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Correlation Structure of the Spanish Stock Market Around COVID-19 Using Random Matrix Theory

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Abstract

In this work we analyze the correlation structure of the Spanish stock market around COVID-19 using random matrix theory (RMT). The results reveal that the empirical spectral distribution of eigenvalues associated with correlation matrices of prices for major companies listed on IBEX35 and IBEXC differs across the analyzed periods. In all cases, it deviates from the theoretical spectral distribution predicted by RMT through the Marchenko-Pastur law. In particular, during the COVID-19 crisis, the maximum eigenvalue exceeds the maximum eigenvalue in different periods before and after the pandemic, effectively capturing the state or mode of the market under crisis conditions. The second-largest eigenvalue facilitates the identification of groups among stocks associated with its corresponding eigenvector. These findings hold potential for developing strategies to assess systemic risk in the Spanish stock market.

Keywords Correlation · Random matrix theory · Spanish stock market

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1 Introduction

Financial crises occur more frequently than commonly anticipated. These crises lead to abrupt shifts in the behavior of financial markets, akin to phase transitions (Bielinskyi et al., 2023). The configuration of market correlations undergoes alterations during these financial upheavals.

In a financial market characterized by a multitude of assets, the predominant eigenvalue of the return correlation matrix serves as a metric for assessing the market's systemic risk. The largest eigenvalue emerges as a reliable gauge of systemic risk (Han et al., 2017). Meanwhile, its associated eigenvector encapsulates the comprehensive dynamics of the entire market and the oscillations in the market's correlation structure also carry significant financial implications for the field of risk management.

In recent years, Random Matrix Theory (RMT) has emerged as a powerful tool for analyzing complex systems, including stock markets. RMT provides a robust framework for distinguishing between meaningful information and noise in correlation matrices. The ability of RMT to filter out noise and highlight significant correlations has been emphasized in multiple studies (Laloux et al., 1999; Plerou et al., 1999;

Plerou et al., 2002). In contrast to traditional methods, such as Principal Component Analysis (PCA) or Singular Value Decomposition (SVD), which primarily focus on dimensionality reduction and identifying dominant patterns in the data, RMT specifically examines the statistical behavior of eigenvalues in correlation matrices. This approach allows RMT to identify eigenvalues that significantly deviate from theoretical predictions, offering valuable insights into the underlying market structure and potential interactions among financial assets. The denoising capability of RMT, based on the Marčenko–Pastur theorem, enables a more accurate depiction of the true correlation structure by filtering out random noise, thus enhancing the reliability of clustering coefficients and other measures of asset interconnectedness (Munnix et al., 2012; Vanni et al., 2024). This makes RMT particularly advantageous in the context of financial markets, characterized by highly volatile and noisy data.

Random matrix theory has found extensive utility in analyzing diverse financial time series (Laloux et al., 1999; Plerou et al., 1999Kwapien et al. 2012). The analysis within RMT centers on the correlation matrix and its associated eigenvalues and eigenvectors. Within the scope of RMT, when the eigenvalues of empirical time series deviate from the predictions, this implies the presence of concealed economic information within these deviating eigenvalues. This phenomenon is particularly applicable in the context of stock markets, where several eigenvalues deviate from expectations according to RMT. Notably, the most prominent among these eigenvalues captures the collective impact of the entire market.

The advent of the COVID-19 pandemic triggered a profound disruption in global financial (Basuony et al., 2021; Chatjuthamard et al., 2021) prompting our research seeks to analyze the repercussions of the pandemic within the specific context of the Spanish stock market. By applying the tools of RMT, we aim to shed light on the intricate dynamics that underpin the correlation patterns among these prominent stocks. We employ the analytical framework of RMT to delve into the returns of the major large-capitalized stocks within the Spanish stock market.

Our research is fundamentally focused on gaining a deeper understanding of the changes that occurred in the correlation structure -both preceding and following the COVID-19 outbreak- within the Spain market. In addition, we focus on unveiling the inherent information contained within the eigenvalues that exhibit deviations predicted by RMT, with the aim of uncovering any hidden insights that might shed light on the underlying dynamics of the Spanish market during this critical period.

The rest of this paper is structured as follows. RMT and Marchenko-Pastur law are reviewed in Sect. 2. Section 3 offers a description of the data sets used. In Sect. 3, we delve into an analysis of the cross-correlation structure within the Spanish stock market and explore the financial insights encapsulated within the highest eigenvalues. Finally, our concluding remarks are presented in Sect. 4.

2 Random Matrix Theory and Marchenko-Pastur Law

2.1 Spectral Distributions Laws

In the context of spectral analysis of financial markets, several spectral distribution laws have been used. The Wishart distribution, for example, is often used in finance to model the covariance matrix of returns when the sample size is smaller than the number of variables. This distribution is useful for understanding the sample covariance matrices of multivariate normal distributions but assumes that the underlying data are Gaussian, which may not always be true for financial data (Muirhead, 2009).

The Wigner semicircle law applies to the eigenvalue distribution of large symmetric matrices with independent, identically distributed entries. This law is particularly useful for understanding the global spectral properties of matrices but does not account for the correlations present in financial data, making it less suitable for our specific context (Wigner, 1958).

Another relevant law is the Tracy-Widom distribution, which describes the fluctuations of the largest eigenvalue of random matrices. This distribution is particularly useful in scenarios where the behavior of the largest eigenvalue is of interest, such as in detecting extreme market conditions or financial crashes (Tracy et al. 1994). However, it does not provide insights into the bulk of the eigenvalue spectrum, an aspect that is important for understanding the overall structure of correlations in financial markets.

The Girko circular law describes the eigenvalue distribution of large random matrices with complex entries and is useful in understanding systems with complex-valued correlations, such as those found in certain communication networks (Girko, 1985). However, it is less applicable in the context of financial markets, where real-valued correlations are more relevant. Additionally, the Heavy-Tailed distribution applies to matrices with entries that have heavy-tailed distributions, capturing the influence of large, infrequent shocks that could significantly impact the system (Bai et al. 2010). While this distribution is important in risk management and modeling extreme events, it does not effectively distinguish between noise and meaningful information in financial data.

The Marčenko–Pastur law, on the other hand, offers a robust framework for distinguishing between signal and noise in large empirical correlation matrices without the assumption of normality (Marchenko et al. 1967). It describes the distribution of eigenvalues of large random matrices with non-trivial correlations and provides a threshold beyond which eigenvalues are likely to carry meaningful information about the underlying correlations among stocks (Bun et al. 2010). In contrast, the Girko circular law deals with the eigenvalue distribution of non-Hermitian random matrices, which is less relevant for symmetric matrices typically used in finance.

The choice of the Marchenko-Pastur law for financial applications is particularly justified by its ability to account for empirical correlations among assets and filter out noise from random fluctuations. This makes it an ideal tool for analyzing the complex interdependencies in financial markets, especially under conditions of market stress or turbulence, such as during the COVID-19 pandemic. By focusing on the Marchenko-Pastur law, our analysis benefits from a detailed understanding of both the bulk behavior and the tail behavior of the eigenvalue spectrum, allowing for a more comprehensive evaluation of market dynamics.

2.2 Marchenko–Pastur law

Consider the following covariance matrix:

$$\mathrm{M} = \frac{\mathrm{XX^T}}{\mathrm{m}}$$

where X is an $\mathrm{n} \times \mathrm{m}$ matrix including independent random variables adhering to the conditions: $\mathrm{E}\left\{\mathrm{X_{jk}}\right\}_{\mathrm{j=1,2,\ldots,n;k=1,2,\ldots,m}} = 0$ and $\mathrm{E}\left\{\left(\mathrm{X_j}\right)^2\right\} = 1$. In this matrix, n represents the number of indexed assets and m is the length of the time series. Note that in this specific case, the covariance matrix coincides with the correlation matrix since the standard deviations of all variables are equal to 1.

The set $\left\{\lambda_j\right\}_{j=1,2,\ldots,n}$ comprises the eigenvalues of M. RMT investigates the statistical properties of the eigenvalues $\left\{\lambda_j\right\}_{j=1,2,\ldots,n}$ of the covariance matrix M:

$$\mathrm{M}\mu^{\mathrm{j}} = \lambda_j \mu^j$$

where μ^j represents the corresponding eigenvectors.

The simplest property of the eigenvalue family associated with a matrix is the density function $\rho(\lambda)$ which counts the average number of eigenvalues within an interval (a, b):

$$\{\lambda_j;\lambda_j \in\}(a, b) = \int_a^b \rho(\lambda) d\lambda$$

The random matrix X was mathematically studied by Marchenko and Pastur (Marchenko et al. 1967). The Marchenko-Pastur law is a probability distribution that describes the limiting distribution of the eigenvalues of a random matrix with independent and identically distributed (i.i.d.) elements. This law is particularly relevant in the context of RMT and is applicable in a number of areas, including principal.

component analysis and the analysis of high-dimensional data. The specific form of the Marchenko-Pastur law is given for square matrices X of dimensions $n \times n$, where m is large and the elements of X are i.i.d. with mean zero and variance σ^2.

The law describes the spectral density of the matrix $\frac{XX^T}{m}$, which is proportional to the sample covariance matrix. In particular, the density function $\rho(\lambda)$ for this matrix is well-known. If $n/m = c < 1$, it is defined as:

$$\rho(\lambda) = \frac{1}{2\pi c\lambda}\sqrt{(b-\lambda)(\lambda-a)}$$

where $a = \lambda_{min} = \left(1 - \sqrt{c}\right)^2$ and $b = \lambda_{max} = \left(1 + \sqrt{c}\right)^2$, and $c = n/m$ The Marchenko-Pastur law is analogous to Wigner's semicircle law (Wigner, 1958). The smallest and largest eigenvalues of a random matrix (Wishart matrix) are denoted as λ_{min} and λ_{max}, respectively. In the case of a random time series, all the eigenvalues of the correlation matrix are expected to fall within the boundaries of $\left[\lambda_{\min}, \lambda_{\max}\right]$. Any deviation from this range is indicative of correlation within the time series.

The Marchenko-Pastur law is useful for understanding the spectral behavior of random matrices in high-dimensional settings and provides an important theoretical tool for analyzing the eigenvalue statistics in high-dimensional problems.

3 Data Set Description

Two stock market indices have been selected from the Madrid Stock Exchange: IBEX35, which includes the 35 largest companies, and IBEX Medium Cap (IBEXC), which groups 20 medium-cap companies listed through the Spanish Stock Exchange Interconnection System (SIBE). Companies which left these indices during the period from January 2018 to February 2023 have been added to better account for the Spanish market during the analyzed period. This yields a total of 57 stocks, see Table 1, where the letters in the Sector column represent the following: H: Healthcare, F: Financial Services, U: Utilities, M, Basic Materials, CC: Consumer Cyclical, CD: Consumer Defensive, CS: Communication Services, I: Industrial, R: Real Estate, T: Technology, and E: Energy.

We compute the logarithmic return series by $r(t) = \ln(P(t+1)) - \ln(P(t))$, where $P(t)$ is the daily closing price, and we divide the complete analysis period into three periods: pre-crisis (02/01/2018 – 31/01/2020), during the crisis (03/02/2020 – 02/01/2021), and post-crisis (03/03/2021 – 17/03/2023). We are interested in

Table 1 List of analyzed stocks of Spanish stock market

Company	Ticker	Sector	Industry
Laboratorios farmaceuticos rovi	ROVI	H	Biotechnology
Almirall	ALM	H	Drug manufacturers
Grifols	GRF	H	Drug manufacturers
Faes Farma	FAE	H	Drug manufacturers
Pharma Mar	PHM	H	Biotechnology
Bankinter	BKT	F	Banks—regional
CaixaBank	CABK	F	Banks—regional
Unicaja Banco	UNI	F	Banks—regional
Banco de Sabadell	SAB	F	Banks—regional
Banco Bilbao Vizcaya Argentaria	BBVA	F	Banks—regional
Grupo Catalana Occidente	GCO	F	Insurance—diversified
Mapfre	MAP	F	Insurance—diversified
Corporación Financiera Alba	ALB	F	Asset management
Redeia Corporación	RED	U	Regulated electric
Solaria Energía y Medio Ambiente	SLR	U	Renewable
Endesa	ELE	U	Regulated electric
Naturgy Energy Group	NTGY	U	Regulated gas
Enagás	ENG	U	Regulated gas
Iberdrola	IBE	U	Diversified
Ercros	ECR	M	Chemicals
Acerinox	ACX	M	Steel
ENCE Energía y Celulosa	ENC	M	Paper & Paper products
ArcelorMittal	MTS	M	Steel
Viscofan	VIS	CC	Packaging & Containers
Vidrala	VID	CC	Packaging & Containers
eDreams ODIGEO	EDR	CC	Travel services
Amadeus IT Group	AMS	CC	Travel services
NH Hotel Group	NHH	CC	Lodging
Melia Hotels International	MEL	CC	Lodging
CIE Automotive	CIE	CC	Auto parts
Gestamp Automoción	GEST	CC	Auto parts
Mediaset España Comunicación	TL5	CC	Media & Publishing
Industria de Diseño Textil	ITX	CC	Apparel retail
Distribuidora Internacional de Alimentación	DIA	CD	Discount stores
Ebro Foods	EBRO	CD	Packaged foods
Telefónica	TEF	CS	Telecom services
Atresmedia Corporación de Medios de Comunicación	A3M	CS	Entertainment
Prosegur Compañía de Seguridad	PSG	I	Security & Protection services
Construcciones y Auxiliar de Ferrocarriles	CAF	I	Railroads
Ferrovial SE	FER	I	Infrastructure operations
Talgo	TLGO	I	Railroads
Applus Services	APPS	I	Specialty business services

Table 1 (continued)

Company	Ticker	Sector	Industry
International Consolidated Airlines Group	IAG	I	Airlines
Aena S.M.E	AENA	I	Airports & Air services
ACS, Actividades de Construcción y Servicios	ACS	I	Engineering & Construction
Grenergy Renovables	GRE	I	Specialty industrial machinery
Sacyr	SCYR	I	Engineering & Construction
Acciona	ANA	I	Engineering & Construction
Fluidra	FDR	I	Specialty industrial machinery
Compañía de Distribución Integral Logista Holdings	LOG	I	Integrated Freight & Logistics
MERLIN Properties SOCIMI	MRL	R	REIT—Diversified
Inmobiliaria Colonial, SOCIMI	COL	R	REIT—Office
Cellnex Telecom	CLNX	R	Real estate services
Indra Sistemas	IDR	T	Information technology services
Global Dominion Access	DOM	T	Information technology services
Repsol	REP	E	Oil & Gas integrated

studying the impact of the COVID-19 pandemic on the structure of market correlations. Therefore, we selected comparable analysis periods before, during, and after the outbreak of COVID-19. To ensure the consistency and relevance of our analysis, we included only the companies that remained listed in the IBEX35 and IBEXC indices throughout the entire analyzed period. This approach ensures that the observed changes in the correlation structure can be attributed to market conditions rather than alterations in the index composition.

4 Results and Discussion

In a random system all eigenvalues of correlation matrix fall within a predetermined interval. Eigenvalues within the limits defined by RMT signify the inherently random behavior of the system. Any deviation from this interval confirms the presence of correlations in the studied system (Rosenow et al., 2000).

Figure 1 displays the correlation matrices for the periods under consideration. A discernible change is noted in the correlation structure of the major assets comprising the Spanish stock market throughout the analyzed periods. During the first year of the COVID-19 pandemic, asset correlations were more pronounced compared to the immediately preceding and subsequent periods. It is crucial to note that correlations were predominantly positive across all analyzed periods, with a notable emphasis on companies in the financial services sector, exhibiting significant positive correlation.

This pronounced correlation within the financial services sector can be attributed to several sector-specific factors. Financial institutions are inherently interconnected through a network of lending, borrowing, and investment activities, which can amplify correlations during periods of market stress (Allen et al. 2000; Davidson,

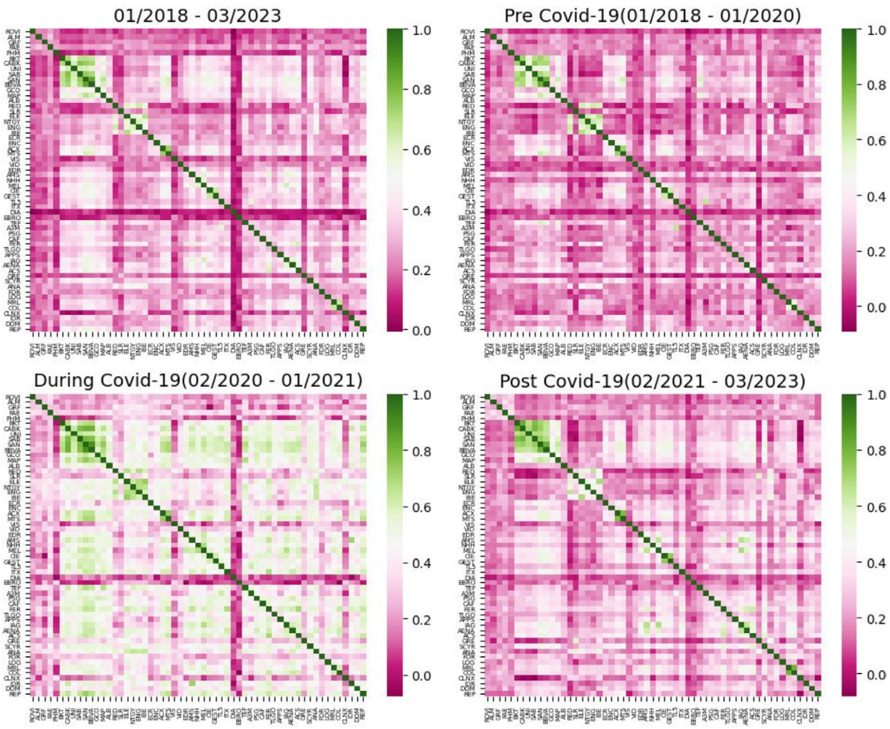

Fig. 1 A Heatmaps of the empirical correlation matrices for the Spanish stock market across four periods: pre-COVID-19, during COVID-19, post-COVID-19, and the complete period

2020). This was further exacerbated by shared exposure to market risks and regulatory responses, such as interest rate cuts and quantitative easing, which uniformly impacted financial institutions (Acharya et al. 2020). Thus, the observed significant positive correlations in the financial services sector can be attributed to both the intrinsic interconnectedness of financial markets and the systemic responses to global economic shocks, reinforcing the sector's susceptibility to contagion effects (Benkraiem et al., 2022).

We also compared the probability distributions of eigenvalues of market correlation matrices with those of random correlation matrices of the same size (Wishart Matrix) during the different periods, see Fig. 2. The majority of eigenvalues from Spanish stock market correlation matrices fall outside the bounds predicted by the Marchenko-Pastur Law of RMT, indicating that interactions among IBEX 35 and IBEX Medium stocks are not entirely random but contain valuable information.

These deviations have critical implications for both investors and policymakers. For investors, the presence of eigenvalues beyond the theoretical limits indicates the existence of underlying market factors and collective behaviors that are not captured by random models. This means that portfolios constructed without considering these correlations may be exposed to higher systemic risk during

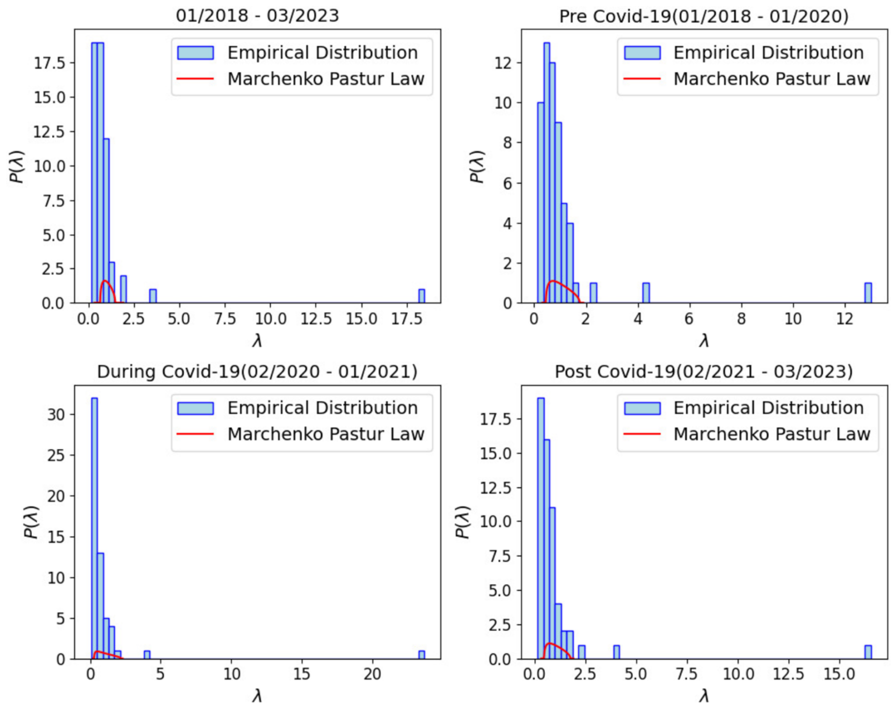

Fig. 2 Theoretical and empirical probability distribution of eigenvalues of the correlation matrices for the Spanish stock market across four periods: pre-COVID-19, during COVID-19, post-COVID-19, and the complete period

periods of market stress, as demonstrated by the increased correlations observed during the COVID-19 crisis (Laloux et al., 1999; Plerou et al., 2002).

For policymakers, understanding these deviations is relevant for financial stability monitoring. The sharp increase in the maximum eigenvalue during the COVID-19 crisis, for instance, reflects heightened market interconnectedness and potential contagion risks among stocks (Munnix et al., 2012). Such information can be pivotal for developing timely regulatory interventions and stress-testing scenarios to mitigate systemic risk. Additionally, recognizing non-random structures in stock correlations can help policymakers implement measures that enhance market resilience, such as circuit breakers or liquidity provisions, which are designed to contain market volatility and prevent cascading failures (Molero et al. 2023; Gang-Jin et al. 2013; Sandoval et al. 2012).

Figure 3 shows the eigenvectors associated with the first largest eigenvalue of correlation matrices, whereas Table 2 presents the maximum and minimum eigenvalues for the analyzed periods along with their theoretical intervals. During the COVID-19 crisis, we observed an 82\% increase in the largest eigenvalue, signifying a substantial alteration in the collective dynamics among stocks and deviating significantly from RMT predictions. This finding underscores the significant

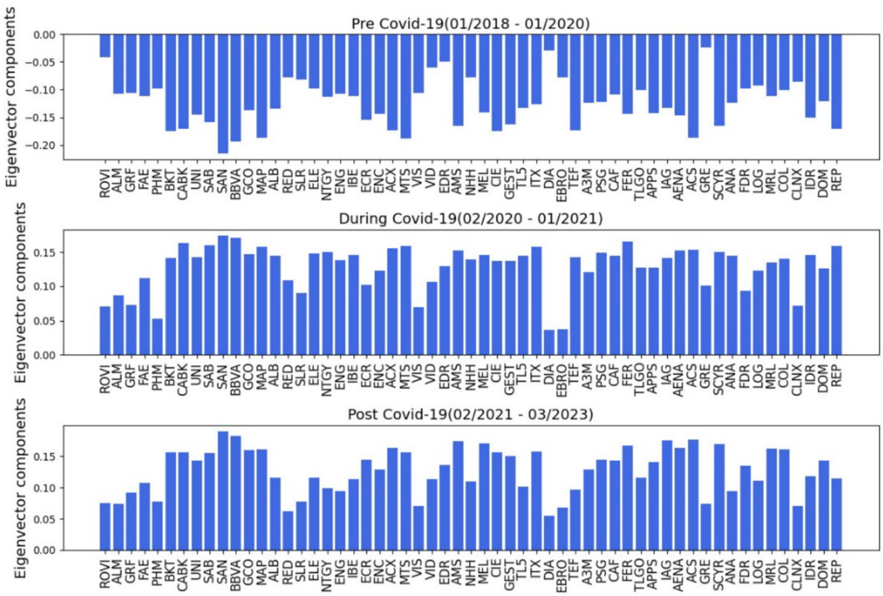

Fig. 3 Eigenvectors associated with the first largest eigenvalue of correlation matrices around COVID-19. Changes in the signs of the eigenvector components are observed between the preCOVID-19 and during COVID-19 periods, reflecting a shift in the collective behavior of the Spanish stock market

Table 2 Eigenvalues of empirical and random correlation matrices for different periods around the COVID-19 pandemic, highlighting deviations from randomness as predicted by random matrix theory

	Lowest	Highest
Pre-COVID-19	0.12852	13.01205
Random Matrix (Pre-COVID-19)	0.45248	1.76179
During COVID-19	0.06220	23.67614
Random Matrix (During COVID-19)	0.27989	2.16368
Post-COVID-19	0.13257	16.54607
Random Matrix (Post-COVID-19)	0.45818	1.75060
Complete period	0.12414	18.47505
Random Matrix (Complete period)	0.62943	1.45595

impact of the crisis on relationships among assets in the Spanish stock market, emphasizing the non-trivial nature of correlations observed during that period.

The eigenvector associated with the second-largest eigenvalue encompasses 57 stocks from both IBEX35 and IBEX Medium, belonging to the same sector (see Fig. 4). We observe that these components categorize the stocks into various clusters containing companies of similar industry types. It is intriguing to note the changes in signs and magnitudes of the eigenvector components for stocks within industry clusters, particularly in Healthcare, Financial, and Utilities services, both before and during COVID-19. Furthermore, it is noteworthy to observe variations in stocks before, during, and after the COVID-19 period for EBRO, VIS and CLNX.

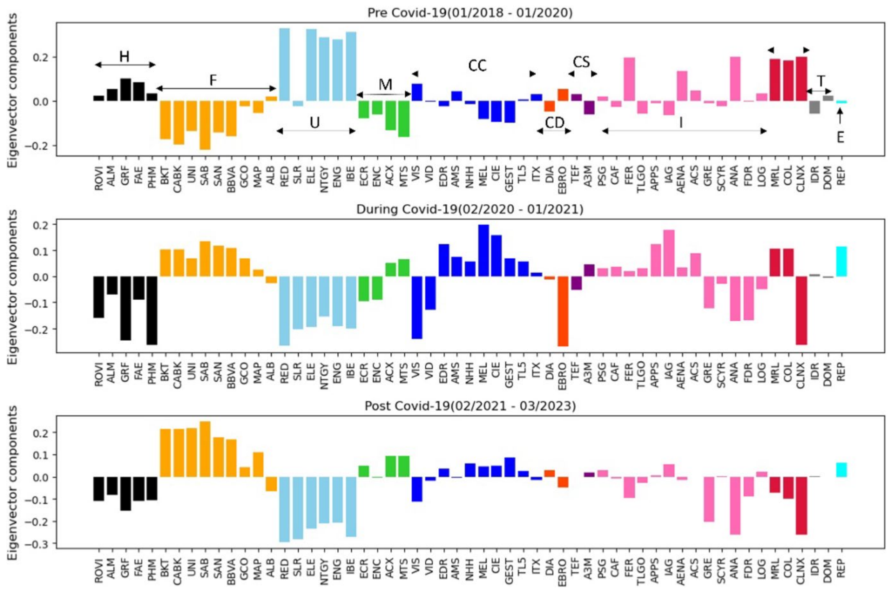

Fig. 4 Eigenvectors associated with the second largest eigenvalue around COVID-19. Colors and acronyms represent the sectors of stocks and clusters of companies within the same industry, indicating similarities in their market behavior

Ebro Foods S.A. is Spain's largest food group, the world's largest producer of rice, and a global producer of pasta (www.ebrofoods.es/en/). Viscofan S.A. is the world leader in casings for meat products, manufacturing casings distributed in more than 100 countries worldwide (www.viscofan.com). Cellnex Telecom, S.A. is a wireless telecommunications infrastructure and services company (https://www.cellnex.com/). These sectors played a pivotal role during the pandemic, involving both food supply chain, as well as telecommunications.

4.1 Eigenportfolios

Differences in the statistical properties of empirical and RMT predicted correlation matrices have been observed. Eigenvalues deviating from the limits set by the RMT are indicative of valuable economic information. It is possible to construct eigenportfolios for each eigenvalue (Dai et al., 2016).

For each eigenvalue λ_k, the return of its corresponding eigenportfolio at time t is given by:

$$G^k(t) = \sum_{j=1}^{n} \mu_j^k r_j(t) / \sum_{j=1}^{n} \mu_j^k$$

where $\sum_{j=1}^{n} \mu_j^k r_j(t)$ represents the projection of the stock market return series on the $k-th$ eigenvector μ^k.

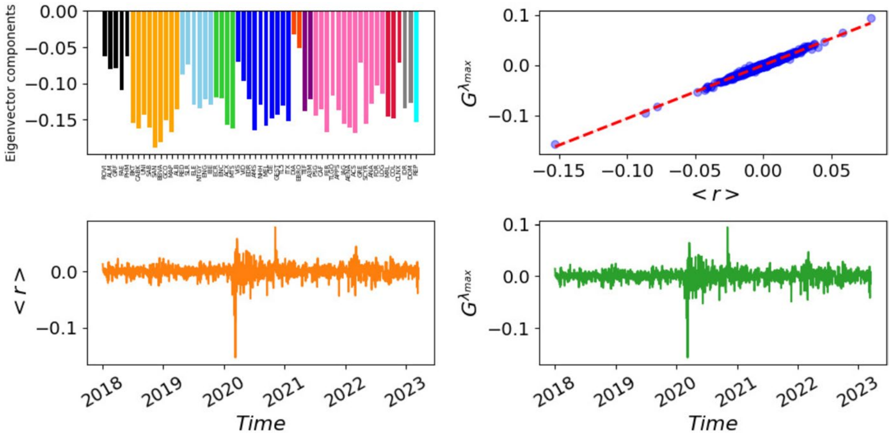

Fig. 5 Relationship between $G^{\lambda_{max}}$ and < r > for λ_{max}

Figure 5 shows an excellent linear relationship with an $R^2 = 0.993$ between the return of the eigenportfolio associated with the largest eigenvalue $G^{\lambda_{max}}(t)$ and the average return < r >. Therefore, the largest eigenvalue λ_{max} reflects a collective mode of the Spanish stock market. The relationship among the first four largest eigenvalues is shown in Fig. 6, which does not demonstrate a clear linear relationship between $G^{\lambda_k}(t)$ and < r > (except to λ_{max}). This implies that these deviating eigenvalues do not exhibit any significant market effects.

4.2 Varying-time Analysis of Largest Eigenvalue

Traditionally, RMT has been employed in a static context, where correlations between financial assets are analyzed over a fixed period without accounting for the

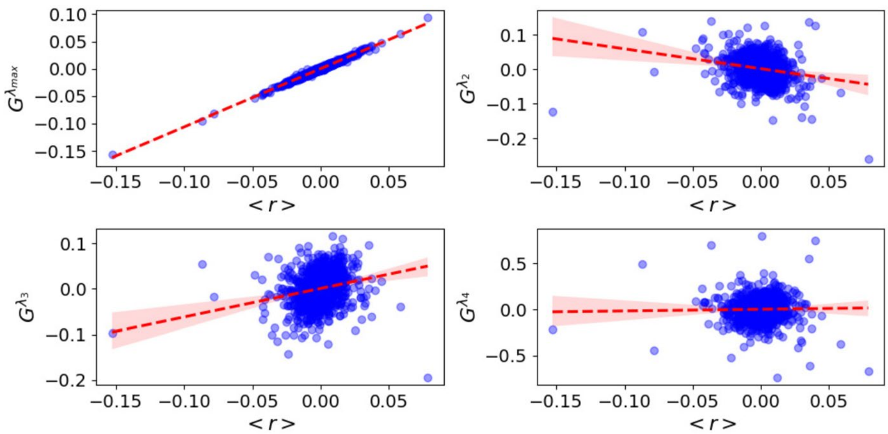

Fig. 6 Relationship between $G^{\lambda_{max}}$ and < r > for λ_{max} for the four largest eigenvalues

dynamic nature of financial markets. This static approach limits the understanding of how correlations evolve over time, especially during periods of market stress or economic shocks.

In our study, we introduce a novel methodological approach to the application of RMT by focusing on a varying-time analysis of the largest eigenvalue of the cross-correlation matrix. To address this limitation, we applied a sliding window approach to perform a dynamic analysis of the largest eigenvalue of the cross-correlation matrix, which provides a time-varying perspective on market behavior.

The largest eigenvalue of the cross-correlation matrix has been assumed to contain rich information about the structure and dynamics of the stock market. We conducted a dynamic analysis of correlation matrices to study the evolution of the maximum eigenvalue. Using a sliding window approach, we calculated correlation matrices and extracted the largest eigenvalue. Figure 7 displays the evolution of the largest eigenvalue for different window sizes (25, 50, 100 and 150 trading days). We found that the value captures various market changes, especially around extreme events such as the COVID-19 crisis, where the value increases rapidly. This suggests that the maximum eigenvalue could serve as a potential indicator of systemic risk and early warning of market dynamics.

This varying-time analysis introduces a new perspective to RMT applications by highlighting the importance of time-dependent correlation structures in financial markets. Unlike traditional static analyses, our approach allows for the detection of

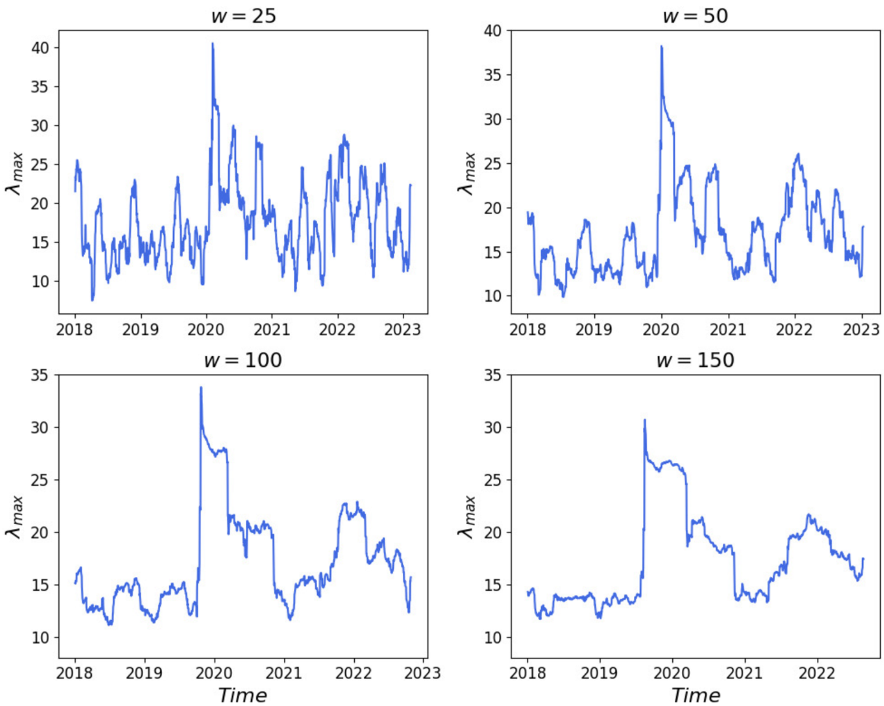

Fig. 7 The evolution of λ_{max} for various sliding windows

temporal changes in market dynamics, which can provide more timely and actionable insights for risk management and policy-making.

Additionally, this dynamic framework can be further expanded by integrating other analytical tools, such as machine learning techniques, to enhance the predictive power and robustness of RMT-based analyses. By advancing beyond the conventional static models, our study contributes a methodological innovation that opens new avenues for research in financial market analysis using RMT.

5 Conclusions

We have analyzed the correlation structure of the Spanish stock market using random matrix theory. We found that the largest eigenvalue reflects its mode, being more pronounced at the beginning of the COVID-19 pandemic, and the second-largest eigenvalue reflects the collective mode of the market. Our investigation not only contributes to our understanding of the structural shifts brought about by external shocks but also has potential implications for risk assessment and management strategies within the Spanish market.

This analysis taps into the rich vein of information embedded within the data, offering insights that could potentially inform investment decisions, portfolio adjustments, and risk mitigation approaches.

By delving into the insights offered by deviated eigenvalues and their correlation matrices, we strive to extract novel insights that could enhance our comprehension of the Spanish stock market's behavior during times of significant stress, such as the COVID-19 pandemic.

In future research, the application of Random Matrix Theory could be extended to other stock markets or financial systems to assess the generalizability and robustness of the findings presented in this study. By analyzing markets with different characteristics, such as emerging markets or markets with high volatility, such as cryptocurrencies, it would be possible to determine whether the deviations from the Marchenko-Pastur law observed in the Spanish stock market are consistent across various financial environments.

Additionally, incorporating more granular data, such as intraday trading information, could provide deeper insights into the dynamics of correlations and their temporal evolution.

Methodological improvements, such as the integration of advanced machine learning techniques to enhance noise filtering or the use of alternative spectral distribution models, could further refine the analysis and lead to more accurate detection of market anomalies. These advancements would not only enhance the robustness of RMT-based analyses but also contribute to the development of more effective risk management strategies in financial markets.

One limitation of this study is the use of daily closing prices, which might not reflect the full complexity of market movements within trading days. For future research, expanding the application of RMT to other stock markets, such as emerging markets or markets with different regulatory environments, could provide a more comprehensive understanding of market correlations and systemic risk. Moreover, analyzing different crisis periods, such as the 2008 financial crisis or regional economic downturns, could offer comparative insights into how various types of crises impact market structures.

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Data availability The data associated with this publication is available with the authors.

Declarations

Conflict of interest The authors have not disclosed any competing interests.

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