastructure supporting cryptocurrencies. This study fills this gap.

While a number of studies make strides in researching the adoption of bitcoins (as outline in the previous subsection), to the best of our knowledge, this chapter provides the first global empirical study on the Bitcoin phenomenon. This study is also the first to empirically analyze the growth of Bitcoin infrastructure. This study thereby contributes to a nascent body of research that delves into exploring the

adoption of financial technologies (Xue et al. 2011, Rau 2017, Haddad and Hornuf 2018, Huang et al. 2019, Yermack 2018, Higgins 2018, Estrin et al. 2018).

This study improves upon current research on adoption of digital currencies by empirically examining actual digital currency support over time in a panel data set. An advantage of this study is having location data, covering the entire world, enabling the use of geospatial data analysis to investigate the role of socio-economic and institutional factors, in parallel to technological and economic factors, in driving their adoption. Recent literature has emphasized the need to integrate the social, economic, and cultural elements when studying entrepreneurial ecosystems (Spigel, 2017). As to the author's best knowledge, there are no empirical studies yet that have simultaneously investigated the relevance of both types of factors for interest in Bitcoin on a global scale. The unique context of cryptocurrency infrastructure allows this study to do so.

By increasing our understanding of what socio-economic and institutional factors that are associated with the adoption of the infrastructure behind virtual currencies, the study offers important insights to scholars seeking to understand the growth of cryptocurrencies to date. These results are also of potential interest to monetary authorities as well as for developers and entrepreneurs in the virtual currency ecosystem, including financial institutions, e-commerce payment system providers or technology companies, which are exploring or planning to issue or accept virtual currencies.

6.4 Theoretical Framework and Hypotheses

In considering what socio-economic and institutional factors that may be related to the intensity of Bitcoin infrastructure adoption, we build on a view of decisions to set up and operate Bitcoin infrastructure as being related to a combination of extrinsic and intrinsic motivations. The launch of the Bitcoin system was embedded in idealistic notions of providing means to replace existing financial structures, and nurturing an alternative monetary and financial system that enables greater anonymity, privacy and autonomy (Bashir, Strickland, & Bohr, 2016; Böhme et al., 2015; Dodd, 2018; Shiller, 2019). Individuals setting up Bitcoin nodes to grow the peer-to-peer network would often do so as an expression of support for Bitcoin as a system and financial phenomenon. Meanwhile, those running a node do so to verify that their own transactions are secure, while it may also be related to bitcoin mining activities, where individuals seek to earn bitcoins. Merchants' willingness to adopt technology necessary to accept bitcoins as payment for their goods is clearly to a large extent driven by business motivations, while the customer preferences to which merchants react to, may considerably be driven by their support for Bitcoin on idealistic grounds. 'Support for Bitcoin' is thus in our study a central (albeit not directly observed) factor.

The growth of Bitcoin infrastructure can be expected to be directly linked not only to support and positive attitudes, but also to the actual use of bitcoin (e.g. in terms of the number of people holding bitcoins). We expect that in the relatively early stage of development that we are studying, the use of bitcoin as a currency and the support for the Bitcoin system are to be understood as interdependent entities. That is, we expect that positive attitudes towards the cryptocurrency will translate into more use, and we expect greater use to spread the interest for (and general awareness of) Bitcoin – i.e. to increase the number of people interested in supporting the Bitcoin network. In developing hypotheses about the adoption of Bitcoin infrastructure, we hence consider what set of socio-economic and institutional factors that may be associated with greater support and use of the cryptocurrency.

6.4.1 *Bitcoin's differentiating technologies*

Cryptocurrencies such as bitcoins have been hailed as pioneering and potentially disruptive financial technologies. Bitcoin's blockchain technology allowed for a novel way of solving the “*double spending problem*” intrinsic to digital currencies, without relying on a central clearinghouse or trusted third party (Folkinshteyn et al. 2015; Böhme et al. 2015). Active support for Bitcoin may hence be understood as being fundamentally related to opportunities enabled from these *differentiating technologies*; making it an attractive substitute to traditional currencies for groups of users (Athey et al., 2016; Ermakova et al., 2017). Opportunities arising due to the differentiating technology underlying Bitcoin stem from its ability to remove the need for a trusted third party or *disintermediation*, and due to its cryptographic technology, that enables *pseudonymity* in online transactions (Cohen 2017).⁶⁸

Preferences for remaining anonymous in financial transactions may be associated with entirely ideological views. In an empirical examination of the related phenomenon of ICOs, Fisch et al. (2018) find such ideological motives to be among the most important drivers behind the early development of ICOs. However, preferences for anonymity also arise due to specific intentions to evade legal authorities. Böhme et al. (2015) document that while consumer payments and buy-and-hold purposes became important drivers of bitcoin adoption in later stages, in the early use of bitcoin, online sale of narcotics and gambling transfers played a very important role.

Against this background, it would seem valid to expect that the global spread of bitcoin has been driven both by its potential role as a partial substitute role for traditional financial services and currencies,

⁶⁸ Such opportunities were in line with influential factors at the very inception of the blockchain within the cyberpunk movement. Bitcoin's white paper outlines anonymity and decentralization as influential factors shaping the evolution of the blockchain sector (Iansiti & Lakhani, 2017). While the developmental motives of the blockchain were anonymity and decentralization, the practical outcome can more exactly be described as it providing *pseudonymity* (Böhme et al., 2015) and disintermediation, not anonymity and decentralization. Eyal and Sirer (2014) state that “At this point, the currency is not decentralized as originally envisioned”. In reality, blockchain has helped create a disintermediated payment system, as well as a disintermediated method of raising venture financing via ICOs.

and by its potential role as facilitator of illicit activity. In what follows, we consider these two alternative accounts for what drives adoption of infrastructure for the supply and demand of bitcoins.

6.4.2 Bitcoin as complement or substitute to established financial systems

The nascent literature on the Bitcoin system and bitcoin currency indicates their financial potential as (a) a new exchange/payment system, (b) an investment, or (c) a speculative trading instrument. Bitcoin's novelty as a payment system is due to its relatively low foreign-exchange transaction costs (Kim, 2017), and its independence from monetary authorities, governments or processing via third-party financial intermediaries. Meanwhile, Glaser et al. (2014) find that uninformed bitcoin users are primarily interested in bitcoin as an alternative investment vehicle, rather than an alternative transaction system. As an investment it increases opportunities for portfolio risk management owing to its very limited correlation with other asset returns such as fiat currencies, stocks, bonds and commodities such as gold (Baur, Dimpfl et al. 2018; Dyhrberg 2016) and hedging against economic uncertainty (Bouri, Gupta et al. 2017; Bauri, Molnár et al. 2017).

While previous academic studies have attributed less (e.g. Blau 2018) or more weight (e.g. Baur, Hong et al. 2018) to speculative trading as the primary use of Bitcoin, it is clear that speculation is a factor behind the rising number of individuals holding bitcoin. To the extent that the adoption of Bitcoin infrastructure is related to the stock of bitcoin holders, geographical variation in Bitcoin infrastructure adoption may be related to geographical differences in the intensity of speculative trading. In this analysis, however, we are primarily concerned with analysing support for Bitcoin infrastructure in relation to the cryptocurrency's potential as complement or substitute to more fundamental functions of the established financial system. This is since node infrastructure are primarily set up to support bitcoins as an exchange and payment system. Merchants' adoption of Bitcoin infrastructure may also be understood as driven by support for Bitcoin, both in regards to the merchants' own views and in regards to the views of customer groups that merchants would want to appeal to.

In the remainder of this section, we describe three sets of factors that may drive support for Bitcoin as a financial exchange/payment system. Bitcoin may substitute for (real or perceived) failings of established financial systems, due to opportunities of disintermediation and decentralization technologies. We first consider Bitcoin as a substitute for fiat currencies in inflation crises. We subsequently consider less acute failings of established financial system, in discussing whether Bitcoin can be considered a viable (potential) substitute to poorly functioning national banking markets. Finally, we consider a more ideological perspective of interest in Bitcoin as being driven by the spread of general attitudes of distrust in banks and the established financial system.

When discussing banking market development, we also acknowledge that financial development may also be expected to drive the interest in cryptocurrencies. If this mechanism dominates, support for Bitcoin and the growth of Bitcoin infrastructure will be stronger – not weaker – in countries with well-developed banking markets.

Inflation

In its capacity as a global currency which is not tied to any particular economy, bitcoin has the potential to act as a hedging opportunity against country-specific risk. In particular, buying bitcoins offers a novel opportunity to hedge against (very) high inflation, in parallel to how gold and other assets have been known to function in the past (Arnold and Auer, 2015). Luther (2016) finds that currency transitions have often occurred during episodes of hyperinflation, exemplified by many Bolivians and Peruvians who switched to US dollars, perceived to be safer, during such national episodes in the 1980s. People affected by very high inflation may therefore become more actively interested in holding and using bitcoin, and in supporting Bitcoin as an alternative financial system.

Cryptocurrencies have indeed been touted by advocates as a means to a less crisis-prone financial system (Maurer et al. 2013) and as a counterweight to (hyper)-inflation (Dierksmeier & Seele, 2018). There are also reports that countries experiencing high inflation have seen surges in interest in bitcoins. This is visible in the example of Venezuela, where inflation soared, trust in the national government policy and currency plummeted and interest in bitcoins increased evidenced by the popularity of bitcoin mining (Kliber, Marszałek, Musiałkowska, & Świerczyńska, 2019). Another noted example is Cyprus during its 2012-2013 financial crisis (Subramanian & Chino, 2015). We hence expect that high inflation levels or inflation crises may systematically affect the adoption of the two types of Bitcoin infrastructure (bitnodes, bitcoin merchants).

Hypothesis 1: *The occurrence of inflation crises is associated with increased adoption of Bitcoin infrastructure*

Banking market development and competition

There is a potential for financial technologies to substitute for deficient provision of traditional banking services, as evidenced e.g. by the use of mobile money accounts to transfer money in Sub-Saharan Africa (Demirguc-Kunt et al. 2018). Digital currencies have been hailed as a promising means to reach businesses and people in remote and marginalized areas (Lagarde, 2018). Around the world, most existing payment systems (e.g. credit and debit cards) rely on transactors to hold bank accounts. It is conceivable that digital currencies could serve as a payment system of choice for the unbanked (i.e. those without bank accounts). In fact, an extensive survey of the Bitcoin community finds that serving the unbanked is one of the foremost purported promises of this currency (Vigna and Casey 2015; see Chapter 8 entitled "Unbanked").

Whereas payment of a minor fee for access to services of an online trading platform is sufficient for a digital currency transaction (Dwyer, 2015), banking systems impose fees on businesses and individuals, in the form of depository and transactional fees. Philippon (2016) finds that the unit cost of financial intermediation has remained consistently and surprisingly expensive from 1886 to 2012. Conventional transactions impose costs ranging from a small percentage (e.g. 1-3% for credit card purchases) up to highs of one fifth of transferred amounts (e.g. international remittances; see Beck and Martínez pería 2011).

By removing the intermediary, the development of Bitcoin has the potential to do away with these costs. Transaction fees for bitcoins are in the 0-1% range (Kaskaloglu, 2014). Bitcoin offers a welcome alternative when high transaction costs of traditional transactions either disincentives the transaction altogether or diminish its benefits (Dierksmeier & Seele, 2018). The ease of exchange via cryptocurrencies can extend much-needed liquidity to recipients of micropayments or loans in developing and underdeveloped countries, offering the world's 'unbanked' millions an unprecedented degree of convenience and security (Vigna & Casey, 2015). Lacking access to a financial institution or the needed documentation to use one, such individuals have to rely on storing cash, endangering themselves and limiting them to transact with those within their physical reach (Dierksmeier & Seele, 2018). As long as access to a mobile phone with SMS technologies or internet connection exists on any device, a whole world of transaction and investment possibilities becomes available (Raymaekers, 2015).

Besides the penetration of banking, underdeveloped competition in the banking market may be another factor driving interest in Bitcoin as a payment system. Low competition within the financial system is expected to be associated with high rents and limited innovation by incumbents, aggravating the frictions of traditional banking services in terms of costs, service availability, and service scope. Therefore, low competition may in principle drive consumers to adopt alternative financial technologies for reasons parallel to those developed above. Moreover, low competition in the banking market stimulates investment in fintech (Thakor 2019). Interest in Bitcoin may follow in the wake of such activity.

In summary, we suggest the following set of hypotheses:

Hypothesis 2a: *The lower the population of financially included adults, the greater the adoption of Bitcoin infrastructure*

Hypothesis 2b: *The lower the level of competition in banking markets, the greater the adoption of Bitcoin infrastructure*

On the other hand, it is also possible that financial development is a prerequisite for the interest in cryptocurrencies. Lacking experience with traditional internet banking services, people may not be prepared to deal in cryptocurrency. A lack of familiarity with financial intermediaries and their services

may also lead to little interest in exploring their alternatives. Such a view would suggest that digital infrastructure aimed at disrupting banking may develop most strongly in environments with the most well-developed banking markets.

Financial literacy and sophistication is a pre-requisite for taking advantage of financial innovations (Campbell, 2006) and engaging in complex financial products, such as stock market investments (van Rooij et al. 2011) or retirement planning (van Rooij et al. 2012). Financial literacy has been shown to underlie financial inclusion and increase the use of financial services (Grohmann, Klühs, & Menkhoff, 2018) and hence, it is likely that a high level of financial literacy and inclusion is required for use of complex financial innovations such as bitcoins. The use of electronic payments has been found to be associated with financial inclusion (c.f. Thakor 2019). Emerging research points to complementarities between banking markets and fintech development (Hornuf, Klus, Lohwasser, & Schwienbacher, 2018; Klus, Lohwasser, Holotiuk, & Moormann, 2019). For example, Gazel and Schwienbacher (2018) find locations with more bank headquarters and financial competition attract more fintech clusters. Such a development can generate externalities in the form of greater know-how of financial technologies, and thereby also interest in cryptocurrencies such as Bitcoin. It is also possible that a more vibrant banking market, where competition drives banks to innovate, banking costumers become less adverse towards trying new electronic services.

Together, these arguments suggest that interest in bitcoin may be highest in countries with well-developed banking systems and high banking market competition.

We consider the following two competing hypotheses:

Hypothesis 2c: *The greater the population of financially included adults, the greater the adoption of Bitcoin infrastructure*

Hypothesis 2d: *The higher the level of competition in banking markets, the greater the adoption of Bitcoin infrastructure*

Trust and social attitudes

A prerequisite for economic exchange, trust has been found to be positively associated with financial development and investments. Researchers have explored its role in online markets such as e-commerce (Ba & Pavlou, 2002), peer-to-peer lending (Duarte et al., 2012) or crowdfunding (Liang, Wu, & Huang, 2019; Rau, 2017). While the blockchain technology may be perceived as reducing the need for direct trust in individuals, many important uses of bitcoin would seem to be positively associated with general trust. We therefore expect higher levels of trust in others to increase interest in Bitcoin, e.g. in the form of increased trade in bitcoins for investment, speculation and online or in-store commerce.

Cohen (2017) documents that bitcoins emerged as part of the 99 percent movement – initiated by the Occupy Wall Street protests – and frustrations with banks that had become too big to fail.⁶⁹ The launch of the Bitcoin system was embedded in idealistic notions of providing means to replace existing financial structures, and nurturing an alternative monetary and financial system that enables greater anonymity, privacy and autonomy (Bashir et al., 2016; Böhme et al., 2015; Dodd, 2018; Shiller, 2019). Via enabling cheap and automated verification on distributed ledgers, the blockchain technology underlying cryptocurrencies allows for trust in an intermediary to be replaced by trust in the devised code and rules that define how the network reaches consensus (Goldfarb & Tucker, 2019). Desire for this replacement is likely greater where trust in financial intermediaries, whom traditionally verified payments, is lower, and can thus motivate the uptake of cryptocurrencies.

While to the best of our knowledge no systematic investigation has been done regarding distrust to banks and financial institutions as a driver of support for Bitcoin, the role of trust to banks has started to be explored in other FinTech settings. Saiedi et al. (2017) and Bertsch et al. (2017), show that a decline in trust in banks and financial institutions increases participation respectively, by lenders and borrowers, in online peer-to-peer (P2P) lending markets. Theoretical papers modelling trust-driven substitutions between intermediaries and fintech firms are also emerging (e.g. Thakor and Merton 2018). We thus posit that lower trust in banks and the financial system underlies the emergence and adoption of bitcoins. In our variable definitions (see Table 6.1), we use *distrust* to mean lack of trust for brevity.

Yermack (2015) reports that one of the major obstacles facing bitcoin in becoming an adopted currency is its extreme time-series volatility. This high volatility is a product of the highly speculative nature of the bitcoin market (Baek & Elbeck, 2015). Yermack (2015) further reports that it is widely understood that most bitcoin transfers involve transactions between speculative investors. Empirical studies corroborate the use of bitcoins as a speculative investment (Baur, Hong, et al., 2018; Bouoiyour & Selmi, 2015) and that it exhibits speculative bubbles (Cheah & Fry, 2015; Fry, 2018). It thus seems reasonable to assume that the interest to buy and hold bitcoins for speculative purposes, and the willingness to accept risk when holding bitcoin to be used for transactions, would require a certain level of risk-willingness. Regional differences in average willingness to take financial risks may therefore affect the use of bitcoin. We expect that the higher the willingness to take risk in a region, the greater the adoption of bitcoins for speculative trading.

In summary, we expect that active support for Bitcoin is associated with a lack of trust in the established financial system. Such support would be manifested e.g. through the running of Bitcoin nodes, and may also affect merchants' willingness to accept bitcoin. Greater trust in other people and higher

⁶⁹ Indeed, in the very first bitcoin mined, its founder, Satoshi Nakamoto, embedded the message “The Times 03/Jan/2009 Chancellor on brink of second bailout for banks”, referring to the Times of London’s same-day headline (Elliott and Duncan 2009).

risk-willingness is expected to facilitate the use of bitcoin, and thereby the interest in adoption of Bitcoin infrastructure in a region – in particular in regards to merchants' adoption of bitcoin payments.

Hypothesis 3a: *The greater the level of trust in others, the greater the adoption of Bitcoin infrastructure*

Hypothesis 3b: *The greater the level of distrust in banks and the financial system, the greater the adoption of Bitcoin infrastructure*

Hypothesis 3c: *The higher the risk-willingness, the greater the adoption of Bitcoin infrastructure*

6.4.3 Bitcoin as a facilitator of illicit activity

Bitcoin's differentiating technology of pseudonymity makes the cryptocurrency interesting for actors pursuing activities of illegal trade such as drug trafficking, weapons trade, and prescription drug trade (Foley et al., 2019). Böhme et al. (2015) describe that the first notable adopters of bitcoin sought greater anonymity and a lack of regulation concerning what could be purchased using the currency. Bohannon (2016) states that bitcoin's purported anonymity made it popular among criminals. A recent study finds that around 25% of all bitcoin users and 44% of all transactions relate to trading in illegal activities (Foley et al., 2019).

The source of almost all bitcoins used for illicit purposes and laundered through exchange services are dark-net marketplaces (Fanusie & Robinson, 2018), i.e. marketplaces on encrypted websites that do not appear through conventional internet browsing. Bitcoin is the primary means of payment on the dark-net (Slobbe, 2016) with estimates showing it accounts for nearly 95% of the transactions on some dark-net marketplaces (K. Smith, 2019). Moreover, trading in bitcoin is also advantageous to sellers of illicit goods sold through such marketplaces. By allowing for pseudonymous exchange, digital currencies such as bitcoin have been identified as ideal money laundering vehicles (FATF, 2014; NDIC, 2008).

In view of these arguments, we expect the *ceteris paribus* interest in bitcoin to be higher in locations with high activity in trade of illegally acquired goods and services, and in locations where financial services related to such trade take place. In particular, Bitcoin has an important role to play in the trade of illegal drugs online (Soska & Christin, 2015). Bitcoins and online drug markets have made it possible to sell drugs to unknown customers, whereas for decades retail drug markets remained localized, i.e. dealers sold primarily to known customers (Aldridge & Décary-Héту, 2016b). Using cryptocurrencies to trade in drugs provides a means for circumventing state prohibition. Furthermore, the opportunity to shift drug trade online, with anonymity relatively well preserved due to the use of bitcoins as means of payment, also allows greater personal security (threat of violence etc.) than buying drugs directly from dealers or contacts (Barratt, Ferris, & Winstock, 2016). Some sellers and buyers of drugs are therefore actively supporting bitcoin in view of its role in enabling on-line acquirement of drugs. It can also be expected

that the use of bitcoin for drug purchases may spill over to other types of use, and thereby stimulate the general interest and familiarity with bitcoin as a means of payment.

Even though cryptocurrency markets create a potentially global platform for drug distribution, they tend to be used for local trade as opposed to cross-border trade (Demant, Munksgaard, Décary-Héту, & Aldridge, 2018). Hence, the adoption of Bitcoin infrastructure can be associated with the level of activity in on-line drug trade across locations. However, reliable measures for such activities are hard to come by. We suggest that the intensity of money-laundering activity and the effectiveness of law enforcement – two factors that are being measured with some reliability for a sufficiently large number of countries for our purpose – can be used as indicators for such demand.

Money-laundering refers to processes whereby the proceeds from illicit trade is being transacted through financial institution so as to hide its origin in illicit activities. A substantial share of such activity is directly related to drug trade. While money laundering may take place across as well as within nations, locations with high levels of trade in drugs would typically rate high on measures of money-laundering activity.

The second factor that we consider concerns to what extent drug trade would require the pseudonymity provided by on-line purchasing using bitcoins. We focus on the level of law enforcement in a country. More effective law enforcement may in principle reduce bitcoin adoption for illicit intent. However, current research suggests that contemporary law enforcement does not possess the capacity to control much internet-related crime (Holt, Smirnova, Chua, & Copes, 2015). In most countries, no particular Internet-mediated drug trafficking investigations are carried out (Lavorgna, 2014). Despite law enforcement efforts, such as the closure of Silk Road and Silk Road 2.0, crypto-markets continue to proliferate and have proven to be extraordinarily resilient (Aldridge & Décary-Héту, 2016a; Soska & Christin, 2015). Drug buyers and sellers using the dark net perceive the likelihood of arrest to be much lower than alternative means (Aldridge & Décary-Héту, 2016a; Barratt et al., 2016; Ormsby, 2016; Van Hout & Bingham, 2014).

We therefore would not expect that stricter law efforts may hamper internet-based drug trade, but it should be expected to affect other forms of buying and selling drugs (e.g. openly on the street). Conditional on the level of demand for illegally acquired goods and services, greater perceptions of the quality of police and courts could therefore drive illicit activity towards online anonymous (or pseudonymous) activities.⁷⁰ In other words, we expect that the greater the likelihood of arrest on the

⁷⁰ In fact, our rule of law variable has a 0.49 correlation with dark-net market drug purchase statistics in 26 countries, reported by Winstock *et al.* (2018).

streets for traditional drug trafficking, the greater the interest in selling drugs online using anonymity-granting technologies. And as argued, we expect such interest to generate support and interest in Bitcoin.

Therefore, we expect that the greater the enforcement of rule of law, the greater the use of bitcoins for illicit activity (conditional on the level of activity of a local drug market). We conclude that the level of drug trade activity in a location can be expected to be related to the extent of money-laundering and to law enforcement effectiveness. On the basis of our expectation that interest in bitcoin is partially driven by on-line drug trading activity, we thus suggest that both money-laundering and law enforcement are related to the adoption of Bitcoin infrastructure.

While we have emphasised above that the level of money-laundering constitutes a useful proxy for trades in illicit goods in a country, it should be noted that some locations may feature as prominent sites for money laundering activity without necessarily being centres of illicit trade. Even where this may be the case (primarily in countries where financial regulation is conducive to money laundering), we expect money-laundering to be associated with interest in bitcoin. Consistent with this expectation, 97% of direct bitcoin payments from identifiable criminal sources were received by exchanges in countries with weak anti-money laundering regulations (CipherTrace 2018). To the extent that they provide anonymity, bitcoins and other cryptocurrencies can be exploited for money-laundering purposes (Evans-Pughe, Novikov, & Vitaliev, 2014; Moser, Bohme, & Breuker, 2013), e.g. in the form of automated laundering operations (McGinn et al., 2016). With the rise of specialized bitcoin money laundering services on the dark-net, such opportunities are becoming available to a broader audience (Albrecht, Duffin, Hawkins, & Morales Rocha, 2019; van Wegberg, Oerlemans, & van Deventer, 2018).

Together, the arguments outlined above can be summarised in the following two hypotheses:

Hypothesis 4: *The more money-laundering activities taking place, the greater the adoption of Bitcoin infrastructure*

Hypothesis 5: *The stronger the rule of law, the greater the adoption of Bitcoin infrastructure*

6.5 Research Design

Many studies on exploring the drivers of financial technologies exploit geographic differences in adoption of these technologies. Studies have used country-level differences in the volume of crowdfunding (Rau, 2017), fintech startups (Haddad & Hornuf, 2019) and ICO volumes (Huang et al., 2019). This chapter also uses country-level heterogeneity, while it also exploits annual variations in stocks of the dependent variables. In addition, as was the case with Chapter 5, social variables are investigated at the region level (equivalent to EU's NUTS-2 regions) herein. This is done because social variables were only

available for a limited subset of countries during the analysis period of 2014-2018,⁷¹ and expanding the observations to the region-level helps utilize as much of the variation in the social variables as possible.

A noticeable gap in the nascent economic research on adoption of cryptocurrencies was a lack of global empirical data showing the geographic distribution of adoption, with reasonable quality. One of the few papers that uses geographical proxies is Athey et al. (2016) which uses Bitcointalk.org, where a small percentage of bloggers may self-report their country of residence. They use known locations for this small percentage to probabilistically classify the remainder of the bitcoin network into four of the worlds' mega-regions, using Machine Learning techniques.

While the pseudonymous nature of cryptocurrencies explains the difficulties in the literature to geographically locate users and network agents, a few sources of information with substantially higher, yet imperfect, reliability exist. This study uses some of these sources, which had so far been neglected. The following subsection details this class of available data.

6.6 Data

The so-far underutilized sources of information in researching cryptocurrency adoption can be divided into a few classes. Firstly, since much of the cryptocurrency community communicates and shares products similarly to the open-source community, open-sourced and crowd-sourced sources of information exist on bitcoin use. Notably, location information for merchants accepting bitcoin are available on CoinMap.com. This website's API enabled accessing a rich dataset utilized for this research. Another example is CoinATMRadar.com, which lists ATMs that accept a cryptocurrency. Secondly, digital entrepreneurs in this community often share programming codes on source-code repositories such as GitHub. The database of bitnodes utilized in this chapter, is built on Python code of a bitcoin network crawler for nodes, which is shared on GitHub⁷². Either the codes or outputs of such programs can be used to obtain data. Thirdly, it is possible to reconstruct the complete network of cryptocurrency transactions and identify individual "users" (market participants) as done by Foley et al. (2019) for bitcoins –even if individual identities are masked using pseudonymous alpha-numeric addresses-. This chapter utilizes the first and second of the data source types described above.

6.6.1 *Dependent variables*

We utilize two global digital infrastructure datasets supporting the use of Bitcoins encompassing the five-year period from 2014 to 2018, one of computers that observably disseminate blockchain information

⁷¹ The World Value Survey's (WVS) 6th wave does survey 60 countries on social characteristics (including trust and financial trust), which is more than the LiTS III survey which surveys 34 countries. However, region-level breakdowns exist for LiTS III which are not publically accessible for WVS.

⁷² <https://github.com/aycowch/bitnodes>

and verify transactions on the Bitcoin network (known as *Bitnodes*; see Figure 6.1 for validation and verification actions in a bitcoin transaction life cycle), and one of merchants accepting bitcoins as payment⁷³.

A *Bitcoin node* is any computer or data processor that connects to the Bitcoin network, in order to receive and send information relating to Bitcoin's blockchain (a growing list of records of bitcoin transactions). Each bitcoin user represents a node on the network. A subset of all nodes are *Full Bitcoin nodes*, which fully download every block and transaction and check them against all rules of Bitcoin (e.g. no double-spending of bitcoins). Any decentralized cryptocurrency depends on such full nodes to ensure its blockchain adheres to agreed-upon rules. Hence, Full Bitcoin nodes are essential to ensure security of Bitcoin's digital ecosystem and for full removal of a need for a trusted alternative node or third party. A user becomes a *Full Bitcoin node* by running a software, called *Bitcoin Core*, on her computer. By default, Full Bitcoin nodes accept incoming connections (in technical terms, are reachable or listening) and upload updated blockchain information to other peers or nodes on the network. These are termed *Bitnodes*, which are reachable full nodes on the network. Our data consists of all *Bitnodes* operating worldwide between 2014 and 2018. While there is no reliable method to determine if these Bitnodes are businesses, individuals, exchanges, bitcoin miners or merchants, there are indications that they are users or businesses transacting in bitcoins or volunteers supporting the network (e.g. more nodes are online during US working hours). Appendix I describes *Bitcoin nodes*, *Bitnodes* and our dataset preparation in greater detail.

Our dataset allows us to construct measures reflecting both the total intensity of Bitnode activity (*Bitnode intensity*) per country or region and year and the average number of *Unique bitnodes* by country or region and year. Figure 6.2 and Figure 6.3 provide a global depiction of these variables. We also construct a measure of node availability by calculating for how many hours there is at least one Bitnode active in a country or region (*Bitnode hours*). For further details, see Table 6.1.

Our data for merchants accepting payments in bitcoin is from CoinMap.org. CoinMap is a website where either business owners or interested customers or users would add a business that accepts bitcoins (or bitcoins together with other cryptocurrencies) as payment in exchange for a service or good. Some of the businesses on these websites only accept bitcoins on their online websites. Soon after launching in 2013, CoinMap became the primary website worldwide, as referred to in online Bitcoin forums, to find businesses where bitcoin holders can spend them. Figure 6.4 depicts the global spread of merchants, whereas the Appendix describes the Bitcoin merchants dataset we use and our dataset preparation in greater detail.

The accumulated stock of merchants recorded on CoinMap may not, however, be an entirely accurate representation of the situation in that year, as there are numerous reported cases of merchants added to the database, who subsequently forego acceptance of bitcoins after months or years of low-

⁷³ Available at an open data repository associated with this publication.

demand (while there is no cost to offering this service other than training cashiers/personnel). In view of this, we choose to focus on annual inflow to the database. Our main dependent variable constructed from this database is hence the number of new bitcoin-accepting merchants in any given year in a country, or sub-country state, province or region. Our dataset does not suffer from survival bias, as even when merchants are removed from the map by users or the web admin, they are not dropped from our database.

Our dataset has the limitation that we only observe non-hidden Full Bitcoin nodes and merchants. *Bitnodes*, being reachable full nodes, are a subset of *Full Bitcoin nodes* keeping the network secure, as some nodes simply do not accept incoming connections, primarily due to installation of firewalls. Some estimates (e.g. Wang and Pustogarov 2017) indicate as many as 6 to 8 times more nodes on the network than our data includes. Similarly, *Bitcoin merchants* do not include merchants who hide their presence from CoinMap or only sell online. Hence, our study is focused on digital infrastructure providers who are openly and visibly supporting the Bitcoin network.

6.6.2 Explanatory variables

We construct a set of country-level variables related to Bitcoin's adoption potential given existing technological factors, its role as potential substitute or complement to established financial institutions or to the cryptocurrency's potential function as a facilitator of illicit activity.

Financial characteristics

In constructing an indicator for inflation as a driver for use of bitcoins, we utilize the concept of an *Inflation Crisis*⁷⁴, defined by Reinhart and Rogoff (2011) as depreciation in currency value of 20-percent per annum. For robustness tests, we also define alternative variables measuring such phenomena called *15% Min Inflation* and *25% Min Inflation* with corresponding alternative thresholds. In further robustness tests, we utilize a continuous measure of *Inflation* along with the square root of *Inflation*. Inflation data is collected from the International Monetary Fund.

Data on the proportion of *unbanked* adults is collected from the World Bank's Financial Inclusion Index. Following Gross et al. (2012), we define the unbanked as individuals older than 15 years without a checking, saving or money market account. A subset of those holding bank accounts, are those with access to internet and mobile banking, which can serve as another proxy of financial inclusion in a digital age. From the same source, we obtain an *Internet banking* variable for robustness of results. We extract data on concentration in the banking industry from the World Bank Global Financial Development Index. We primarily use *Five-bank asset concentration*, the asset concentration of the largest five banks in each country. For use in robustness testing, we also use *Three-bank asset concentration*, which is the asset concentration of the largest three banks in each country.

⁷⁴ It is notable that currency crashes and inflation crises go hand in hand as shown by Reinhart and Rogoff (2011)

Figure 6.1. Validation and verification role of nodes in the Bitcoin transaction life cycle (see red boxes). Infographic modified from original by Patrícia Estavão (printed with her permission under license [CC BY-SA 4.0](https://creativecommons.org/licenses/by-sa/4.0/)), available at patestevao.com/work/

Figure 6.2. Global Map of *Bitnode intensity* (Monthly measure, averaged over 2014-2018; See Table 6.1 for variable definition). Top 15 countries are Monaco, Netherlands, Singapore, Lithuania, Luxembourg, Germany, Ireland, Switzerland, Sweden, Belize, Slovenia, Canada, Latvia, Finland, and Hong Kong.

Figure 6.3. Global Map of *Unique bitnodes* (Averaged for every hour over 2014-2018; See Table 6.1 for variable definition). Top 15 countries are San Marino, Austria, Sweden, Germany, Luxembourg, Croatia, Switzerland, Netherlands, Slovenia, Lithuania, Monaco, Australia, Bulgaria, Finland, and UK.

Figure 6.4. Total Bitcoin merchants per million users (See Table 6.1 for variable definition). Top 15 countries are San Marino, Liechtenstein, Slovenia, Czech Republic, Montenegro, Belize, Estonia, Lithuania, Austria, Switzerland, Slovakia, Monaco, Latvia, Malta, and Greece.

Criminality characteristics

The US' Bureau of International Narcotics and Law Enforcement Affairs performs an annual assessment of the risk of money laundering in 200 countries and jurisdictions. The bureau identifies “*major money laundering countries*” as those whose “*financial institutions engage in transactions involving significant amounts of proceeds from international narcotics trafficking*”. The definition of ‘financial institutions’ employed by the bureau in the period we study includes digital currencies and “*other value transfer systems*”. We introduce an indicator variable (*money laundering*) that takes the value one if a country is included in the bureau’s list in a given year.

As an indicator for the level of law enforcement, we obtain from the Worldwide Governance Indicators of the World Bank a *rule of law* variable. This variable captures the likelihood of crime and violence, and the extent to which agents abide by and have confidence in the rules of society, in particular the quality of police, courts, contract enforcement and property rights.

Social characteristics

We obtain social characteristic variables of general risk-taking, general trust, and trust in banks and the financial system from the Life in Transition (LITS III) survey which was carried out in 34 countries from 2014 to 2016. While data used to create most of the independent variables described previously was only available on the level of countries, LITS data can be broken down to the (sub-national) regional level, corresponding to states, provinces or administrative regions in the 34 countries where this survey was carried out. The LITS survey was, however, only carried out once during the period that we investigate in this chapter⁷⁵, meaning that we have no time variation to exploit for this analysis. In order to utilize as much of the variation in the data as possible, exploring the role of these social characteristics is carried out at the regional rather than national level. This has the consequence that analyses investigating the role of social characteristics are restricted to regions in 34 countries (294 regions) predominantly in Europe, instead of our full set of countries, and these variables are cross-sectional.

6.6.3 Control variables

This study furthermore constructs a number of control variables related to fundamental economic and legal prerequisites for the growth of Bitcoin infrastructure.

Participation in any financial system is strongly tied to the availability of economic resources. In our analysis of global adoption of Bitcoin infrastructure, variations in economic strength across countries and regions is therefore a natural first factor to consider. We control for GDP using World Bank data.

⁷⁵ Authors are not aware of any multinational social surveys which is carried out annually, and even if such a survey existed, social characteristics typically do not change much one year to another (e.g. see Hoffman et al. 2009 for an explanation of how general trust changes over intermediate time horizons).

Alongside economic strength, we also expect technological development to be strongly related to the spread of Bitcoin infrastructure. It is therefore important that our modelling exercise takes the level of technological development into account. In particular, as an internet-enabled technology, bitcoin adoption is only feasible for users who have regular access to the internet. We are, however, reluctant to introduce separate control variables for such factors in order to avoid overfitting our models, and in order to avoid introducing multicollinearity issues (the level of technological development across countries is well-known to co-vary with e.g. economic and institutional variables (Czernich, Falck, Kretschmer, & Woessmann, 2011; Greenstein & Spiller, 1996) and our main control variable of GDP per capita is highly correlated (0.89) with internet penetration in our dataset). Instead, all our main dependent variables measuring the penetration of Bitcoin infrastructure are normalized by internet penetration, i.e. the percentage of internet users in a country.

As a virtual currency with the potential to disrupt existing payment systems and possibly even monetary systems (Böhme et al., 2015), bitcoin aims to rival fiat currencies issued by central banks. Barriers to adoption in each jurisdiction for bitcoins are largely enforced by regulation. Most regulation vis-à-vis bitcoins are issued by a country's financial regulatory authorities (Law Library of Congress, 2018). As suggested by public choice theory (Stigler 1971), incumbents may lobby for regulation to keep out competitors and create rents for themselves. To the extent that bitcoin rivals government-issued currencies, regulatory barriers on bitcoins by governments can hamper their adoption. We create a longitudinal indicator variable, *Restrictive regulation*, equal to one in a country and for all the years in which restrictive (i.e. contentious or hostile) regulation is in effect in a country by its financial regulator on either transacting in bitcoin or buying and selling goods or services in exchange for bitcoins. Hostile regulation towards bitcoin consists of regulatory authorities imposing full prohibition of its use, or partial prohibitions such as barring financial institutions from dealing with it. Contentious regulation towards bitcoin consists of some legal restrictions against use of bitcoin (incl. imposition of cumbersome compliance requirements) or warnings against bitcoin use by regulatory authorities going beyond discouragement (incl. statements that bitcoin transactions may cause violation of anti-money laundering or terrorist financing rules). This is a longitudinal measure. Information about regulation on bitcoin trade is hand collected from the US Library of Congress, bitlegal.io, and Wikipedia.

A list of all dependent and explanatory variables used in the analysis and their definitions are described in Table 6.1, where Panel A documents our country-level analysis and Panel B the regional-level analysis. Summary statistics for all our variables are presented in Table 6.2 and a correlation matrix is available in O D (Table 0.1).

Table 6.1. Variable description and data sources

Variable	Description	Source	Source variable name
Panel A			
Bitnode intensity	An intensity measure of the number of active Bitnodes in a country multiplied by how many hours each was active in a month, standardized by the number of hours in a month and averaged to produce an annual measure (by taking the mean of results for the first month of each quarter). Standardized by dividing it by the jurisdiction's population of internet users in millions (see Internet variable).		Constructed from API-extracted data in JSON format
Unique bitnodes	Number of unique Bitnodes in a country in a month. This measure is then made into an annual measure, by averaging its value for the first month of each quarter of a year. Standardized by dividing it by jurisdiction's population of internet users in millions.	Bitcoin node data are from bitnodes.com	Constructed from API-extracted data in JSON format
Bitnode hours	Number of hours in a month where at least one Bitnode from a country is active		Constructed from API-extracted data in JSON format
Bitcoin merchants	Number of new bitcoin merchants in a country in a year, as per timing it was added on CoinMap's map	Bitcoin Merchant data are from CoinMap.com	Constructed from API-extracted data
Bitnode intensity _{pc}	Similar to Bitnode intensity, but standardized by population in millions	Bitnodes.com	
Unique bitnodes _{pc}	Similar to Unique bitnode, but standardized by population in millions	Bitnodes.com	
Bitcoin merchants _{pc}	Similar to Bitnode Merchants, but standardized by population in millions	CoinMap.com	
GDP per capita	Log of annual GDP per capita in a country. GDP is at purchaser's prices converted into current US dollars	World Bank WDI (2018)	NY.GDP.MKTP.CD
Restrictive regulation	An indicator variable equal to one in years in which hostile or contentious regulation against the use of bitcoins is issued. Hostile regulation towards bitcoin consists of regulatory authorities imposing full prohibition of its use, or partial prohibitions such as barring financial institutions from dealing with it. Contentious regulation towards bitcoin consists of some legal restrictions against use of bitcoin (incl. imposition of cumbersome compliance requirements) or warnings against bitcoin use by regulatory authorities going beyond discouragement (incl. statements that bitcoin transactions may cause violation of anti-money laundering or terrorist financing rules). Variable equals zero for countries that have no regulatory framework or a favourable regulatory framework for bitcoins.	Hand-collected data from Law Library of Congress (2018), bitlegal.io, and Wikipedia	
Population	Total population in a country in millions. Mid-year estimates.	World Bank WDI (2018)	SP.POP.TOTL
Internet penetration	Percentage of inhabitants using the internet in a year	International Telecommunications Unit (ITU) (2018)	
Broadband penetration	Percentage of inhabitants with fixed (wired)-broadband subscription in a year		
ICT market development	A composite index of a nation's development in ICT. The index includes three aspects of digitalization: ICT capability (skills and knowledge), access to ICT infrastructure, and use of intensity of ICT.	Measuring the Information Society Reports, ITU (2015-2018)	ID (ICT Development Index)
Latest technology	National average of response to "In your country, to what extent are the latest technologies available? [1 = not available; 7 = widely available]"	World Economic Forum, Global Competitiveness Report, Executive Opinion Surveys (2014-2018)	EOSQ067
Internet servers	Secure internet servers per million people using encryption technology in Internet transactions	World Bank and https://www.netcraft.com	IT.NET.SECR.P6

Mobile subscriptions	The variable measures the number of mobile telephone subscriptions per 100 adults in the population. A subscription refers to a public mobile telephone service that provides access to the public-switched phone network using cellular technology, including the count of pre-paid SIM cards active in the final three months of the year.	World Telecommunication/ICT Development report and database	
Electricity cost	Electricity cost is the total median cost in percentage of income per capita associated with completing procedures to connect a warehouse to electricity.	World Bank Doing Business Reports (2014-2018)	
Inflation crisis	An indicator variable equal to one if in a country the annual decline in the average Consumer Price Index is greater than 20% following Reinhart and Rogoff (2011)	Raw Data are from International Monetary Fund (IMF)'s World Economic Outlook (2018)	
Inflation	The average annual change in Consumer Price Index as a ratio.		
Unbanked	% aged 15+ without account ownership at a financial institution and without a mobile-money-service provider	WB Global Findex Database	FX.OWN.TOTL.ZS
Internet banking	% aged 15+ who have used the internet or a mobile phone to access an account		Fin5.d.1
Five-bank asset concentration	Assets of five largest banks as a share of all banking assets. These include all earning assets, cash and due from banks, foreclosed real estate, fixed assets, goodwill, other intangibles, current tax assets, deferred tax, discontinued operations and other assets.	World Bank's Global Financial Development Index (GFDI 2018); Raw Data are from Bankscope and Orbis Bank Focus, Bureau van Dijk	GFDD.OI.06
Three-bank asset concentration	Assets of three largest commercial banks as a share of all commercial banking assets.		GFDD.OI.01
Rule of law	Captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular, the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. This variable ranges from approximately -2.5 (weak) to 2.5 (strong) values for rule of law.	World Bank Worldwide Governance Indicators (2018)	RQ.EST
Organized crime	National average of response to "In your country, to what extent does organized crime (mafia-oriented racketeering, extortion) impose costs on businesses? [1 = not at all; 7 = to a great extent]"	World Economic Forum, Global Competitiveness Report, Executive Opinion Surveys (2014-2018)	EOSQ055
Crime and violence costs	National average of response to "In your country, to what extent does organized crime (mafia-oriented racketeering, extortion) impose costs on businesses? [1 = to a great extent—imposes huge costs; 7 = not at all—imposes no costs]"		EOSQ034
Money laundering	Countries identified as heavily engaged in “currency transactions involving significant amounts of proceeds from international narcotics trafficking.”	US Dept. of State Bureau for International Narcotics and Law Enforcement Affairs (2018)	

Panel B

Bitnode intensity	An intensity measure of the number of active Bitnodes in a region multiplied by how many hours each was active in a month, divided by the number of hours in a month and averaged to produce an annual measure (by taking the mean of results for the first month of each quarter). Standardized by dividing it by the jurisdiction's population of internet users in millions (see Internet Users variable).		Constructed from API-extracted data
Unique bitnodes	Number of unique bitnodes in a statistical region in a month made into an annual measure, by averaging its value for the first month of each quarter of a year. Standardized by dividing it by jurisdiction's population of internet users in millions.	Bitcoin node data are from bitnodes.com	Constructed from API-extracted data
Bitnode hours	Number of hours in a month in which at least one bitnode from a region is active.		Constructed from API-extracted data
Bitcoin merchants	Number of new bitcoin merchants in a statistical region in a year, as per timing it was added on CoinMap's map	Bitcoin Merchant data are from CoinMap.com	Constructed from API-extracted data

High risk willingness	A region's average of an indicator variable for each LiTS III's survey respondent, equal to one if response to this question, is above 8: "Please, rate your willingness to take risks, in general, on a scale from 1 to 10, where 1 means that you are not willing to take risks at all, and 10 means that you are very much willing to take risks."	EBRD (2016) Life in Transition Societies (LiTS) Survey III; US Data are complemented with same question in FINRA (2015)'s National Financial Capabilities Study in 2015	Q4.28 in LiTS III; J2 in NFCS
Trust in others	A region's average of an index standardized to run from -1 to 1, in answering to "Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people? Please answer on a scale of 1 to 5, where 1 means that you have complete distrust and 5 means that you have complete trust."		Q4.03 in LiTS III; TRUST in GSS
Distrust in banks & financial system	A statistical region's average of an index standardized to run from -1 to 1, in answering to "To what extent do you trust banks and the financial system? Please answer on a scale of 1 to 5, where 1 means that you have complete distrust and 5 means that you have complete trust."	EBRD (2016) LiTS Survey III; US Data are complemented using the same question's response using NORC (2016)'s General Social Survey (GSS) Geo-sensitive data	Q4.04j in LiTS III; CONFINAN in GSS
Distrust in other institutions	A region's average of indices standardized to run from -1 to 1, in answering to, similar to that above, on the following institutions, other than banks and the financial system: The Government/Cabinet of Ministers, the Parliament, Courts, the Military, The police, Unions and Religious Institutions.		Q4.04b, e, f, h, I, m & n in LiTS III; Trust in the same institutions in GSS
Bitcoin price	Annually-averaged price of Bitcoin in thousands of USD, from quotes on four large Bitcoin exchanges of 2014-2018, namely Bitstamp, Kraken, Coinbase and Gdax	www.cryptodatadownload.com/ ; Accessed on September 3, 2018	BTC/USD

Table 6.2. Summary statistics for panels A and B

Panel A - Country-year level dataset (2014-2018; 137 countries)						
Variable Name	Obs.	Mean	Std. dev.	Min	Median	Max
Dependent Variables						
Bitnode intensity	685	2.02	4.07	0.0	0.2	34.9
Unique bitnodes	685	15.12	23.45	0.0	3.6	123.4
Bitnode hours	685	431.46	334.30	0.0	608.8	750.0
Bitcoin merchants	685	1.32	5.05	0.0	0.2	114.0
Bitnode intensity _{pc}	685	1.65	3.52	0.0	0.1	30.8
Unique bitnodes _{pc}	685	11.70	19.40	0.0	1.9	114.2
Bitcoin merchants _{pc}	685	0.98	3.99	0.0	0.1	90.9
Control Variables						
GDP per capita	685	8.80	1.46	5.7	8.8	11.7
Restrictive regulation	685	0.11	0.32	0.0	0.0	1.0
Population	685	51.22	166.39	0.1	11.2	1394.1
Technological Variables						
Internet penetration	685	54.68	27.71	3.3	59.1	97.6
Broadband penetration	685	14.45	13.79	0.0	9.9	55.7
ICT market development	685	5.27	2.23	1.2	5.3	8.9
Latest technology	685	4.84	0.94	2.3	4.8	6.6
Internet servers	685	4.07	11.24	0.0	0.2	123.1
Mobile subscriptions	685	113.39	34.07	25.0	115.4	259.4
Financial Variables						
Inflation crisis	685	0.04	0.20	0.0	0.0	1.0
Inflation	685	0.05	0.07	-0.0	0.0	0.4
Unbanked	685	38.56	27.59	0.0	37.9	93.6
Internet banking	685	27.89	21.89	0.4	23.5	85.1
Five-bank asset concentration	685	78.84	16.19	27.5	80.9	100.0
Three-bank asset concentration	685	63.94	18.47	18.4	64.0	100.0
Criminality Variables						
Rule of law	685	0.06	0.99	-2.3	-0.1	2.1
Organized crime	665	4.77	1.02	1.5	4.8	6.9
Crime and violence costs	685	4.45	1.07	1.5	4.5	6.8
Money laundering	685	0.36	0.48	0.0	0.0	1.0
Alternative Variables						
Shadow economy	670	30.22	12.76	8.1	30.2	63.3
Taxation	580	25.82	12.49	-1.3	24.7	65.0
Tax burden	665	77.62	12.00	37.2	79.2	99.9
Tax haven	685	0.06	0.23	0.0	0.0	1.0
Stock market return	440	0.67	25.77	-72.1	-1.9	282.9
Crisis stock market return	460	-2.77	19.70	-51.7	-4.6	52.5
Bitcoin mining country	685	0.07	0.26	0.0	0.0	1.0
Bitcoin mining MWs	670	1.85	11.28	0.0	0.0	111.0
Electricity price	685	21.98	76.11	0.7	14.3	1038.0
Electricity cost	685	1329.8	3006.7	0.0	308.2	28965.9

Table 6.2. Summary statistics for panels A and B (Cont.)

Panel B – Region-year level dataset (2014-2018; 294 NUTS2 or equiv. regions in 34 countries)						
Dependent Variables						
Bitnode intensity	1470	2.17	4.71	0.0	0.4	59.7
Unique bitnodes	1470	17.37	33.31	0.0	5.9	486.5
Bitcoin merchants	1470	2.03	6.90	0.0	0.0	109.7
Social Variables						
High risk willingness	1470	0.16	0.12	0.0	0.1	0.7
Trust to Others	1470	-0.05	0.26	-0.8	-0.1	1.0
Distrust in banks & financial system	1470	0.09	0.31	-0.9	0.1	1.0
Distrust in other institutions	1470	0.01	0.24	-0.9	0.0	0.8
Interaction Variable						
Bitcoin price	1470	2.76	3.21	0.3	0.6	8.5

6.7 Methodology

6.7.1 Country-level analyses

We construct a panel-data structured database of countries and years for adoption of non-hidden Bitcoin nodes and Bitcoin merchants, as well as our independent variables. We limit our database to 2014 to 2018, the period for which full Bitcoin node and merchant data are available. We regress our measures of infrastructure adoption over two baseline variables of *GDP per capita* and *restrictive regulations* - capturing fundamental economic and legal country-level characteristics - as well as our independent variables.

In our country-level analyses, we limit our analysis to 137 countries in which all our explanatory variables are available from their respective data sources for all years in our database. The variable with the most limited global coverage, % of unbanked, was restricted due to the breadth of coverage of the World Bank's Financial Inclusion survey. We refer to the resulting database as Panel A, for which summary statistics are available in Table 6.2. Having reduced our sample from 201 countries respectively for which we have Bitnode and CoinMap data⁷⁶ to 137 countries may introduce a sample selection bias. While this choice was driven by a need to have values for all independent variables used in the analysis, it is justifiable as the excluded nations are smaller in size by orders of magnitude and often reliable statistics on financial and criminal characteristics unavailable for them⁷⁷.

⁷⁶ 147 countries have been reported to have at least one Bitcoin merchant, with 28 having only one. We have coded the countries without reported merchants on CoinMap as having no merchants. Given that the median GDP per capita of these countries is below \$1000, it is reasonable to assume that no merchants existed in these nations.

⁷⁷ In fact, the median population of the excluded 60 countries is less than 0.3 million while for those included in the analyses it is 11.7 million.

Our dependent variables take the value 0 for a non-trivial share of our observations (i.e. for countries and years in which no Bitcoin infrastructure is detected), and can thus be thought of as censored variables. In our country-year analyses, we therefore run random-effects Tobit models lower-censored at zero with panel-data adjusted bootstrapped standard errors⁷⁸. We employ the following model specification, where the subscripts i and t , refer to countries and years respectively:

$$\begin{aligned}
& \textit{Bitcoin Infrastructure Adoption Variable}_{it} \\
&= \beta_1 \times \ln(\textit{GDP})_{it} + \beta_2 \times \textit{Restrictive regulation}_{it} + \beta_3 \times \textit{Inflation crisis}_{it} \\
&+ \beta_4 \times \textit{Unbanked}_{it} + \beta_5 \times \textit{Five bank asset concentration}_{it} \\
&+ \beta_6 \times \textit{Money laundering}_{it} + \beta_7 \times \textit{Rule of law}_{it} + \textit{WR}_i + \zeta_t + \textit{WR}_i \times \zeta_t \\
&+ \varepsilon_{it} \quad (6)
\end{aligned}$$

Our Bitcoin infrastructure adoption variables are *bitnode intensity*, *unique bitnodes*, *bitnode hours* and *Bitcoin merchants*. The world region fixed effects ($\textit{WR}_i$) and year fixed effects (ζ_t), respectively control for systematic differences across world regions⁷⁹, and for changes in the price of bitcoin and in global macroeconomic conditions over time. Our interactions of world region and year fixed effects ($\textit{WR}_i \times \zeta_t$) absorb the effect of world region-specific shocks or time trends in adoption of bitcoins. Given the country-year level variation of our Panel A data, these controls are stringent enough to tease out the effect of our country-level variables. The limited variation of our country-level characteristics during the five years of observation does not allow for the inclusion of country-level fixed effects⁸⁰. We cluster all regression standard errors at the country level. In robustness tests, we cluster our results at the country and the year level, and results do not significantly change.

6.7.2 Regional level analysis

Our region-year analyses are meant to investigate the effect of social variables such as general and institutional trust, and risk willingness on the adoption of Bitcoin infrastructure. Our social variables are derived from the Life in Transition Societies (LiTS III) Survey carried out between 2014 and 2016 of 51,000 households in 34 countries. To this end, we construct a database of averages of social variables for the 294 statistical regions surveyed, which are primarily located in nations in Eastern Europe and Central Asia, as well as Germany, Italy, Greece. We make adjustments to ensure our dependent variable database regions match statistical regions from the LiTS III survey, and then calculate region-level dependent variables of *bitnode intensity*, *unique bitnodes* and *bitnode hours*. We complement this data with

⁷⁸ This entails blocked bootstrapping with countries as blocks, for the bootstrapped clustering.

⁷⁹ Defined using the World Bank's division of nations into world regions of North America, Europe & Central Asia, East Asia & Pacific, Latin America & Caribbean, Middle East & North Africa, Sub-Saharan Africa, and South Asia

⁸⁰ Upon their inclusion, many of our country-level variables would be omitted, due to their limited time-series variation from 2014 to 2018 in variables such as Restrictive regulation.

population statistics from European or national statistics agencies for these 34 countries. Hence, we have effectively restricted our analysis from 137 countries in the country-year level database in Panel A, to a subset of 34 countries in the region-year level database in panel B (with 294 regions). Summary statistics for Panel B are available in Table 6.2.

Our region-level analyses use the following random-effects Tobit regression model, where subscripts j and t , refer respectively to sub-national administrative or statistical regions and years:

Bitcoin Infrastructure Adoption Variable $_{jt}$

$$\begin{aligned} &= \beta_8 \times \ln(GDP)_{it} + \beta_9 \times \text{Restrictive regulation}_{it} + \beta_{10} \times \text{High risk willingness}_{jt} \\ &+ \beta_{11} \times \text{Trust in others}_{jt} + \beta_{12} \times \text{Distrust in banks \& the financial System}_{jt} \\ &+ \beta_{13} \times \text{Distrust in other institutions}_{jt} + c_i + \zeta_t + \varepsilon_{it} \end{aligned} \quad (7)$$

This equation involves our baseline characteristics of logged *GDP* and *restrictive regulation* to control for the heterogeneity specific to the economic and legal conditions, with our social characteristic variables following. Our region-level empirical models using equation 7 control for systematic differences across nations using country fixed effects (c_i) and for macro-economic conditions using year fixed effects (ζ_t). Similar to Giannetti and Wang (2016), we control for *distrust* (lack of trust) *in other institutions* unrelated to banks and the financial system, to separate the specific effect of distrust to banks from any idiosyncratic relationship between general institutional sentiments and Bitcoin infrastructure adoption. In additional tests, we interact *high risk willingness* with *bitcoin price* to examine how this social characteristic varies with price increases.

6.8 Results

6.8.1 Financial and criminality drivers

Our first set of analyses focus on associations between use and running of bitnodes or merchants and the criminality and financial characteristics discussed previously. We first report results on *bitnodes* and subsequently on *Bitcoin merchants*.

Table 6.3 reports results of our random effects regressions for three dependent variables measuring the frequency of bitnode activity in a country, relative to the number of internet users. These dependent variables are standardized measures described in Table 6.1, namely *bitnode intensity*, *unique bitnodes* and *bitnode hours*. In all regression models (1) to (4), our primary dependent variable of *bitnode intensity* is regressed against a baseline of controls, *GDP per capita* and a dummy variable for *restrictive regulation* being in effect. Models (2) and (3) add financial characteristics and criminality characteristics, respectively, and model (4) expands the baseline estimation to include both sets of financial and criminality characteristics. The magnitude and standard deviations of coefficients for either sets of variables do not alter in a

significant way and are robust to inclusion of both. Models (5) and (6) respectively regress *unique bitnodes* and *bitnode hours* on the full set of country-level characteristics. The 0 D, Table 0.2 through Table D.4 show the effect of each individual variable being added separately to the baseline model, for each of our dependent variables.

Model 1 is our baseline model. Fixed effects for years, world regions and their interactions together with our two basic controls account for a substantial fraction of the variation in *Bitnode intensity*, corresponding to a pseudo R^2 of 0.34. As expected, more restrictive regulations vis-à-vis bitcoins are associated with below-average total intensity of Bitnode activity (models 1 to 4), but with the occurrence of an above-average number of *unique bitnodes*. The effect of restrictive regulation is clearly driven by differences on the intensive margin (i.e. how many hours a month Bitnodes are available) rather than difference on the extensive margin (i.e. how many unique Bitnodes are being run in a country). This may indicate that while restrictive regulation reduces the actual use of bitcoins, primarily by making the exchange of bitcoins to fiat currencies illegal and secondarily by forbidding the trade of cryptocurrencies, it does not effectively suppress the general interest in Bitcoin as a phenomenon, and to contributing to its infrastructure⁸¹.

The occurrence of an *inflation crisis* is associated with an increase in the number of *unique bitnodes* in a country ($p < 0.01$). The coefficient estimate indicates that the onset of an inflation crisis in a country is associated with an uptake of 47% of the average and 30% of the standard deviation of the number of *unique bitnodes* in a country. We run robustness tests by altering the inflation crisis cut-off to a minimum of 15% or 25% of annual inflation and find similar results (See 0 D, Table D.5). This speaks to bitcoins being utilized for financial hedging where currency devaluations greatly erode the value of a national currency, consistent with hypothesis 1.

While a greater fraction of unbanked in a country is not found to be associated with the intensity of use of Bitnodes (models 2, 4), it is negatively associated with the number of unique Bitnode users (model 5, $p < 0.05$). This result goes against the notion that Bitcoin infrastructure is being set up as a substitute to the financial system in countries where financial inclusion and penetration is low, but rather that Bitcoin infrastructure emerge where the penetration of the financial system is greater. This result goes against our hypothesis 2a, in favour of our counter-hypothesis 2c.

The coefficient on *Five-bank asset concentration* in model 6 is negative and significant at 1%, indicating that greater concentration in the financial sector reduces the intensity of use of Bitnodes. This result goes against our hypothesis 2b assertion, in favour of the opposing hypothesis 2d. Together with the findings for unbanked populations, results point to the penetration of Bitcoin infrastructure increasing in well-

⁸¹ Plausibly, this increase in the extensive margin may result from greater publicity of bitcoins following national restrictions.

developed banking systems (hypotheses 2c and 2d), where the general familiarity with online finance is greater and the related digital entrepreneurial ecosystem is more vibrant.

Countries with high risk of drug-related *money laundering* tend to exhibit greater *Bitnode intensity* of activity (model 4, $p < 0.05$) and Bitnode adopters (model 5, $p < 0.01$) and provide significantly more active hours of supply of Bitcoin nodes (model 6, $p < 0.001$). This latter coefficient estimate for money laundering is significant at the 1% level and suggests that countries that have a high-risk of money laundering, all else equal, run Bitcoin nodes for ~ 7 days more in a month ($=176.3/24$) than other countries. Our hypothesis 4 is therefore validated.

The variable *Rule of law* pertains to society's perception of the likelihood of crime and violence, as well as their confidence in the quality of the police, courts, contract enforcement and property rights in each country. It is strongly associated with increases in Bitnode use intensity (model 4, $p < 0.05$) and the number of *unique bitnodes* (model 5, $p < 0.001$). These are in agreement with our hypothesis 5. We note, however, that our Rule of law measure could be thought of as having two distinct components: the dependability of law enforcement, as well as the likelihood of crime and violence. Our hypothesised relationship relates to the former of these aspects. We therefore undertake further analysis in order to ensure that our estimates on Rule of law are not driven by the Bitcoin infrastructure penetration being greater in countries with more crime and violence.

We use costs to businesses associated with crime and violence, the sub-index *crime and violence costs* of the World Economic Forum's Global Competitiveness Index, as a proxy for the intensity of crime and violence in nations. A related variable from the same source, the degree of *Organized crime*, is also investigated. Inserting these variables into our main models yields insignificant estimates throughout. We interpret these results (reported in 0 D, Table D.6) to indicate that the association between *Rule of law* and our dependent variables is, as argued in the corresponding hypothesis, driven by country-level differences in the reliability and effectiveness of police and the legal system.

Table 6.4 presents the results of our analyses on determinants of adoption of Bitcoin merchants globally on the same countries and using the same Panel A database on which our Table 6.3 results are based on. Similar to Table 6.3, models 2 and 3 progressively add national financial and criminality characteristics to our baseline model (1). We expand the baseline estimation in model (4) to include both sets of characteristics.

Table 6.3. Financial and criminality drivers of Bitcoin nodes (Panel A; Country-year level)

Dependent Variables:	(1)	(2)	(3)	(4)	(5)	(6)
	Bitnode intensity				Unique bitnodes	Bitnode hours
Financial Characteristics						
Inflation crisis		0.338 (0.386)		0.530+ (0.306)	7.038** (2.596)	50.642 (65.208)
Unbanked		-0.006 (0.013)		0.008 (0.009)	-0.189* (0.078)	-2.309 (1.421)
Five-bank asset concentration		-0.004 (0.015)		0.003 (0.013)	0.011 (0.069)	-5.080** (1.676)
Criminality Characteristics						
Money laundering			1.302* (0.568)	1.347* (0.604)	6.916** (2.381)	176.344*** (53.490)
Rule of law			1.343** (0.424)	1.445** (0.474)	9.323*** (2.557)	88.669+ (45.858)
Baseline Controls						
GDP per capita	1.425*** (0.363)	1.338*** (0.378)	0.617 (0.415)	0.681 (0.457)	0.039 (2.209)	72.001* (34.734)
Restrictive regulation	-0.574+ (0.314)	-0.581* (0.291)	-0.553+ (0.290)	-0.529 (0.324)	3.069* (1.347)	32.565 (39.446)
Constant	-11.455*** (3.123)	-10.185** (3.616)	-5.464 (3.573)	-6.624 (4.347)	19.808 (20.597)	382.419 (431.859)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Panel Data Specifications	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit
Observations	685	685	685	685	685	685
Number of Countries	137	137	137	137	137	137
Pseudo R-Squared	0.34	0.4	0.34	0.41	0.62	0.22
Log-likelihood	-1314.9	-1314.6	-1306.7	-1306.1	-2268.1	-2386.8
RHO	0.74	0.74	0.72	0.72	0.54	0.62

Notes: All models are Tobit random effects models lower-censored at 0 and their associated pseudo R-squared are reported. Panel-data adjusted bootstrapped standard errors, clustered at the country level, are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level. Models 6 and 9 are additionally upper-censored at 750 (upper limit of active Bitnode hours in a month).

Table 6.4. Financial and criminality drivers of Bitcoin merchants (Panel A; Country-year level)

Dependent Variable:	(1)	(2)	(3)	(4)
Financial Characteristics				
Inflation crisis		-0.418 (1.175)		0.639 (1.807)
Unbanked		-0.059+ (0.031)		-0.048+ (0.029)
Five-bank asset concentration		-0.041 (0.032)		-0.037 (0.037)
Criminality Characteristics				
Money laundering			1.163* (0.560)	0.761 (0.867)
Rule of law			1.448* (0.712)	1.303* (0.628)
Baseline Characteristics				
GDP per capita	1.401* (0.552)	0.481 (0.495)	0.368 (0.531)	-0.234 (0.579)
Restrictive regulation	-0.020 (0.997)	-0.667 (0.922)	0.111 (0.736)	-0.388 (0.908)
Constant	-12.041* (5.301)	1.336 (4.511)	-3.980 (4.916)	6.166 (5.096)
Year FEs	Yes	Yes	Yes	Yes
World Region FEs	Yes	Yes	Yes	Yes
Year-World Region FEs	Yes	Yes	Yes	Yes
Panel Data Specification	Tobit	Tobit	Tobit	Tobit
Observations	685	685	685	685
Number of Countries	137	137	137	137
Log-likelihood	-1418.2	-1415.8	-1415.1	-1413.7
RHO	0.23	0.23	0.22	0.22

Notes: All models are Tobit random effects models lower-censored at 0. Panel-data adjusted bootstrapped standard errors, clustered at the country level, and are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level.

Table 6.5. Social drivers of adoption of Bitcoin infrastructure (Panel B; Region-year level)

Dependent Variables:	(1) Bitnode intensity	(2) Unique bitnodes	(3) Bitcoin merchants	(4) Bitnode intensity	(5) Unique bitnodes	(6) Bitcoin merchants
Social Characteristics						
High risk willingness	4.848 (3.421)	27.595 -23.031	17.267*** (4.552)	6.309+ (3.400)	38.307 (23.387)	20.057** (6.603)
High risk willingness x Bitcoin price				-0.581** (0.000)	-4.928* (0.002)	-1.824* (0.911)
Trust in others	1.804 (1.229)	17.246+ -9.43	-0.819 (2.561)	1.945 (1.186)	17.833+ (9.374)	0.441 (2.713)
Distrust in banks & financial system	4.383** (1.638)	25.271* -12.525	-0.942 (3.210)	4.266** (1.581)	24.855* (12.449)	2.581 (3.310)
Distrust in other institutions	-2.827 (2.311)	-18.204 -16.9	-8.955* (4.354)	-2.632 (2.248)	-17.708 (16.809)	-3.834 (4.351)
Bitcoin price				0.011 (0.038)	-2.985*** (0.391)	0.269 (0.169)
Baseline Characteristics						
GDP per capita	-1.886* (0.869)	-33.543*** -8.313	-6.211 (4.548)	-1.884* (0.821)	-33.558*** (8.239)	-6.341 (4.225)
Restrictive regulation	-0.139 (0.422)	3.468 -4.051	-0.441 (2.254)	0.049 (0.401)	5.212 (4.036)	0.240 (2.133)
Constant	8.381 (7.710)	239.257*** -71.928	35.253 (38.691)	8.424 (7.301)	239.675*** (71.287)	32.577 (35.990)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Panel Data Specifications	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit
Observations	1470	1470	1470	1470	1470	1470
Number of Statistical Regions	294	294	294	294	294	294
Number of Countries	34	34	34	34	34	34
Log-likelihood	-2800.7	-5221.2	-2742.9	-2796.7	-5218.4	-2740.9
RHO	0.78	0.59	0.24	0.78	0.59	0.24

Notes: All models are Tobit random effects models, lower censored at 0 and their associated overall R-squared is reported. Their standard errors are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level.

Model 4 seems to indicate that national financial characteristics dominate criminality explanations in acceptance of bitcoins by merchants. Our coefficient estimates on the *Unbanked* fraction ($\beta = -0.048$) in model 4 is statistically significant at the 10% level, suggesting that adoption of bitcoins by merchants is more popular in locations where adults have bank accounts to a greater extent in agreement with hypothesis 2c rather than 2a. Together with the results in the same direction in Table 6.3 and contrary to a widely purported promise of bitcoins (see e.g. Vigna and Casey 2015), this points to a picture of Bitcoin infrastructure serving the banked population more than the unbanked. It is noteworthy that our *Bitcoin merchants* variable is more concentrated in certain countries, especially in the earlier years of the sample. This has the effect that the broad and stringent set of fixed effects interacting world regions and year dummies, and our baseline characteristics, account for a great deal of the variation in our data, reducing the variation that can be attributed exclusively to our exploratory variables.

The coefficient estimate on *rule of law* is significant ($p < 0.05$) in models (3) and (4) where we control for other covariates and money laundering is only statistically significant in model (3), in agreement with our hypothesis 5.

6.8.2 Social drivers

Table 6.5 presents the results of our region-level analyses. This set of analysis uses regional-level versions of the dependent variables and baseline characteristics of Table 6.3, and in addition includes social variables and country-level fixed effects in order to control for unobserved country-level heterogeneity. Country-level differences in financial and criminality factors are absorbed by these fixed effects and are not included individually in this analysis. Dependent variables are standardized by the number of internet users. Year fixed effects control for unobserved year-specific events.

Models 1 and 2 present estimates of the model specification in equation (7) for *bitnode intensity* and *unique bitnodes*. In regressing the *trust in others* variable against *unique bitnodes*, the coefficient estimate of model (1) is insignificant. In model (2), the coefficient of $\beta = 17.2$ is significant at the 10% level. In terms of magnitude, these suggest that a one standard deviation decrease in *trust in others* is associated with 4.5 fewer unique bitnode adopters per million internet users or 31.3% of average adopters of bitnodes in statistical regions. We thus find only weak and partial support for hypothesis 3a.

The coefficient estimate for our variable *distrust in banks and the financial system* is statistically significant in models (1) to (2), respectively at the 1% and 5% level. In terms of magnitude, a one standard deviation increase in distrust in banks and the financial system equivalent to 31% more distrustful people⁸² is associated with an increase of 8 *unique bitnode* adopters per million internet users (equivalent to 54% of

⁸² Equivalent to 115% of the time-wise increase in Americans' distrust in banks seen from 2006 till 2010 (which was 26.7% based on the Gallup survey), the year this distrust peaked at the height of the financial crisis.

mean adopters in statistical regions), or an increase equivalent to 34% of the standard deviation of *bitnode intensity*. These effects are fairly large, and corroborate the role of crisis-related factors and distrust in banks being a factor in the early use of other peer-to-peer FinTech technologies (see e.g. Saiedi et al. 2017; Thakor and Merton 2018), in agreement with hypothesis 3b.⁸³

Model 3 documents region-level social determinants of the adoption of bitcoin by merchants. Our hypothesized trust variables do not yield any statistically significant association to merchants' rate of adoption of bitcoin. However, our measure of self-reported willingness to take risks by individuals is found to be significant at the 0.1% level consistent with our hypothesis 3c. This suggests that adoption of bitcoins by merchants occurs more where the population have a higher tendency to engage in risky and speculative behaviour.

We conduct a further test regarding the hypothesis 3c. In developing this hypothesis, we argued that risk-willingness can be expected to be associated with the penetration of Bitcoin infrastructure since the level risk-willingness could be expected to influence how many people that are interested in holding bitcoin. If this is the case, we should be able to observe signs of Countercyclical Risk Aversion. Such behaviour, which has been identified as explaining behaviour on the stock market (Cohn, Engelmann, Fehr, & Maréchal, 2015; Guiso, Sapienza, & Zingales, 2018), would imply that when prices go down, generally risk-averse individuals are even less willing than before to take on risks. While risk-willingness would generally be associated with greater participation in financial markets, this association would hence in the presence of countercyclical risk aversion be strengthened in periods when assets trade at a relatively lower price. We test this prediction in models 4 to 6 which use the same variables used respectively in models 1 through 3, but add an interaction term of the annually-averaged *bitcoin price* variable with *high risk willingness*. The estimates on these interaction terms are consistently and significantly negative. We interpret these findings as providing relatively strong support for hypothesis 3c, and for the notion that there is greater interest to hold bitcoins – both by merchants themselves and by their costumers – in regions with higher levels of risk-taking.

6.8.3 Robustness tests

We consider a range of robustness tests to lend empirical support to our findings, with respect to (i) alternative definitions of variables utilized to test our hypotheses, (ii) an alternative modelling approach, and (iii) alternative strategies for choosing the reference sample (e.g. restricting analysis to geographies with non-zero infrastructure).

⁸³ Given Bitcoin's origins in the cypherpunk and crypto-anarchist subcultures (Swartz, 2018), it is possible that distrust in government may be have greater association with the adoption of bitcoin. We explored this, by substituting for *distrust in banks* with a similarly-constructed *distrust in government* variable from the same sources, and do not find any explanatory power to this latter variable in regressing either of our Bitcoin infrastructure variables.

We investigate the construct validity of our financial variables by constructing alternative measures relating to the relevant hypotheses. These alternative variables are listed along with the original variables in Table 6.1. Each alternative measure is significantly correlated, at below 1% significance, with the original variable.

The results of this exercise are shown in Table 6.6 Models 1 and 4 are provided for easy reference and are duplicates of models 5 and 6 in Table 6.3. In model 2, a linear and quadratic combination of the continuous measure *inflation* are replacing the indicator variable *inflation crisis*. A non-linear specification is used since our Hypothesis 1 states that it is very high inflation levels which are expected to be associated with greater uptake of Bitcoin infrastructure. In agreement with such hypothesizing, the estimate on the quadratic component is positive and significant at 5%. Moreover, *inflation* and *inflation²* are jointly significant at less than 0.1%. The coefficients imply that on average, starting at inflation values of 15.1% increases in inflation contribute to broadening the population of bitcoin adopters. In further work, reported in Table D.5 of Appendix D, we confirm that using indicator variables for >15% or >25 % inflation, instead of the >20% indicator used in our main analysis yields qualitatively similar results.

In model 3, we replace *unbanked* for the proportion of those with *internet banking*. We find a positive and significant coefficient on this variable, which as before supports our hypothesis 2c that greater financial inclusion leads to greater adoption of Bitcoin infrastructure. In model 5 we replace *five-bank asset concentration* with another measure for the concentration in the banking industry of *three-bank asset concentration*. Also, with this alternative measure, we find support for our hypothesis 2d in that greater competition in the banking sector is associated with greater uptake of Bitcoin infrastructure.

Next, we consider an alternative modelling approach. While we have presented our two sets of analyses of Bitnodes and merchants in parallel, our separate econometric models for these two could be under-utilizing our related dependent variables. Since there may be unobserved factors (e.g. the number of bitcoin users in a country) which are related to both the intensity of bitnode operations and the number of *Bitcoin merchants*, the error terms (or unaccounted part) of each model could be expected to be positively correlated. Running these two sets of analysis as a system is therefore of interest. We implement a Generalized Simultaneous Equation Model (GSEM). Table 6.7 reports results of a Tobit model fitted with GSEM for three possible pairings of our three bitnode dependent variables with our *Bitcoin merchant* variable. Our results are highly similar to those found using single equation models (models 4 to 6 in Table 6.3; model 4 in Table 6.4). In model 1, *rule of law* is more significant in explaining *bitnode intensity* at 0.1% with a greater coefficient magnitude, while other variables retain their significance. Meanwhile, *rule of law* is similarly significant in explaining *Bitcoin merchants*. Results for *unique bitnodes* and *bitnode hours* in models 2 and 3 are very similar to our previous findings in our main analysis in Table 6.3 and confirm our previous findings.

Table 6.6. Robustness tests with alternative measures for financial variables (Panel A; Country-year level)

Dependent Variables:	(1)	(2)	(3)	(4)	(5)
	Unique bitnodes			Bitnode hours	
Inflation crisis	7.038** (2.596)		6.204* (2.943)	50.642 (65.208)	50.322 (69.477)
Inflation		-22.106 (28.046)			
Inflation ₂		146.589* (69.948)			
Unbanked	-0.189* (0.078)	-0.177* (0.074)		-2.309 (1.421)	-2.373 (1.588)
Internet banking			0.168* (0.079)		
Five-bank asset concentration	0.011 (0.069)	0.011 (0.063)	0.008 (0.062)	-5.080** (1.676)	
Three-bank asset concentration					-4.647*** (1.255)
GDP per capita	0.039 (2.209)	1.072 (1.884)	1.072 (1.884)	72.001* (34.734)	71.732* (33.292)
Restrictive regulation	3.069* (1.347)	3.368* (1.580)	3.368* (1.580)	32.565 (39.446)	30.525 (46.289)
Money laundering	6.916** (2.381)	6.939** (2.295)	6.939** (2.295)	176.344*** (53.490)	180.962*** (38.249)
Rule of law	9.323*** (2.557)	9.477*** (2.534)	9.477*** (2.534)	88.669+ (45.858)	84.178* (39.757)
Constant	19.808 (20.597)	- 0.718 (14.874)	-0.718 (14.874)	382.419 (431.859)	292.711 (386.696)
Year and World Region FEs	Yes	Yes	Yes	Yes	Yes
Year-World Region FEs	Yes	Yes	Yes	Yes	Yes
Observations	685	685	685	685	685
Log-likelihood	-2268.1	-2264.9	-2269.5	-2385.1	-2264.9
Number of Countries	137	137	137	137	137
RHO	0.54	0.54	0.52	0.62	0.61

Notes: All models are Tobit random effects models lower-censored at 0 and their associated pseudo R-squared are reported. Panel-data adjusted bootstrapped standard errors, clustered at the country level, are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level. Models 4 and 5 are additionally upper-censored at 750 (upper limit of active Bitnode hours in a month).

Table 6.7. Robustness tests using generalized simultaneous equation modelling (Panel A; Country-year level)

Dependent Variables:	(1)		(2)		(3)	
	Bitnode intensity	Bitcoin merchants	Unique bitnodes	Bitcoin merchants	Bitnode hours	Bitcoin merchants
Financial Characteristics						
Inflation crisis	1.534+	1.149	11.008**	1.149	87.005	1.149
	(0.852)	(1.120)	(3.806)	(1.120)	(77.197)	(1.120)
Unbanked	0.010	-0.049	-0.129*	-0.049	-1.585	-0.049
	(0.011)	(0.032)	(0.061)	(0.032)	(1.349)	(0.032)
Five-bank asset concentration	0.011	-0.038	0.010	-0.038	-5.084***	-0.038
	(0.018)	(0.036)	(0.068)	(0.036)	(1.244)	(0.036)
Criminality Characteristics						
Money laundering	1.481*	0.594	6.942**	0.594	111.079**	0.594
	(0.635)	(0.653)	(2.454)	(0.653)	(37.625)	(0.653)
Rule of law	1.937***	1.173*	9.693***	1.173*	73.946*	1.173*
	(0.457)	(0.566)	(1.942)	(0.566)	(34.603)	(0.566)
Baseline Characteristics						
GDP per capita	0.552+	-0.162	1.147	-0.162	43.281	-0.162
	(0.329)	(0.504)	(1.514)	(0.504)	(31.870)	(0.504)
Restrictive regulation	-0.122	-0.692	0.024	-0.692	19.883	-0.692
	(0.404)	(0.772)	(1.781)	(0.772)	(49.044)	(0.772)
Constant	-6.473*	5.854	7.629	5.854	493.289	5.854
	(3.257)	(5.702)	(15.480)	(5.702)	(318.059)	(5.702)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	685		685		685	
Log-likelihood	-2960.1		-3814.1		-5410.2	
Number of Countries	137		137		137	

Notes: All models are Generalized Simultaneous Equation Models fitted with Tobit models lower-censored at 0 and their associated log-likelihoods are reported. Standard errors, clustered at the country level, are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level.

Finally, we repeat our main analyses excluding countries in which no bitnode activity (7 countries) or Bitcoin merchants (24 countries) exist during our sample period. Table D.8 and Table D.9 of Appendix D, present these results respectively for our financial and criminality variables analysis (Panel A; Country-Years) and for our social variables analysis (Panel B; Region-Year). This is to investigate to what extent our results are driven by countries that do not have any Bitcoin infrastructure at any time of observation. Our coefficient magnitudes are very similar and statistical significances remain largely unchanged from our main findings presented earlier.

6.8.4 *Additional analysis*

In this section, we perform additional analysis in order to set our main analysis into context. Specifically, we investigate a set of factors beyond the main variables and controls used in the main model, which may drive the diffusion of Bitcoin infrastructure. In a first set of analysis, we explore a wider set of measures of technological development. Thereafter, we seek to rule out the following alternative explanations: (i) shadow economy and tax evasion, (ii) rewards in cryptocurrency mining of bitcoins, and (iii) hedging of equity markets.

Technological/Infrastructural characteristics

In our main models, we account for the role of technological development by normalizing the dependent variables by the number of internet users. In further work, we construct a range of variables to explore further nuances in the relationship between technological development and the penetration of Bitcoin infrastructure.

Since Information and Communication Technology (ICT) is an enabler and prerequisite for financial technologies (Haddad & Hornuf, 2019; Huang et al., 2019), as first order tests, we explore measures accounting for more advanced types of internet use. Beyond the previously used *internet penetration*, we also extract measures of *broadband penetration* and *mobile telephone subscriptions* from the International Telecommunications Unit (ITU)'s World Telecommunication/ICT Development reports, respectively defined as percentage of households with access to broadband, and the number of mobile telephone transactions per 100 adults in the population. We obtain *ICT capabilities* and *ICT market development* from the ITU's Measuring the Information Society Reports; the former measures user sophistication as a composite index of adult literacy, and secondary and tertiary education, and the latter measures Information and Communication Technology (ICT) development as a composite index of ICT infrastructure, ICT capabilities (skills and knowledge) and ICT use of intensity. We measure the extent to which the *latest technology* is available, using the Executive Opinion Survey of the World Economic Forum's Global Competitiveness Report. We obtain *internet servers* data from the World Bank and netcraft.com, as the number of servers using encryption technology in internet communication per one million people. We utilize *electricity cost* and *electricity price* data from the World Bank's Doing Business

datasets, respectively measuring the median cost in percent terms relative to income per capita of connecting and running a warehouse with electricity, and the price in US cents per kWh of monthly electricity consumption for a warehouse based in the largest business city of a country for the month of March.

Table 6.8 shows the effect of these variables on per-capita standardized dependent variables. Model 1 shows, for reference, the relationship between *GDP per capita* and *bitnode intensity*. In all other models, we do not include *GDP per capita* due to very high correlations – as high as 0.91 – with the technology variables (see Appendix D, Table 0.1). Models 2 and 3 respectively show that *internet* and *broadband penetration* are significant (at 0.1% and 5% respectively) in explaining *bitnode intensity*. Models 4 through to 7 examine the effect of each explanatory variable in equation (6) independently on *bitnode intensity*. *ICT market development* and *latest technology* are highly significant (at 0.1%), whilst *secure internet servers* and *mobile subscribers* are significant at 10% and 5% respectively. While not reported, we also tested *ICT capabilities* separately which was highly significant at 0.1%. Models 9 through to 12 represent the results of Equation (6), by progressively regressing all infrastructural variables onto our three per-capita dependent variables. *ICT market development* and *latest technology* remain positive and significant in most regressions at 0.1% and below-10% respectively. This aligns with the expectation that Bitcoin infrastructure are more likely to appear in countries where ICT is more advanced. Still, analysis of the pseudo-R²s suggest that economic strength (*GDP per capita*) is a more efficient predictor of Bitcoin infrastructure penetration than *ICT market development*. This supports our choice to anchor our main analysis in models controlling for this factor.

Alternative explanations for bitcoin adoption

We additionally test a range of other variables argued for in the emerging literature to drive the use of cryptocurrencies⁸⁴. Since they enable global transactions, digital assets can be used for shadow banking and tax evasion (Van Alstyne, 2014). Currently, many national governments and their tax administrations are in the process of penning legislation on assets held in cryptocurrencies, while international task forces are devised to combat cryptocurrency-enabled tax crime (J5, 2018). Most countries, however, have still not imposed any regulation or indeed effective regulation (Akins, Chapman, & Gordon, 2015; Marian, 2013). Hence, it is conceivable that bitcoins and Bitcoin infrastructure would find the greatest use and support where incentives for tax avoidance and evasion are highest. To test this, in Table 6.9 and Table 6.10 we separately regress our dependent variables of *bitnode intensity* and *Bitcoin merchants*, on measures for the size of the shadow economy relative to the GDP (*shadow economy*), an indicator variable for whether a jurisdiction is a tax haven (*tax haven*), tax rates on income and capital gains (*taxation*), and a measure of

⁸⁴ Internet Appendix, Table IA.IV provides the variable description and data sources for these variables. Our analyses of these additional characteristics, reported in Table 9a or 9b, are restricted to fewer than all 137 countries in Panel A, as certain variable sources do not report values for all countries in our sample.

tax burden across countries (*tax burden*). We maintain the baseline controls, but omit other controls to avoid confounding of variables. We do not find an indication to support the shadow economy and taxation drivers (Table 6.9 and Table 6.10; Models 1 to 4). This could be attributed either to more hidden uses of bitcoins in such nations or that the new potentials that cryptocurrencies enable for tax evasion and shadow economy, are not yet extensive enough to constitute a large part of bitcoin use.

It is possible that use of Bitcoin infrastructures (esp. Bitcoin nodes) are primarily being driven by cryptocurrency miners vying to reap the financial rewards associated with mining bitcoins. Hence, we explore if bitcoin mining is a major driver of adoption of our variables, by regressing a *bitcoin mining* country indicator variable for countries identified by the Cambridge Centre for Alternative Finance's two versions of the Global Cryptocurrency Benchmarking Study (Hileman & Rauchs, 2017; Rauchs et al., 2018) as having medium-to-large scale mining operations, and additionally find no significant effect in our robustness tests (Table 6.9 and Table 6.10; Model 5). We include estimates of *mining intensity* (in MW) and do not find any significant effect in our robustness tests (Table 6.9 and Table 6.10; Model 6). We attribute this to operation of Bitcoin nodes being driven by other than purely financial incentives and rewards to mine bitcoins, while this may still be a contributing factor. Bitcoin mining facilities are highly concentrated in certain countries with cheap and reliable electricity, cold climate and friendly regulatory environment (e.g. Rauchs et al. 2018 identify only 128 mining facilities worldwide, where only 7 countries are mining more than 40MW whereas 1.7GW have been identified worldwide), whereas nodes are less concentrated. In fact, Miller et al. (2018) find only 2% of nodes on the Bitcoin network to account for three quarters of the mining power. We additionally test *electricity prices* in USD per kWh in different countries and years and similarly find no effect (Table 6.9 and Table 6.10; Model 7).

One of the touted benefits of cryptocurrencies in the financial literature has been in enabling diversification (Bouri et al. 2019a) or as a hedge against equity markets (Bouri et al. 2019b), although some studies have found them to be a weak hedge for stock markets (Kliber et al., 2019; Shahzad, Bouri, Roubaud, Kristoufek, & Lucey, 2019). Certainly bitcoins are held due to their speculative nature (Rauchs et al. 2018; Baur, Hong, et al. 2018), in congruence with the reported effects of our *High risk willingness* variable, in addition to serving as an alternative investment (Glaser et al., 2014). We test to see if Bitcoin infrastructure has seen an uptick worldwide as a hedge for low returns in national stock markets. Model 8 in Table 6.9 and Table 6.10 presents results of that and does not show evidence for hedging as a main driver of bitcoin use. In Model 9 of these tables, we additionally test to see if purely low returns during the global financial crisis can be attributable to an upsurge in adoption, and similarly do not find statistically significant effects on our *crisis stock market return* variable.

Table 6.8. Technological/infrastructural drivers of Bitcoin nodes (Panel A; Country-year level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent Variables:	Bitnode intensity _{pc}							Unique bitnodes _{pc}		Bitnode hours	Bitcoin merchants _{pc}
Internet penetration		0.044*** (0.013)									
Broadband penetration			0.080* (0.035)								
ICT market development				0.613*** (0.173)				0.43*** (0.100)	6.393*** (0.925)	103.41*** (23.450)	0.487* (0.224)
Latest technology					1.344*** (0.339)			0.628* (0.271)	2.540 (1.740)	63.585+ (37.540)	0.744+ (0.404)
Internet servers						0.079+ (0.046)		0.079+ (0.041)	-0.011 (0.137)	-4.988 (13.35)	0.017 (0.045)
Mobile subscriptions							0.017* (0.008)	0.006 (0.007)	0.004 (0.045)	-0.374 (0.849)	-0.002 (0.008)
GDP per capita	1.333*** (0.352)										
Restrictive regulation		-0.652+ (0.337)	-0.577 (0.382)	-0.520+ (0.314)	-0.653* (0.306)	-0.160 (0.189)	-0.558+ (0.303)	-0.126 (0.255)	3.610*** (1.069)	24.854 (38.522)	0.009 (0.564)
Constant	-11.0*** (3.127)	-1.131+ (0.603)	-0.025 (0.692)	-2.31* (0.926)	-5.8*** (1.553)	1.080* (0.534)	-0.936 (1.200)	-5.34** (1.325)	-26.59** (9.417)	-84.64 (244.682)	-5.921* (2.665)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel Data Specification	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit
Observations	685	685	685	685	685	685	685	685	685	685	685
Number of Countries	137	137	137	137	137	137	137	137	137	137	137
Pseudo R-Squared	0.37	0.31	0.35	0.33	0.36	0.40	0.24	0.48	< 0	< 0	< 0
Log-likelihood	-1235.1	-1246.3	-1247.2	-1243.3	-1239.8	-1208.4	-1249.1	-1190.6	-2248.6	-2351.5	-1404.0
RHO	0.72	0.76	0.75	0.75	0.73	0.77	0.79	0.71	0.60	0.70	0.23

Notes: All models are Tobit random effects models lower-censored at 0 and their associated pseudo R-squared are reported. Panel-data adjusted bootstrapped standard errors, clustered at the country level, are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level. Model (13) is additionally upper-censored at 750 (upper limit of active Bitnode hours in a month).

Table 6.9. Additional Analysis on the Role of Alternative Potential Drivers (Panel A; Country-year level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	Bitnode intensity								
Shadow economy	-0.037 (0.031)								
Tax haven		-1.052 (0.665)							
Taxation			0.011 (0.021)						
Tax burden				-0.011 (0.027)					
Bitcoin mining country					0.374 (0.996)				
Bitcoin mining MWs						-0.013 (0.031)			
Electricity price							-0.002 (0.035)		
Stock market return								-0.002 (0.005)	
Crisis stock market return									0.005 (0.019)
GDP per capita	1.173** (0.373)	1.452*** (0.377)	1.735*** (0.421)	1.640*** (0.334)	1.420*** (0.333)	1.408*** (0.351)	1.425*** (0.334)	1.680*** (0.370)	1.384** (0.477)
Restrictive regulation	-0.500 (0.348)	-0.579* (0.279)	-0.474 (0.363)	-0.570+ (0.331)	-0.582* (0.295)	-0.466 (0.293)	-0.582* (0.283)	-0.636 (0.439)	-0.744 (0.490)
Constant	-8.222* (3.646)	-11.567*** (3.065)	-14.639*** (3.731)	-12.552** (4.325)	-11.480*** (2.869)	-11.260*** (2.936)	-11.281*** (3.366)	-13.802*** (3.326)	-10.959** (4.252)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	670	685	580	665	685	670	685	440	460
Log-likelihood	-1291.6	-1314.4	-1131.3	-1267.2	-1314.8	-1269.2	-314.6	-975.1	-1023.1
Number of Countries	134	137	116	134	137	134	137	92	92
RHO	0.74	0.74	0.77	0.75	0.74	0.75	0.74	0.76	0.75

Notes: All models are Tobit random effects models lower-censored at 0 and their associated pseudo R-squared are reported. Panel-data adjusted bootstrapped standard errors, clustered at the country level, are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level.

Table 6.10. Additional Analysis on the Role of Alternative Potential Drivers (Panel A; Country-year level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	Bitnode Merchants								
Shadow economy	-0.003 (0.033)								
Tax haven		-0.431 (1.276)							
Taxation			0.003 (0.038)						
Tax burden				-0.071 (0.047)					
Bitcoin mining country					1.003 (1.283)				
Bitcoin mining MWs						0.002 (0.031)			
Electricity price							0.020 (0.025)		
Stock market return								0.020 (0.019)	
Crisis stock market return									-0.010 (0.025)
GDP per capita	1.343* (0.648)	1.413** (0.492)	1.550* (0.633)	1.137** (0.438)	1.387** (0.535)	1.474** (0.557)	1.372* (0.588)	0.590 (0.364)	0.689+ (0.362)
Restrictive Bitcoin Regulation	-0.024 (0.821)	-0.024 (0.750)	0.461 (0.941)	-0.129 (0.793)	-0.109 (0.725)	-0.132 (1.040)	-0.053 (0.970)	-0.035 (0.708)	-1.203 (1.315)
Constant	-11.121+ (6.577)	-12.096* (4.786)	-13.596* (5.954)	-3.933 (4.898)	-12.092* (5.281)	-12.620* (5.213)	-11.805* (5.633)	-4.499 (3.641)	-5.190 (3.540)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	670	685	580	665	685	670	685	440	460
Log-likelihood	-1382.1	-1418.2	-1278.1	-1407.8	-1418.0	-1377.5	-1417.8	-1151.0	-1195.8
Number of Countries	134	137	116	134	137	134	137	92	92
RHO	0.23	0.23	0.21	0.20	0.23	0.23	0.23	0.18	0.19

Notes: All models are Tobit random effects models lower-censored at 0 and their associated pseudo R-squared are reported. Panel-data adjusted bootstrapped standard errors, clustered at the country level, are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level.

6.9 Discussion

To date, bitcoin is clearly the most prominent and widespread cryptocurrency. A decade on from the first bitcoin transaction, this chapter studies the determinants of adoption of infrastructure supporting bitcoin's use as a digital currency. Infrastructure supporting Bitcoin's peer-to-peer network (the hosting of bitnodes, which are infrastructure meant to validate and verify transactions) as well as infrastructure facilitating the integration of bitcoin into the regular economy (merchants' acceptance of bitcoins as payment) has been explored. The results are summarized in Table 6.11.

Table 6.11. Summary of hypotheses and results of hypothesis tests

Hypothesis number	Hypothesis	Results	Support for nodes and/or merchants?
H1	The occurrence of inflation crises is associated with increased adoption of Bitcoin infrastructure.	Supported	Nodes
H2a (vs. countering H2c)	The lower (for H2c: greater) the population of financially included adults, the greater the adoption of Bitcoin infrastructure.	H2a rejected in favour of H2c	Nodes and partially merchants
H2b (vs. countering H2d)	The lower (for H2d: higher) the level of competition in banking markets, the greater the adoption of Bitcoin infrastructure.	H2b rejected in favour of H2d	Nodes
H3a	The greater the level of trust in others, the greater the adoption of Bitcoin infrastructure.	Partially supported	Nodes
H3b	The greater the level of distrust in banks and the financial system, the greater the adoption of Bitcoin infrastructure.	Supported	Nodes
H3c	The higher the risk-willingness, the greater the adoption of Bitcoin infrastructure.	Supported	Merchants and partially nodes
H4	The more money-laundering activities taking place, the greater the adoption of Bitcoin infrastructure.	Supported	Nodes and partially merchants
H5	The stronger the rule of law, the greater the adoption of Bitcoin infrastructure.	Supported	Nodes and merchants

Our results offer some support for the view that bitcoin adoption is driven by perceived failings of traditional financial institutions and systems (see e.g. Cohen 2017; Shiller 2019; Vigna and Casey 2015). In particular, we find more activity in the running of Bitcoin nodes in regions with low trust in banks and the financial system. These corroborate the role of distrust in banks, which spread widely in the aftermath of the financial crisis of 2007-2009, being a factor in the early use of other peer-to-peer fintech technologies (see e.g. Saiedi et al. 2017; Bertsch et al. 2017; Thakor and Merton 2018). We also find greater supply of and demand for Bitcoin infrastructure in years in which countries undergo inflation crises, potentially indicative of a loss of faith in central-bank issued currencies or using bitcoin as an investment or store of value. Our findings suggest that the ideological motives for use of cryptocurrencies

in entrepreneurial financing (e.g. Fisch et al. 2018) extend to sentiments of infrastructure adopters, who are active supporters of the cryptocurrency ecosystem.

Furthermore, we find that lower industry concentration in the banking market – which we take to indicate higher banking competition – are positively associated with running of Bitcoin nodes. This finding is in line with contrary to findings for certain peer-to-peer financial technologies (e.g. crowdfunding by Rau 2017), but in line with studies finding complementarities between banking markets and fintech development (Hornuf et al., 2018; Klus et al., 2019). Our data also indicate that contrary to expectations put forth by some (e.g. Killeen 2015; Vigna and Casey 2015), greater Bitcoin infrastructure adoption has not yet emerged in countries with a larger unbanked population. Together, these results paint a picture of bitcoins being used as a complement to existing financial institutions, rather than a substitute. It is likely that, as a recent study by Yermack (2018) of FinTech adoption in Africa suggests, a lack of information technology infrastructure underlies failures of FinTech platforms to succeed in countries with low financial inclusion.

Geographical variation in self-reported willingness to take risks is found to be correlated to the acceptance of bitcoins by merchants, suggesting that the high volatility of bitcoins and uncertain regulatory environment reduces its appeal in more risk-averse societies.

Our results also support the view that bitcoin adoption is driven partly by the cryptocurrency's usefulness in allowing illicit business activity. Greater rule of law increases the adoption of both types of Bitcoin infrastructure we have analysed. Higher rule of law may plausibly spur those desiring to engage in illicit activity in countries with high quality of police and courts to turn to online trade as a safer means of procuring illegal drugs (Barratt et al., 2016). Results suggest that countries home to a greater risk of money laundering are more likely to host infrastructure for bitcoin transaction verification and validation, being in line with evidence that bitcoins are utilized greatly for drug trade and other illicit activities (Athey et al., 2016; Böhme et al., 2015; Foley et al., 2019).

Finally, our results lend support for Bitcoin node infrastructure being driven, to a greater extent, by banking market development, crime and societal distrust in banks and the financial system, while they lend support for Bitcoin merchants being driven more by risk willingness and criminality measures (specifically rule of law). While the emergence of these infrastructures coincides across geographies (c.f. Figs. 1b and 2) and time (c.f. Figs. 3 and 4), results suggest they may be subject to different mechanisms. A possible interpretation is that the pattern for nodes reflects attitudes to a greater extent (or *active support for Bitcoin*), whereas the pattern for merchants reflects the user base more (or *interest in Bitcoin*).

6.10 Limitations

Our study has certain limitations relating to the availability of data. One such limitation is that we do not directly observe the use of bitcoin as a currency (e.g. in the number of people holding bitcoin in a country). We are therefore not able to explore to what extent the associations that our study uncovers are driven by country-level differences in bitcoin adoption, or by other related factors. A further limitation of our study that is in measuring the penetration of Bitcoin infrastructure across space and time, we are only capturing nodes and merchants who do not hide their location. We believe such open support for Bitcoin's network to provide a proxy for the adoption of Bitcoin infrastructure. Nevertheless, our inability to observe hidden infrastructure can result in underweighting the role of certain characteristics in assessing drivers of cryptocurrency infrastructure. In particular, more sophisticated users and criminals using bitcoins are more likely to use firewalls to avoid revealing their network presence. We therefore suggest that the size of the effect we attribute to such technological or criminality characteristics can be seen as a lower-bound to their true effect. Hence, by directly measuring open support for the digital currency ecosystem, this study determines the effect of financial characteristics on bitcoin adoption, while ascribing lower-bound for the effects of technological, criminality and social drivers.

In choosing appropriate variables to specify and test hypotheses about illicit activities as drivers of interest in Bitcoin, we had to resort to measures that we expect to proxy for illicit activities, since more direct measures were not available with sufficient global comparability. We did not, for example, use actual dark-net drug sales or drug-trade statistics (e.g. the Global Drug Survey; see UNODC 2019), as they are currently only available for a limited subset of countries, and with varying degrees of reliability. Another limitation is the lack of appropriate proxies for certain relevant constructs related to attitudes towards cryptocurrencies and their potential advantages over fiat currencies. For example, cultural preferences for privacy is a potentially relevant factor, and data is available from surveys. However, recent research casts doubts as to their reliability due to the Digital Privacy Paradox, in that stated privacy preferences are different from observed privacy preferences (Athey, Catalini, & Tucker, 2017). Certain relevant national characteristics were also omitted as they underlie utilized variables, as is for instance the case of financial literacy (not included as a separate variable; Grohmann et al. 2018) and financial inclusion (included in our models).

6.11 Conclusions and Implications

The global spread of the use of cryptocurrencies is a notable feature of the 21st century economy. Already an important locus of entrepreneurial activity, cryptocurrencies can alter the business models of existing actors within entrepreneurial finance (Joern H. Block, Colombo, Cumming, & Vismara, 2018) and are expected to have significant consequences for business in the relatively near future (e.g. see Dierksmeier

and Seele 2018). Understanding the drivers behind their spread thus far is therefore important to scholars studying digital currencies and their role in present and future digital entrepreneurial ecosystems.

While papers on potential risks and opportunities posed by cryptocurrencies are flourishing (e.g. Choo 2015; Dierksmeier and Seele 2018; Kethineni and Cao 2019; Tasca 2015), as well as those posed by blockchains and ICOs (e.g. Kewell et al. 2017; Martino et al. 2019), little is empirically known about the spread, growth and patterns of use of these innovations. To the best of our knowledge, this chapter is the first academic empirical inquiry with global geographic coverage of the emergence of Bitcoin as an alternative financial system. A significant contribution of this study is therefore analyzing large global cryptocurrency databases and providing the annualized data online⁸⁵ for further empirical studies in this nascent and emerging field. The study also offers important insights to scholars seeking to understand the growth of cryptocurrencies through a grounded global analysis, not least to separate a great deal of myth from facts.

While descriptive in nature, our results paint a picture of the adoption of cryptocurrencies as being related to its usefulness as a complement to traditional financial services. Such usefulness derives on the one hand from inefficiencies and failings (e.g. inflation crises) of traditional economic or financial systems, and on the other hand on the opportunity to conduct illegal or shady transactions using cryptocurrency.

We now turn to the implications of our study for various scholars, as well as for institutions which may shape, regulate or lend oversight to digital currencies now or in the future.

6.11.1 Implications for scholars of digital currency

With the support for cryptocurrency infrastructure and interest in making financial transactions using cryptocurrencies expected to keep growing over time, further research should seek to explore further what drives participation, and what consequences such support may have on incumbent financial structures. This study has demonstrated that institutional and social factors had important roles to play in the growth of the Bitcoin system to date, which suggests that such factors should be carefully considered also in future research on digital currency development.

The study shows that despite the much-touted promise of bitcoins (e.g. Dierksmeier and Seele 2018; Killeen 2015; Vigna and Casey 2015) and blockchain technologies (e.g. Larios-Hernández 2017) in increasing financial inclusion and poverty reduction, it is the countries where such issues are less poignant that have the strongest penetration of Bitcoin infrastructure. On the one hand, this finding calls for further research on barriers to adoption of digital currency in less developed settings, and how these may be overcome. On the other hand, our results may be seen as fuel for a broader discussion about the role

⁸⁵ To be made available upon publication at an open data repository, recommended by Springer Nature

of cryptocurrencies. While clearly potentially helpful for citizens of countries beset by hyperinflation, evidence on the strong connection to illicit activity and the, as of yet, unrealized promise of providing a means to increase financial inclusion would seem to weigh in with arguments that the cryptocurrency's growth is to be seen as cause for concern – e.g. in the light of price manipulation (Griffin & Shams, 2019), heavy electricity use associated with Bitcoin mining (Krause & Tolaymat, 2018) and the increased occurrence of cybercrimes and frauds involving cryptocurrencies (Corbet, Cumming, Lucey, Peat, & Vigne, 2019; Kamps & Kleinberg, 2018; Li, Shin, & Wang, 2018; Su, 2019).

6.11.2 Implications for actors in digital ecosystems

This chapter depicts how a decentralized infrastructural system grows organically and offers indirect evidence of motives that underlie the fast-growing and evolving digital currency ecosystem. Our findings indicating that interest in Bitcoin thus far is strongest in the most financially well-developed locations may spur entrepreneurs in the digital currency ecosystem to develop new means to simplify the process of using bitcoins for it to have a chance of reaching the unbanked, or integrating their products on more widespread communication technologies (e.g. mobile phones). Some efforts, such as the integration of bitcoin on the popular M-Pesa system in Kenya (Vigna & Casey, 2015) have been made, while of greater use towards poverty reduction could be focusing on e.g. reducing persistently-high international remittance fees (Beck and Martínez Pería 2011).

Technology firms planning or exploring to issue their own digital currencies, such as Facebook's Libra project (Libra Association 2019), can draw lessons from the historical patterns of adoption of bitcoins depicted in this chapter. In particular, the findings indicating that interest in Bitcoin is associated with distrust in banks and established financial institutions, would seem to point to an advantage that can be exploited in marketing new currencies. The greater trust of consumers in technology companies than in banks (Bain & Company 2019; Forbes 2015) could provide an edge in harnessing fintech technologies, albeit if they can retain such trust (Nair, 2019).

6.11.3 Implications for central banks and public authorities

The debate on the risk and opportunities of central banks issuing cryptocurrencies, or more broadly central bank digital currencies (CBDC), is intensifying (Borio et al., 2017; Conti-Brown, Lastra, Raskin, & Yermack, 2018; Engert & Fung, 2017; Niepelt, 2020). Many central banks currently conduct research on digital currency issuance (Cœuré, 2018). The real-world uptake and support for bitcoins can be seen as a case study for the risks and demand for preserving anonymity in digital transactions, as alluded to in Acquisti et al.'s (2016) survey on the economics of privacy. The history of bitcoin use so far can help inform CBDC-design as regulators weigh trade-offs between the need to control transaction fraud and the desire to avoid invasive or costly monitoring of individuals. Some economic theorists suggest that

this trade-off will exist despite any technological progress (Kahn, McAndrews, & Roberds, 2005; Kahn & Roberds, 2008).

The correlation of distrust in banks with bitcoin adoption should be of concern to financial regulators for whom financial stability and transactions through legitimate monetary channels is tantamount. Nowhere is this more a concern than in countries experiencing very high inflation. Low faith in the currency's stability, coupled with a distrust in the national financial system, can drive the populace into digital currencies, rendering a monetary authorities' monetary supply less effective.

Law enforcement agencies must react to the use of digital assets for narcotics-related money laundering. Finally, there is cause for concern for tax administrations and revenue agencies in use of digital currencies for tax evasion, as evidenced by formation of international task forces (J5 2018). Further studies could shed more light on empirically establishing the extent of use of cryptocurrencies for money laundering and tax evasion.

7 Conclusions: The Global Financial Crisis in Perspective

The common thread (or to borrow a Swedish word “röd tråd”, literally meaning red thread; or to borrow a musical term, leitmotif) of the cover essay to this dissertation has been the global financial crisis. Half of the thesis discusses the financing decisions of firms during the financial crisis, and adverse outcomes of inability to attain outside capital during the crisis. The focus has been on SMEs, which are the predominant form of enterprise, and account for 70% of jobs and between 50 to 60% of added value in OECD countries, and 45% of employment and 33% of GDP in emerging economics (OECD, 2016).

These studies, together with numerous others on corporate investments during or following the recession (reviewed by Guler et al., 2019), indicate that the financial crisis resulted in declines in firm investments, with smaller firms and low-liquidity firms experiencing a stronger decline (Balduzzi et al., 2018; Berg, 2018; Cingano et al., 2016). It is alarming that innovative SMEs were more likely to be rejected in their financing applications than other firms, and that this worsened substantially in the crisis (Lee et al., 2015), all while these firms are most likely to create new markets and drive the growth of an economy, following recessions.

The other half of the thesis, finds that the adoption of two types of financial technologies increases with greater distrust in banks, which was exacerbated as a result of the financial crisis. One financial innovation type, meaning decentralized cryptocurrencies, was realized in October 2008 with the publication of the whitepaper for Bitcoin, at the height of the financial crisis. The very first transaction in Bitcoins bore a message of dissatisfaction with use of tax-payers’ funds to bail out banks. Chapter 6 shows that when countries experience inflation and monetary crises, adoption of bitcoins increases. In addition, Chapter 5 shows that this distrust in banks is a societal response to actual financial sector frauds and failures of commercial banks. It is feasible that the global financial crisis accelerated spurring certain innovations, which can alter the landscape of the financial industry.

This thesis therefore explores two sides of the financial crisis: The more immediately clear value-destroying side, and a less obvious value-adding side. The rapid growth of peer-to-peer financial technologies of P2P lending or cryptocurrencies, as well as other fintech startups, hints at a process of creative destruction in the spirit of Schumpeter’s influential book, “Capitalism, Socialism and Democracy”.

7.1 The Crisis as a Source of Value Destruction

While Gertler & Gilchrist (2018) do state that financial distress in each of the economy’s three main sectors – financial intermediaries, households and nonfinancial firms- played a significant role in the evolution of the Great Recession, they find that the recent recession would have been relatively mild without the disruption of credit provision of financial intermediaries. Following such credit shocks, the

global financial crisis severely reduced short-term corporate investments in both capital expenditures and innovation, lessening employment and value-added of firms, as well as the short-term willingness of firms to invest in innovation (Campello et al., 2010; Cingano et al., 2016; Mark Gertler & Gilchrist, 2018; Paunov, 2012).

Beyond the short-term and over a longer horizon, firm performance and productivity decreased for firms whose investment plans reduced following capital frictions (Paper III; Manaresi & Pierri, 2017).

Not only were the short-term effects of the financial crisis value-destroying, the recovery from the crisis has been slow. Reinhart & Rogoff (2009) have shown that recoveries from financial crises are typically much longer than normal. There is some evidence that credit market contractions persisted both for small businesses (Chen, Hanson, & Stein, 2017) and households (Jones, Midrigan, & Philippon, 2011).

7.2 The Crisis as a Source of Creative Destruction?

“The opening up of new markets ... illustrate the process of industrial mutation that incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one ... [The process] must be seen in its role in the perennial gale of creative destruction; it cannot be understood on the hypothesis that there is a perennial lull.”

- Joseph Schumpeter (1942), Capitalism, Socialism and Democracy.

“During the recession of the long waves, an especially large number of important discoveries and inventions in the technique of production and communication are made, which, however, are usually applied on a large scale only at the beginning of the next long upswing.”

- Kondratieff (1925 [1935], p. 111)

“Over the long run, the process of creative destruction accounts for over 50 percent of productivity growth”

- Caballero (2008)

A contribution of this thesis is in demonstrating that through a channel of lowering trust in established financial institutions and the financial system, the global financial crisis, spurs on the use of alternative financial markets and currencies. In doing so, it can be seen that this financial crisis, and perhaps other economic crises, are a source of creative destruction as well, in that new forms of doing business come to replace the old.

Innovation research has shown that the economic turmoil of the financial crisis has favored small firms that are responsive to new market opportunities, such as those in pursuit of more explorative strategies (Archibugi et al., 2013).

It is telling that the financial innovations in Fintech 3.0 (see subsection 2.2) arise outside of banks and traditional financial institutions. A few, such as decentralized cryptocurrencies, have grown from outside of any institution, even if many cryptocurrencies and ICOs are issued now by organizations.

Filippetti & Archibugi (2011) compare the drop in innovation investments of firms across European countries and find that the competence and quality of human resources, specialization in the high-technology sector and development of the financial system help firms offset the effect of the financial crisis on innovation investments.

What is strikingly similar between the national conditions needed to offset the crisis' effects on innovation investments and the conditions bringing about Fintech 3.0, is the requirement for a skilled labor force and high-tech infrastructure (Haddad & Hornuf, 2019) and developed financial and banking systems (Haddad & Hornuf, 2019; Saiedi et al., 2020). These conditions being in place outside of traditional financial institutions, at the time of the global financial crisis, could be seen as a catalyst for the rise and uptake of financial innovations in the post-crisis fintech 3.0 era.

What is notable about the developers of cryptocurrencies and ICOs, is that they rely on the public to improve their products and innovations. Most cryptocurrencies and ICOs make their source code accessible for the community at large, who can report defects for fixing (Fisch, 2019). This hints at the community acting as innovators in these technologies. One can draw parallels to the literature discussing users as innovators (Bogers, Afuah, & Bastian, 2010) which finds that users are particularly good at developing radically new, breakthrough innovations (Lettl, Herstatt, & Gemuenden, 2006; Lilien, Morrison, Searls, Sonnack, & Hippel, 2002), except that in Fintech 3.0, technologically-savvy members of the public some of whom are dissatisfied with the traditional financial system, are the innovators.

These hint at some of the creative destruction forces of financial crises.⁸⁶ Future research can shed light on to what extent financial crises do spur the gale of creative destruction.

⁸⁶ This section analyzed the process of creative destruction building on research by innovation scholars and with the point of view that some innovations may occur or be accelerated in use *due to* the occurrence of the crisis. Some economists have also studied whether *reallocations* of creative destruction, in restructuring of firms, are helped or hindered by the recession, and they find that they are mostly hindered (Legrand & Hagemann, 2017). This thesis views these as separate effects of the process of creative destruction, with an important distinction that the first may occur inside or outside of firms. The extent to which either dominates may depend on the extent to which recessions or depressions become “pathological” -to borrow a term used by Schumpeter (1942, pp. 349–50)-, or physiological (Legrand & Hagemann, 2017).

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Appendix A. Chapter 3: Additional Table

Table A.1. Firm-Specific Determinants of all SME Decisions on Various Financing Instruments (SAFE Analysis)

Financing Instrument: Firm-Specific Factors	Bank Loan		Trade Credit		Credit Lines		Other External Finance	
	Apply for	Obtain	Apply for	Obtain	Apply for	Obtain	Apply for	Obtain
Turnover								
Turnover +	0.101*** (0.023)	0.0991 (0.067)	0.0983*** (0.026)	0.0651 (0.060)	0.100*** (0.023)	-0.0579 (0.086)	0.0952*** (0.026)	0.181** (0.081)
Turnover -	0.0224 (0.027)	-0.003 (0.060)	0.0613** (0.029)	0.0273 (0.059)	0.000418 (0.027)	-0.0202 (0.058)	0.0212 (0.030)	0.101 (0.083)
Fixed Investments								
Fixed Investment +	0.168*** (0.021)	0.170** (0.072)	-0.0472** (0.024)	0.112* (0.063)	0.000940 (0.021)	0.0363 (0.053)	0.137*** (0.024)	0.145* (0.084)
Fixed Investment -	0.0142 (0.028)	-0.286*** (0.064)	0.0982*** (0.031)	-0.0297 (0.069)	0.0648** (0.028)	-0.301*** (0.059)	0.075** (0.031)	-0.146 (0.096)
Profit								
Profit +	-0.036 (0.024)	0.006 (0.059)	-0.0173 (0.026)	0.004 (0.058)	-0.067*** (0.024)	0.0276 (0.071)	-0.0297 (0.026)	0.029 (0.082)
Profit -	0.072*** (0.024)	-0.129** (0.056)	0.0724*** (0.026)	-0.162** (0.078)	0.0719*** (0.024)	-0.119* (0.063)	0.0995*** (0.027)	-0.0621 (0.092)
Debt/Assets								
Debt/Assets +	0.350*** (0.024)	-0.267*** (0.083)	0.171*** (0.027)	-0.0217 (0.077)	0.361*** (0.024)	-0.217 (0.219)	0.244*** (0.026)	-0.0556 (0.122)
Debt/Assets -	0.137*** (0.021)	-0.0804 (0.058)	0.0796*** (0.023)	0.0441 (0.051)	0.122*** (0.021)	-0.0370 (0.096)	0.0473** (0.023)	0.0260 (0.072)
Angel or VC Ownership	0.0436 (0.114)	0.0330 (0.274)	0.0344 (0.129)	0.238 (0.339)	-0.0803 (0.119)	0.160 (0.328)	0.140 (0.122)	0.531 (0.359)
Public Firm	-0.193** (0.085)	0.165 (0.237)	-0.0310 (0.088)	-0.00942 (0.158)	-0.114 (0.080)	0.741*** (0.283)	-0.0103 (0.081)	0.0311 (0.208)
Family/Entrepreneur Ownership	0.0323 (0.023)	0.004 (0.052)	0.0602** (0.026)	0.0557 (0.052)	0.0343 (0.023)	0.0335 (0.060)	0.122*** (0.024)	0.00328 (0.082)
Other Firm Ownership	-0.127*** (0.037)	0.142 (0.092)	0.00937 (0.041)	0.00575 (0.079)	-0.0317 (0.036)	0.180** (0.089)	0.121*** (0.035)	0.148 (0.109)
Credit History								
Credit History +	0.231*** (0.021)	-0.0249 (0.072)	0.154*** (0.023)	0.117** (0.056)	0.158*** (0.021)	0.0448 (0.131)	0.148*** (0.023)	-0.0349 (0.091)
Credit History -	0.306*** (0.031)	-0.673*** (0.067)	0.278*** (0.034)	-0.355** (0.163)	0.423*** (0.031)	-0.683*** (0.179)	0.372*** (0.033)	-0.392** (0.200)
Innovation	0.0977*** (0.020)	-0.190*** (0.047)	0.112*** (0.023)	-0.0276 (0.060)	0.108*** (0.020)	-0.102 (0.072)	0.0804*** (0.022)	-0.131* (0.078)

Firm Makes Own Financing Choices	0.414*** (0.039)	-0.0197 (0.135)	0.0594 (0.040)	0.108 (0.077)	0.289*** (0.037)	-0.159 (0.197)	-0.105*** (0.034)	-0.111 (0.104)
Age								
Reference: <2 years								
2-5 years	0.0860 (0.119)	0.279 (0.278)	-0.113 (0.128)	-0.128 (0.225)	0.0259 (0.112)	-0.242 (0.236)	-0.0357 (0.118)	-0.280 (0.320)
5-10 years	0.122 (0.115)	0.498* (0.278)	-0.146 (0.127)	-0.0513 (0.230)	0.0748 (0.106)	0.157 (0.245)	-0.135 (0.112)	-0.176 (0.305)
>10 years	0.160 (0.112)	0.453* (0.274)	-0.218* (0.123)	0.0176 (0.230)	0.0455 (0.103)	0.0759 (0.230)	-0.220** (0.109)	-0.226 (0.300)
Growth Outlook								
Growth Outlook +	0.0745*** (0.023)		0.133*** (0.021)		0.0547** (0.023)		0.111*** (0.023)	
Growth Outlook -	-0.0221 (0.029)		0.108*** (0.026)		0.0421 (0.038)		0.0838*** (0.028)	
Industry-Specific Factor								
Industry Dependence on Financing Instrument	2.574*** (0.914)		2.448** (1.107)		3.593*** (1.120)		6.552*** (1.273)	
Turnover Size Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employees Size Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,837		31,837		31,837		31,837	

Note: *, ** and *** indicate that the estimator's p-value is respectively less than 0.1, 0.05 and 0.01. All standard errors are clustered at the firm level. Turnover size controls are for turnover size categories of <€500k, between €500k and €1m, between €1m and €2m, between €2m and €10m, between €10m and €50m, and above €50m. Employee size controls are for employee categories of up to 10 employees, between 10 and 49 employees and 50 to 249 employees. These control for firm size, above which the effect of changes in financial statement items on our dependent variables of interest are reported herein.

Appendix B. Chapter 4: Additional Tables

Table B.1. Effect of Financing Rejection on Survival

This table reports the results of a logit model. Associated R-squared value is reported. Standard errors, clustered at the firm level, are reported in parentheses. The symbols ***, ** and * mean that the reported coefficients are statistically different from zero, respectively, at the 1, 5 and 10 percent level. Sample size of 4,508 firms is less than 6,344 firms (reported as having a demand for external financing in Table 4.2) due to observations with missing financials for 2009 dropping out of the regression. Lagged values represent 2009 financials since the firm active status (dependent variable) is recorded in 2010. This equation follows the linear (non-splined) logistics model used by Giordani et al. (2014), who regress a dummy for firm bankruptcy on lagged values for firm leverage, EBIT/Total Assets, Cash Ratio, Size, Age, GDP and Repo Rate. GDP differences are captured by country dummies in this table, and the cross-sectional nature of the regression cannot account for repo-rate variations.

Dependent Variable:	(1) Dummy for Active Firm in 2010
Rejection in 2009	0.087 (0.085)
Lagged Leverage	-2.602*** (0.274)
Lagged ROA	3.225*** (0.417)
Lagged Current Assets/Total Assets	-0.071 (0.070)
Lagged Assets (Log)	-0.017 (0.033)
Constant	3.419** (1.433)
Firm Age FEs	Yes
Sector FEs	Yes
Country FEs	Yes
Observations	4,508
R-Squared	27%

Table B.2. Effect of Financing Rejection on Investments – Robustness to Additional Controls

This table reports the results of estimating investment Equation (3), if *cash flow* is used instead of *ROA* a financial flow measure (i.e. income or cash flow statement item) and additional controls of *sales*, measuring firm size, and an indicator variable for *distress* are included. These additional controls follow investment regressors used by Lemmon and Roberts (2010). All models are fixed effects models and their associated R-squared are reported. Data are from Amadeus and EFIGE for the period 2006 to 2011 for column 1, and for the period 2006 to 2010 for column 2. Firm-year observations with negative capital expenditures are excluded. Standard errors, clustered at the firm level, are reported in parentheses. The symbols ***, ** and * mean that the reported coefficients are statistically different from zero, respectively, at the 1, 5 and 10 percent level.

	<u>3-years post-2009 effect</u>	<u>2-years post-2009 effect</u>
	Gross PPE	Gross PPE
	(1)	(2)
Rejection x post	-0.903** (0.395)	-1.478*** (0.479)
Sales Growth	0.252 (0.511)	-0.097 (0.660)
Cash flow	10.867*** (2.259)	12.468*** (2.733)
Distress	0.265 (0.321)	0.130 (0.382)
Sales	1.806*** (0.382)	2.540*** (0.518)
Firm FEs	Yes	Yes
Year FEs	Yes	Yes
Observations	9,604	8,135
R-Squared	29%	32%

Table B.3. Effect of Financing Rejection on Investments, Including Observations with Negative Capital Expenditure

This table reports the results of estimating investment Equation (3). All models are fixed effects models and their associated R-squared are reported. Data are from Amadeus and EFIGE for the period 2006 to 2011 for column 1, and for the period 2006 to 2010 for the column 2. Firm-year observations with negative capital expenditures are included. Standard errors, clustered at the firm level, are reported in parentheses. The symbols ***, ** and * mean that the reported coefficients are statistically different from zero, respectively, at the 1, 5 and 10 percent level.

	3-years post-2009 effect	2-years post-2009 effect
	Gross PPE	Gross PPE
	(1)	(2)
Rejection x post	-0.424 (0.392)	-1.195** (0.465)
Sales Growth	1.892*** (0.463)	1.810*** (0.595)
ROA	6.567*** (1.573)	7.890*** (2.116)
Firm FEs	Yes	Yes
Year FEs	Yes	Yes
Observations	10,666	8,809
R-Squared	25%	28%

Table B.4. Average Effect of Financing Rejection on Investments – Robustness to Additional Controls

This table reports the results of estimating investment Equation (4), if *cash flow* is used instead of *ROA* a financial flow measure (i.e. income or cash flow statement item) and additional controls of *sales*, measuring firm size, and an indicator variable for *distress* are included. These additional controls follow investment regressors used by Lemmon and Roberts (2010). All models are OLS models and their associated R-squared are reported. Data are from Amadeus and EFIGE for the period 2006 to 2011 for column 1, and for the period 2006 to 2010 for column 2. The Pre-2009 Investments variable is calculated by averaging for PPE investments in 2006 to 2008, and the other variables are averaged over the subsequent 3-years (2-years) for column 1 (column 2). Standard errors, clustered at the firm level, are reported in parentheses. The symbols ***, ** and * mean that the reported coefficients are statistically different from zero, respectively, at the 1, 5 and 10 percent level.

	Average 3 years post-2009	Average 2 years post-2009
	Gross PPE	Gross PPE
	(1)	(2)
Rejection	-0.693** (0.280)	-1.514*** (0.372)
Sales growth	3.258*** (1.070)	3.962*** (1.277)
Cash flow	17.941*** (3.377)	16.663*** (4.110)
Distress	-0.465 (0.507)	-0.932 (0.576)
Sales	0.109 (0.120)	-0.069 (0.150)
Pre-2009 Investments	0.046* (0.025)	0.046 (0.033)
Constant	0.688 (1.708)	5.948*** (1.731)
Sector FEs	Yes	Yes
Country FEs	Yes	Yes
Observations	1,869	1,689
R-Squared	10%	9%

Table B.5. Cushioning Effect of Liquidity on Investments – Robustness to Using Liquidity Ratio

All models are fixed effects models and their associated R-squared are reported. Data are from Amadeus and EFIGE for the period 2006 to 2011 for columns 1 to 5, and for the period 2006 to 2010 for column 6. Firm-year observations with negative capital expenditures are excluded. Standard errors, clustered at the firm level, are reported in parentheses. The symbols ***, ** and * mean that the reported coefficients are statistically different from zero, respectively, at the 1, 5 and 10 percent level.

	3-years post-2009 effects			2-years post-2009 effects		
	Gross PPE	Gross FA	Net PPE	Gross PPE	Gross FA	Net PPE
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity ratio x post	0.202 (0.277)	0.219 (0.295)	0.197 (0.261)	0.795*** (0.287)	0.780** (0.308)	0.795*** (0.282)
Rejection x post	-0.847** (0.402)	-0.913** (0.429)	-0.826** (0.387)	-1.487*** (0.479)	-1.567*** (0.507)	-1.483*** (0.459)
Sales Growth	1.300*** (0.487)	1.607*** (0.561)	0.475 (0.469)	1.276** (0.626)	1.587** (0.712)	0.481 (0.602)
ROA	6.914*** (1.670)	6.839*** (1.879)	7.903*** (1.670)	8.672*** (2.188)	8.419*** (2.458)	9.303*** (2.153)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,853	9,853	9,853	8,359	8,359	8,359
R-Squared	28%	26%	24%	32%	30%	28%

Appendix C. Chapter 5: Part I - Additional Tables and Figures

Table C.1. Variable Description and Data Sources of main analyses

Variable	Description	Source
Participation Indicator	A dummy variable for each listing for whether a resident from a state has bid on it (=1) or not (=0)	Prosper.com
Participation Amount	Total amount of bidding on each listing from each state	Prosper.com
Distrust in banks	The state/regional average of a dummy variable for each respondent, equal to 1 if a respondent answered "hardly any" to the question: "As far as the people running [these institutions] are concerned, would you say you have a great deal of confidence, only some confidence, or hardly any confidence at all in them? [A. Banks and Financial Institutions]".	General Social Survey (GSS), National Opinion Research Center (NORC)
Trust in others	The state/regional average of a dummy variable for each respondent, equal to 1 if a respondent answered "Yes" to the question: "Do you think most people can be trusted?" and equal to 0 if a respondent answered "No".	GSS, NORC
Distrust in government	The state/regional average of a dummy variable for each respondent, equal to 1 if a respondent answered "hardly any" to the question: "As far as the people running [these institutions] are concerned, would you say you have a great deal of confidence, only some confidence, or hardly any confidence at all in them? [Federal Government]".	GSS, NORC
Borrower Banking Density	Number of bank branches in the borrower or lister's state per state population	Calculated from FDIC, Branch Data
Listing Size	Natural Logarithm of total dollar amount that the borrower or lister has requested in the listing.	Prosper.com
High-Risk Listing	A dummy variable equal to 1 if the listing is posted by a borrower with credit categories of C or lower (i.e. D, E and HR; corresponding to a credit score lower than 680). The credit categories are AA, A, B, C, D, E and HR, where AA is the lowest risk (credit score 720 to 759) and HR is the highest risk (credit score lower than 560, or lower than 540 prior to Feb 12, 2007).	Prosper.com
Debt to income ratio	Total current debt of a borrower or lister divided by their annual gross non-housing income	Prosper.com
Homeownership	Whether the borrower or lister is a verified homeowner at the time of creation of the listing.	Prosper.com
Lending distance	Natural logarithm of geographic distance between the population-weighted centroid of land areas of the loan applicant's (lister's) state to that of the bidder's state	
Internet access	Percentage of individuals in a state/region who live in households with internet access.	US Census
State GDP per capita (log)	Log of GDP per capita within state, quarterly data	US Bureau of Economic Analysis (BEA)
State GDP growth	Growth of GDP per capita within a state over that of the prior year	Calculated from BEA data
State population (log)	Log of the population estimate in a state on July 1st of a year	US Census

Continued

TABLE C.1. (Continued)

Variable	Description	Source
State P2P demand	Ratio of P2P listings per capita by borrowers in a state available in a calendar month to that by all US borrowers	Prosper.com
Financial Literacy	Average correct answers to five questions from 400 to 600 state residents' respondents on basic financial knowledge on inflation, cumulative interest, diversification's effect on risk-adjusted returns, interest rates and their relationship to bond prices	National Financial Capabilities Study (NFCS)
New firms	Annual change in net total number of firms in a state (compared to the prior year)	US Census, Business Patterns program
Science & Engineering specialization	Percentage of science and engineering graduate students in a state to total graduate student enrolments in a state	US National Science Foundation and National Center for Education Statistics
Cybercriminality	Number of cybercriminal activity perpetrators per 100,000 residents of a state	Federal Bureau of Investigation, National White Collar Crime Center
Banking Density	Number of bank branches in a state per state population	Calculated from Federal Deposit Insurance Corporation (FDIC), Branch Data
Population Density	State population in 1,000s per square kilometer of state land area	US Census
Working age population	Fraction of the population in a state in a given year whom are aged between 25 and 64 years of age	US Census
Male	Fraction of males to total population in a state in a given year	US Census
White	Fraction of the total population in a state in a given year who self-identify as white	US Census
Hispanic	Fraction of the total population in a state in a given year who self-identify as Hispanic	US Census
Republican	Fraction of the total votes in a state cast for Republican Candidates in the 2008 General Elections (US President, Senate and House of Representative races combined)	US Federal Election Commission
Protestant	Fraction of the total population in a state in the period 2000-2004 whom self-identify as protestant	Gallup Poll
Jewish	Fraction of the total population in a given year whom are Jewish	Association for the Social Scientific Study of Jewry

Table C.2. Correlation Table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
Participation Indicator	1.00																						
Participation Amount	0.39	1.00																					
Distrust in banks	-0.01	0.00	1.00																				
Trust in others	0.02	0.00	-0.25	1.00																			
Distrust in government	0.00	0.01	-0.14	-0.11	1.00																		
Lending distance (log)	-0.03	-0.04	-0.01	0.05	0.01	1.00																	
Internet access	0.10	0.06	0.12	0.40	-0.09	0.05	1.00																
GDP per capita	0.00	0.01	0.26	0.22	-0.15	0.00	0.20	1.00															
GDP growth	-0.07	-0.02	-0.23	0.10	0.33	0.06	-0.19	0.17	1.00														
Population	0.25	0.27	-0.06	-0.10	0.05	-0.12	0.07	-0.08	-0.14	1.00													
State P2P demand	-0.01	0.00	-0.10	0.28	0.06	0.02	0.19	0.07	0.23	-0.10	1.00												
Financial literacy	0.03	0.03	0.02	0.36	-0.05	0.08	0.56	0.00	0.05	-0.01	0.27	1.00											
New firms	-0.03	0.00	-0.19	-0.16	0.15	0.03	-0.35	0.05	0.55	-0.03	0.13	0.01	1.00										
Science & Engineering	0.04	0.07	0.05	0.05	0.40	0.02	0.19	0.26	0.32	0.16	0.20	0.10	0.08	1.00									
Cybercriminality	0.03	0.04	0.01	0.01	-0.06	0.03	0.06	0.32	0.20	0.04	0.13	0.18	0.54	-0.01	1.00								
Banking density	-0.14	-0.13	-0.22	0.18	-0.08	-0.05	-0.09	0.02	0.10	-0.41	-0.01	-0.16	-0.12	-0.04	-0.15	1.00							
Population density	-0.02	-0.02	0.20	0.17	-0.24	-0.02	-0.01	0.92	0.04	-0.12	-0.04	-0.12	0.02	0.05	0.30	0.07	1.00						
Working age population	0.04	0.02	0.03	0.25	-0.15	0.01	0.38	0.54	-0.02	-0.05	0.10	0.01	-0.02	-0.07	0.29	-0.20	0.50	1.00					
Male	-0.02	0.03	-0.25	0.26	0.18	0.11	0.10	-0.39	0.38	0.00	0.35	0.46	0.19	0.28	-0.04	-0.06	-0.55	-0.38	1.00				
White	-0.04	-0.02	-0.17	0.13	0.12	-0.06	0.05	-0.48	0.13	-0.01	0.05	0.22	-0.02	-0.05	-0.15	0.34	-0.51	-0.37	0.39	1.00			
Hispanic	0.14	0.16	0.19	0.00	0.30	0.00	0.03	0.05	0.10	0.52	-0.02	0.16	0.12	0.36	0.08	-0.52	-0.03	-0.18	0.26	0.01	1.00		
Republican	-0.07	-0.04	-0.14	-0.08	0.22	-0.04	-0.31	-0.59	0.20	-0.03	0.14	-0.05	0.13	0.03	-0.24	0.12	-0.61	-0.55	0.44	0.49	-0.07	1.00	
Protestant	-0.09	-0.07	-0.10	-0.19	0.04	-0.08	-0.60	-0.43	0.04	-0.14	0.03	-0.44	0.03	-0.32	-0.22	0.29	-0.31	-0.25	0.04	0.14	-0.35	0.52	1.00
Jewish	0.16	0.11	0.16	0.05	-0.10	-0.05	0.39	0.46	-0.16	0.39	-0.11	0.03	-0.10	0.09	0.23	-0.22	0.41	0.43	-0.50	-0.27	0.24	-0.53	-0.65

Table C.3. Variable Description and Data Sources of additional analyses

Panel A: US Bank Deposit Analysis (i.e. Appendix 8) Variables		
Variable	Description	Source
Deposits (\$)	Total consolidated deposits of an FDIC-insured banking institution, as recorded at the end of the calendar year	Deposits, other and total liabilities from FDIC; Data on last calendar years' quarterly call reports (Statements of Condition and Income)
Deposits Ratio	A percentage defined as an FDIC-insured banking institution's total deposits divided by their total liabilities, as recorded at the end of the calendar year.	
Other Liabilities Ratio	A percentage defined as an FDIC-insured banking institution's other liabilities divided by their total liabilities, as recorded at the end of the calendar year.	
Trust variables	Same as in Panels A & B.	GSS, NORC
State GDP per capita	Same as in Panel A	US Bureau of Economic Analysis (BEA)
State GDP growth	Same as in Panel A	Calculated from BEA data
State Population	Same as in Panel A	US Census
Financial literacy	Same as in Panel A, yet NCFS data were available for 2009, 2012 and 2015. Linearly interpolated between these years and assumed constant for 2001-2009.	National Financial Capabilities Study (NFCS)
New firms	Same as in Panel A	US Census, Business Patterns program
Banking density	Same as in Panel A	FDIC, Branch Data
Population density	State population per square kilometer of state land area	US Census
Percentage of Seniors	Percentage of the population in a state in a year above 65 years of age; as used as an instrument for local supply of deposits and capital by Becker (2007)	US Census
Working age population	Percentage of the population in a state in a year between 25 and 64 years of age	US Census
Male	Same as in Panel A, in percentage terms.	US Census
White	Same as in Panel A, in percentage terms.	US Census
Hispanic	Same as in Panel A, in percentage terms.	US Census
Jewish	Same as in Panel A, in percentage terms.	Assoc. for Social Scientific Study of Jewry

Continued

Table C.3. (Continued)

Panel B: Bank Failure and Financial Institutions Fraud Analysis (i.e. Table 5.3) Variables		
Variable	Description	Source
Trust variables	Same as in Panel A	GSS, NORC
Bank Failures	Number of FDIC-insured banks with failure status in a state since the last GSS surveying round, divided by the total domestic deposits of banks in that state in the survey year	FDIC, Failure / Branch Data
FDIC Est. Losses of Bank Failures	FDIC-estimated losses by FDIC-insured banking institutions that have failed that were located in a state since the last GSS surveying round, divided by the total domestic deposits of banks in that state in the survey year	FDIC
Penalties for Frauds	Log of average of all civil and criminal monetary penalties (in \$MM) assessed against financial institutions and their employees headquartered in a state in a given year, their parent and subsidiaries. These consist of prejudgment interest, disgorgement, civil fines, criminal restitution, and criminal fines, imposed by the Securities and Exchange Commission (SEC) or the Department of Justice (DOJ). Including charges of financial misrepresentation under three sections of the Securities Exchange Act of 1934 as amended by the FCPA: 15 USC §§ 78.m(b) and rules under the Code of Federal Regulations 17 CFR240.13b2-1 and 13b2-2. See Karpoff et al. (2017) for a thorough explanation.	Database developed by (Karpoff, Lee, et al. 2008a, b) and explained by Karpoff et al. (2017) and Call et al. (2018)
Other Penalties for Frauds	All civil and criminal monetary penalties (in \$MM) assessed against all agent firms and/or respondents (e.g. bankers, auditors, suppliers) in connection with the fraud of target financial firms headquartered in a state since the last GSS survey round; Added to firm and employee penalties (& logged) to use for robustness.	
Frauds' Prison Sentences	Log of mean of all frauds' incarcerations in months, consisting of prison, jail, home detention, and halfway house in a state since the last GSS survey round, for employees named in SEC/DOJ enforcement action	
Male	Fraction of male GSS respondents in a state in a given survey round	
Protestant/Jewish	Fraction of GSS respondents in a state in a survey round whom self-identify as Protestant or Jewish	GSS, NORC
Republican	Fraction of GSS respondents in a state in a survey round whom declare themselves to be Republicans	GSS, NORC
White/Hispanic	Fraction of GSS respondents in a state in a survey round whom self-declare as White and/or Hispanic	GSS, NORC
Age	Average age of GSS respondents in a state	GSS, NORC
Years of Education	Average years of formal education attained by GSS respondents in a state in a given survey round	GSS, NORC
Employment	Fraction of GSS respondents in a state in a survey round whom work full-time or part-time	GSS, NORC
High Income	Fraction of GSS respondents in a state in a survey round with household income above the US median annual household income	GSS, NORC
State GDP growth	Same as in Panel A	GSS, NORC; BEA
State GDP	Same as in Panel A	BEA

Table C.4. Data Summary Statistics

Panel A: US Bank Deposit Analysis Data (N = 95,626)					
Variable Name	Mean	SD	Median	Min	Max
<i>Dependent variables</i>					
Deposits (\$)	0.260	1.278	0.107	0.000	119.652
Deposits Ratio	93.470	8.830	96.284	0.000	99.998
Other Liabilities Ratio	0.981	4.198	0.575	0.001	100.000
<i>State Trust Measures</i>					
Distrust in financial institutions	0.240	0.129	0.222	0.000	1.000
Trust in others	0.376	0.119	0.375	0.000	1.000
Distrust in government	0.374	0.125	0.371	0.000	1.000
<i>Control variables</i>					
GDP per capita	45.384	8.851	44.322	23.640	185.678
GDP growth	3.774	2.958	3.816	-13.396	19.014
Population	8792158	8132576	5101004	153854	39250017
Financial literacy	3.005	0.140	2.995	2.529	3.656
New firm creation density	-8.229	32.247	0.140	-185.819	8.257
Banking density	0.349	0.086	0.344	0.171	0.646
Population density	71.532	106.873	40.889	0.429	4311.203
Percentage of Seniors	12.297	1.972	12.124	5.551	19.866
Working age population	52.446	1.127	52.417	47.796	58.952
Male	49.196	0.467	49.106	47.110	51.796
White	81.015	7.769	81.560	25.573	96.960
Hispanic	12.263	11.243	7.642	0.892	48.528
Jewish	1.403	1.576	0.843	0.029	8.983

Continued

Table C.4. (Continued)

Panel B: Bank Failure and Fraud Analysis Variables (N = 810)					
Variable Name	Mean	SD	Median	Min	Max
<i>State Trust Measures</i>					
Distrust in financial institutions	0.201	0.138	0.174	0.000	1.000
Trust in others	0.395	0.159	0.387	0.000	1.000
Distrust in other institutions	0.225	0.068	0.221	0.062	0.625
Bank Failures	3.756	14.491	1.000	0.000	256.00
<i>Bank Failure and Fraud Measures</i>					
Bank Failures (standardized)	0.088	0.224	0.004	0.000	2.455
FDIC Est. Losses of Bank Failures (standardized)	0.003	0.014	0.000	0.000	0.189
Financial Institution Fraud Frequency	0.175	0.581	0.000	0.000	7.000
SEC's Firm Penalties for Financial Institution Frauds	1.578	19.054	0.000	0.000	400.000
SEC's Employee Penalties for Financial Institution Frauds	10.953	159.465	0.000	0.000	3476.15
Other Penalties for Financial Institution Frauds	13.403	276.509	0.000	0.000	7532.12
Prison Sentences for Financial Institution Frauds	3.823	28.666	1.000	1.000	457.000
<i>Controls</i>					
Age	45.863	4.784	45.849	28.000	79.000
Years of Education	12.943	1.197	13.017	7.333	18.200
Male	0.434	0.101	0.434	0.000	1.000
High Income	0.507	0.157	0.508	0.000	1.000
White	0.811	0.183	0.859	0.000	1.000
Hispanic	0.027	0.069	0.000	0.000	0.583
Republican	0.351	0.135	0.347	0.000	0.909
Protestant	0.624	0.211	0.630	0.000	1.000
Jewish	0.018	0.046	0.000	0.000	0.800
State GDP Growth (annual)	6.162	3.840	5.741	-13.800	23.800

Figure C.1. Marginal effect of distrust in bank, trust in others, and distrust in government. Figure on the lefts correspond to the model 1 of Table 5.2, the figure to the right correspond to model 3 of Table 5.2.

Figure C.2. Marginal effect of interaction term in model 5 and 6 of Table 5.2. Figure on the left corresponds to the model 5 of Table 5.2, the figure to the right corresponds to model 6 of Table 5.2.

Figure C.3. Comparison of Distrust in Banks and Financial Institutions from the US General Social Survey (GSS) & the Gallup Survey

Figure C.4. Failures, Frauds and Distrust in Banks and Financial Institutions

Figure C.5. Estimated Bank Losses, Fraud Penalties and Distrust in Banks and Financial Institutions

Appendix C. Chapter 5: Part II – UK Peer-to-Peer Lending Data

Our database on UK peer-to-peer lending is obtained from the Open Data Institute.⁸⁷ This comprehensive database of UK peer-to-peer lending from October 2010 to May 2013 was collected using data from the three largest P2P platforms in the UK, namely Zopa Funding Circle and RateSetter.

This dataset has the remarkable advantage of covering peer-to-peer loans of over 92 percent of the UK crowdfunding market (Bholat and Atz, 2016) from October 2010, the earliest date in which all platforms are operating, until May 2013. This means the data does not suffer from sample selection issues pertaining to participation of investors in a singular P2P lending platform. It comprises details of 13,924,547 loan parts (i.e. individual loan contracts), totalling 59,851 individual loans amounting to £378 million in loan value, including information on the geographic distribution (i.e. districts or UK regions of residence) of lenders and borrowers. The median number of loan parts comprising a loan is 340 loan parts. There were 48,891 lenders in the database and 59,851 borrowers. The median and average amount lent were respectively £7,736 and £1,290, while those values for borrowed loan sizes are respectively £4,160 and £6,320.

Table 0.5. UK Regional Loan Participation in UK P2P Loan Markets

Dependent Variables	Model 1		Model 2		Model 3	
	Region Participation Indicator		Region Participation Amount (Log)			
Distrust in Financial Institutions	0.05***	(0.01)	1.38***	(0.04)	1.09***	(0.03)
Trust in Others	0.03***	(0.01)	0.87***	(0.05)	0.85***	(0.04)
Trust in Government	0.05***	(0.01)	1.21***	(0.06)	0.55***	(0.06)
Loan FEs	Included		Included		Included	
Observations	658,361		658,361		658,361	
Specification	OLS		Tobit		OLS	
Adjusted/Pseudo-R ²	0.68				0.28	

Notes: The level of analysis is P2P loan-regions. Trust data from 11 UK regions are utilized for 59,851 loans, constituting the 658,361 (11 × 59,851) sample observations. For a description of all variables, see Panel D of Table C., and for summary statistics, see Panel D of Table C.. All regressions include as controls state population (logged), GDP per capita (logged), GDP pc growth, different region indicators and internet access. Standard errors are reported in parentheses and are clustered at the loan level. The symbols ***, **, * mean that the reported coefficients are statistically different from zero, respectively, at the 0.1 , 1, and 5 percent level.

⁸⁷ The database is available for download at <http://smtm.labs.theodi.org>

Table C.6. Variable Description and Data Sources

Panel D: Study on UK P2P Loan Markets (i.e. Table A4i)		
Variables	Description	Source
Regional participation indicator	A dummy variable for each loan for whether a resident from the region has lent (=1) an amount or not (=0)	Open Data Institute
Regional participation in loan	Total amount of money lent to each loan from each region	Open Data Institute
Borrower rate (%)	Effective interest rate paid by the borrower	Open Data Institute
Different region indicator	A dummy variable for whether the borrower and lender are from the same UK region (=1) or not (=0)	
GDP per capita	Log of annual regional GDP per capita (in Euros)	Eurostat
Annual GDP growth	Growth of GDP per capita in a region over that of the prior year	Calculated from Eurostat
Population (Log)	Log of the population estimate in a state on July 1st of a year	Eurostat
Internet access	Average percentage of a region's population over the age of 16 who have used the internet during the last three months	Office for National Statistics
Trust/Distrust Variables	Constructed similar to variable for US study (Panel A), given the same standard trust survey questions.	EBRD LiTS II Survey

Table C.7. Data Summary Statistics (N = 658,361)

Panel D: Study on UK P2P Loan Markets (i.e. Table A4i)					
	Mean	SD	Min	Median	Max
Dependent Variables					
Region P2P participation indicator	0.839	0.368	0	1	1
Regional participation in loan	£570.7	£1,529	£0	£230	£187,560
Regional Trust Measures					
Distrust in banks and financial system	0.602	0.0878	0.446	0.61	0.718
Trust in others	0.671	0.0522	0.586	0.69	0.737
Trust in government	0.371	0.0798	0.230	0.36	0.482
Controls					
Different region indicator	0.911	0.285	0	1	1
GDP per capita	€29,080	€8,086	€20,200	€26,500	€54,200
GDP growth	0.0450	0.0473	-0.0201	0.0396	0.111
Population	5,601,881	1,796,739	2,581,100	5,327,240	8,758,890
Internet access indicator	0.806	0.0318	0.717	0.80	0.878

Table 0.8. US Regressions of US Single State Bank Deposits on Trust Variables

	(1) Deposits (\$)	(2) Deposits Ratio (%)	(3) Other Liabilities Ratio (%)
Distrust in bank	-0.141*** (0.036)	-1.813* (0.788)	0.570*** (0.153)
Trust in others	-0.018 (0.023)	3.986 (2.472)	0.067 (0.096)
Distrust in government	-0.017 (0.038)	4.488 (4.173)	0.018 (0.117)
Controls	Yes	Yes	Yes
Institution FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Sample Period	2001-2016	2001-2016	2001-2016
Specification	OLS	OLS	OLS
Observations	95,626	95,626	95,626
Adjusted R-squared	0.91	0.76	0.85

Notes: All regressions include all controls: GDP per capita, GDP growth, population, P2P Demand, Financial literacy, New firms, Science & Engineering specialization, Cybercriminality, banking density, Population density, Seniors (% of population 65+) Working age population, Male, White, Hispanic, Republican, Protestant, Jewish. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level.

Appendix D. Chapter 6: Part I - Bitcoin Infrastructure

Bitcoin nodes

Relating to the supply-side of global bitcoin infrastructure, we focus our study on Bitcoin nodes, i.e. *bitnodes*. Bitcoin relies on a decentralized network of nodes, which use computational proofs-of-work to reach consensus on the bitcoin blockchain (Nakamoto 2008). To validate and relay transactions, the Bitcoin network must broadcast messages using nodes (see Figure 6.1 for validation and verification actions in a bitcoin transaction life cycle). To ensure security and to prevent circumvention of consensus rules such as double-spending (i.e. when a user attempts to spend the same bitcoin twice), each node uses a randomized protocol to select eight peers with which it establishes long-lived *outgoing connections*, and exchange views of the state of the blockchain with their incoming and outgoing peers in order to verify and validate new transactions (Heilman, Kendler, and Zohar 2015).

If a node fully validates every block and transaction, by independently checking them against all consensus rules of Bitcoin, it is termed a full node. Some of the primary consensus rules of Bitcoin, verified by full nodes, are: (a) Spent transactions require correct signatures, (b) Blocks may only release a limited number of bitcoins as a block reward, (c) Blocks and transactions are to follow the consensus format and (d) A transaction output cannot be double-spent. Such full nodes would require a bitcoin core client installed on a computer connected to the internet. A full node contains the entire record of bitcoin's blockchain, a distributed public ledger of all transactions⁸⁸. Archival or listening nodes (also called reachable nodes) are a subset of full nodes that accept incoming connections and upload or “relay” complete copies of archival bitcoin blocks and transaction data to peers on the bitcoin network. They are useful for bootstrapping new full node peers or helping light-weight nodes discover their balance. Light-weight nodes are meant for market participants who do not want to run full nodes and use a Simplified Payment Verification method to verify transactions by downloading only a part of the blockchain (e.g. only block headers and partial blocks).

Running a full node is the only way for a bitcoin market participant to independently ascertain that all consensus rules are followed and for full removal of a need for a trusted alternative node or third party. Running full nodes also much increases a market participants' security as many attacks against lightweight nodes do not affect full nodes, and they offer the most privatized and anonymized way to transact in bitcoins, hiding addresses belonging to the full node operator. It is hence in the interest of market participants to run a full node⁸⁹.

Bitcoin nodes contribute to bitcoin's aim to serve as a medium of exchange, and contribute to bitcoin's goal to serve as a store of value. Nodes are critical to the functioning of the entire bitcoin ecosystem and

⁸⁸ The size of the entire blockchain has exponentially increased, from 21.7GB to 176.5GB from Sept 2014 to 2018. Through the same time period the price of storage has decreased by ~45% (<http://jcmr.net/diskprice.htm>).

⁸⁹ https://en.bitcoin.it/wiki/Clearing_Up_Misconceptions_About_Full_Nodes#Myth:_There_is_no_incentive_to_run_nodes_so_the_network_relies_on_altruism

were a core part of the functioning of Bitcoin’s blockchain from its design inception. Figure 6.2 shows a global map of the revealed intensity of bitcoin node adoption, averaged for the five years from 2014 to 2018. Figure 6.3 shows a map of the number of non-hidden unique bitcoin nodes per month, averaged for the same period.

Bitnodes dataset preparation

We obtain data on reachable (aka listening) full nodes on the Bitcoin network from [Bitnodes.earn.com](https://bitnodes.earn.com/).⁹⁰ Our database contains all reachable nodes running Bitcoin protocol version 70001 (i.e. Bitcoin core 0.8.x), which was introduced on February 2013⁹¹, or later versions. These nodes may or may not be full nodes; however, they have been set up to be reachable. Reachable nodes have port 8333, or a port they have configured the software to, open for incoming connections. The default configuration in node software is to have listening enabled. However, home connections are usually filtered by a modem or router. Bitcoin core will request automatic configuration of your router to allow incoming connections. Unfortunately, many routers do not allow automatic configuration and require manual configuration. Moreover, firewalls may also need to be configured to allow inbound connections to port 8333. Hence, it is conceivable that there are as many as 6 to 8 times more nodes on the network than our database could reach (Wang and Pustogarov 2017). However, our database can be assumed to provide a reasonable proxy for the total geographical distribution of nodes in the bitcoin network.

From the extensive Bitnode database (~1 Terabyte), location-specific measures for the adoption of Bitcoin nodes was constructed through the following procedure:

- (a) Downloading ultra-compressed files containing thousands of JSON files for first month of each quarter, with each JSON file being a python-crawled database snapshot taken nearly every 6 minutes containing such information as IP addresses, city, country & coordinate information relating to nodes
- (b) Retaining every 10th file corresponding to nearly hourly records of all crawled non-hidden Bitcoin nodes
- (c) Re-structuring the hourly files to form monthly databases
- (d) Calculating all variables separately for countries and administrative regions of 34 countries included in LITS III survey. The region-level analysis consisted of:
 - i. Matching world cities to NUTS-2 regions of 34 countries in Life in Transition Societies’ Social Survey

⁹⁰ Network snapshots are taken every few minutes in JSON format, and have been compressed and stored in monthly Tarball files from September 2014 onwards. The python crawler implementation of this website is made available by Addy Yeow on GitHub, <https://github.com/ayeowch/bitnodes>

⁹¹ To illustrate speed of adoption of a protocol, a year on from release of the following protocol, nearly 98% of nodes had updated to the newer protocol.

- ii. Geo-locating regions of unidentified IP addresses, using geo-location tools of IP addresses meant for the STATA software, specifically the SSC package `geocode_ip`, written by Correia (2017), yet modified to use the API service from ipgeolocation.io.
- (e) Creating country-year and region-year data of non-hidden bitcoin node use, in a panel data structure. There are 201 countries worldwide for which in at least one year between 2014 and 2018 a Bitnode is operated.

The Bitnodes' database uses Python's GeoIP2 geo-locating package to identify countries of nodes. Also the geolocation we use to locate unidentified IP addresses uses two alternative and independent IP databases. These IP address geolocation services state the accuracy of IP geolocation to be around 95% to 99% at the country-level, and 55% to 80% at the region level (See <https://www.iplocation.net/geolocation-accuracy>). Gueye et al. (2011), Komosny et al. (2017) and Shavitt and Zilberman (2011) find that the main geolocation databases are accurate at the country level. Hence, our Bitnode analyses at the country and region level, while providing a best-estimate of location of bitcoin nodes, is limited by the accuracy of geo-location.

Bitcoin merchants

We also study bitcoin infrastructure driving the demand for bitcoins, using data on how many merchants that accept bitcoin as a currency for selling their goods or services. By adopting bitcoin payment technology, merchants contribute to bitcoin serving as a medium of exchange. They also facilitate bitcoin's adoption as a unit of account, by enabling the quotation of prices in bitcoins.

Merchants' adoption of technology to accept bitcoins as payment should largely be driven by perceived demand for such services among its customers. A certain amount of computer savviness would be expected for merchants to start accepting bitcoins; businesses would need to download a bitcoin client and give customers a bitcoin address where payments can be sent. However, bitcoin payment service providers such as Bitpay, Bitgo or Coinbase.com offer web and mobile apps that simplify the process of becoming a bitcoin-accepting merchant.

It has been reported that merchants reported satisfaction with bitcoin payment processing due to its strikingly low-cost (Böhme et al. 2015). As an example, Coinbase (the largest bitcoin payment processing firm) currently charges zero fees on incoming payments, greatly reduced from the fees they bear when credit card are used for payment. Compared to other payment forms, however, bitcoin payments expose the merchants to a new type of volatility risk, since the exchange rate of any bitcoins that is received in payment may vary substantially over time. Payments can be accepted using hardware terminals, touch screen apps or simple wallet addresses using QR codes. Most bitcoin merchants prefer to minimize the volatility risk of holding bitcoins by offloading or selling bitcoins as soon as possible after the sale of their service or product.

While this study is focused on infrastructure supporting Bitcoin, many infrastructure providers for Bitcoins simultaneously extend support to other cryptocurrencies, as has become prevalent with multi-currency platforms payment service providers used by cryptocurrency merchants. Figure D.2 shows the monthly frequency of Bitnode intensity over time since the data became available.

Bitcoin merchants dataset preparation

Our data for merchants accepting payments in bitcoin is extracted from data stored using CoinMap's API (The data is available at <https://coinmap.org/api/v1/venues/>, whereas an R-code was written to convert the JSON format data to a Stata-readable format). CoinMap is a website where either business owners or interested customers or users would add a business that accepts bitcoins (or bitcoin and other cryptocurrencies) as payment in exchange for a service or good. Some of the businesses on these websites only accept bitcoins on their online websites.

CoinMap started in early 2013 with self-reporting of venues on an OpenStreetMap⁹² map, being done by adding a tag of bitcoin=yes (or selecting bitcoin as a payment type in a pre-defined drop-down list) to venues on its extensive interactive map. One would have needed to sign up and enter in edit mode and use OpenStreetMap's user-friendly editor interface to select a building or business and tag it as accepting bitcoins. CoinMap would synchronize with any such entries made into OpenStreetMap up until the middle of 2017, after which OpenStreetMap integration stopped and adding venues on CoinMap's own interface by logging in via Google/Facebook/etc. and right-clicking, became the only way to add a bitcoin-accepting merchant. Soon after launching in 2013, CoinMap became the primary website worldwide, as referred to in online Bitcoin forums, to find businesses where bitcoin holders can spend their bitcoins. On online forums, bitcoin enthusiasts express a great desire to develop an extensive network of merchants that accept bitcoins, so it could serve their hope for it to serve as a formidable alternative to fiat currencies.

The data contains coordinates and categories of businesses accepting bitcoins as payment, together with the date and time they were added to CoinMap's online map. The top categories are shopping, food, ATMs, lodging, cafes, nightlife and sports venues. We geo-locate all addresses using the coordinates provided to identify which city, state and country they are located in. As of the end of 2018, the database consists of 14,149 venues. Removing duplicated entries of venues, our final list has 13741 merchants. Figure D.1 shows the monthly frequency of addition of bitcoin merchants over time on CoinMap since its inception. No data is available on the size of transactions.

⁹² OpenStreetMap is one of the world's largest collaborate mapping projects. Developed as a free editable map of the world in 2004, it is used by large established corporations as well as independent website owners to develop a navigable map with complete business/institutional venue information. As the world's largest database of buildings, OpenStreetMap covers an extensive database of businesses.

Figure D.1. Monthly time-series variation of addition of Bitcoin merchants worldwide on CoinMap

Figure D.2. Quarterly time-series variation of Bitnode intensity Worldwide

Appendix D: Chapter 6: Part II – Additional Tables and Figures

Table 0.1. Correlation matrix

Variable No./Name	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 Bitnode intensity	1															
2 Unique bitnodes	0.66	1														
3 Bitnode Hours	0.45	0.52	1													
4 Bitcoin merchants	0.25	0.24	0.2	1												
5 GDP per capita	0.52	0.59	0.64	0.21	1											
6 Restrictive regulation	-0.16	-0.19	-0.04	-0.08	-0.09	1										
7 Internet penetration	0.48	0.53	0.68	0.21	0.89	-0.05	1									
8 Broadband penetration	0.6	0.66	0.64	0.25	0.83	-0.15	0.83	1								
9 ICT market development	0.53	0.61	0.7	0.22	0.91	-0.07	0.95	0.89	1							
10 Latest technology	0.52	0.56	0.55	0.19	0.8	-0.09	0.76	0.75	0.78	1						
11 Secure Internet servers	0.63	0.29	0.31	0.22	0.42	-0.11	0.39	0.49	0.43	0.4	1					
12 Mobile subscriptions	0.2	0.26	0.38	0.09	0.57	0.03	0.56	0.38	0.58	0.45	0.13	1				
13 Electricity cost	-0.2	-0.24	-0.41	-0.09	-0.56	-0.07	-0.52	-0.39	-0.53	-0.43	-0.15	-0.45	1			
14 Inflation crisis	-0.09	-0.09	-0.09	-0.03	-0.07	-0.03	-0.14	-0.13	-0.13	-0.3	-0.07	-0.18	0.15	1		
15 Inflation	-0.22	-0.23	-0.21	-0.08	-0.27	-0.05	-0.31	-0.32	-0.31	-0.45	-0.15	-0.27	0.21	0.82	1	
16 Unbanked	-0.51	-0.58	-0.59	-0.23	-0.82	0.02	-0.77	-0.81	-0.83	-0.77	-0.41	-0.48	0.44	0.16	0.32	1
17 Internet banking	0.56	0.54	0.35	0.19	0.58	-0.11	0.51	0.62	0.55	0.64	0.43	0.17	-0.12	-0.07	-0.19	-0.68
18 5-bank asset concentration	0.09	0.07	-0.2	0.03	0.09	-0.22	0.04	0.1	0.04	0.06	0.07	-0.05	0.12	0.01	-0.07	-0.05
19 3-bank asset concentration	0.14	0.1	-0.2	0.01	0.08	-0.21	0.03	0.11	0.04	0.04	0.08	-0.05	0.1	0.04	-0.02	-0.04
20 Rule of law	0.61	0.65	0.57	0.22	0.78	-0.16	0.76	0.82	0.8	0.86	0.47	0.45	-0.4	-0.29	-0.47	-0.8
21 Organized crime	0.4	0.42	0.27	0.15	0.54	-0.06	0.54	0.51	0.54	0.6	0.27	0.37	-0.24	-0.19	-0.35	-0.53
22 Crime and violence costs	0.35	0.41	0.28	0.15	0.52	-0.04	0.53	0.51	0.54	0.55	0.26	0.34	-0.23	-0.18	-0.32	-0.48
23 Money laundering	0.21	0.2	0.39	0.03	0.28	0.02	0.21	0.23	0.23	0.22	0.12	0.12	-0.19	0	0	-0.23
24 Shadow economy	-0.42	-0.44	-0.44	-0.15	-0.68	0.06	-0.61	-0.62	-0.65	-0.64	-0.36	-0.31	0.32	0.01	0.17	0.64
25 Taxation	0.02	-0.03	0.08	-0.06	0.12	-0.06	0.01	0.05	0.01	0.19	0.13	-0.07	-0.1	-0.02	-0.02	-0.1
26 Tax burden	-0.27	-0.4	-0.27	-0.17	-0.29	0.15	-0.2	-0.47	-0.27	-0.35	-0.28	0.11	-0.04	-0.01	0.09	0.36
27 Tax haven	-0.1	-0.1	-0.04	-0.04	0.11	0.01	0.08	0.02	0.08	0.13	-0.08	0.21	-0.09	-0.05	-0.04	-0.11
28 Stock market return	-0.02	-0.09	0.04	0.03	-0.01	-0.05	0.02	0.01	0.02	-0.03	0	-0.02	-0.03	0.21	0.2	-0.02
29 Crisis stock market return	-0.14	-0.22	-0.11	-0.15	-0.02	0.04	-0.15	-0.28	-0.18	-0.01	-0.09	0.05	0.05	0.08	0.16	0.2
30 Bitcoin mining country	0.16	0.17	0.27	0.03	0.19	0.08	0.18	0.21	0.21	0.12	0.1	0.18	-0.04	0.08	0.05	-0.24
31 Bitcoin mining MWs	0.02	0.01	0.16	-0.02	0.06	0.18	0.04	0.11	0.07	0	0.01	0.01	-0.06	-0.03	-0.06	-0.1
32 Electricity price	-0.03	-0.01	0.08	0	0.01	-0.04	0.01	-0.02	0	-0.1	-0.03	-0.07	0.19	0.4	0.45	-0.03

Table D.1. Correlation matrix (Cont.)

Variable No./Name	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
1 Bitnode intensity																
2 Unique bitnodes																
3 Bitnode Hours																
4 Bitcoin merchants																
5 GDP per capita																
6 Restrictive regulation																
7 Internet penetration																
8 Broadband penetration																
9 ICT market development																
10 Latest technology																
11 Secure Internet servers																
12 Mobile subscriptions																
13 Electricity cost																
14 Inflation crisis																
15 Inflation																
16 Unbanked																
17 Internet banking	1															
18 5-bank asset concentration	0.16	1														
19 3-bank asset concentration	0.15	0.94	1													
20 Rule of law	0.68	0.09	0.07	1												
21 Organized crime	0.53	0.17	0.15	0.7	1											
22 Crime and violence costs	0.45	0.08	0.07	0.61	0.91	1										
23 Money laundering	0.12	-0.29	-0.24	0.13	-0.06	-0.1	1									
24 Shadow economy	-0.53	-0.08	-0.1	-0.68	-0.46	-0.46	-0.11	1								
25 Taxation	0.13	0.03	0	0.2	-0.02	-0.1	0.13	-0.13	1							
26 Tax burden	-0.49	-0.07	-0.08	-0.42	-0.12	-0.09	-0.15	0.25	-0.29	1						
27 Tax haven	0.04	0.07	0.04	0.05	0.07	0	-0.06	-0.02	-0.04	0.1	1					
28 Stock market return	0.01	0	0	-0.05	-0.09	-0.1	0.01	-0.02	0.07	-0.03	-0.02	1				
29 Crisis stock market return	-0.06	-0.08	-0.09	-0.08	0.01	-0.07	0.21	0.01	0.17	0.04	0.13	-0.01	1			
30 Bitcoin mining country	0.25	-0.11	-0.08	0.18	0.09	0.09	0.14	-0.1	0.1	-0.06	-0.07	0.11	0.06	1		
31 Bitcoin mining MWs	0.09	-0.15	-0.12	0.05	0.06	0.09	0.1	-0.07	0.05	-0.05	-0.04	0.03	0.05	0.7	1	
32 Electricity price	0.02	-0.03	-0.03	-0.18	-0.19	-0.22	0.13	0	0.13	-0.05	-0.03	0.38	0.02	0.3	-0.05	1

Table 0.2. Robustness regressions on Bitnode intensity by adding exploratory variables in isolation to baseline regression (Panel A)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Bitnode intensity					
Financial Characteristics						
Inflation crisis	0.530+ (0.306)	0.654* (0.285)				
Unbanked	0.008 (0.009)		-0.006 (0.013)			
5-bank asset concentration	0.003 (0.013)			0.000 (0.015)		
Criminality Characteristics						
Money laundering	1.347* (0.604)				1.156+ (0.610)	
Rule of law	1.445** (0.474)					1.267* (0.508)
Baseline Characteristics						
GDP per capita	0.681 (0.457)	1.428*** (0.337)	1.339** (0.499)	1.424*** (0.320)	1.335*** (0.356)	0.761+ (0.395)
Restrictive regulation	-0.529 (0.324)	-0.574 (0.377)	-0.584+ (0.332)	-0.573+ (0.329)	-0.586+ (0.343)	-0.541 (0.354)
Constant	-6.624 (4.347)	-11.482*** (2.827)	-10.492* (4.802)	-11.482*** (3.012)	-11.358*** (3.132)	-5.935+ (3.434)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Panel Data Specification	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit
Observations	685	685	685	685	685	685
Number of Countries	137	137	137	137	137	137
Pseudo R-Squared	0.41	0.36	0.36	0.36	0.37	0.40
Log-likelihood	-1306.1	-1314.8	-1314.8	-1314.9	-1312.9	-1309.4
RHO	0.72	0.74	0.74	0.74	0.74	0.73

Notes: All models are Tobit random effects models lower-censored at 0 and their associated pseudo R-squared are reported. Panel-data adjusted bootstrapped standard errors, clustered at the country level, are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level.

Table D.3. Robustness regressions on Unique bitnodes by adding exploratory variables in isolation to baseline regression (Panel A)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Unique bitnode					
Financial Characteristics						
Inflation crisis	7.038** (2.596)	5.875* (2.445)				
Unbanked	-0.189* (0.078)		-0.288*** (0.070)			
5-bank asset concentration	0.011 (0.069)			0.013 (0.082)		
Criminality Characteristics						
Money laundering	6.916** (2.381)				5.853* (2.770)	
Rule of law	9.323*** (2.557)					9.845*** (2.332)
Baseline Characteristics						
GDP per capita	0.039 (2.209)	8.946*** (1.536)	4.292* (1.749)	8.903*** (1.376)	8.446*** (1.198)	3.342+ (1.784)
Restrictive regulation	3.069* (1.347)	3.384* (1.365)	2.708* (1.354)	3.386* (1.341)	3.188* (1.596)	3.663** (1.265)
Constant	19.808 (20.597)	-58.362*** (12.931)	-6.835 (16.692)	-58.966*** (14.654)	-57.456*** (10.462)	-11.338 (14.818)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Panel Data Specification	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit
Observations	685	685	685	685	685	685
Number of Countries	137	137	137	137	137	137
Pseudo R-Squared	0.62	0.58	0.58	0.58	0.58	0.61
Log-likelihood	-2266.7	-2294.4	-2284.1	-2294.6	-2292.0	-2279.5
RHO	0.54	0.58	0.58	0.58	0.57	0.56

Notes: All models are Tobit random effects models lower-censored at 0 and their associated pseudo R-squared are reported. Panel-data adjusted bootstrapped standard errors, clustered at the country level, are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level.

Table D.4. Robustness regressions on Bitnode hours by adding exploratory variables in isolation to baseline regression (Panel A)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Bitnode hours					
Financial Characteristics						
Inflation crisis	50.642 (65.208)	21.316 (75.872)				
Unbanked	-2.309 (1.421)		-2.883* (1.316)			
5-bank asset concentration	-5.080** (1.676)			-5.709*** (1.583)		
Criminality Characteristics						
Money laundering	176.344*** (53.490)				214.910*** (55.422)	
Rule of law	88.669+ (45.858)					78.177 (53.565)
Baseline Characteristics						
GDP per capita	72.001* (34.734)	163.076*** (30.603)	117.830*** (32.456)	173.152*** (27.254)	145.646*** (23.679)	119.839** (40.040)
Restrictive regulation	32.565 (39.446)	47.150 (34.713)	43.588 (44.952)	30.404 (47.014)	45.289 (47.311)	51.749 (54.152)
Constant	382.419 (431.859)	-762.920* (328.849)	-259.390 (417.735)	-415.942 (355.106)	-740.771* (330.463)	-400.660 (384.618)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Panel Data Specification	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit
Observations	685	685	685	685	685	685
Number of Countries	137	137	137	137	137	137
Log-likelihood	-2386.8	-2402.9	-2397.6	-2397.4	-2403.4	-2405.2
RHO	0.62	0.69	0.69	0.65	0.66	0.69

Notes: All models are Tobit random effects models lower-censored at 0 and upper censored at 750 (upper limit of active Bitnode hours in a month) and their associated pseudo R-squared are reported. Panel-data adjusted bootstrapped standard errors, clustered at the country level, are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level.

Table D.5. Robustness regressions substituting Inflation crisis with a 15 % or 25% min inflation (Panel A)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables:	Bitnode intensity	Unique bitnodes	Bitnode hours	Bitnode intensity	Unique bitnodes	Bitnode hours
Financial Characteristics						
25% Min Inflation	0.677 (0.490)	8.580** (3.202)	74.911 (97.863)			
15% Min Inflation				0.775* (0.334)	8.038** (2.452)	121.690+ (64.821)
Unbanked	0.008 (0.009)	-0.189** (0.073)	-2.320 (1.623)	0.008 (0.009)	-0.190* (0.081)	-2.376+ (1.353)
5-bank asset concentration	0.003 (0.016)	0.013 (0.067)	-5.071** (1.555)	0.004 (0.013)	0.015 (0.072)	-5.035** (1.679)
Criminality Characteristics						
Money laundering	1.348** (0.491)	6.945** (2.532)	176.610*** (53.588)	1.331** (0.510)	6.825** (2.263)	175.268** (59.596)
Rule of law	1.469** (0.503)	9.634*** (2.649)	92.375* (46.450)	1.470** (0.458)	9.513*** (2.301)	96.620+ (53.552)
Baseline Characteristics						
GDP per capita	0.656 (0.475)	-0.238 (2.095)	68.815+ (38.871)	0.679 (0.466)	0.009 (1.860)	68.917+ (39.943)
Restrictive regulation	-0.534 (0.357)	3.016+ (1.549)	32.214 (38.786)	-0.479 (0.372)	3.572* (1.518)	40.662 (37.398)
Constant	-6.412 (4.460)	22.056 (19.682)	409.386 (420.884)	-6.618 (4.342)	19.767 (18.050)	406.150 (403.880)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-World Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	685	685	685	685	685	685
Pseudo R-Squared	0.42	0.63	0.32	0.41	0.67	0.32
Number of Countries	137	137	137	137	137	137

Notes: All models are Tobit random effects models lower censored at 0 and their associated overall R-squared is reported. Panel-data bootstrapped standard errors, clustered at the country level, are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level. Models (3) and (6) are in addition upper-censored at 750 (upper limit of active Bitnode hours in a month).

Table D.6. Disentangling the effect of Rule of law on Bitcoin infrastructure adoption (Panel A; Country-year level)

Dependent Variables:	(1) Bitnode intensity	(2) Bitcoin merchants	(3) Bitnode intensity	(4) Bitcoin merchants
Organized crime	0.152 (0.188)	-0.419 (0.373)		
Crime and violence costs			-0.016 (0.221)	-0.656 (0.486)
Money laundering	0.992 (0.656)	0.516 (0.724)	1.117+ (0.596)	0.554 (0.718)
Inflation crisis	0.395 (0.447)	-0.241 (0.993)	0.285 (0.418)	-0.783 (5.133)
Unbanked	0.009 (0.011)	-0.050 (0.035)	-0.004 (0.012)	-0.050+ (0.030)
Five-bank asset concentration	0.008 (0.019)	-0.011 (0.026)	0.008 (0.014)	-0.023 (0.028)
GDP per capita	1.696*** (0.480)	0.786 (0.690)	1.278** (0.443)	0.742 (0.515)
Restrictive Bitcoin Regulation	-0.603+ (0.316)	-0.588 (0.680)	-0.612+ (0.335)	-0.558 (0.859)
Constant	-16.043*** (4.393)	-1.822 (6.132)	-11.075* (4.367)	0.523 (4.174)
Year FEs	Yes	Yes	Yes	Yes
World Region FEs	Yes	Yes	Yes	Yes
Year-World Region FEs	Yes	Yes	Yes	Yes
Observations	665	665	685	685
Log-likelihood	-1231.9	-1393.8	-1279.6	-1400.4
Number of Countries	133	133	137	137
RHO	0.75	0.20	0.73	0.22

Notes: All models are Tobit random effects models lower-censored at 0 and their associated pseudo R-squared are reported. Panel-data adjusted bootstrapped standard errors, clustered at the country level, are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level. Models 1 and 2 exclude the 4 countries of Belize, Bermuda, Cayman Islands and Syria, as no value was reported for the variable *Organized crime* from the data source.

Table D.7. Variable description and data sources of variables for alternative explanation analysis

Variable	Description	Source	Source Variable Name
Panel A			
Shadow economy	Size estimates of the shadow economy as a percentage of a nation's GDP, based on last available year reported	Elgin and Öztunalı (2012)	
Tax haven	Indicator variable equal to 1 for countries either black-listed or grey-listed by the EU as non-cooperative tax jurisdictions	ec.europa.eu/taxation_customs/tax-common-eu-list_en, accessed on December 6, 2018	
Taxation	Taxes on income, profits, and capital gains are levied on the actual or presumptive net income of individuals, on the profits of corporations and enterprises, and on capital gains, whether realized or not, on land, securities, and other assets. Intragovernmental payments are eliminated in consolidation.	International Monetary Fund, Government Finance Statistics Yearbook and data files	GC.TAX.YPKG.RV.ZS
Tax burden	Composite index of the tax burden, including direct taxes, in terms of the top marginal tax rates on individual and corporate incomes, and overall taxes, consisting of all forms of direct and indirect taxation at all governmental levels, as a percentage of GDP. This variable is defined on a 100-tax burden scale, such that highest values correspond to lower tax burden and vice versa. The variable is standardized in regression analyses.	The Heritage Foundation, 2014-2018	Tax burden (or Fiscal Freedom from 2016)
Bitcoin mining country	Indicator variable equal to 1 for countries identified as having high levels of activity of bitcoin or crypto-asset mining facilities	Hileman and Rauchs (2017) and Rauchs et al. (2018)	
Bitcoin mining MWs	National aggregated capacity of facilities used for crypto-asset mining measured in megawatts (MW)	Hileman and Rauchs (2017)	
Electricity price	Price of electricity in US cents per kWh. A monthly electricity consumption is assumed, for which a bill is then computed for a warehouse based in the largest business city of the economy for the month of March	World Bank Doing Business Reports (2014-2018); "Getting Electricity" section	
Stock market return	The percentage U.S. dollar price change in the country-specific stock markets covered by the S&P/IFCI and S&P/Frontier BMI country indices (2014-2018)	World Bank obtained from: Standard & Poor's, Global Stock Markets Factbook and supplemental S&P data.	CM.MKT.INDX.ZG
Crisis stock market return	The percentage U.S. dollar price change in the country-specific stock markets covered by the S&P/IFCI and S&P/Frontier BMI country indices for the years of 2008-2009	World Bank obtained from: Standard & Poor's, Global Stock Markets Factbook and supplemental S&P data.	CM.MKT.INDX.ZG

Table D.8. Robustness tests of financial & criminality drivers excluding countries without Bitcoin infrastructure (Panel A; Country-year level)

Dependent Variables:	(1) Bitnode intensity >0	(2) Unique bitnodes >0	(3) Bitnode hours >0	(4) Bitcoin merchants > 0
Financial Characteristics				
Inflation crisis	0.656* (0.331)	8.508** (3.109)	63.253 (80.025)	1.690 (1.276)
Unbanked	0.011 (0.011)	-0.176* (0.088)	-2.069 (1.515)	-0.035+ (0.018)
Five-bank asset concentration	0.009 (0.014)	0.040 (0.064)	-4.496** (1.659)	-0.014 (0.027)
Criminality Characteristics				
Money laundering	1.392* (0.607)	7.231** (2.443)	181.439** (57.945)	0.475 (0.595)
Rule of law	1.538** (0.482)	10.075*** (2.493)	99.385+ (51.276)	0.860+ (0.513)
Baseline Controls				
GDP per capita	0.557 (0.512)	-0.709 (1.749)	58.254 (43.641)	0.048 (0.435)
Restrictive regulation	-0.543* (0.257)	3.012* (1.472)	31.062 (45.992)	-1.027 (0.756)
Constant	-6.048 (4.790)	23.508 (18.356)	446.380 (438.980)	2.214 (5.210)
Year FEs	Yes	Yes	Yes	Yes
World Region FEs	Yes	Yes	Yes	Yes
Year-World Region FEs	Yes	Yes	Yes	Yes
Panel Data Specifications	Tobit	Tobit	Tobit	Tobit
Observations	650	650	650	565
Number of Countries	130	130	130	113
Pseudo R-Squared	0.44	0.65	0.23	< 0
Log-likelihood	-1301.6	-2262.9	-2382.4	-1386.3
RHO	0.71	0.53	0.61	0.16

Notes: All models are Tobit random effects models and their associated overall R-squared is reported. Panel-data bootstrapped standard errors, clustered at the country level, are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level. Model (3) is upper-censored at 750 (upper limit of active Bitnode hours in a month).

Table D.9. Robustness tests of social drivers excluding regions without Bitcoin infrastructure (Panel B; Region-year level)

Dependent Variables:	(1)	(2)	(3)	(4)	(5)	(6)
	Bitnode intensity > 0	Unique bitnodes > 0	Bitcoin merchants > 0	Bitnode intensity > 0	Unique bitnodes > 0	Bitcoin merchants > 0
Social Characteristics						
High risk willingness	4.414 (3.631)	20.920 (23.771)	14.357* (6.367)	5.974 (3.670)	34.322 (24.362)	20.175** (6.985)
High risk willingness x Bitcoin price				-0.605** (0.211)	-5.402* (2.168)	-2.012* (0.991)
						0.292 (0.178)
Bitcoin price				0.013 (0.039)	-2.999*** (0.397)	0.292 (0.178)
Trust in others	1.949 (1.219)	19.573* (9.458)	-2.093 (2.656)	2.062+ (1.216)	20.139* (9.449)	-1.981 (2.653)
Distrust in banks & financial system	4.309** (1.603)	24.170* (12.305)	2.876 (2.864)	4.302** (1.599)	24.117* (12.294)	2.836 (2.861)
Distrust in other institutions	-3.376 (2.279)	-24.477 (16.552)	-6.207 (3.900)	-3.409 (2.275)	-24.462 (16.543)	-6.181 (3.897)
Baseline Characteristics						
GDP per capita	-1.911* (0.842)	-33.624*** (8.510)	-6.408 (4.470)	-1.919* (0.837)	-33.743*** (8.473)	-6.181 (4.453)
Restrictive regulation	-0.059 (0.406)	4.217 (4.108)	-0.480 (2.246)	0.058 (0.407)	5.220 (4.126)	0.190 (2.266)
Constant	17.323* (8.220)	307.839*** (76.940)	48.074 (38.258)	17.229* (8.183)	308.580*** (76.645)	45.291 (38.128)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Panel Data Specifications	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit
Observations	1210	1210	1000	1210	1210	1000
Number of Regions	242	242	200	242	242	200
Number of Countries	34	34	31	34	34	31
Log-likelihood	-2771.9	-5182.3	-2652.4	-2767.7	-5179.1	-2650.3
Rho	0.77	0.55	0.08	0.77	0.55	0.08

Notes: All models are Tobit random effects models and their associated overall R-squared is reported. Panel-data bootstrapped standard errors, clustered at the country level, are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1, 1, 5 and 10 percent level.