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ON THE CONNECTEDNESS OF THE WORLD'S LARGEST BANKS:

A DIEBOLD & YILMAZ APPROACH.

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ABSTRACT

The study investigates the financial spillovers existing among the world's 14 major equity indexes and 70 largest banks. By employing the Diebold and Yilmaz (2009; 2012) approach, the aim is to estimate the transmission of their return and volatility shocks. However, while the preliminary analysis reveals that the U.S. and the E.U. are the most interconnected regions, the main results come from the global banking network. After tackling the high-dimensionality of the VAR through FEVD feature selection, the analysis reduces the dataset and shows that East Asia is still the most represented region. Even though China accounts for more than a third of the banks, its spillover transmission is extremely low. Hence, our directed graphs divide China from Western countries, leading the former to create a different and separate cluster. When using a 200 rolling-window approach, the analysis shows that banks react to all major financial shocks, mainly the 2015 stock market sell-offs, the 2019 repo crisis, and the COVID-19 pandemic. During that time period, while the region with the highest spillover transmission is represented by the U.S., the one with the lowest return and volatility spillovers appears to be East Asia, particularly China. To explain shocks' transmissions, the analysis considers twelve variables deriving from banks' financial statements, balance sheets, or valuations (e.g. revenues, total assets, total debt, deposits). However, even if with simple linear regression models there is a low explanatory power, random forests can explain more than 90% of the variance. Unfortunately, this is no longer valid for volatilities, displaying more spikes than trends and leading any model to be less robust than that of returns.

Il seguente studio analizza gli *spillovers* esistenti tra i 14 principali indici azionari e le 70 maggiori banche al mondo. Utilizzando l'approccio di Diebold e Yilmaz (2009; 2012), l'analisi mira a quantificare la trasmissione dei loro shock, sia in termini di rendimenti che di volatilità. Sebbene l'analisi preliminare possa già rivelare un primo risultato, vale a dire che le zone con la maggior interdipendenza sono gli Stati Uniti e l'Unione Europea, le conclusioni più interessanti derivano dalla rete bancaria globale. Dopo aver risolto il problema dell'alta dimensionalità del dataset e dimezzato il numero di osservazioni, l'Asia Orientale rappresentava oltre un terzo dei dati. Ciò nonostante, gli spillovers trasmessi dalle relative banche sono risultati estremamente bassi, andando a creare un cluster diverso rispetto a quello delle banche occidentali. Con l'utilizzo di 200 finestre mobili, è stato possibile dimostrare che la maggioranza delle banche ha reagito alle principali crisi degli ultimi dieci anni, tra cui il crollo del mercato azionario del 2015, la crisi del mercato Repo del 2019 e il COVID-19. Nel corso degli ultimi anni, mentre ad aver trasmesso il maggior numero di spillover sono stati gli Stati Uniti, il minore è stato associato all'Asia e nello specifico alla Cina. Al fine di spiegare l'andamento degli spillover, lo studio si è concluso con l'esecuzione di molteplici regressioni e di una random forest. Più precisamente, le variabili considerate sono state selezionate dai bilanci, situazioni patrimoniali e valutazioni delle banche (i.e. ricavi, attività totali, debito totale, depositi). Tuttavia, anche se i modelli lineari hanno avuto una bassa efficacia, le random forests sono riuscite a spiegare il $78\% - 90\%$ della varianza.

INTRODUCTION

The main aim of the study is to identify the financial spillovers existing among the world's 14 major equity indexes and 70 largest banks, active since 2004. Precisely, the analysis spans from 2004 to 2024 and has at its core the Forecast Error Variance Decomposition (FEVD) of their weekly returns and Garman-Klass volatilities[1].

The estimation of their cross-variance shares is grounded on the spillover index of Diebold & Yilmaz (2012). Thereafter, return and volatility time series are modeled through a Vector Autoregression (VAR) model of the Sims (1980) tradition.

As of today, the existing literature has extended the Diebold and Yilmaz approach in various directions. During the years, their framework has been applied to stocks (Diebold and Yilmaz, 2014), sovereign bonds (Alter and Beyer, 2014; Demirer et al., 2018), and Credit Default Swaps (CDSs) (Greenwood-Nimmo et al., 2019)[2].

Besides the application of the spillover index to equity and bonds, spillover indexes have been used to assess the interdependence among exchange rates (Bubák et al., 2011), commodity prices like crude oil (Kang et al., 2017; Wang et al., 2018), and more recently even cryprocurrencies (Moratis, 2021; Elsayed et al., 2022).

What is common is the relevance that systemic risk assumes in the global financial system. Defined by Smaga et al. (2014) as the transmission of shocks between the entities of the financial system, it is seen by major central banks, such as the Czech National Bank or Riskbank, as a proper "*threat to the financial system*".

Aware that contagion serves as the mechanism through which instabilities escalate, we analyzed financial spillovers during: (i) the 2008 U.S. housing market collapse, (ii) the sovereign debt crisis, (iii) the recession caused by the COVID-19 outbreak, and (iv) the current historical period, characterized by stock markets' stability.

The choice of analyzing only equities derives from the results of Beirne and Gieck (2012). After having controlled for the interactions in other asset classes, including bonds, they demonstrated that interdependence across countries is more evident in equity markets, particularly if one includes emerging economies as well.

Acknowledging the past literature, the contribution of the following research is to provide a micro and a macro perspective to financial connectedness. Hence, before applying the spillover measures to the 70 banks of the sample, we chose to perform a preliminary analysis on the interdependence of 14 major equity indexes[3].

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[1] Garman-Klass estimation was preferred to the Parkinson one for the inclusion of open and close prices.

[2] CDSs were analyzed even by Bratis et al. in their «*Sovereign credit and geopolitical risks during and after the EMU crisis*». International Journal of Finance & Economics. 2023.

[3] In 2010-2015, we added three indexes to account for the spillovers of Portugal, Ireland and Greece.

Precisely, the thesis is composed of six chapters. *Chapter 1* offers an overview of the increasing integration of the global economy since the mid-1950s. By covering the period spanning from the establishment of the IMF to the aftermath of the GFC, it serves as a basis to comprehend the historical evolution of interconnectdness.

Chapter 2 discusses the challenge of defining and quantifying systemic risk, whose indirect nature led to a lack of academic consensus. Beside the different definitions of systemic risk, the chapter covers the elements contributing to its growth and the role of contagion, identified as the mechanism through which instability escalates.

Chapter 3 introduces Diebold and Yilmaz's 2009 approach for measuring financial assets' return and volatility spillovers, with a focus on global equity markets. Here, the attention is directed to the spillover index, a measure based on the forecast error variance decomposition to quantify interconnectedness among assets and markets.

The chapter also highlights the limitations of the basic framework and explores the extension proposed by Diebold and Yilmaz in 2012. The new approach enables in fact to measure directional spillovers and net pairwise spillovers, granting a deeper understanding of the transmission of return and volatility shocks in equity markets.

The last theoretical chapter, *Chapter 4*, analyzes the existing strategies for handling financial networks. In fact, as high-dimensional VAR models are extremely useful for estimating spillovers, but pose challenges for their complexity, dimensionality is normally reduced with factor models, shrinkage methods, and sparse modelling.

Chapter 5 offers an overview of the data, made up of the returns and the volatilities of 14 major equity indexes from 01-01-2004 to 01-01-2024. It later discusses the evolution of return and volatility spillovers over the major crises of the time period, notably (i) the GFC, (ii) the sovereign debt crisis, and (iii) the COVID-19 outbreak.

The main finding is that during the 2008 crisis Asian spillovers towards the rest of the world were still relatively low. The most interconnected countries were indeed the U.S. and the E.U. MSs. Yet, the contagion effects of the U.S. were more visible through volatility spillovers, placing the nation as the first spillover transmitter.

A further result regarded the 2020 crisis. Despite originating in East Asia, financial shocks transmitted from the region did not noticeably affect U.S. and E.U. equities. With 91.09% of its forecast error variance explained by other indexes, the Indian stock market was the most impacted, mainly because of its internal fragilities[4].

Recognizing the dynamic nature of equity markets, *Chapter 5* estimates return and volatility spillovers with a rolling-window approach. Such analysis, encompassing three different cycles, revealed that return spillovers exhibit smoother trends, with Western indexes acting as net spillover transmitters and Eastern ones as receivers.

[4] Due to its low productivity and unstable economic indicators, India was susceptible to crises.

At the heart of the analysis, *Chapter 6* extends the examination of spillovers to the world's largest banks. Yet, before estimating their interdependence, it is crucial to address the high-dimensionality of VAR models. For this reason, the chapter starts by comparing major regularization methods, such as the Lasso and Elastic Net.

After the comparison, the chapter employs a variant of variance thresholding, using the Forecast Error Variance Decomposition (FEVD). Later on, it halves the dataset from 100 to 46 banks, mantaining the original balance while increasing efficiency; as a result, Chinese banks continue representing more than a third of the data.

By using a VAR(1) for returns and a VAR(10) for volatilities, *Chapter 6* continues the analysis by considering static spillovers. The major result not only reveals that the banking network is composed of two clusters, but confirms our first hypothesis: "*There is a minimal shock transmission from China to other financial markets*".

While we can identify two clusters, one with Western banks and a smaller one with Chinese banks, the Industrial and Commerical Bank of China (1398.HK) and Bank of Communications Co. (3328.HK) act as bridges with the global banking industry and alleviate the isolation caused by China's limited market-based approaches.

Following the static analysis, *Chapter 6* incorporates a 200-week rolling windows approach to return and volatility spillovers. Yet, after revealing that the main bursts occurred in response to (i) the 2015 stock market sell-offs, (ii) the 2019 Repo crisis, and (iii) the COVID-19 pandemic, it redistributes banks based on their country.

While identifying the primary geographical regions of the 46 banks, namely North America, East Asia, and Europe, the chapter highlights that while U.S. banks often act as net spillover transmitters, China tends to be a net receiver. Yet, the behaviour of European banks depends on their country, size, and share of foreign assets.

In *Chapter 7*, the study tries to identify the factors affecting net return and volatility spillovers by adopting a regression approach. The selected variables are revenues, DPS, complex financial products, total assets, debt, deposits capital adequacy, EV, non-performing loans, P/B, P/E, and a dummy variable for Western countries[5].

Focusing on net return spillovers, results indicate that complex products, the Price-to-Book (P/B) and the Price-to-Earnings (P/E) ratio are not statistically significant. Yet, to improve the explanatory power of the model (43%), the chapter employs a Generalized Additive Model (GAM) (83%) and a random forest (90.63%).

Differently, net volatility spillovers appeared complex to analyze. In fact, *Chapter 7* suggest that volatility is influenced by factors beyonf financial metrics, including market sentiment and internal shocks. Despite challenges in predicting volatilities, random forests continue to explain a high variance share, almost equal to 78%.

[5] The variable assumes a value of 1 if the bank is headquartered in a Western country, and 0 otherwise.

1. FINANCIAL MARKETS' INTERDEPENDENCE.

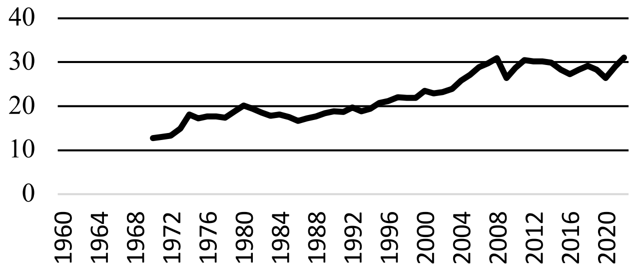
1.1 INTERCONNECTED ECONOMIES.

Integration in the global economy is increasing since the mid-1950s. The first signs of economic interdependence date back to the aftermath of World War II, precisely to the establishment of the IMF, the World Bank and the GATT. The aim of such institutions was indeed to promote economic stability and cooperation, contrasting the restrictions on international trade and the tight controls on capital movements.

The Liberal International Economic Order led soon to an unprecedented period of growth: the Golden Age of international trade. Temporarily halted during the 1973 oil crisis, worldwide integration survived even the heightened trade barriers set up by governments to face balance of payments disequilibria and indebtedness.

A crystal clear evidence that after the 1970s recession international trade continued to grow comes from the global exports of goods & services as a % of GDP (*Figure 1*). Over the past five decades the percentage increased from 12.7% to 31%, with spillover effects coming from Asia's advancement in the global economy.

Figure 1. World exports of goods & services as a % of GDP (1960-2022):

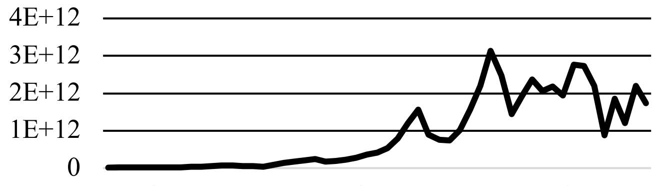


Data source: World Bank

Goods & services constitute just one of the channels through which connectedness manifests. From the mid-seventies the relaxation on capital movements restrictions and the adoption of flexible exchange rates induced a surge in international capital flows too, including government flows, banking transactions and investments.

The growth of financial flows can be seen from Foreign Direct Investments (FDI), cross-border investments granting more than 10% of voting rights: from 1990 their volumes quintupled, reaching a value of $\$1{,}294{,}738$ million in 2022.

Figure 2. World foreign direct investment (1970-2022):



Data source: World Bank

1.2 DEFINITION OF CONTAGION.

"Connectedness issues arise everywhere in modern life, from power grids to social networks and nowhere they are more central than in finance and macroeconomics - two areas that are intimately connected (Diebold and Yilmaz, 2015, xi)."

Even though financial interdependence triggered an increase in capital movements, it intensified the risk of contagion. Broadly, contagion refers to the transmission of run-like behaviours from one financial institution to another, resulting in a decline in the availability of funding in the financial system (Kaufman, 1992).

The exposure of financial institutions to contagion risks comes from their reliance on short-term borrowing to finance long-term investment activities. Such a set-up exposes them to the possibility of sudden withdrawal of funding by short-term debt investors, which could lead to forced sell-offs and a decline in asset values.

Financial contagion becomes particularly dangerous when it is indiscriminate, thus when it affects not just troubled markets and insolvent institutions, but also healthy economies and solvent entities. A comparable scenario occurred during 2008, with the U.S. housing bubble and the collapse of the subprime mortgage market.

In the indiscriminate setting, investors' decisions to exit are driven more by a lack of information rather than specific risks associated with individual institutions and markets. A situation that "*may lead to the failure of other financial intermediaries, even when they are not subject to the same original shocks*" (Trichet, 2009).

Over the past three decades, the dynamic of financial contagion has even evolved, shifting from traditional banking institutions to non-bank financial intermediaries. This conversion has been mostly favoured by the proliferation of complex financial instruments, such as derivatives, asset-backed securities and structured products.

Commonly referred to as the shadow banking sector of the economy (FED, 2013), non-bank entities perform similar operations to traditional banks but do not rely on deposits: they in fact depend on short-term borrowing markets for funding, which saw the increasing presence of money market funds and securities lenders.

What adds complexity are the layers of intermediation required to originate credits for non-bank entities. During an initial phase, they source funds from commercial paper markets and longer-term notes. The loans are then stored in various conduits, funded using asset-backed commercial paper (ABCP).

The resulting asset-backed securities are temporarily held on broker-dealer trading books, funded by short-term secured repurchase agreements (repos) and structured into synthetic collateralized debt obligations (CDOs). Further intermediation may then occur through structured investment vehicles or credit hedge funds.

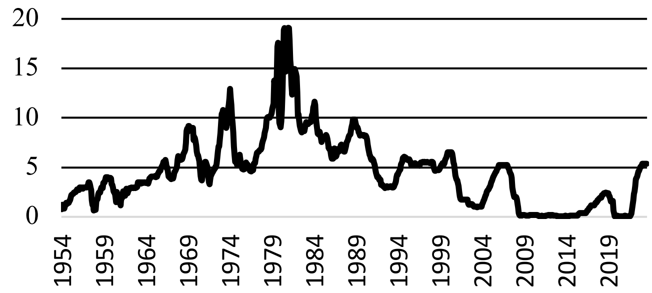
But are these short-term financial instruments worth the contagion risk they pose?

1.3 THE GLOBAL FINANCIAL CRISIS DYNAMICS.

To address the question it is essential to revisit the Global Financial Crisis of 2007-2008, the worst economic decline since the Great Depression of 1929-1939. At its core there was the collapse of the U.S. housing market, which led to the failure of 492 banks (FDIC, 2004-2013) and posed a threat to the global financial system.

The catalyst was the Federal Reserve (Fed), which responded to the mild recession of 2001 by implementing aggressive rate cuts. From May 2000 to December 2001 the Fed reduced the federal funds rate – the interest rate at which commercial banks exchange funds overnight – from 6.5% to 1.75% (FED, 2010).

Figure 3. Federal Funds Effective Rate (1970-2022):



Data source: FRED

The decrease in interest rates facilitated the extension of consumer credit at lower prime rates, which are typically 3% above the federal funds rate, and incentivized banks to start lending more to subprime borrowers – households with higher credit risks – albeit the higher risk was compensated by a higher interest rate.

Low-cost credit induced consumers to buy durable goods; in particular appliances, cars and houses. Such trend precipitated in the U.S. housing bubble, characterized by a rapid increase in property prices, far above their intrinsic value, as well as by an increasing speculation in the American housing market.

The second trigger of the GFC was the alteration in banking regulation of the 1980, which permitted to financial institutions to structure subprime loans with a balloon payment or variable interest rates. Although these conditions increased the default risk, banks could always repossess the property and sell it for a higher price.

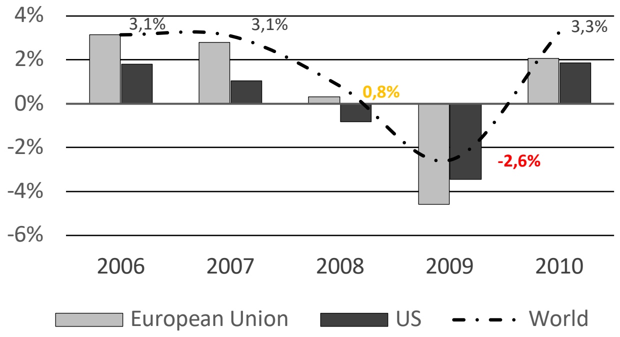
Contributing to the popularity of subprime loans there were even the securitization practices of the early 2000s: banks bundled together multiple subprime mortgages and less risky forms of consumer debt. These assets were then sold as securities in capital markets, especially to other banks and hedge funds.

The growth in contagion risk was not only due to securitization processes. Starting from 1993, the Depression-era Glass-Steagall Act allowed banks, securities' firms and insurance companies to pursue mergers, leading to the creation of banks whose failure would have jeopardized the whole economy: the so-called "too big to fail".

All these factors contributed to a series of events that settled the start of the crisis. From June 2004 to June 2006, the Fed rose interest rates, causing the first defaults of subprime borrowers, mostly among those that were under a flexible rate regime. Concurrently, the saturation of the housing market made home prices slow down.

As defaults continued, Mortgage-Backed Securities (MBSs) loose their value, with the first consequences on banks and investors. Since they were bought and sold by other countries as well, the losses were not limited to the portfolios of U.S. banks and investors: among the regions that the crisis affected the most there was Europe.

Figure 4. GDP per capita growth (2006-2010):



Data source: World Bank

By 2007, the devaluation of MBSs by rating agencies caused substantial losses to both banks and mortgage lenders. The breakdown point was reached in April 2007, when one of the most important subprime creditors, New Century Financial Corp., filed for bankruptcy and led to a series of closures in the subprime lending sector.

Lack of transparency worsened the crisis: due to the complexity of MBSs structure, it was difficult to evaluate the exposure of banks to subprime debt. This uncertainty caused doubts on the financial health of institutions, forcing the Fed to start buying federal funds in August and reduce the rate, which surpassed 5.25%.

Despite these efforts, financial stability remained elusive, inducing other rate cuts. In the same months, Northern Rock, a major UK mortgage lender, faced a liquidity crunch, requiring a bailout from the Bank of England: an event that triggered the first bank run in the UK in over a century.

In March, Bear Stearns, a prestigious Wall Street firm, faced insolvency and was acquired by JPMorgan Chase, which however incurred substantial losses. To avoid systemic collapses, while the Fed acquired $30 billion of Bear Stearns risky assets, the U.S. Treasury took over both Fannie Mae[6] and Freddie Mac[7] for $1.6 trillion.

[6] Fannie Mae: Federal National Mortgage Association (1938).

[7] Freddie Mac: Federal Home Loan Mortgage Corporation (1970).

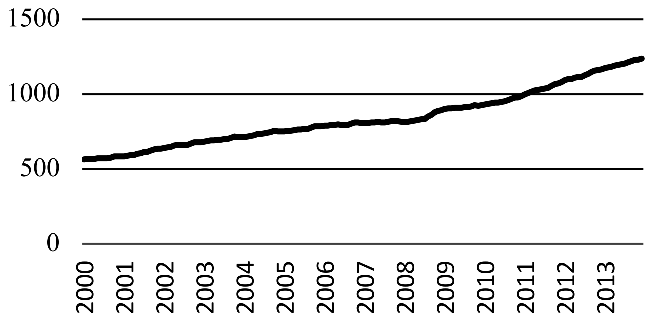
Shortly after, the U.S. investment bank Lehman Brothers, with $639 billion assets, declared bankruptcy. The outcome was an impact on the balance sheets of all banks that extended their loans to Lehman, as well as a drop in interbank lending. In this case, however, the U.S. Treasury department refused to take it over.

In the next day, the Federal Reserve decided to intervene by offering an $85 billion loan to AIG, the largest insurance company in the U.S., to cover the losses deriving from selling credit default swaps (CDSs): contracts safeguarding all holders of debt instruments, such as MBSs, in case of default on the related loans.

Soon, the Bush administration recognized the need for a government intervention, establishing the Emergency Economic Stabilization Act (EESA) and the Troubled Asset Relief Program (TARP) to purchase $700 billion in risky assets. By the end of 2008, the U.S. government became part-owner of over 200 institutions.

The response of the government was reinforced by the unprecedented quantitative easing programs of the Fed, permitting the central bank to increase liquidity while purchasing U.S. Treasury bonds or MBSs from prime mortgages, offering loans to owners of securities and buying debt from Fannie Mae and Freddie Mac.

Figure 5. Currency in circulation (2000-2014):



Data source: World Bank

By the end of the programs, in 2014, the Fed injected in the U.S. economy over $4 trillion. The recovery from the Great Recession required other $787 billion of the 2009 American Recovery and Reinvestment Act[8] to become effective: in the same year, in fact, financial markets regained stability and GDP started growing.

To prevent long-term contagion risk, instead, the U.S. Congress passed the Dodd-Frank Wall Street Reform (2009) aimed at prohibiting banks speculative activities, monitoring systemic risk with the FSOC[9], regulating derivatives, requiring higher levels of capital and imposing standards for mortgages.

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[8] American Recovery and Reinvestment Act: stimulus package passed by the 111th congress and signed by President Obama to create jobs and fund projects in infrastructure, education, health and green energy.

[9] Financial Stability Oversight Council: U.S. federal government body established by the Dodd-Frank Act to identify systemic risks and coordinate regulatory responses to threats of financial stability.

1.3 FROM WALL STREET TO THE EUROZONE.

The GFC did not only lead to a liquidity crunch in the U.S. banking sector. In 2009, it culminated in the European sovereign debt crisis, affecting the PIIGS[10] countries and exposing the structural deficiencies of the European Monetary Union (EMU).

The first Eurozone country to be heavily hit by a crisis was Greece, whose October 2009 elections made the opposition, the Panhellenic Socialist Movement, win. The new prime minister, George Papandreou, discovered soon the excessive borrowing of the previous administration and estimated a higher yearly budget deficit: 12.5%.

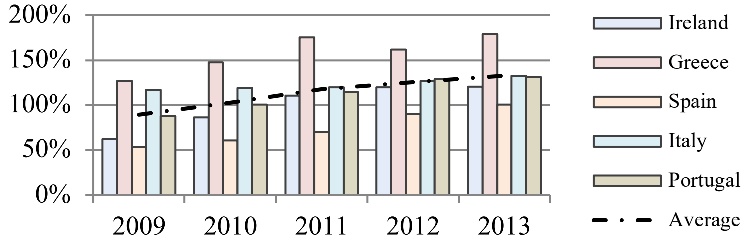
The deficit was four times higher than permitted by the Maastricht Treaty's limits and made rating agencies, firstly Fitch and Standard & Poor's, downgrade its credit rating. The event triggered a chain reaction: the Greek stock market drastically fell and sovereign debt reached $400 billion, nearly 113% of the national GDP.

After the downgrade to junk status of the Greek credit rating, a $143 billion bailout package was agreed by Papandreou, the IMF, and Eurozone lenders. To face the high volatility in the euro, instead, the IMF established a $1 trillion emergency fund: by June 2010, the euro plummeted to $1.19, its lowest since March 2006.

"*Looking at Europe from afar it must be difficult to understand the Eurozone crisis. How could a small nation's refinancing difficulties trigger a systemic crisis for the euro that brought financial markets to the brink?*" (Baldwin and Giavazzi, 2010).

Being part of the Eurozone, Greece shares the same currency as the others member States, making its stability crucial for the the entire ecosystem. From 2009 to 2013, investors' confidence deteriorated, causing a housing bubble in Spain, a depressed banking sector in Ireland and a sluggish economic growth in Portugal and Italy.

Figure 6. Gross Government Debt as a % of GDP (2009-2013):



Data source: World Bank

As the debt crisis was revealing the Eurozone regulatory framework flaws, leaders obliged signatories to cap government deficits at 3% of GDP, created a permanent bailout fund with the European Stability Mechanism and combined mostly 6.000 institutions in a banking union aimed at supervising the reserves of capital.

[10] PIIGS countries: Portugal, Italy, Ireland, Greece and Spain.

2. SYSTEMIC RISK MEASUREMENT.

2.1 SYSTEMIC RISK OVERVIEW.

In 2008-2009 economists realized how connected financial markets were: the U.S. subprime mortgage crisis did not just impact one market, as the interconnectedness of financial markets made it spread across the globe. Hence, while interdependence increases competitiveness, it also spreads risks during economic downturns.

Starting from the GCF, it became essential to quantify the systemic risks originated from interconnectedness: a rough task, as Smaga (2014) underlined that there is no academic consensus around systemic risk. The only certainty is that it encompasses individual risks faced by institutions: credit[11], liquidity[12] and operational[13] risks.

One of the major difficulties in defining what systemic risk is arises from its nature. Although individual risks are related to a specific financial entity, systemic risk is indirect. Yet, it is often related to (i) the growth of financial markets, (ii) regulatory frameworks, and (iii) the collective actions of financial market participants.

These features have been identified by the majority of the comparative studies that tried to provide a definition. In 2000, Dow suggested that systemic risk stems from excessive risky behaviours by individual or groups of traders, a culture prioritizing short-term gains, management failures and banks' exposure to symmetric shocks.

Analyses conducted by Bisias et al. (2012) and de Haan (2003) pinpoint that based on the aspect that one emphasizes, i.e. imbalances, information asymmetry or asset bubbles, systemic risk has a specific definition. This is the reason why to quantify its magnitude, diverse measures and principles must be adopted.

Broadly, Eijffinger's (2012) analysis conveys that systemic risk causes a fall in the confidence of investors, as well as an increase in uncertainty on the functioning of the whole financial system and its counterparts. In few words, the author identified systemic risk with the risk of contagion and adverse effects on the real economy.

Consistently, as noted by Smaga (2013), central banks avoid proposing definitions of systemic risk. Oosterloo and de Haan's 2003 survey highlights that central banks often prioritize defining financial instability over the former risk, often associated with " *a threat to the financial system*" (i.e. Czech National Bank or Riksbank).

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[11] Credit risk: the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms (Basel Committee on Banking Supervision).

[12] Liquidity risk: the risk to an institution's financial condition or safety and soundness arising from its inability to meet contractual obligations (Basel Committee on Banking Supervision).

[13] Operational risk: the risk of loss resulting from inadequate or failed internal processes, people, and systems or from external events (Basel Committee on Banking Supervision).

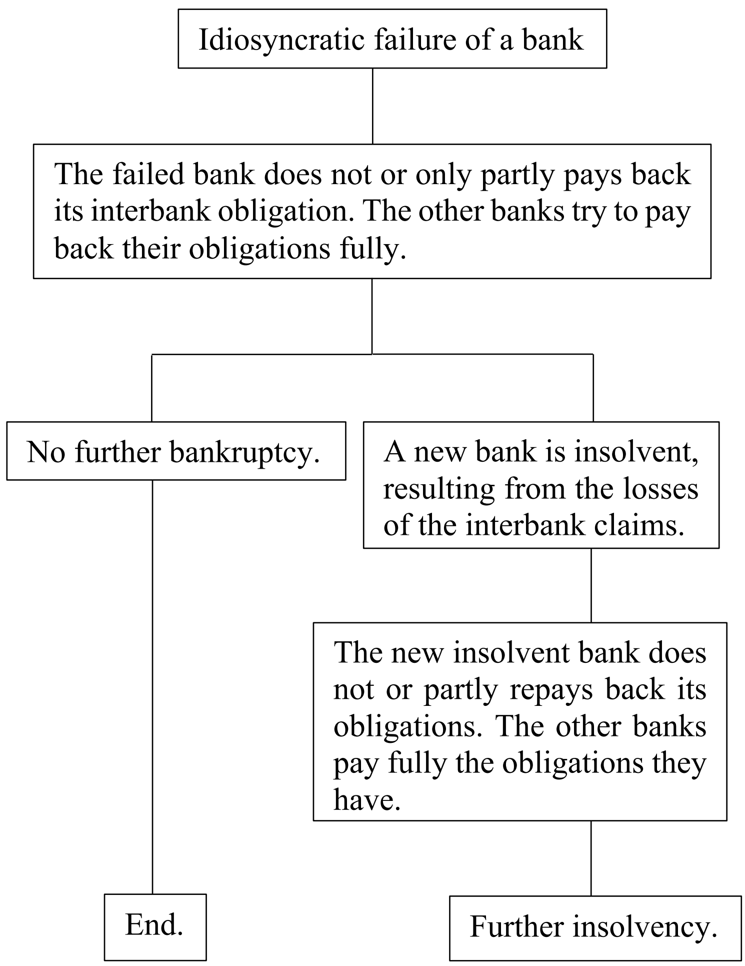
Based on Smaga (2014), which examined the prevalent systemic risk definitions:

- Systemic risk is depicted as a phenomenon that affects a large portion of the financial system. It can disrupt the performance and the market functioning under several aspects, particularly regarding financial intermediation.
- Central to the concept of systemic risk is the propagation of shocks among the interconnected entities of the financial system, which ultimately has an effect on the goods and services sector, hence in the real economy.
- It gained popularity in the mid-1990s, when the academia emphasized the contagion effect. After the GFC, instead, there was a shift in focus towards the disruption in the functioning of the financial system, i.e. defaults.

As a consequence, the author identified systemic risk as "*the risk that a shock will result in such a significant materialization of imbalances that it will spread on a scale that impairs the functioning of the financial system and to the extent that it adversely affects the real economy*" (Smaga, 2014).

Based on the previous systemic risk definition "*contagion serves as the mechanism through which instability escalates across the whole financial system*". Essentially, it occurs when (i) the spread of shocks exceeds what can be justified by economic fundamentals, (ii) fluctuations are extreme and (iii) there are domino effects.

Figure 6. The procedure of domino effects of Lublóy (2004):



3 DIEBOLD AND YILMAZ FRAMEWORK.

3.1 FOUNDATIONS OF SPILLOVER ANALYSIS.

Oxford Reference defines spillovers as «*unpriced and indirect effects of economic activity*». Yet, spillovers are categorized into economic (e.g. trade, exchange rates, migration) and financial (e.g. banking systems, financial flows). In either case, the pre-Diebold and Yilmaz literature is quite wide and dates back to Keynes.

As highlighted by Korinek, Loungani, and Ostry (2022), Keynes and Harry Dexter White were the first to recognize cross-border spillovers and influence the original Articles of Agreement for the International Monetary Fund (IMF). These contracts, in fact, allowed countries to manage financial instability with capital controls.

In the early 1950s, Meade (1951) observed that a country's economic disturbances could impact the imports and exports of its trade partners. However, when dealing with international trade, it is essential to mention Obstfeld and Rogoff (1995), who argued that variations in capital flows could result into cross-border shocks.

Yet, one of the earliest models that formalized the idea of spillovers was developed by Mundell and Fleming (1960). Despite Corsetti (2007) believed that their model was subclassed by the New Open Economy Macroeconomics (NOEM), it analysed the impact of fiscal and monetary policies in presence of open economies[14].

Turning to finance, in the 1990s, King and Wadhwani (1990) observed that a stock market crisis could trigger another stock market crash via the influence on investor behaviour. Yet, the most relevant paper of the period pertains to Engle and Granger (1987), whose work influenced the research of Campbell and Shiller (1987).

Precisely, in their paper "*Cointegration and tests of present value models*" (1987), Campbell and Shiller tested whether stock prices and dividends were cointegrated. Here, two time series are said to be cointegrated if they have a common stochastic drift; this was the case, since prices and dividends often tend to move together.

On the volatility side, the most relevant models are the Autoregressive Conditional Heteroskedasticity (ARCH) model developed by Engle (1982) and the Generalized ARCH (GARCH) model formulated by Bollerslev (1986). These models were also employed by Hamao et al. (1990) to demonstrate price and volatility effects.

Precisely, the research paper of Hamao et al. (1990) "*Correlations in price changes and volatility across international stock markets*" studied how changes in the price and volatility of a stock market (e.g. New York, Tokyo) impact others, contributing significantly to the literature on cross-market price and volatility spillovers.

[14] The Mundell and Fleming (1960) model places a particular relevance on exchange rates.

In the same year, Engle, Ito, and Lin (1990) distinguished transmission patterns by introducing the concepts of "*meteor showers*" and "*heat waves*". While the former implies that volatility in a forex market could potentially affect volatility in another market, the latter refers to the persistence of volatility in the same market[15].

After examining early volatility spillover models, we can now review the literature on contagion. Hence, in the early 2000s, Forbes and Rigobon (2002) distinguished interdependence from contagion. In fact, after adjusting for increases in volatility, financial crises cannot significantly impact stock market co-movements[16].

Forbes and Rigobon (2002) are not the only scholars to focus on contagion. Amidst the Asian crisis (1997-1998), Baig and Goldfajn (1999) analyzed currency market, stock market, interest rate, and sovereign spread correlations to confirm that "*there was an element of financial panic at the onset of the [1990s] Asian crises*".

Beside the Asian crisis, Kaminsky and Reinhart (2000) studied financial contagion even during the Mexican peso crisis (1994-1995), the Russian crisis (1998) and the Brazilian crisis (1999). Their major result was that herd instincts[17] could determine the spread of a crisis, but that the cause were still economic fundamentals.

In such a context, Diebold and Yilmaz (2009) developed the spillover index, which measures the return and volatility spillovers transmitted between different markets, assets, and regions. Hence, as we will observe in *Chapter 3.2*, this index permitted scholars to confirm the interconnected nature of the global financial system.

Moving to more recent papers, in "*How sovereign is sovereign credit risk?*" (2011) Longstaff, Pan, Pedersen, and Singleton assessed the propagation of 2008 liquidity shocks across global markets; particularly, they examined how changes in liquidity impacted both sovereign bond spreads and Credit Default Swaps (CDS).

In the same year, Adrian and Brunnermeier (2016) developed another approach to quantify systemic risk, known as Conditional Value at Risk (CoVaR). Precisely, it quantifies the value at risk of the whole financial system given a specific distressed institution; it is in fact used to identify systematically important entities.

Over the next years, we expect the spillover literature to continue growing. In fact, in the last decades, various scholars started quantifying spillovers by implementing Lévy copulas (Kallsen and Tankov, 2006), multivariate GARCH estimation of the CoVaR (Girardi and Ergün, 2013), and machine learning (Bussmann et al., 2020).

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[15] Engle, Ito, and Lin (1990) focused on volatility spillovers between the most important currency markets (e.g. yen/dollar, pound/dollar).

[16] They demonstrated that contagion is not caused by structural changes, but only by increased volatility.

[17] According to Cambridge Dictionary, a herd instinct is «*a situation in which people act like everyone else without considering the reason why*».

3.2 THE SPILLOVER INDEX.

In *Measuring Financial Asset Return and Volatility Spillovers with Application to Global Equity Markets* (2009), Diebold and Yilmaz present a metric for measuring the interconnectedness of asset returns and volatilities, both during normal market conditions and crisis periods, with a time period spanning from the 1990s to 2009.

Since the interest towards financial markets interdependence has emerged with the 1990s Asian crisis, the authors introduced the spillover index, a quantitative metric fluctuating over time. This stands as a further contribute to the research of King et al. (1994) and Forbes and Rigobon (2002), focusing on correlation coefficients.

In the basic Diebold and Yilmaz framework (2009), the spillover index is obtained from a vector autoregression (VAR) of the Sims (1980) tradition. The approach adopted by the authors is however different, since they estimate spillover effects across markets using the variance decomposition.

For simplicity, let consider a bivariate covariance stationary vector autoregression model (VAR) with one lag:

$x_t = \Phi x_{t-1} + \varepsilon_t$, $\varepsilon_t \sim i.i.d.(0, \Sigma)$, where $\Sigma = var(\varepsilon_t)$

Here, $x_t{}' = (x_{1t}, x_{2t})$, and Φ is a $2x2$ parameter matrix, hence in a matrix form:

$$\begin{pmatrix} x_{1t} \\ x_{2t} \end{pmatrix} = \begin{pmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{pmatrix} \begin{pmatrix} x_{1(t-1)} \\ x_{2(t-1)} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

From which the VAR equations, describing the dynamics of the VAR system, are:

$$x_{1t} = \phi_{11} x_{1(t-1)} + \phi_{12} x_{2(t-1)} + \varepsilon_{1t}$$
$$x_{2t} = \phi_{21} x_{1(t-1)} + \phi_{22} x_{2(t-1)} + \varepsilon_{2t}$$

Covariance stationarity allows us to use also a moving average representation:

$$x_t = \Theta(L)\varepsilon_t$$

With $\Theta(L) = (I - \Phi L)^{-1}$, although we can write the MA representation as:

$$x_t = \mathrm{A}(L) u_t$$

Where $\mathrm{A}(L) = \Theta(L) Q_t^{-1}$, $u_t = Q_t \varepsilon_t$, $E(u_t u_t') = I$[18] and Q_t^{-1} is "*the unique lower-triangular Cholesky factor*[19] *of the covariance matrix of* ε_t" (Diebold and Yilmaz).

[18] The identity holds because the covariance matrix of the residuals is the identity matrix.

[19] Decomposition of a positive-definite matrix in the product of a lower triangular matrix and its transpose.

Once having considered the moving average representation, it is possible to exploit the Wiener-Kolmogorov formula to obtain the optimal[20] one-step-ahead forecast:

$$x_{t+1,t} = E[x_{t+1}|\mathrm{F}_t] = E[\Phi x_t + \varepsilon_{t+1}|\mathrm{F}_t] = E[\Phi x_t|\mathrm{F}_t] + \mathrm{E}[\varepsilon_{t+1}|\mathrm{F}_t] = \Phi \mathrm{x}_\mathrm{t}$$

Where the error vector of the forecast can be represented as the difference between the actual value of the time series at time $t+1$ and the forecasted value $x_{t+1,t}$:

$$e_{t+1,t} = x_{t+1} - x_{t+1,t} = A_0 u_{t+1} = A_0 u_{t+1} = \begin{pmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t+1} \\ \varepsilon_{2,t+1} \end{pmatrix}$$

With covariance matrix $E\left(e_{t+1,t}e'_{t+1,t}\right) = A_0 E(u_t u_t')A_0' = A_0 I A_0' = A_0 A_0'$. Thus, for every variable x_i in the system, the one-step-ahead forecast error is determined by the elements of the A_0 matrix. As a result, the sum of squares of the elements corresponding to the forecast errors are:

$$a_{0,11}^2 + a_{0,12}^2$$
$$a_{0,21}^2 + a_{0,22}^2$$

Analyzing the previous expression, it is evident that the Forecasting Error Variance Decomposition (FEVD) allows to split the forecast error variance of every variable into various parts, attributable to the different shocks affecting the system. Diebold and Yilmaz (2009) believe that such an approach answers to the question:

"*What fraction of the one-step-ahead error variance in forecasting x_1 is driven by shocks in x_1? By shocks in x_2? Or similarly, what fraction of the error variance in forecasting x_2 is due to shocks to x_1? By shocks in x_2?*".

To continue, the authors define the «own variance shares» as the proportion of the forecast error variances in predicting x_i attributable to the shocks occurring within that same variable x_i, where $i = 1,2$. On the contrary, they call the other proportion «cross-variance shares» or even «spillovers».

As a result, «cross-variance shares», related to the interconnectedness side, are the proportion of forecast error variances in predicting x_i attributable to all the shocks occurring in another variable x_j, where $i, j = 1,2$ but $i \neq j$. Thus, in the first-order two-variable VAR case there are only two spillovers:

- x_{2t} disturbances impacting on the forecast error variance of x_{1t}, accounting for $a_{0,12}^2$ of the total variance $a_{0,11}^2 + a_{0,12}^2$.
- x_{1t} disturbances impacting on the forecast error variance of x_{2t}, accounting for $a_{0,21}^2$ of the total variance $a_{0,21}^2 + a_{0,22}^2$.

[20] The Wiener-Kolmogorov prediction formula provides an optimal forecast in the sense that it minimizes the Mean Squared Error (MSE) of the forecast.

Being the overall spillover equal to $a_{0,12}^2 + a_{0,21}^2$ it is possible to construct an index by comparing it to the total forecast error variance $a_{0,11}^2 + a_{0,12}^2 + a_{0,21}^2 + a_{0,22}^2 = trace(A_0 A_0{}')$. The spillover index is therefore obtained by converting the previous ratio to a percentage:

$$S = \frac{a_{0,12}^2 + a_{0,21}^2}{trace(A_0 A_0{}')} x100$$

However, since the Diebold and Yilmaz (2009) index can not only be applied to a $VAR(1)$, it is possible to generalize the reasoning to the case in which there are p different lags and consider a $VAR(p)$ model:

$$x_t = \Phi_1 x_{t-1} + \Phi_2 x_{t-2} + \cdots + \Phi_{\mathrm{p}} x_{t-p} + \varepsilon_t$$

From which with a one step-ahead forecast:

$$S_1 = \frac{\sum_{i,j=1}^{N} a_{0,ij}^2}{trace(A_0 A'_0)} x100$$

Whereas with a H-step ahead forecast:

$$S_H = \frac{\sum_{h=1}^{H-1} \sum_{i,j=1}^{N} a_{h,ij}^2}{\sum_{h=1}^{H-1} trace(A_h A'_h)} x100$$

In the 2009 version Diebold & Yilmaz applied the spillover index to nominal local-currency stock market indexes from January 1992 to November 2007. The markets they considered for the analysis were divided in developed, i.e. U.S., Germany and Hong Kong, and emerging, i.e. Indonesia, South Korea, Philippines and Thailand.

Once having computed the returns as the change in log prices from Friday to Friday and accounted for inflation, the authors computed the return spillovers on the entire sample. Then, to track the spillover variations over time they sequentially analysed the data, using rolling windows of 200-weeks[21].

Interconnectedness can be further displayed through the «spillover table», in which every ij-th entry stands for the estimated contribution to the forecast error variance of the variable i, in their case a country, resulting from shocks to variable j. Hence, the off-diagonal column or row sums are the numerator of the spillover index.

The findings suggest that return spillovers display no burst but an increasing trend, associated with the rising financial market integration. Volatility spillovers showed an opposite behaviour: bursts during crisis periods, when the normal functioning of financial markets is disrupted, but no particular trend over the long-run.

[21] For rolling window analysis sizes of 50 to 250 periods are the most frequently employed.

3.3 DIRECTIONAL SPILLOVERS.

As already seen, Diebold and Yilmaz quantified financial interconnectedness with the spillover index, capturing return and volatility spillovers through the FEVD of VARs. Yet, as of 2009, their measure was affected by two significant limitations:

- Even if variable ordering should not impact spillover measures, the reliance on the Cholesky-factor identification made variance decompositions strictly tied to the parameters' structure.
- Previously, the metric was only applied to cross-country spillovers. Hence, it excluded spillovers across stocks of the same index, i.e. the $Dow\ Jones$[22], or across assets, i.e. bonds and equity.

Given the previous weaknesses, Diebold and Yilmaz extended the framework with their 2012 paper *Better to give than to receive: Predictive directional measurement of volatility spillovers*. In the revised version, indeed, they considered a generalized VAR approach, independent of ordering and including directional spillovers.

To begin with, let x_t be a N-variables covariance stationary $VAR(p)$ model:

$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$ with $\varepsilon \sim (0, \sum)$ a vector of $i.i.d.$ shocks.

Which in a moving average representation can be rewritten as:

$x_t = \sum_{i=1}^{\infty} A_i \varepsilon_{t-i}$ with recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$[23].

Following the base case, they obtain the contributions of the shocks by adopting a FEVD approach. A novelty is the absence of the Cholesky factorizations, ensuring orthogonal innovations but inducing order-dependence: an issue that can be solved through the generalized VAR approach (Koop, Peseran and Potter, 1996)[24].

The variance decomposition measure of Koop, Pesaran and Potter (KPPS) can still analyze the dynamic impact of shocks in multivariate time series, but does not have assumptions on variable ordering. This comes at a cost, since shocks are correlated and the forecast error variance contributions do no more sum to one.

Once again, Diebold and Yilmaz define the «own variance shares» as the shares of the forecast error variances of every variable x_i deriving from shocks in x_i, for $i = 1,2 \ldots, N$. As in the 2009 framework, even the «cross variance shares» are still the forecast error variance shares of x_i arising from shocks to x_j, for $i \neq j$.

[22] Dow Jones Industrial Average: stock market index measuring the performance of 30 large and publicly traded U.S. companies.

[23] As usual, A_0 is an NxN identity matrix with $A_i = 0\ \forall i < 0$.

[24] An additional contribution to the GVAR framework comes from Pesaran and Shin (1998).

What changes is the H-step ahead forecast error variance decomposition. With the KPPS measure, indeed, it becomes:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ij}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma e_i\right)}$$

With σ_{ij} being the standard deviation of the j-th equation shock, e_i a vector having one in the i-th position and zeros in all the others, $\sum$ the shocks variance-covariance matrix and $\sum_{j=1}^{N}\theta_{ij}^{g}(H)$ the sum of the contributions to the forecast error variance:

$$\sum_{j=1}^{N}\theta_{ij}^{g}(H) \neq 1$$

Next, it is possible to normalize the entries of the variance decomposition matrix[25]:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)}$$

From which the total volatility spillover index can be represented as the sum of the normalized terms of the variance decomposition matrix divided by the overall sum of the elements. Thus, it measures the portion of volatility transmissions across all pairs of markets relative to the total volatility in the system:

$$S^{g}(H) = \frac{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}100 = \frac{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}100$$

The total spillover index, quantifying the impact of volatility shocks on the overall forecast error variance, is not the only measure that Diebold and Yilmaz introduced in their 2012 study. Thereafter, they computed the directional spillovers, indicating the spillovers received by the market i from all the other markets j[26]:

$$S_{i\cdot}^{g}(H) = \frac{\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}100 = \frac{\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}100$$

Or, alternatively, analyzing the spillovers transmitted by market i to all markets j, it is possible to measure the proportion of volatility shocks originating from market i and transmitted to the other markets, relative to the total volatility transmission:

$$S_{\cdot i}^{g}(H) = \frac{\sum_{j=1}^{N}\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}100 = \frac{\sum_{j=1}^{N}\tilde{\theta}_{ji}^{g}(H)}{N}100$$

[25] Even though the normalization passes through the sum of the rows of the variance decomposition matrix, an alternative is using the column sum.

[26] The measure was not considered in the 2009 framework as it requires variance decompositions invariant to variable ordering.

As a consequence, the total spillovers can be decomposed in the various directional spillovers coming from or to a particular source, which can be a market. However, they calculated even net spillovers: the differences between the shocks transmitted to the markets j from the market i and the shocks received from the markets j.

Apart from the net volatility spillovers, which from market i to other markets j are:

$$S_i^g(H) = S_{\cdot i}{}^g(H) - S_{i\cdot}{}^g(H)$$

It is feasible to analyze net pairwise spillovers, the last measure of the 2012 study. Measuring the contribution of every market volatility to the others, the net pairwise volatility spillovers are computed as:

$$S_{ij}^g(H) = \left(\frac{\tilde{\theta}_{ji}^g(H)}{\sum_{i,k=1}^N \tilde{\theta}_{ik}^g(H)} - \frac{\tilde{\theta}_{ij}^g(H)}{\sum_{j,k=1}^N \tilde{\theta}_{jk}^g(H)}\right)100 = \left(\frac{\tilde{\theta}_{ji}^g(H) - \tilde{\theta}_{ij}^g(H)}{N}\right)100$$

Thus, they are the difference between the shocks from the market i to the market j and the shocks from the market j to the market i. In simpler terms, they quantify the net effect of volatility transmissions between two markets. If $S_{ij}^g(H)$ is positive, it indicates that market i transmits more volatility to market j than the opposite.

In *Better to give than to receive* Diebold & Yilmaz focus on the volatility of returns of four U.S. asset classes. With this aim, they took into account the S&P 500 index, the 10-year Treasury bond yield, the dollar index futures and the Dow-Jones index. In all cases, to estimate daily volatility they calculated the daily variance as[27]:

$$\tilde{\sigma}_{it}{}^2 = 0.361x\left[\left(In(P_{it}^{max}) - In\left(P_{it}^{min}\right)\right]^2\right.$$

With P_{max} being the high price and P_{min} the low price for market i on day t.

However, since $\tilde{\sigma}_{it}{}^2$ just estimates the daily variance, on an annual basis it becomes $\hat{\sigma}_{it} = 100\sqrt{365 \cdot \tilde{\sigma}_{it}{}^2}$. With this measure, the key findings are that: (i) while bonds and stocks are equally volatile, commodities and FX markets are not, (ii) volatility has high persistence[28] and (iii) during crises, markets exhibit volatility spikes.

Even if the metrics differ, the spillover table and the 200-week rolling-window are constructed in the same way as in the 2009 approach. Overall, the results achieved is that during economic downturns, such as in 2008, the relevance of the volatility spillovers from the stock market to other markets increases[29].

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[27] The approach derives from Parkinson (1980).

[28] A similar result was achieved by Andersen, Bollerslev, Christoffersen and Diebold (2006).

[29] The finding can be also reached with the high state/low state indicator of Edwards & Sumsel (2001).

4 HANDLING FINANCIAL NETWORKS.

4.1 HIGH-DIMENSIONAL VARS.

As previously observed by Korobilis and Yilmaz (2018) the estimation of financial spillovers requires high-dimensional VARs. However, the issue of dimensionality can be tackled with various approaches, first of all through different factor models, which gained popularity in the late 1990s and early 2000s.

Over the past three decades, in fact, the prediction of extensive time series data has relied more and more on dynamic factor models. Their efficacy, initially illustrated by Forni et al. (2000) was further confirmed by Stock and Watson (2002b), which captured the common features of a wide range of macroeconomic variables[30].

In addressing the challenges of high-dimensionality, shrinkage methods and sparse modeling (Tibshirani, 1996; Zou, 2006; Yuan and Lin, 2006) are gaining a notable attention too. Unlike factor models, used to find a common structures among time-series, shrinkage methods impose specific structures on parameter vectors.

Sparse VAR models, in particular, provide distinct advantages over factor models. In the first place, they facilitate direct analysis of variable-to-variable relationships, including impulse response and FEVD (Kock and Callot, 2015). Furthermore, their one-step estimation allows for a greater efficiency (Basu and Michailidis, 2015).

In addition to sparse VAR models, there are other variants designed to handle high-dimensional datasets, such as Bayesian VAR models (Ban´bura et al., 2010). Their popularity comes from their robust parameter estimates and high accuracy, but the careful specification of prior distributions may pose implementation challenges.

Despite the existence of additional techniques, including regularized VAR models (Kock and Callot, 2015; Demirer et al., 2018) and low-rank VAR models (Carriero et al., 2011), it is relevant to mention that the dimensionality problem does not only come from incorporating and modeling numerous time series (Basu et al., 2015).

The major difficulty arises from the parameter space of VAR models, which grows quadratically with the number of variables and leads to a depletion of the available degrees of freedom. As a result, if a VAR has $p = 4$ lags and a number of variables equal to $J = 60$, there will be $14{,}400$ parameters to estimate from the data.

A heavy parametrization could constitute a serious threat to the estimation of high-dimensional VARs (Hecq et al., 2023). However, scholars are solving the difficulty by adopting regularization techniques like the LASSO, which "*perform better than standard Bayesian methods*" (García and Rambaud, 2022).

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[30] These include GDP growth rates, inflation rates, interest rates, unemployment rates, consumer spending, investment levels and other key economic indicators.

4.2 LASSO AND ADAPTIVE LASSO.

The discussion on high-dimensional VARs suggests that when working with large datasets, dimension reduction is essential. In fact, although we often minimize the error by including a large number of variables, the selected model should also be interpretable (Fan et al., 2015) and satisfy four different criteria:

- Prediction accuracy, measuring what percentage of predictions are correct.
- Interpretability, indicating how much the models' decisions are intelligible.
- Stability, assessing how consistent the model performance is with new data.
- Calculation complexity, determining the computational resources required.

With this respect, Ordinary Least Squares (OLS) regressions offer interpretability, yet often lead to overfitting and a low predictive accuracy. Ridge regressions solve the issue by shrinking the coefficients, but they are not capable of reducing variable dimensionality, resulting in less interpretable models.

To address the issue, in 1996 Tibshirani proposed a model called Lasso, satisfying the model selection criteria. However, before analysing the regularization method, it is necessary to define what a Ridge regression is. Firstly introduced by Hoerl and Kennard in 1970, Ridge regression comes from OLS and imposes that:

$$\hat{\beta}_{ridge} = \arg\min_{\beta}\left\{\|Y - X\beta\|^2 + \lambda_1 \textstyle\sum_j \beta_j^2\right\}$$

Therefore, it is a linear regression method that adds a penalty to the traditional least squares objective function. Its penalty term, commonly referred to as the «L2 norm penalty», is proportional to the square of the coefficients, and it encourages smaller but non-zero coefficients (Hoerl and Kennard, 1970).

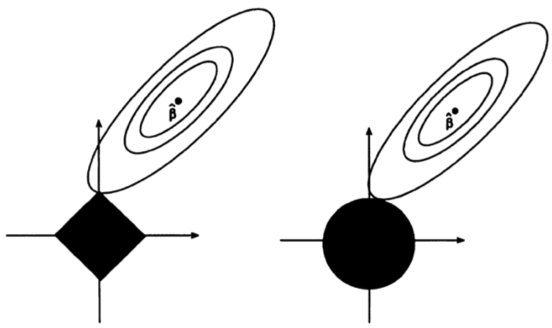
Lasso, on the other hand, adds a penalty term proportional to the absolute value of the coefficients, known as the «L1 norm penalty». Its penalty term not only shrinks the coefficients, but has also the power of setting some coefficients exactly to zero, performing as a result variable selection:

$$\hat{\beta}_{lasso} = arg\min_{\beta}\left\{\|Y - X\beta\|^2 + \lambda \textstyle\sum_j |\beta_j|\right\}$$

Considering only two coefficients, respectively $\hat{\beta}_1$ and $\hat{\beta}_2$, the advantages of Lasso over Ridge are evident. In the case of Lasso regressions, the penalty term is linear and assumes a diamond shape. Hence, the intersection with the constraint boundary occurs only when one of the two coefficients is exactly zero (*Figure 7*).

On the other hand, the penalty term of the Ridge regression is squared and assumes a circular shape. This shape implies that the constraint boundary intersects with the coefficient space at points where neither $\hat{\beta}_1$ nor $\hat{\beta}_2$ are exactly zero. Consequently, Ridge regressions tend to shrink coefficients to zero without eliminating them.

Figure 7. L1 norm penalty versus L2 norm penalty:



Data source: Tibshirani (1996)

As already discussed, Lasso combines the advantages of both Ridge regression and subset selection. It performs variable selection and continous shrinkage, balancing the bias-variance trade-off[31] (Zou, 2006) and improving prediction accuracy. Still, it suffers from relevant limitations, among which the absence of oracle properties.

In the context of statistical modeling, oracle properties refer to desirable properties that an estimator should possess. Specifically, with variable selection methods like Lasso, having oracle properties means that the estimator should be efficient and in particular (i) consistent, (ii) unbiased, and (iii) asymptotically normal (Zou, 2006).

However, according to Fan and Li (2001), Lasso's bias issues result in the absence of oracle properties. Yet, the systematic deviations of the model's predictions from the true values suggest that Lasso might not accurately estimate the coefficients of the model, leading to inconsistent estimators.

Additionally, high correlations among predictors make Lasso performance lower. Zou's research highlighted that even if predictors are independent, the performance might not increase. This is particularly true in the cases in which the dimensionality of the data is high and there are substantial correlations among variables.

To resolve the issue Zou (2006) proposed the adaptive Lasso estimator, a variation of the Lasso regression method that adapts the penalty weights for every predictor. The adaptive weighting allows the model to shrink less relevant variables in a more aggressive way, while still preserving the more important ones:

$$\hat{\beta}_{alasso} = \arg\min_{\beta}\left\{\|Y - X\beta\|^2 + \lambda \sum_j \frac{1}{\omega_j}\left|\beta_j\right|\right\}$$

Where $\omega_j = \left(\left|\hat{\beta}_{OLS_j}\right|\right)^{\gamma}$ are the weights for regression coefficients[32].

[31] Balance between bias, which arises from oversimplified models, and variance, which comes from models being too sensitive to training data fluctuations.

[32] Normally, the largest coefficients receive the smallest weights and vice versa.

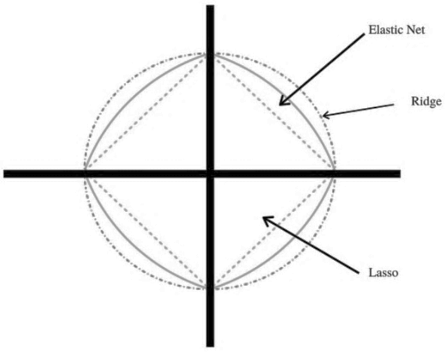
4.3 ELASTIC NET TECHNIQUES.

Similarly to the adaptive Lasso, the Elastic Net (Enet) technique was developed as a response to the limitations of the Lasso regression, specifically in managing high predictor correlation. In the Enet, variable selection is performed through a mixture of L1 and L2 penalties (Zou and Hastie 2005), resulting in the following estimator:

$$\bar{\beta}_{elasticnet} = \arg\min_{\beta} \begin{Bmatrix} \|Y - X\beta\|^2 \\ +\lambda_1 \sum_j |\beta_j| + \lambda_2 \sum_j |\beta_j|^2 \end{Bmatrix} \text{ with } \lambda_1 \sum_j |\beta_j| + \lambda_2 \sum_j |\beta_j|^2 < t$$

Apart from mentioning that the Enet estimator is characterized by positive weights, reason why $\lambda_1, \lambda_2 > 0$, it is possible to notice that as λ_1 approaches zero, the Enet behaves as a Ridge regression, and vice versa for Lasso. Consequently, the method can be perceived as a combination of Lasso and Ridge (*Figure 8*).

Figure 7. L1 norm penalty versus L2 norm penalty:



Data source: CFI

Even though Enet demonstrates progress in generating sparse models with a good prediction accuracy, particularly in cases of high predictor correlation, it still lacks some oracle properties. Hence, to improve the technique Zou and Zhang combined it with the adaptive Lasso method[33] (Zou and Zhang, 2009).

In any case, to select the optimal value of the tuning parameter λ it is necessary to employ model selection criteria, quantifying the goodness of fit of each model and penalizing complexity. Specifically, the research will focus on the most commonly used criteria, namely the Akaike and the Bayesian information criteria:

- The Akaike Information Criterion (AIC) is defined as $AIC = 2k - 2In(L)$, where k represents the number of parameters and L the likelihood function.
- The Bayesian Information Criterion (BIC) is instead used when information is incomplete. Defined as $BIC = 2In(k) - 2In(L)$, it still penalizes model complexity, but it places a heavier penalty on models with more parameters.

[33] Since the best performing model is recognized in the adaptive Lasso, in the empirical study Enet will not be considered.

5. PRELIMINARY ANALYSIS.

5.1 DATASET.

Based on the results of Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012) the study aims to compute the most acknowledged connectivity measures, notably the spillover index and the dynamic spillovers. Hereafter, to estimate these metrics, we considered 14 equity indexes of the major economies of the world.

The preliminary analysis, preceding the application of the connectdeness measures to 70 leading banks, ranges from 2004-01-01 to 2024-01-01 and includes different stock markets, precisely the U.S., the U.K., Germany, France, Italy, Spain, Canada, Brazil, Mexico, Australia, India, Hong Kong, Japan and South Korea (*Figure 8*).

Figure 8. Equity indexes (2004-2024):

Index name	*Country*	*Composition*	*Market Cap.*
S&P 500 (GSPC)	U.S.	500 large U.S. stocks	$43.25 trillion
Nikkei 225 (N225)	Japan	225 blue-chip companies listed on the TSE	$4.66 trillion
S&P/TSX (GSPTSE)	Canada	250 companies listed on the TSX	$3.49 trillion
FTSE 100 (FTSE)	U.K.	100 largest companies in the LSE by Market Cap.	$2.46 trillion
CAC 40 (FCHI)	France	40 largest companies of the Euronext Paris	$2.03 trillion
KOSPI (KS11)	South Korea	200 common stocks listed on the KPX	$1.88 trillion
S&P/ASX 200 (AXJO)	Australia	200 largest companies listed on the ASX	$1.63 trillion
DAX (GDAXI)	Germany	40 major companies trading on the FSE	$1.4 trillion
Hang Seng (HSI)	Hong Kong	82 largest companies listed on the HKEX	$1.4 trillion
BSE SENSEX (BSESN)	India	30 large companies listed on the BSE	$1 trillion

IBOVESPA (BVSP)	Brazil	50 stocks of the São Paulo Stock Exchange	$960.40 billion
IPC Index (MXX)	Mexico	35 stocks of the Mexican Stock Exchange	$594.22 billion
IBEX 35 (IBEX)	Spain	35 stocks traded on the Madrid Stock Exchange	$587.27 billion
FTSE MIB (FTSEMIB.MI)	Italy	40 top traded stocks on the Borsa Italiana	$548.37 billion

Data source: Refinitiv, Nikkei 225 and CEIC, as of 15/03/2024, except for KS11 and BVSP.

With the goal of analyzing the indexes' return and volatility spillovers, it is crucial to show how did we compute returns. Adopting Yahoo Finance as a source, returns were determined by calculating the difference in natural logarithms of their weekly adjusted closing prices $r_t = In(P_t) - In(P_{t-1})$, tracked from Friday to Friday.

In the period spanning from 2004-01-01 to 2024-01-01 we accounted for a total of 1040 weeks, excluding just 3 observations for a data availability reason. The series of returns with which we worked on are showed in *Appendix 1* and have significant spikes in economic downturns, firstly during the 2008 housing market collapse.

In the series of returns, the peaks coincide with the major crises of the last 20 years, notably: (i) the 2008 GFC, (ii) the sovereign debt crisis starting at the end of 2009, and (iii) the WHO's announcement of COVID-19 as a pandemic. Turbulent market periods tend in fact to influence investor sentiment, leading to critical fluctuations.

As illustrated in *Figure 10* and *Appendix 2*, returns data exhibit the typical features observed in stock markets, firstly the deviation from a normal distribution. Yet, for all 14 indexes kurtosis values exceed 3[34] and skewness values are negative, reason why financial investors should expect frequent small gains and fewer large losses.

Besides non-normality, it is worth observing that the Akaike Information Criterion (AIC) suggests to use a $VAR(1)$ model. Applying a one-period lag, the Augmented Dickey-Fuller[35] test, conducted at a critical value of 5% and 10%, provides strong evidence against the presence of a unit root, suggesting stationary[36] time series.

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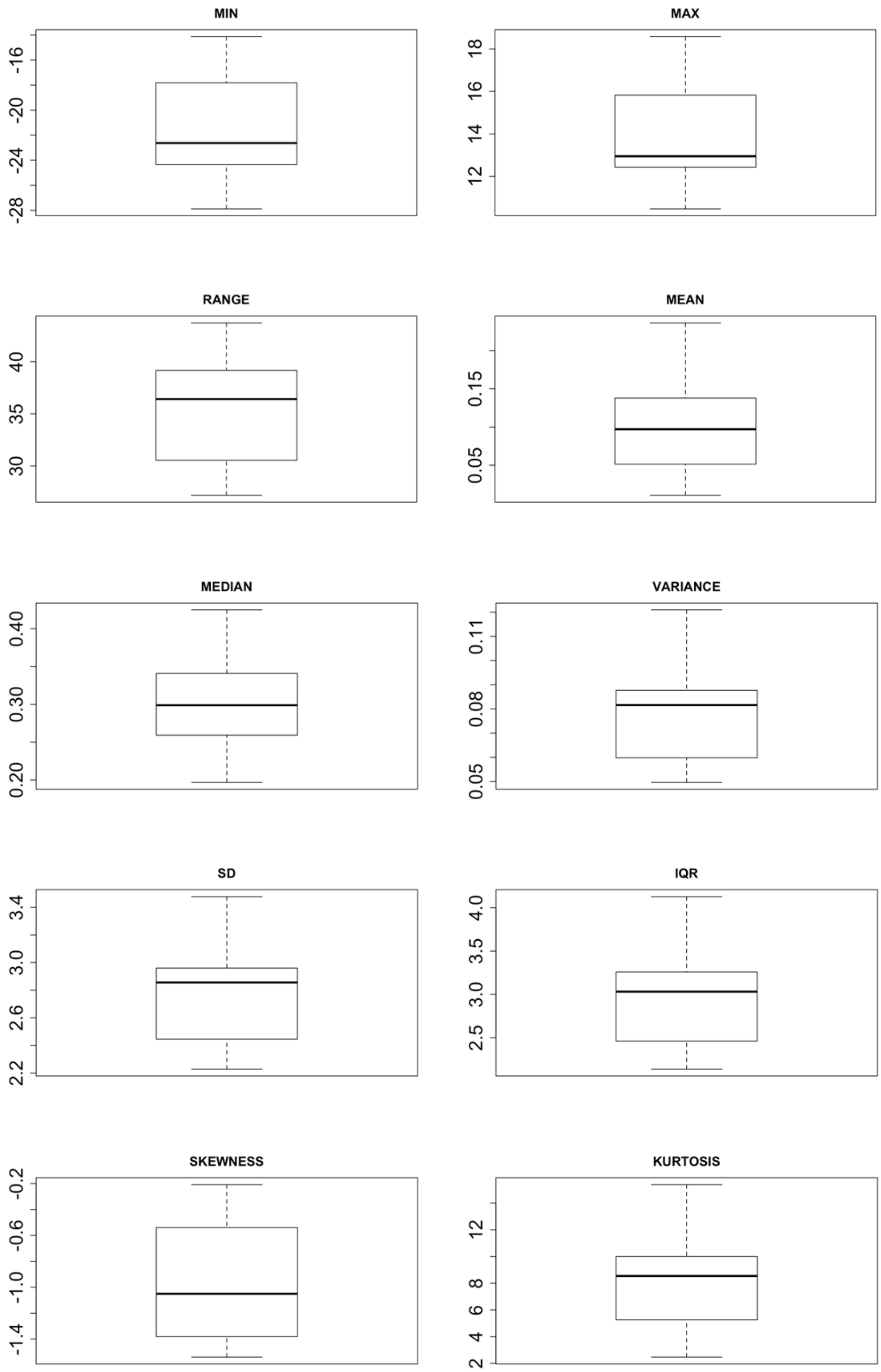
[34] Since in a normal distribution the kurtosis is 3, kurtosis values greater than 3 imply leptokurtosis.

[35] The Augmented Dickey-Fuller (ADF) test assumes the presence of a unit root under the null H_0.

[36] While for the covariance stationarity there is a reference in *Note 9*, a process is said to be strictly stationary if, for any of the values of $h_1, h_2, \dots, h_n$, the joint distribution of $(Y_t, Y_{t+h}, \dots, Y_{t+h_n})$ depends only on the intervals $h_1, h_2, \dots, h_n$ but not on the date t itself : $f(Y_t, Y_{t+h_1}, \dots, Y_{t+h_n}) = f(Y_\tau, Y_{\tau+h_1}, \dots, Y_{\tau+h_n}) \forall t, h$.

Figure 10. Descriptive statistics - Returns (2004-2024):

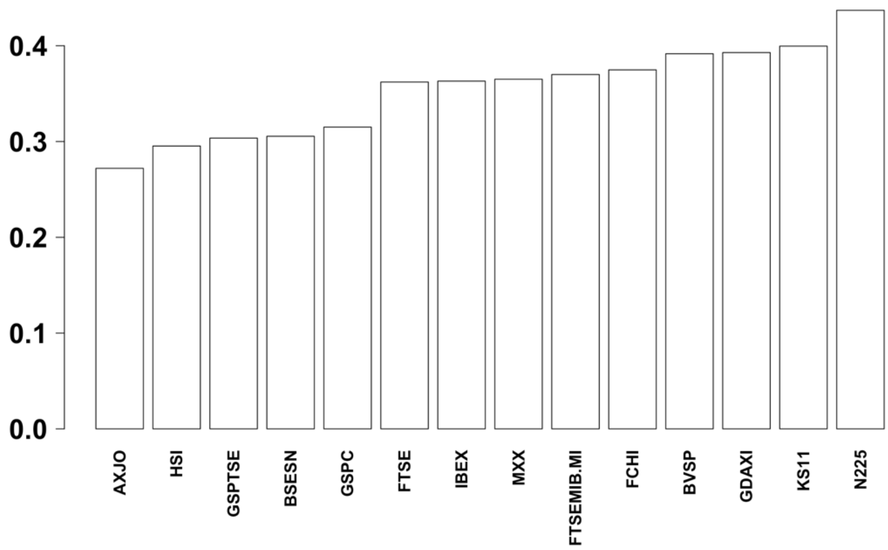


Data source: Yahoo Finance. All data, skewness and kurtosis apart, are in %.

Breaking down the returns' statistics, it is worth mentioning that the average range is 35.34%. Specifically, the lowest return range (27.20%) relates to the Australian S&P/ASX 200 Index (AXJO). The highest return range (43.70%), 16.50% above the former, is represented by the Japanese Nikkei 225 Index (N225) (*Figure 11*).

Their difference can be explained with various factors. First of all, the composition of the indexes. The S&P500/ASX 200 Index is highly weighted towards financials, basic materials, and healthcare. Yet, the Nikkei 225 Index (N225) includes mainly companies associated to the IT, consumer discretionary, and industrial sectors.

Figure 11. Return range (2004-2024):



Data source: Yahoo Finance.

Shifting towards volatilities, we did not use the formula employed by Diebold and Yilmaz (2012). As already seen, their estimation comes from Parkinson (1980) and captures the estimated volatility on a market i as the difference between the natural logarithm of the highest and lowest price. Thus, their volatilities are calculated as:

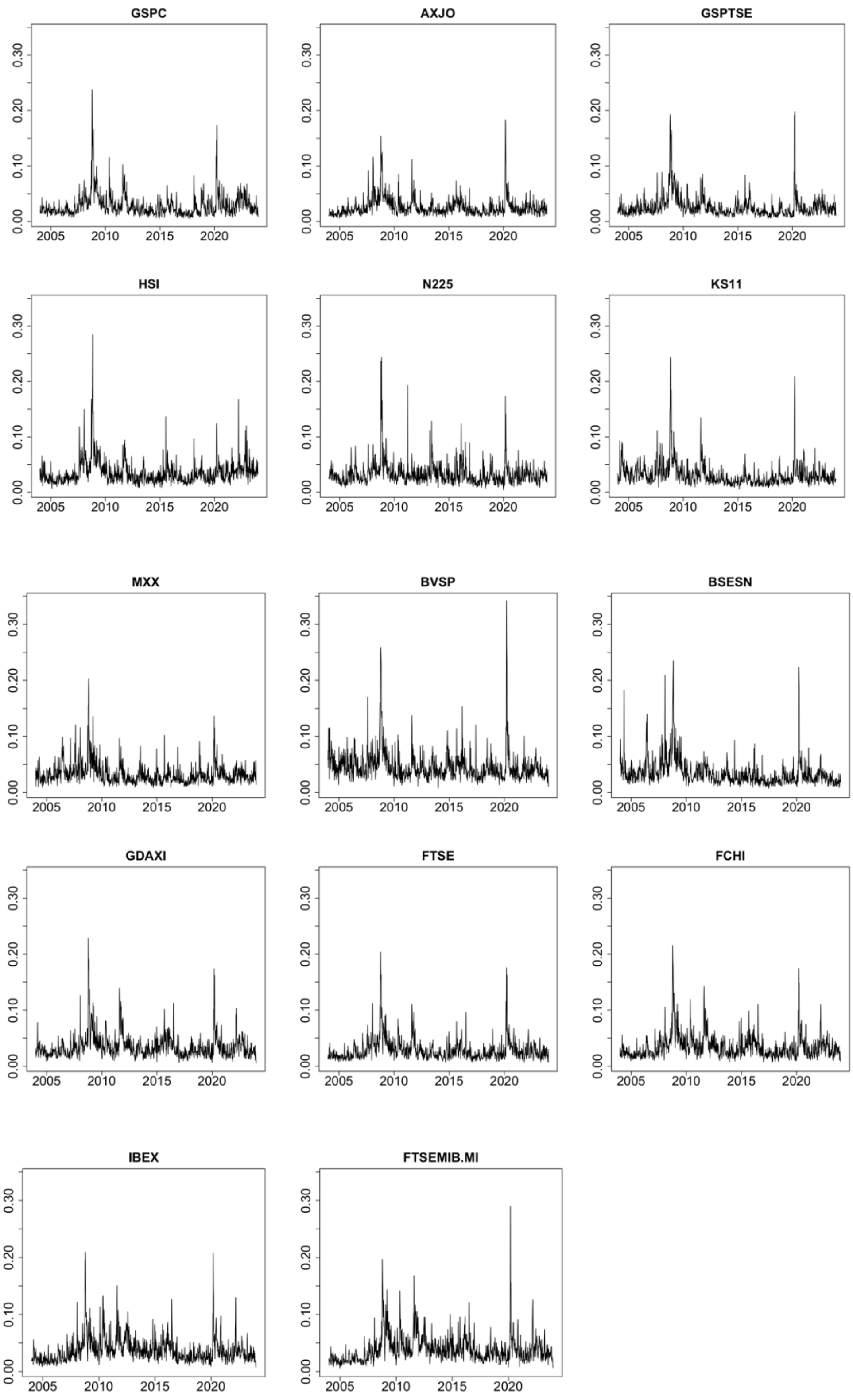
$$\tilde{\sigma}_P{}^2 = 0.361x\left[In\left(\frac{P_{it}^{max}}{P_{it}^{min}}\right)\right]^2$$

A slightly more accurate metric for calculating volatilities comes indeed from the Garman-Klass volatility estimator (1980), with opening and closing prices as well:

$$\tilde{\sigma}_{GK}{}^2 = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{1}{2}In\left(\frac{P_{it}^{max}}{P_{it}^{min}}\right)\right)^2 - \frac{1}{N}\sum_{i=1}^{N}(2In2-1)\left(In\left(\frac{P_{it}^{close}}{P_{it}^{open}}\right)\right)$$

Similarly to the case of returns, the final sample for the volatilities consists of 1041 data. Still, the range over which the German-Klass estimator was applied was more or less the same as the range of returns. From 2004-01-01 to 2024-01-01, therefore for the entire sample, the series of volatilities are represented in *Figure 12*.

Figure 12. Time series - Volatilities (2004-2024):



Data source: Yahoo Finance.

Although it has already been observed with the returns time series, volatilities rose during: (i) the 2008 credit crunch, (ii) the sovereign debt crisis originating in 2009, and (iii) the economic downturn caused by the COVID-19 pandemic. However, in the last case, there are more information on the volatilities of the various regions.

Apart from the events that impacted all the 14 indexes, the Japanese earthquake in 2011 highly influenced the Nikkei 225 Index (N225), and the 2019 political unrest in Hong Kong had significant consequences on the Hang Seng Index (HSI). Minor shocks occurred also with respect to the 2015 terrorist attacks in France (FCHI)[37].

Overall, volatilities obey to common stylized facts (*Figure 13, Appendix 3*). Within markets, it is normal to observe both a low mean and median, suggesting that stock market volatilities are low most of the times, but they still show occasional spikes.

What is surprising is that the Australian S&P/ASX 200 Index (AXJO) is once more the index with the lowest range (17.74%), even if we are dealing with volatilities. The opposite does not hold, since the equity index with the highest range is not the Nikkei 225 Index (N225), but the Brazilian Bovespa Index (BVSP) (33.40%).

Their discrepancy could be explained by the difference between the Australian and Brazilian economies. From 2004, the Australian region has regularly demonstrated positive growth rates (4.3% in 2022, World Bank), stable inflation levels (6.6% in 2022, World Bank), a resilient financial system, and reliable political institutions.

Also Brazil, from 2004, has experienced a period of rapid growth. That being said, starting in 2014, political corruption scandals and nationwide protests destabilized its economic landscape (Marquetti et al., 2018). Their combined impacts provoked low economic growth, rising unemployment and a deteriorating fiscal health.

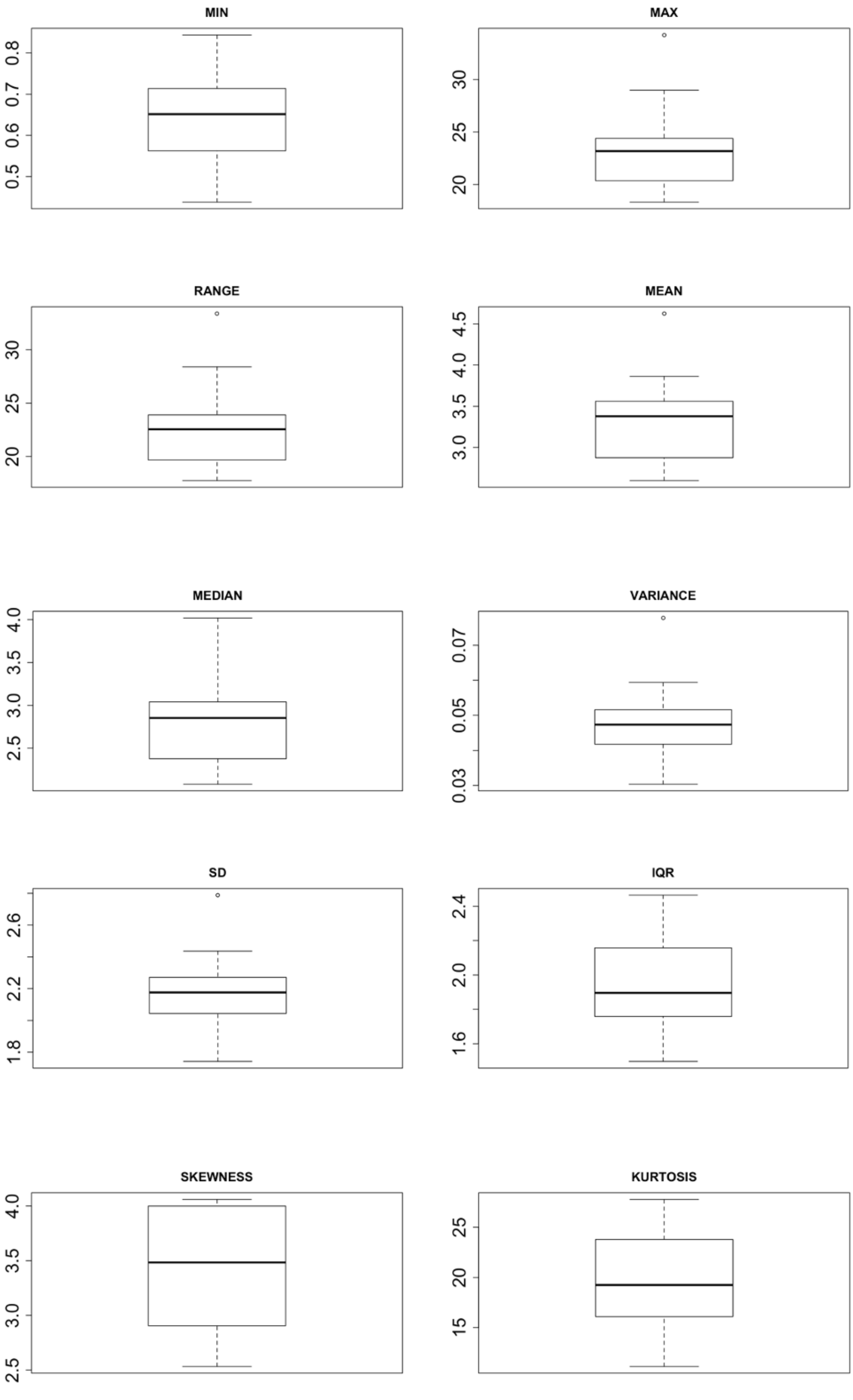
The 2014 downturn contributed to worsen Brazil's position in the global economy. Still today, when compared to Australia, it exhibits lower GDP growth rates (2.9% in 2022, World Bank), higher inflation rates (9.3% in 2022, World Bank), reliance on an agricultural system that is often subject to crises, and political instability.

In line with returns, kurtosis values are higher than 3, implying that extreme events occur more than in normal distributions. Likewise, positive skewness indicates that the distribution of volatilities is skewed to the right. Hence, in the chosen sampling period, relatively high values of volatility occur more frequently than low levels.

Conducting an ADF test with volatility data yields similar results to those observed in the return scenario. Its p-values are higher than the significance level, leading to the rejection of the null hypothesis and indicating that all series are stationary. Yet, the difference is that the AIC suggested to use a $VAR(4)$ instead of a $VAR(1)$.

[37] While these spikes can be attributed to specific events, their overall significance is low.

Figure 13. Descriptive statistics - Volatilities (2004-2024):



Data source: Yahoo Finance. All data, skewness and kurtosis apart, are in %.

5.2 SPILLOVER TABLES.

Once having seen the statistical summary of the 14 indexes in the past 20 years, it is possible to start partitioning the dataset. The first period, covering the 18 months of the Great Recession[38], runs from 2004-01-01 to 2009-01-01 and is characterized by a strong economic instability, alongside with high stock market fluctuations.

To begin with, as indicated by the AIC, the time series have been modelled with a $VAR(1)$ for returns and $VAR(10)$ for volatilities[39]. As in Diebold and Yilmaz, the first measure that we analyzed is the spillover index, used by scholars to quantify the transmission of spillovers between different markets, assets, and regions:

$$SI = \frac{\sum_{k,j\in\{i..K\},k\neq j} FEVD_j^k(h)}{\sum_{k,j\in\{1..K\}} FEVD_j^k(h)}$$

However, given the complexity of representing spillovers for 14 distinct variables, we employed a connectdeness table. In our context, it measures the propagation of return and volatility spillovers among stock market indexes. The matrix, displayed in *Figure 14*, helped us capturing the volume of interdependence among markets.

Figure 14. Diebold – Yilmaz Connectedness Table (FEVD)[40]:

$k\downarrow$ $j\rightarrow$	Country 1	Country 2	...	Country N	From Others
Country 1	d_{11}^H	d_{12}^H	...	d_{1N}^H	$\sum_{j=\{1..N\}\backslash 1} d_{1j}^H$
Country 2	d_{21}^H	d_{22}^H	...	d_{2N}^H	$\sum_{j=\{1..N\}\backslash 2} d_{2j}^H$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
Country N	d_{N1}^H	d_{N2}^H	...	d_{NN}^H	$\sum_{j=\{1..N\}\backslash N} d_{Nj}^H$
To other	$\sum_{k=\{1..N\}\backslash 1} d_{k1}^H$	$\sum_{k=\{1..N\}\backslash 2} d_{k2}^H$	...	$\sum_{k=\{1..N\}\backslash N} d_{kN}^H$	$\frac{1}{N}\sum_{k,j=\{1..N\},i\neq j} d_{ij}^H$

Data source: Diebold & Yilmaz, 2012.

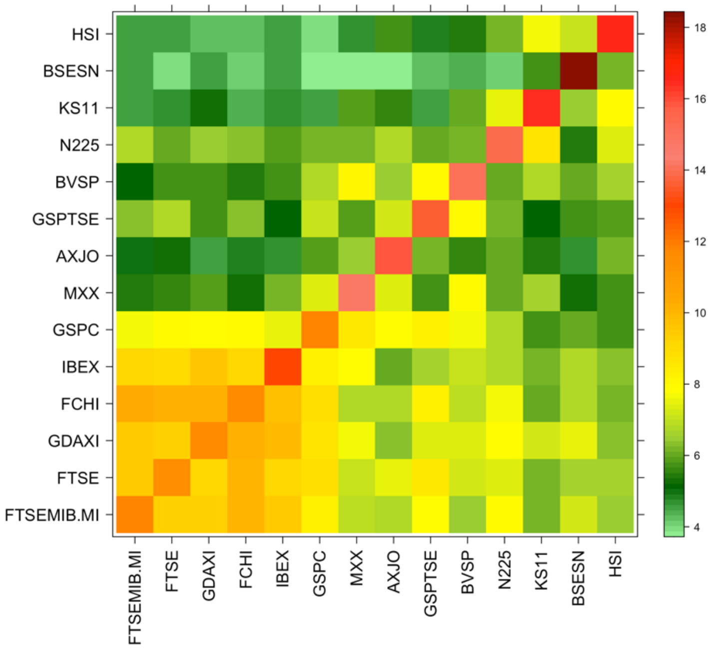
[38] According to the National Bureau of Economic Research the recession period went from 2007-12-31 to 2009-06-30.

[39] Although the lags from 2004-01-01 to 2024-01-01 were $p = 1$ and $p = 4$, to improve accuracy they were adjusted for each different period.

[40] $d_{kj}^H \equiv FEVD_j^k(h = H)$.

Although the reference to the connectdeness table is in the appendix (*Appendix 4*), to better understand the return spillovers among the 14 indexes we decided to show a heat map[41] (*Figure 15*) whose colour-key spans from the smallest (3.72%) to the largest (18.44%) cross-variance share and from which we omitted own shares[42].

Figure 15. Spillover table heat map – Returns (2004-2009):



Data source: Yahoo Finance.

Here, the lowest spillovers (3.72%) are from the Indian S&P BSE SENSEX Index (BSESN) to the U.S. S&P 500 Index (GSPC). During the early and mid-2000s, the Bombay stock market fluctuations had a higher impact on the rest of Asia, but only a modest effect on the U.S., with which the country shared a low fraction of FDI.

Their financial interdependence began rising after the 2005 Trade Policy Forum, a programme aimed at increasing trade and investment flows between the countries. As of 2022, India's FDI in the U.S. was $3.7 billion (USTR, 2024), up to 7% from 2021, and return spillovers increased to 5.13%, higher than the 2004-2009 level[43].

Even the second-to-last value regards India. Hence, the spillover table implies that the Indian S&P BSE SENSEX Index (BSESN) is responsible for just 3.76% of the forecast error variance in the Mexican IPC Index (MXX). The value increases only to 3.79% with return spillovers to the Australian S&P/ASX 200 Index (AXJO).

[41] According to Lord et al. (2021), a heat map is «a representation of data in the form of a map in which data values are represented by colours».

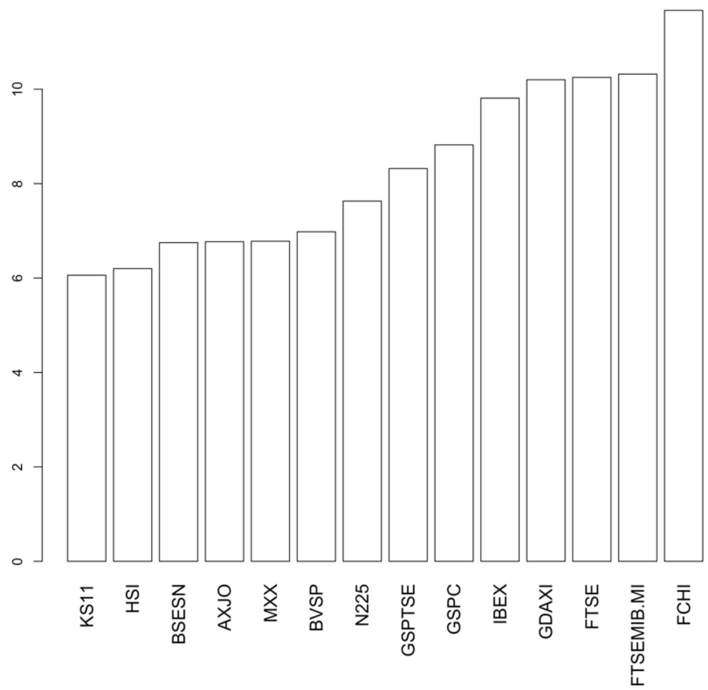
[42] The main diagonal of the spillover table was omitted as own-variance shares were always the highest.

The first result that can be seen from the lowest 25-th percentile $(3.72\% - 5.68\%)$ is that Asian countries are responsible just for a small fraction of the error variance in forecasting European, American, and Australian returns. This is in line with the effects of the GFC, which spread from the U.S. and impacted firstly E.U. countries.

Yet, excluding the main diagonal of the spillover table, the highest return spillovers (10.3%) are from the French CAC 40 Index (FCHI) to the Italian FTSE MIB Index (FTSEMIB.MI). This may have occurred as the domestic demand shock of France could have affected the confidence of national investors.

The trend occurs with the next highest return spillovers. In the period ranging from 2004 to 2009, the French CAC 40 Index (FCHI) constitutes 10.25% of the forecast error variance in the U.K. FTSE 100 Index (FTSE), a fraction that lowerst only to 10.20% when analyzing the German DAX 40 Index (GDAXI) returns (*Figure 16*).

Figure 16. Spillovers transmitted from France - Returns (2004-2009):



Data source: Yahoo Finance.

However, the French CAC 40 Index (CAC) is not the stock market index justifying the majority of spillovers. By analyzing the total connectedness to others, the index with the highest return spillovers is the German DAX 40 Index (DAX). By viewing the ranking, what is evident is that E.U. countries have a higher share than the U.S.

In the spillover table for volatilities, the matters reverse. Hence, to better catch the contagion effect of the U.S., it is necessary to consider volatility spillovers, whose table is in the appendix (*Appendix 5*) and whose heat map is below (*Figure 17*). At first sight, the only similarity is that the lowest volatility spillovers are from Asia.

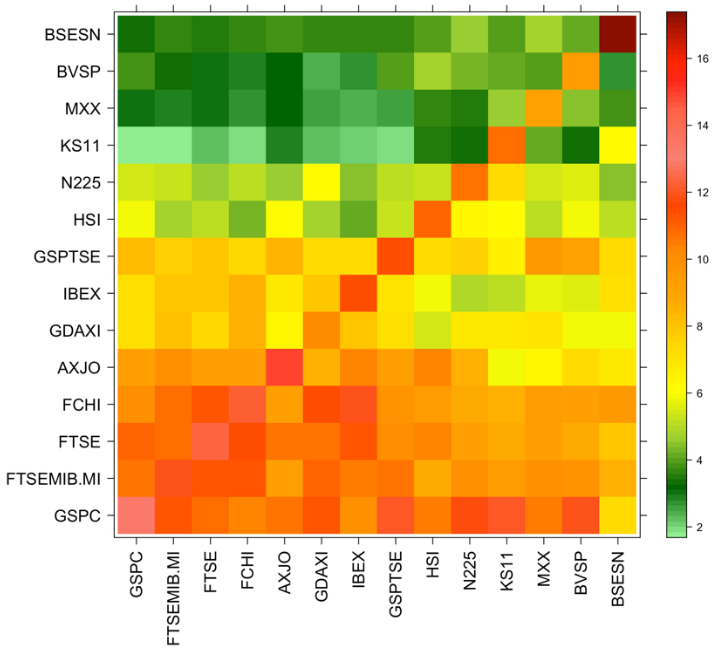
At the bottom, there are the forecast error variances explained by the South Korean KOSPI (KS11) Index. As a matter of fact, the South Korean stock market explains 1.64% of the error variance in the Canadian S&P/TSX Index (GSPTSE) volatility. The pattern is repeated with the majority of the American and E.U. equity indexes.

Accounting for the volatility spillovers "*from*" and "*to*" other economies, the South Korean KOSPI Index (KS11) appears 44.1% of the times within the lowest 25-th percentile (1.64% – 4.83%). Including the other Asian countries, the % increases to 73%, leading to a question. Where does the resilience of the region come from?

As stated by the IMF, it derived from the reforms adopted by commercial banks to face the 1997 crisis. This "*allowed Asian interbank markets to remain calm while interbank markets in the U.S. and Europe were in chaos*" (Hoe and Xiong, 2008).

What deviates from the return scenario is the strong presence of the U.S. Here, the S&P 500 Index (GSPC) accounts for the majority of the forecast error variances in the volatility of the other indexes (C. to others including own: 155.83%), resulting in a undeniable result: the contagion of the U.S. passed through volatilities.

Figure 17. Spillover table heat map – Volatilities (2004-2009):

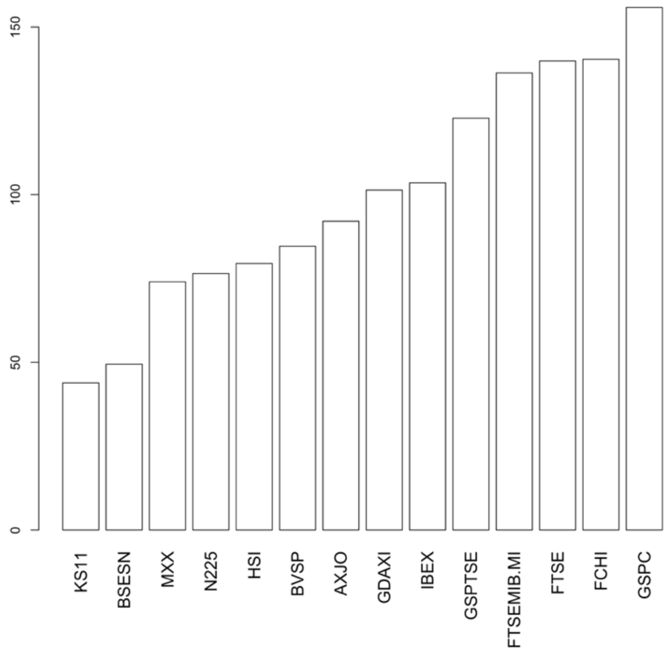


Data source: Yahoo Finance.

During the 2008 crisis the U.S. explained on average 11% of the variance of every stock market included in the sample. Among them, the stock market index that the S&P 500 Index (GSPC) affected the most was the Canadian S&P/TSX Composite Index (GSPTSE) (12.5%), since the two economies are strictly connected.

From 2004 to 2009, the only indexes with a C. to others approaching the U.S. were: (i) the French CAC 40 Index (FCHI) (140.35%), (ii) the English FTSE 100 Index (FTSE) (139.85%), and (iii) the Italian FTSE MIB (FTSEMIB.MI) (136.3%). A result (*Figure 18*) that sets the basis for analyzing the contagion across Europe.

Figure 18. C. to others including own – volatilities (2004-2009):



Data source: Yahoo Finance.

SOVEREIGN DEBT CRISIS

Heading to the next volatile period, we analyze the sovereign debt crisis. As PIIGS countries played a relevant role between 2009-01-01 and 2015-01-01 we increased the computational effort by accounting for 17 equity indexes. According to *Figure 19*, the markets that we added to the list belong to Greece, Portugal, and Ireland.

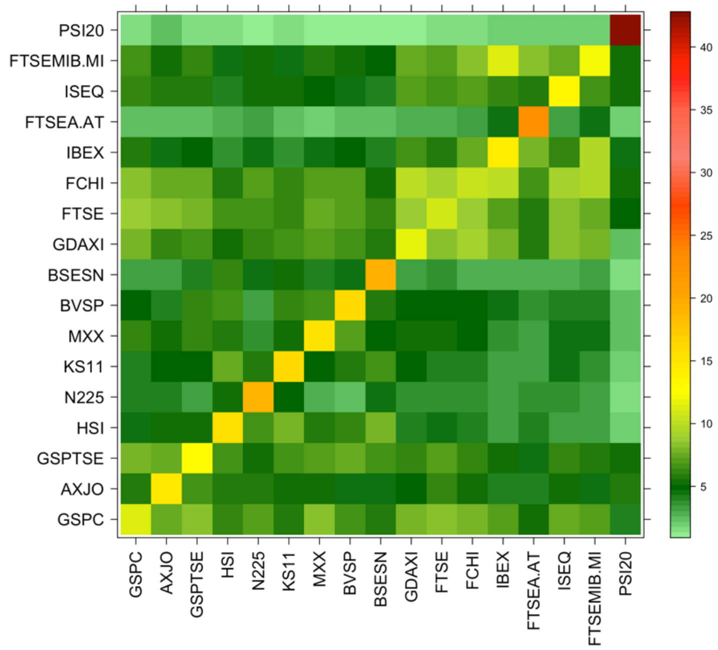
Figure 19. New equity indexes:

Index name	Country	Composition	Market Cap.
ISEQ 20 (ISEQ)	Ireland	20 stocks with the highest Market Cap.	$132.72 billion
FTSE ATHEX Index (FTSEA.AT)	Greece	60 components from the Athens Stock Exchange	$31.55 billion
PSI 20 (PSI20)	Portugal	20 stocks with the highest Market Cap.	$14.04 billion

Data source: Refinitiv.

Once having executed an ADF test and confirmed that the 17 series are stationary, it is possible to focus on their return spillovers (*Appendix 6, Figure 20*) and ignore the volatility counterpart (*Appendix 7*).[44] Even so, in the period spanning from the Greek elections to the mid-2010, equities were not impacted as much as bonds.

Figure 20. Spillover table heat map – Returns (2009-2015):



Data source: Yahoo Finance.

The right corner of the heat map indicates that there have been just a few spillovers between the PIIGS indexes: (i) the Portuguese PSI-20 Index (PSI20), (ii) the Irish ISEQ 20 Index (ISEQ), (iii) the Italian FTSE MIB Index (FTSEMIB.MI), (iv) the Greek FTSE/ATHEX Index (FTSEA.AT) and the Spanish IBEX Index (IBEX).

Yet, except for the Italian FTSE MIB Index (FTSEMIB.MI), return spillovers are lower than what we would have expected. As a matter of fact, during the sovereign debt crisis, PIIGS indexes exhibited substantial values of own-variance shares, but lower connectedness compared to the period from 2004-01-01 to 2009-01-01.

A clear evidence derives from the Portuguese PSI 20 Index (PSI20) returns, whose C. from others including own amounted to 67.22%. By omitting the % of forecast error variance explained by itself (42.81%), cross-variance shares are the 24.41%, a negligible value if compared to the 121.6% of the French CAC 40 Index (FCHI).

As such, the sovereign debt crisis lacked the widespread contagion risk of the 2008 crunch, but did a similar domino effect occurr from 2019-01-01 to 2023-01-01?

[44] Since the crisis was transmitted through the bond market, volatility spillovers were significantly lower.

COVID-19 CRISIS

Examining the timeframe from 2019-01-01 to 2023-01-01 requires mentioning the COVID-19 crisis. The coronavirus, firstly detected in China, led the World Health Organization (WHO) to state a Public Health Emergency of International Concern (PHEIC) in 2020-01-30 and a global pandemic in 2020-05-11 (WHO, 2024).

The crisis, defined by the UN Secretary-General Antonio Guterres as "*humanity's worst crisis since World War II*", threatened the growth of countries and resulted in an estimated loss of $2.7 trillion to the economy (Bloomberg, 2020). The impact was evident in financial markets too, with the S&P 500 losing 34% in March 2020.

Regarding the effects of the COVID-19 pandemic on financial markets, significant results were achieved by Zhao et al. (2022), according to which the crisis impacted developed economies through supply reduction and economic instability. Relevant impacts were also caused by the negative confidence and expectations of investors.

Contributing to the literature there is even the research conducted by Baker et al. (2020) and Benkraiem et al. (2022). In line with the results that we obtained by using Diebold & Yilmaz measures (2012), they demonstrated that the COVID-19 outbreak had a higher impact in countries that did not belong the East Asia.

Yet, Gunay and Can (2022) highlighted that the core of the financial crisis and the relative interconnections are independent to the origin of the COVID-19 pandemic. Despite the virus spread in China, American markets showed the highest contagion effects and volatility spillovers, similarly to what happened during the 2008 crisis.

The reason is that, even if developed countries better react to crises, they cause and receive a more spillovers than developing ones. Still, in absence of financial shocks spreading from East Asia to America, the findings are just valid for external events.

Apart from the methodology, what differentiates our study from the research paper of Benkraiem et al. (2022) is the geographical focus. While the authors focused on the impacts of the pandemic on just East Asian and American markets, we analyze financial spillovers, by including various European countries as well.

Before diving in the volatility spillover table (*Figure 21*), it might be interesting to mention that Benkraiem found that from 2014 until 2021 the most intense financial contagion verified in the U.S., followed by Brazil, Mexico, and Argentina. Instead, in our study the first country is India, followed by Italy, Canada, and France.

Precisely, 91.09% of the forecast error variance in India can be explained by other indexes. Among them, the most significant ones are the Australian S&P/ASX 200 (AXJO) (13.98%), the U.K. FTSE 100 Index (FTSE) (9.20%) and the Canadian S&P/TSX Index (GSPTSE), which yields a slightly lower share (8.44%).

The reason why the Indian market saw a peak in contagion can be found by reading the study of Capelle-Blancard and Desroziers (2020). They showed that pandemic effects were higher in areas with structural economic fragility. Hence, less resilient economies had higher impacts, despite being less vulnerable to the pandemic.

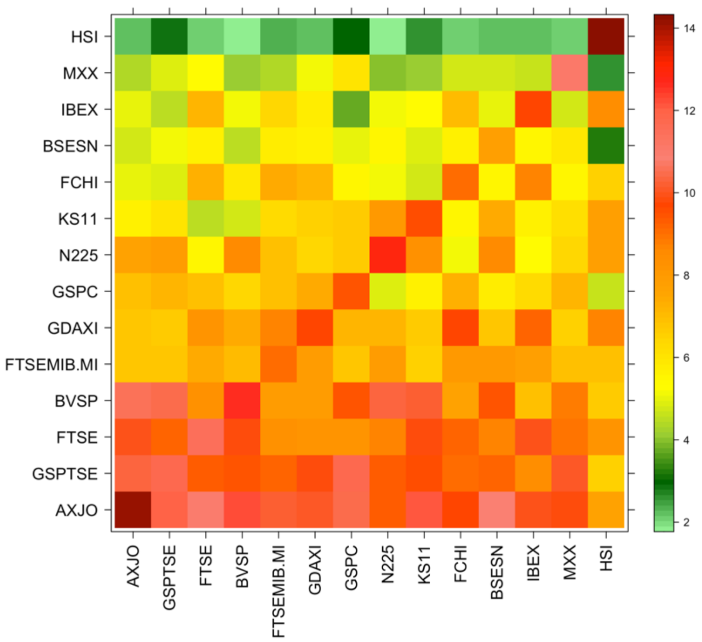
Besides the pandemic, it is worth noticing that the period spanning from 2019-01-01 to 2023-01-01 includes the escalation of the Russo-Ukrainian War, leading to a disruption in the exports of crude oil, fertilizers, and food grains (FAO, 2022). An interesting insight, since India imports $32.8 billion from Russia (OEC, 2022).

Heading to the second-ranked market, 89.35% of the forecast error variance of the Italian FTSE MIB Index (FTSEMIB.MI) is explained by other indexes, mainly by European ones. Among them, with a 9.70%, the French CAC 40 Index (FCHI).

However, the findings are extremely similar when it comes to the East-Asia region. In either studies, the stock market with the highest contagion is South Korea, while Hong Kong the lowest. A widely acknowledged explanation is that the geographic proximity of Hong Kong to China permitted it to quickly react to the pandemic[45].

Specifically, the Hong Kong market demonstrated the lowest connectedness from others of the total sample (80.94%), followed by Australia (81.89%), and Mexico (83.83%). Considering that during the COVID-19 crisis the range spanned from 80.94% to 91.09%, connectedness from others is much higher than in 2009-2015.

Figure 21. Spillover table heat map – Volatilities (2019-2023):



Data source: Yahoo Finance.

[45] Already on January 6, the Hong Kong government activated a «Steering Committee».

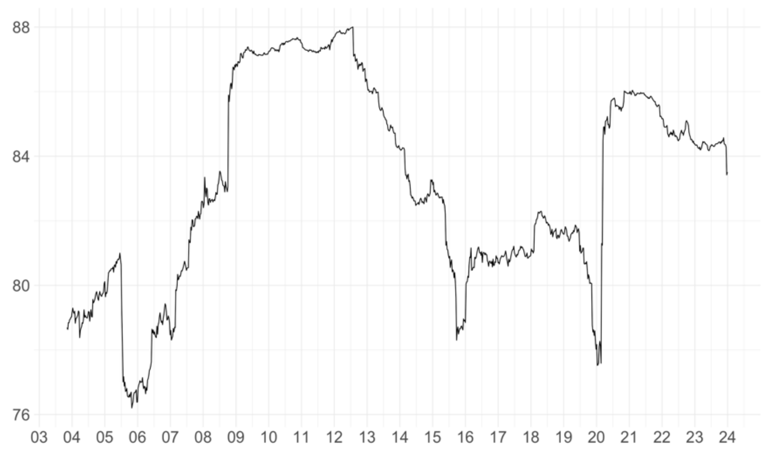
5.3 DYNAMIC SPILLOVERS.

As already mentioned, the period from 2004 to 2024 was marked by various short-term bursts: (i) the U.S. housing market collapse, (ii) the sovereign debt crisis, and (iii) the COVID-19 outbreak. Still, by targeting just brief intervals, it is not possible to discuss long-term trends, first of all the decline in contagion from the GFC.

Such improvement was favoured by market stability, which reduced volatility and intense price movements. From 2013, the economic growth of most E.U. countries saw an upward trend (Tuca, 2014). Alongside with the GDP increase, the reduction in spillovers was favoured even by regulatory changes, mainly the Dodd-Frank act.

Anyways, as financial markets are dynamic and their relationship varies over time, estimating spillovers with a static approach may not be enough. In light of this, we decided to study return spillovers between the 14 stock market indexes with a 200-week rolling window[46] and display within *Figure 22* their variation over time.

Figure 22. Total spillovers - Returns (2004-2024):



Data source: Yahoo Finance.

With a value exceeding 76% in the opening window, the total spillover return plot mainly varies between 80% and 84%. The lowest value (76%) occurred at the end of 2005, the period preceding the GFC. Instead, the highest (88%) corresponds to the mid-2012, where the U.S. contagion to others reached its highest peak.

Anyways, by looking at the whole period, it is possible to recognize various cycles. The first, encompassing the 2008 crisis and the sovereign debt crisis, began in 2006 and ended in 2015, touching a range between 76% and 88%. However, the second, ranging from 2015 to 2020, has never been analyzed throughout the whole study.

[46] The 200-week rolling window was the better in displaying long-term trends.

Contrarily to the crises that were already mentioned, the rise in return spillovers of 2015 is not due to a single event. The increase might be caused by the "*2015-2016 stock market selloff*", a period of economic turbulence characterized by a wide fall in stock prices and initially motivated by China's GDP slowdown (IMF, 2016).

Although the devaluation of the yuan was the main reason why investors lose their confidence, pessimism was heightened by: (i) the Greek debt default in June 2015, (ii) a fall in oil prices, (iii) the end of the U.S. quantitative easing in October 2014, (iv) an increase in bond yields in 2016, and (v) the 2016 referendum on Brexit.

"*The market turbulence earlier this year is a reminder that economic and financial shocks can rapidly reverberate throughout the worldwide economy, threatening to overwhelm policy frameworks that are not sufficiently strong, and push countries into a phase of economic and financial stagnation*". (IMF Annual Report, 2016).

The last cycle, shorter and higher than the previous one, started on the onset of the COVID-19 crisis, when investors faced the damages caused by the lockdowns and were uncertain on the future economic growth of all countries (Adrian et al., 2022). An unpredictability that led return spillovers come back to the 2009-2013 levels.

A view shared by Ullah et al. (2023) as well, since they believe that: "*Stock markets experienced unprecedented volatility during this period, reflecting the uncertainty and the economic disruptions caused by the pandemic. As a result, investors faced heightened uncertainty and rapidly changing financial markets' conditions*".

Amidst 2023, instead, return spillovers started lowering towards 84%. This result was reached with the measures adopted to face the crisis, like government stimulus packages ($3.3 trillion in 2020, IMF), additional injections and loans ($4.5 trillion in 2020, IMF), interest rates reduction policies and quantitative easing programs.

To better comprehend the transmission of risk across the 14 indexes, it is necessary to integrate total volatility spillovers. As for returns, volatility spillovers have been estimated with a 200 week rolling window. Yet, the cycles correspond to the same periods of returns, precisely to: (i) 2006-2015, (ii) 2015-2020 and (iii) 2020-2024.

Although the peaks in the connectedness from others occur in similar timeframes, *Figure 23* exhibits more bursts than clear trends. It becomes particularly evident during 2008 and at the end of 2014, where instead of displaying a gradual decrease, volatility fell sharply. As for cycles, the first is instead more difficult to recognize.

Still, when observing volatility spillovers during crisis periods, they display higher peaks compared to returns. Throughout the U.S. housing market collapse, spillover effects driven by volatilities surpassed 90%, 3% higher than what we observed in *Figure 22*. A value that becomes even higher if considering the 2020 crisis (6%).

The reason behind the bursts displayed by volatility spillovers may be information transmission. As they are closely related to the dissemination of information, when unexpected news are heard, they can quickly propagate in the stock market. A well-known example is the collapse of Lehman Brothers, occurred in 2008-09-15.

On the opposite hand, return spillovers are often driven by changes in fundamental factors, including economic indicators, corporate earnings, and the performance of the industry. These changes in fundamentals are however gradually incorporated into stock prices, leading to spillover trends rather than high bursts (Habibi, 2022).

By considering periods displaying fewer crises, such as from 1990 to 2009, which includes only the 1997 Asian financial crisis and the onset of the 2008 stock market downturn, their distinction is even more noticeable. Accordingly, for such period, Diebold and Yilmaz (2011) showed that volatility spillovers had no peculiar trend.

Figure 23. Total spillovers - Volatilities (2004-2024):

Data source: Yahoo Finance.

Even if *Figure 22* and *Figure 23* provide a first insight on total spillovers, they do not provide any information on their direction. For this reason, we will proceed by analyzing directional spillovers, measuring the spillovers received to and from a particular market j[47].

Once having computed dynamic spillovers for each of the 14 stock market indexes, we plotted their transmission in *Figure 24* for returns and *Figure 25* for volatilities. For both, we considered the period going from 2000-01-01 to 2024-01-01, rolling-windows of 200 observations and the same lags used in the previous analyses[48].

[47] While the directional spillovers to others is the sum of $S_{i.}^{g}(H) = \frac{\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} 100$, from others is the sum of $S_{.i}^{g}(H) = \frac{\sum_{j=1}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} 100$.

[48] From 2000-01-01 to 2024-01-01, lags are $p = 1$ for returns and $p = 4$ for volatilities.

Estimating the return spillovers from each index, these appear smooth over time. Among them, the indexes exhibiting the highest fluctuations are the Japanese N225 Index (N225) and the Brazilian BOVESPA Index (BVSP). In relation to the former, the rise is partially explained by the Asian integration in financial markets.

In the Brazilian case the upward trend started around 2007 and, similarly to Japan, it did not continue, but it stopped in 2015. Although the initial rise can be explained by the impacts of the GFC, in the long-term it could have been caused by the severe crises that Brazil experienced from mid-2014, due to its political instabilities[49].

All other stock markets were characterized by regular spillovers, even though some spikes can be observed in occurrence of crises. Throughout 2008, the highest surge occurred in the U.S. S&P 500 Index (GSPC), followed by the Canadian S&P/TSX (GSPTSE), confirming that the direction was from North American countries.

Sharp increases were observed also in the COVID-19 outbreak. What is interesting is that in 2020 the Hong Kong Hang Seng Index (HSI) did not show a spectacular rise. As just explained in *Chapter 5.2*, this could be due to the rapid implementation of pandemic measures in the region, which helped Hong Kong to lower contagion.

Pandemic-related spikes are, instead, particularly evident in Oceania, America and Europe. Yet, some EU countries, including France with its CAC 40 Index (FCHI), maintained the same level of spillover transmission. This occurred both in the case of returns and volatilities, reason why France can be seen as a spillover receiver.

Greater clarity can be achieved by switching to volatilities (*Figure 28*). Instead of showing clear trends, the «*directional spillover volatility plots*» highlight more the bursts to which financial markets were subject to in the past 20 years. In the figure, the highest spike is represented by Brazil, reflecting the shocks of its stock market.

Apart from noticing that the volatility transmission is even higher compared to the return counterpart, which settles at maximum 8%, it is possible to make a comment on Australia. From the COVID-19 crisis it became one of the stock markets able to explain the majority of the forecast error variances in volatilities (10%).

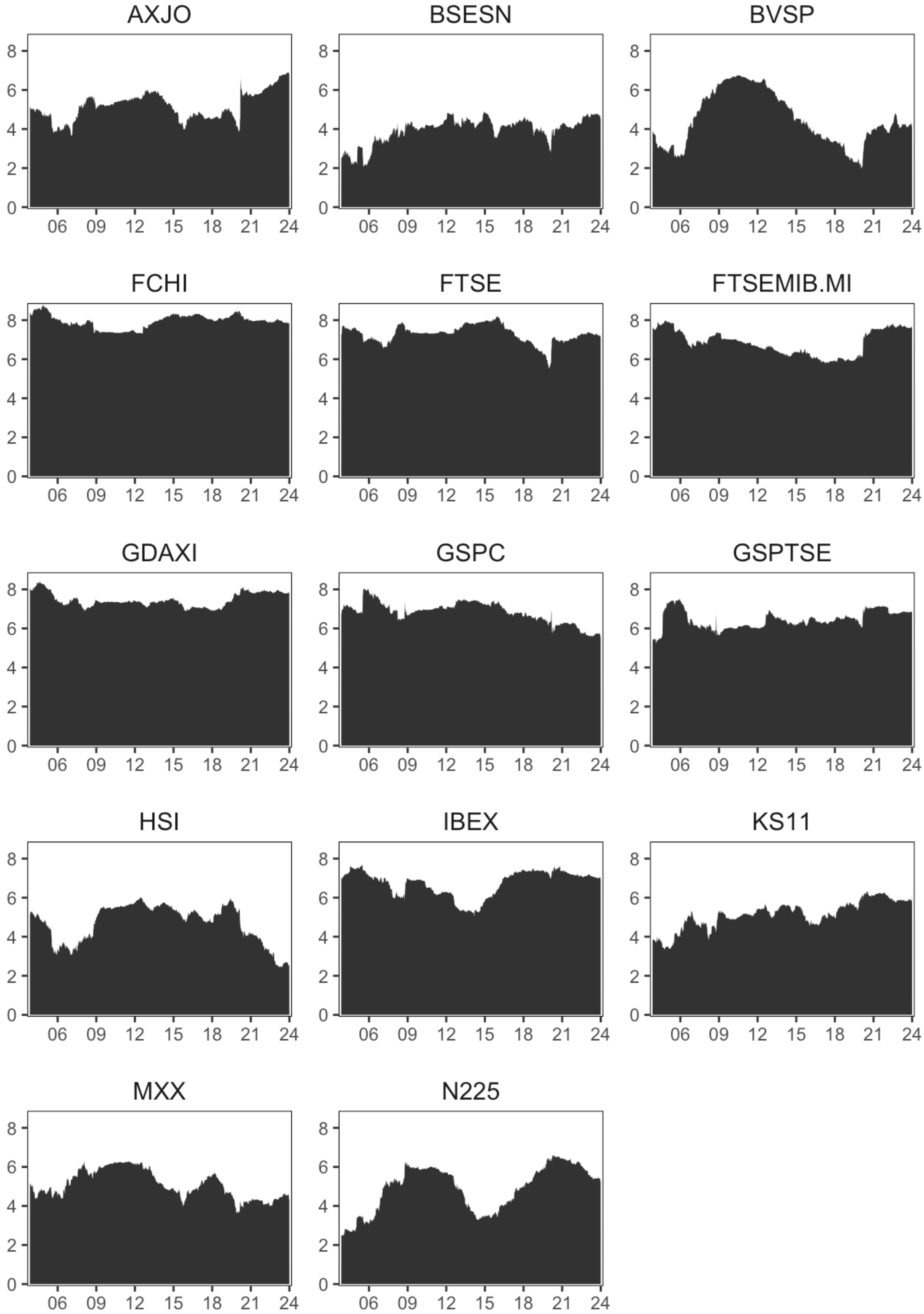
Comparing the S&P/ASX 200 Index (AXJO) with the Canadian S&P/TSX Index (FCHI), the value doubles. This can be explained by the recession that the country is facing. Over the 12 months to December 2023, the Australian economy reduced by 1% per capita, the slowest growth since the 1990 crisis (Deloitte, 2024)[50].

Yet, the trend does not solely concern Australia, as "*A quarter of G20 nations have recorded a technical recession or narrowly avoided one*" (Jim Chalmers, 2024).

[49] Apart from the impeachment of President Rousseff, in 2014 there was a commodity price shock.

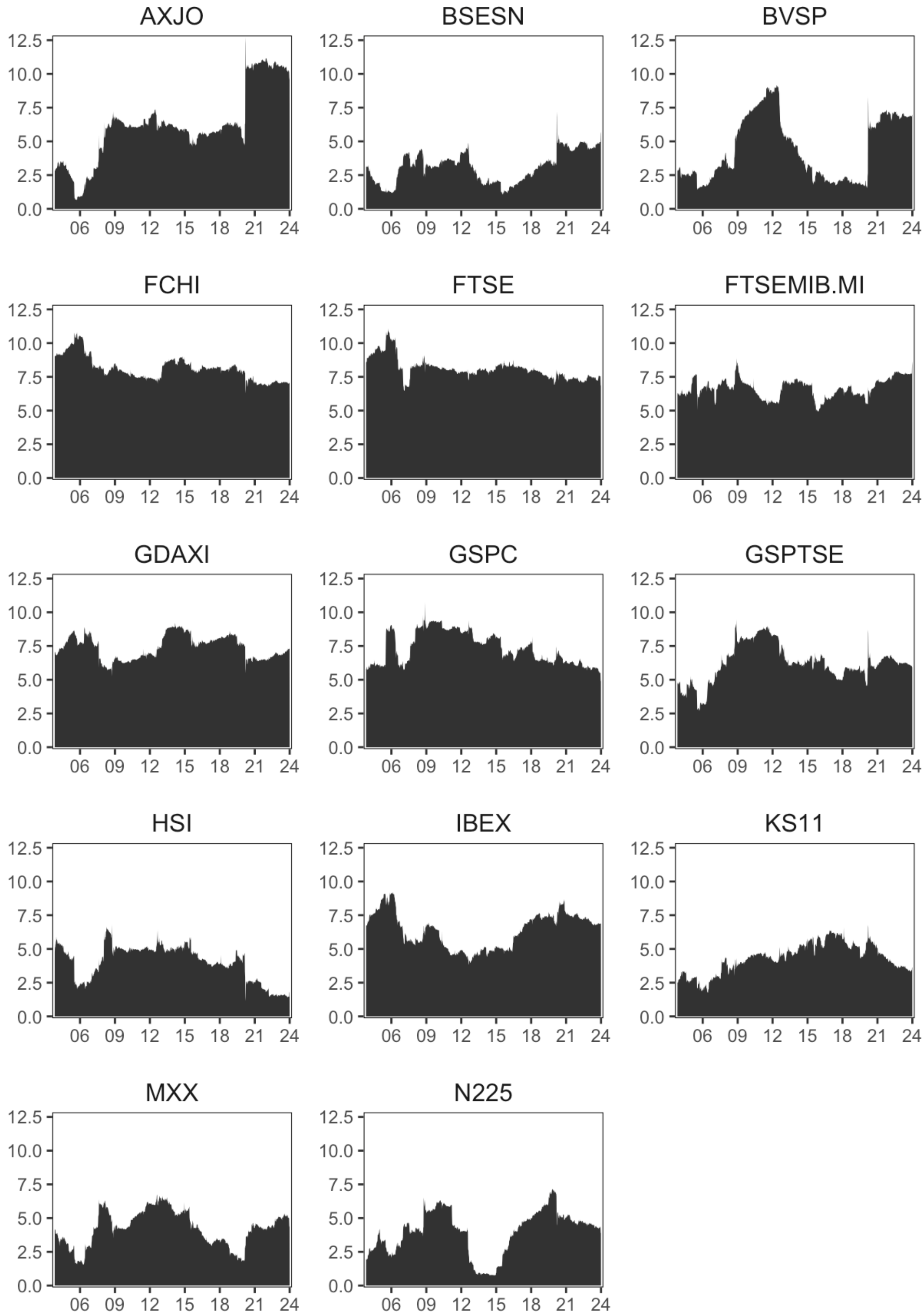
[50] Accounting for the slowest rate, the period related to the COVID-19 outbreak was excluded.

Figure 24. Directional spillovers *FROM* 14 markets - Returns (2004-2024):



Data source: Yahoo Finance.

Figure 25. Directional spillovers *FROM* 14 markets - Volatilities (2004-2024):



Data source: Yahoo Finance.

Subtracting the spillovers generated and received[51] by index j, it is possible to obtain the so-called «*net spillovers*», displayed in *Figure 26* for returns and *Figure 27* for volatilities. There, while a positive value suggests that the index is a net generator of spillovers, a negative value implies the opposite.

The first result that can be reached is that the majority of European indexes are net generators of return and volatility spillovers. A trend that does not hold true for the Spanish IBEX 35 Index (IBEX), since from 2012 to 2016 Spain became a spillover receiver. Historically, the period became known as the «*Spanish financial crisis*».

As demonstrated by Royo (2020), before the 2008 recession the Spanish economy hit its consecutive 14-th year of expansion. Over the preceding 20 years, its GDP grew until reaching 90% of the EU15 average. The country's boom, which made investors optimist, was so long-lasting that competed just with the Irish golden age.

Yet, at the time of the U.S. housing market collapse, Spain did not develop enough its fundamentals, including its low productivity, low-intensity sectors and unstable family indebtedness's. The main difficulty, and the reason why it suffered the most spillovers, can be that 60% of companys' benefits came from trade (Royo, 2020).

Inversely, Oceanian and Asian indexes, apart from the COVID-19 period onward, have traditionally been net spillover receivers, both of returns and volatilities. Still, not all of them generated more shocks than what they received during the pandemic crisis, since the Hong Kong Hang Seng Index (HSI) did not reverse its pattern.

Observing volatilities, South Korea became a net transmitter of spillovers just in the period ranging from 2015 to 2018. The period, which has not been analyzed in previous chapter, was marked by political instabilities. Particularly, by the protests against the President Park Geun-hye, preceding its impeachment on corruption.

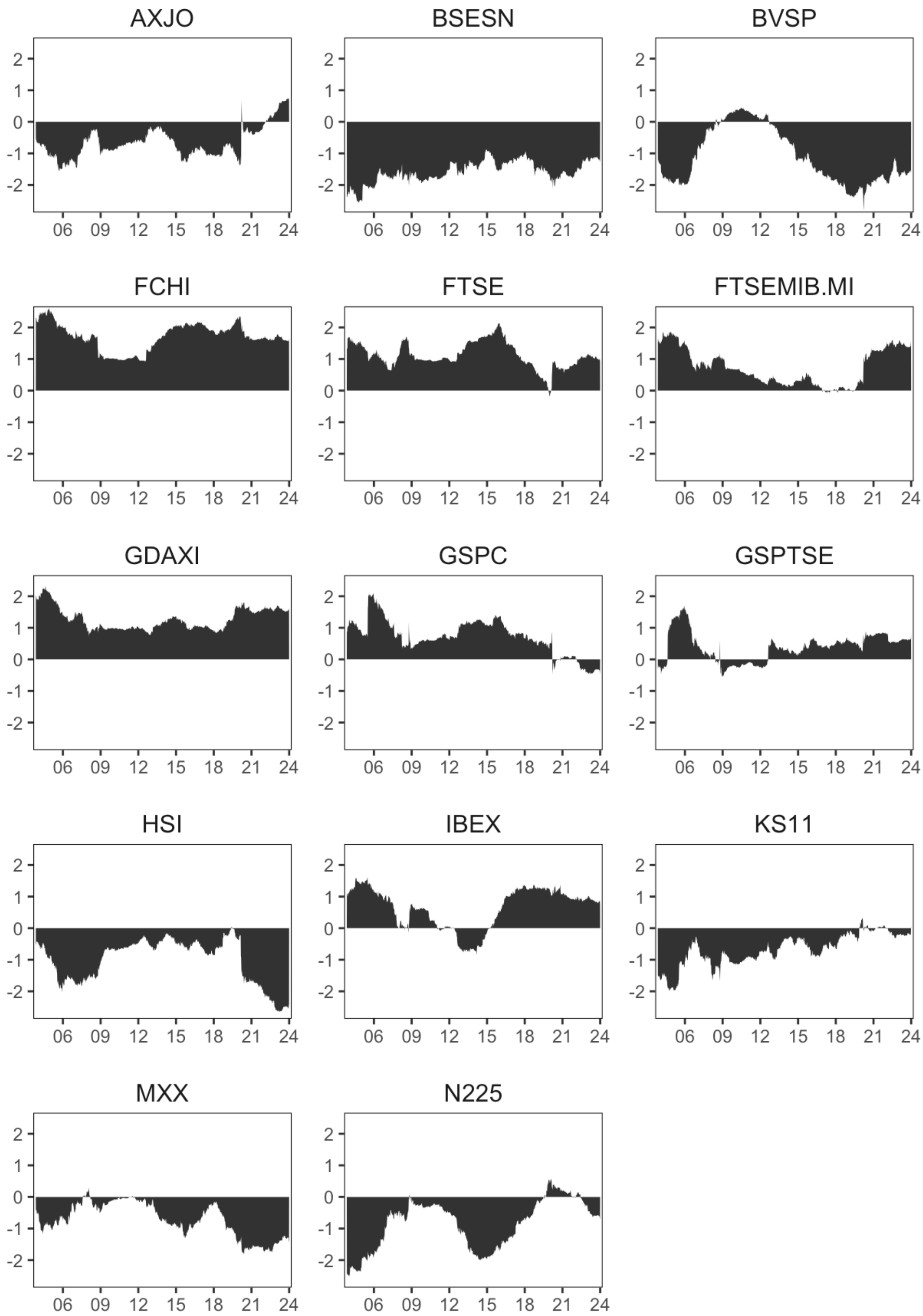
As last, the net spillover graphs confirm the 2008 transmissions from the American region, mainly from the U.S. S&P 500 Index (GSPC). Over the financial crisis, the U.S. caused 3% more shocks to the rest of the sample than the ones received. Still, because of its bursts, from the side of volatilities it is difficult to trace a pattern.

With the Canadian S&P/TSX Index (GSPTSE) and the Brazilian BOVESPA Index (BVSP), the net transmission is much more visible from volatility plots. This might happen since the countries are not as integrated as the U.S. in global stock markets, hence display high spillovers only in occurrence of major shocks, such as in 2008.

To further analyze the relations among the 14 stock market indexes, we estimated even the return and volatility «*net pairwise spillovers*». The measure, computed for the first time by Diebold and Yilmaz, quantifies the extent to which shocks in a market affects another, while controlling for spillovers in other directions.

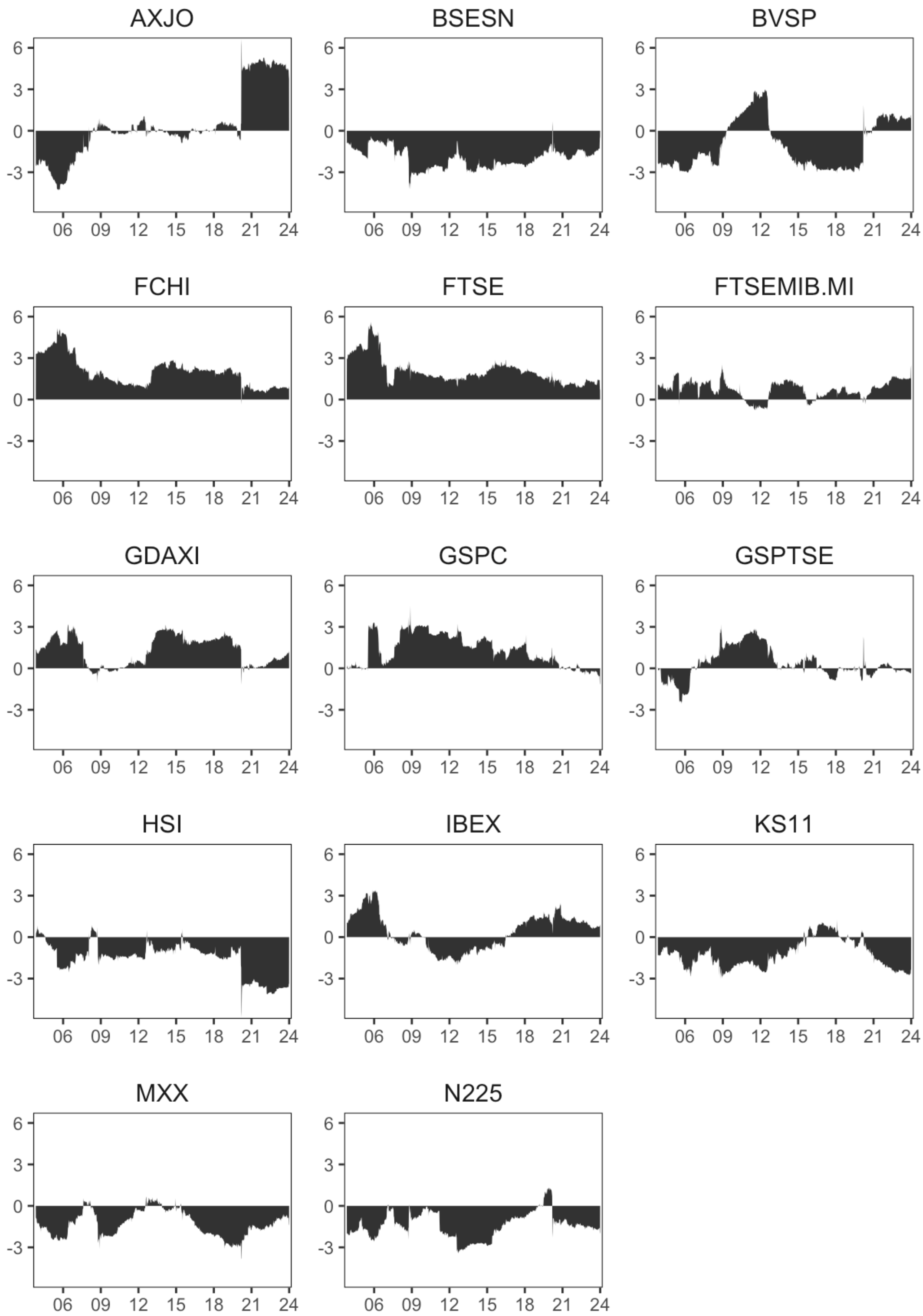
[51] A reference can be found in *Appendix 10* for returns and *11* for volatilities.

Figure 26. Net directional spillovers - Returns (2004-2024):



Data source: Yahoo Finance.

Figure 27. Net directional spillovers - Volatilities (2004-2024):



Data source: Yahoo Finance.

Since the contagion among the 14 stock market indexes can be better perceived by observing volatilities, we leave out net pairwise return spillovers and focus just on the net pairwise volatility spillovers (*Figure 28*), estimated by Diebold and Yilmaz (2012) as the difference between the spillovers of market i to j and market j to i:

$$S_{ij}^{g}(H) = \left(\frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{N}\right) 100$$

At first sight, European countries exhibit the lowest net pairwise spillovers, except from the pairs involving the Spanish IBEX Index (IBEX). The rationale behind the absence of indexes that strongly overtake the others is that E.U. members share the same currency, uniform monetary policies, and strong trade alliances.

Yet, when compared to other E.U. countries, the FTSE MIB Index (FTSEMIB.MI) remains slightly below the zero line. A possible explanation lies in the Market Cap. of the other indexes. The value of the FTSE MIB ($548.37 bn) is among the lowest of the dataset, approaching only the Spanish IBEX Index ($587.27 bn) value.

Historically, European stock market benchmarks have been net volatility spillover transmitters. This holds true when considering the spillovers transmitted from E.U. equities to Asian and minor American stock markets, represented in the sample by the Mexican IPC Index (MXX) and the Brazilian Bovespa Index (BVSP).

Until 2020, the pattern held even for the Australian S&P/ASX 200 Index (AXJO). However, in the most recent years it ceased to be a net volatility spillover receiver, becoming a trasmitter. This is especially clear in the case of the German DAX 40 Index (GDAXI), which has traditionally explained a higher fraction of its FEV.

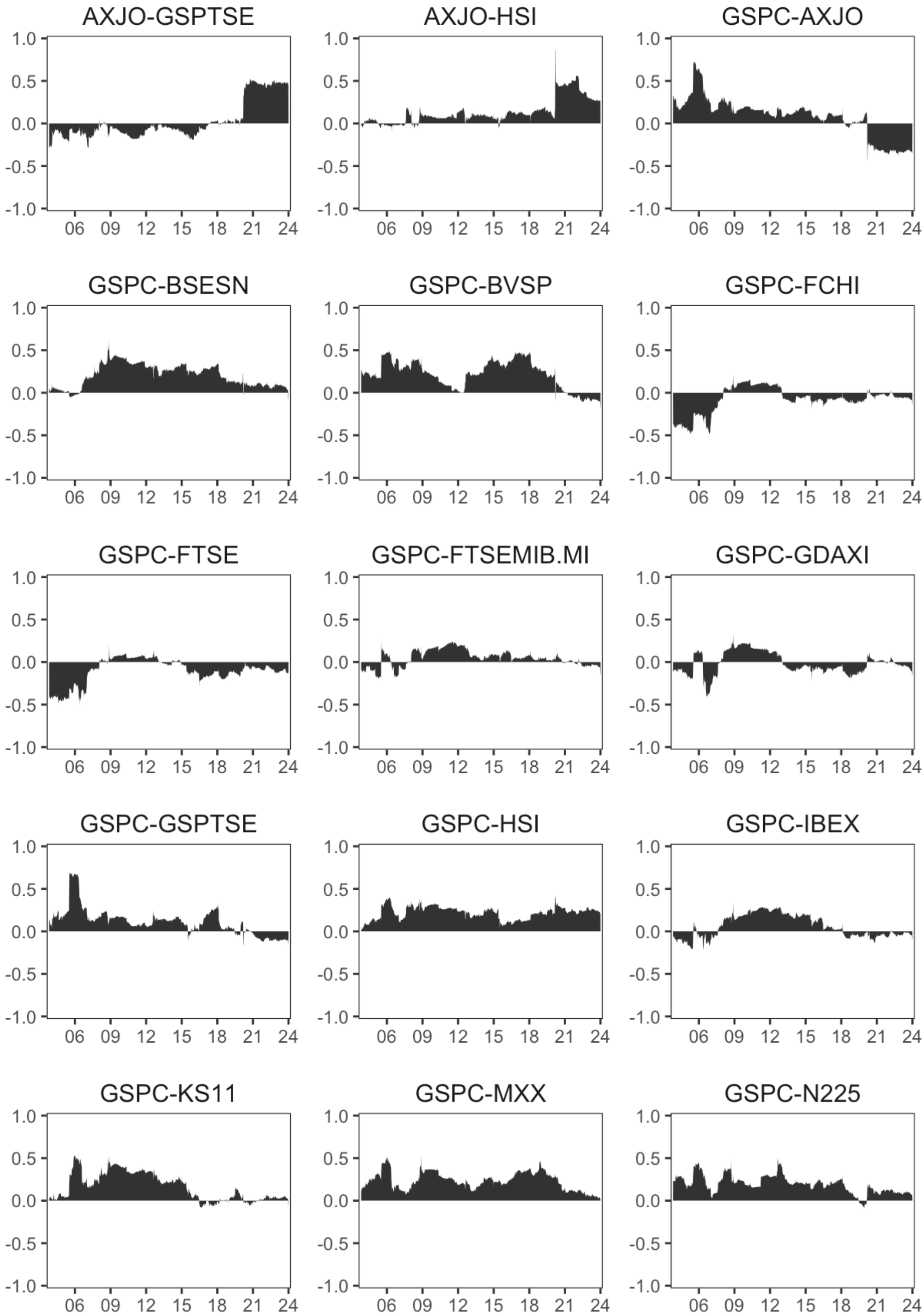
Apart from strong E.U. indexes, notably the German DAX 40 Index (GDAXI), the U.S. S&P 500 index bears nearly always positive values. It is particularly evident if compared to Asian and other minor American markets. To better observe it, we can take the pair formed together with the Brazilian Bovespa Index (BVSP).

These observations are consistent with the findings obtained in the entire analysis. Briefly, the measures adopted after the GFC helped reducing the contagion among stock markets pertaining to America and Europe. A trend that regarded only partly Asian countries, as the 1997 crisis made their financial institutions more resilient.

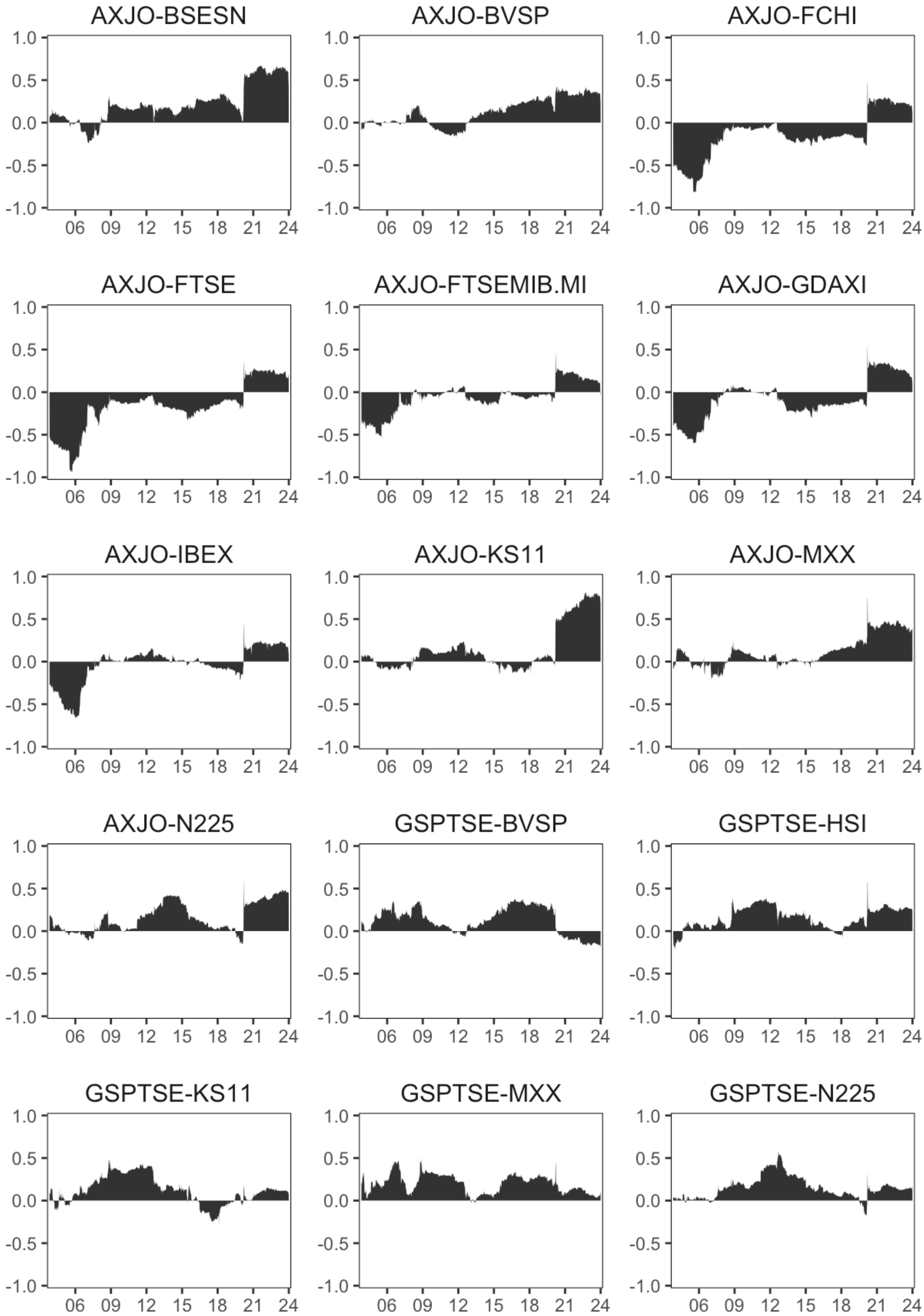
Nonetheless, from 2004 to 2024 globalization has increased the contagion between Asian and Western stock market indexes. Yet, excluding the COVID-19 outbreak, the net transmission of return and volatility spillovers usually occurs from America and Europe towards Asia, notably to India, Japan, South Korea and Hong Kong.

European countries' connectdness, first of all with the U.S., has always remained considerably high. Still, when comparing stock markets between Europe and North America, one of the countries often tends to overtake the spillovers of the other.

Figure 28. Net pairwise directional spillovers - Volatilities (2004-2024):



Data source: Yahoo Finance.



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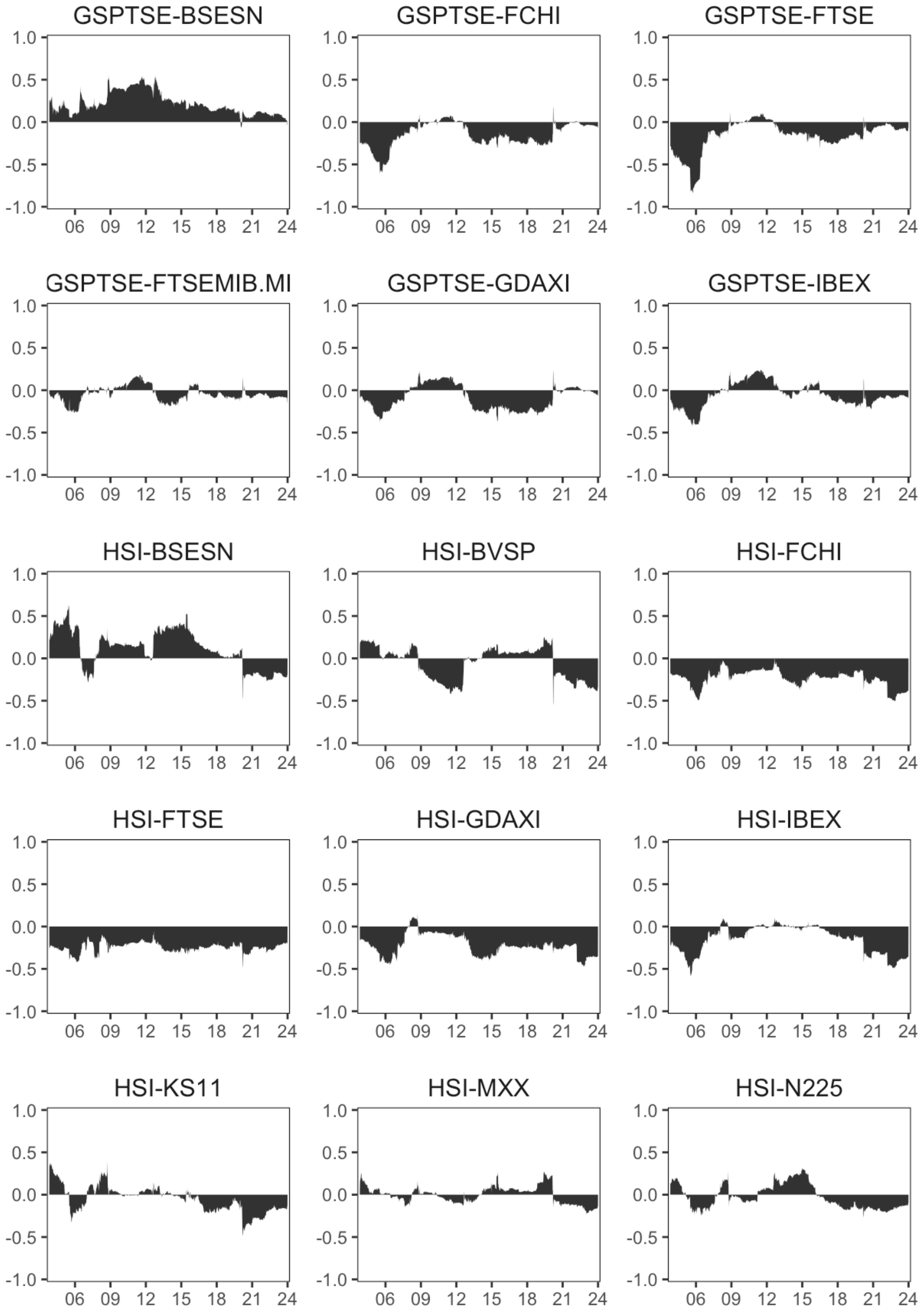
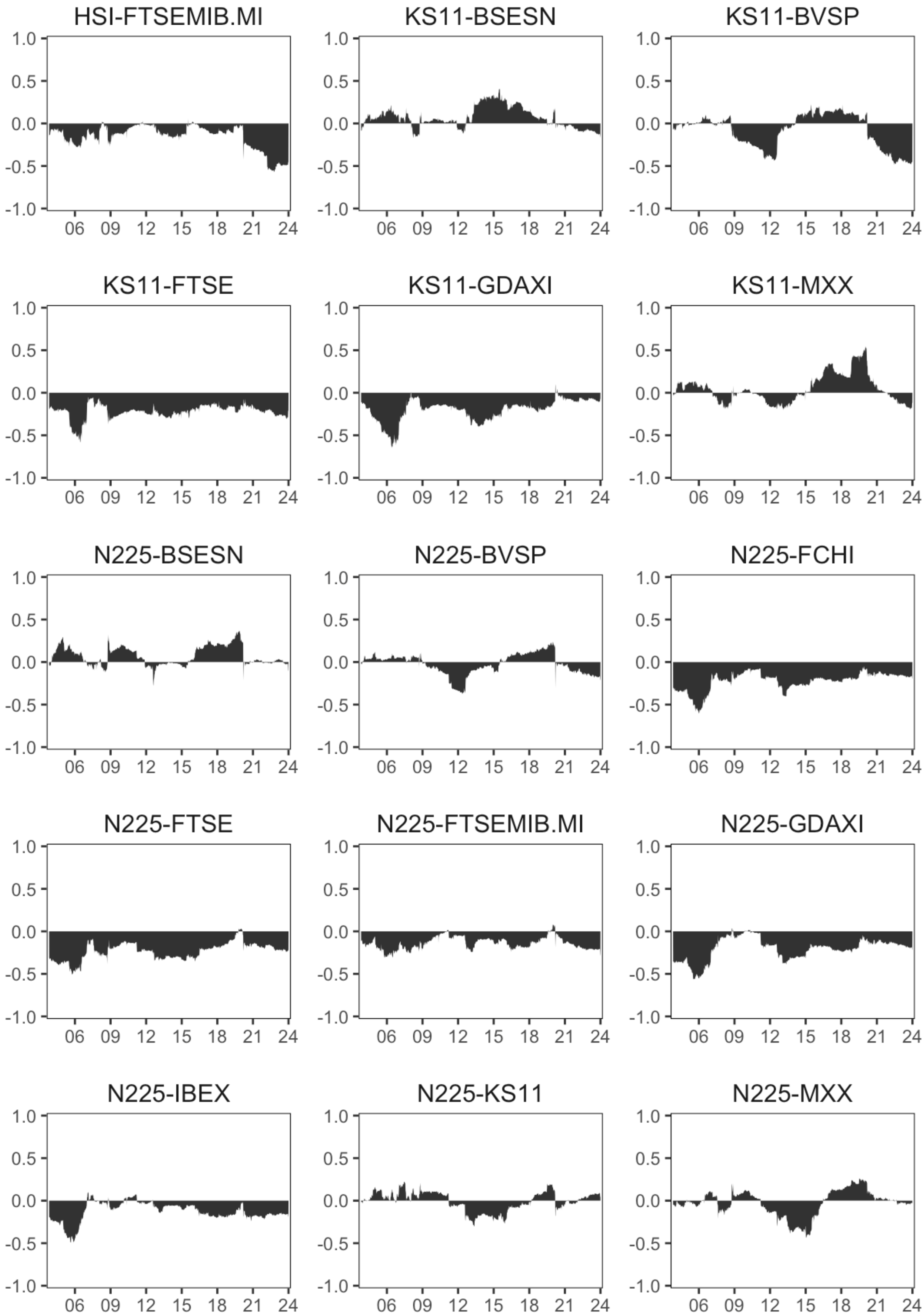
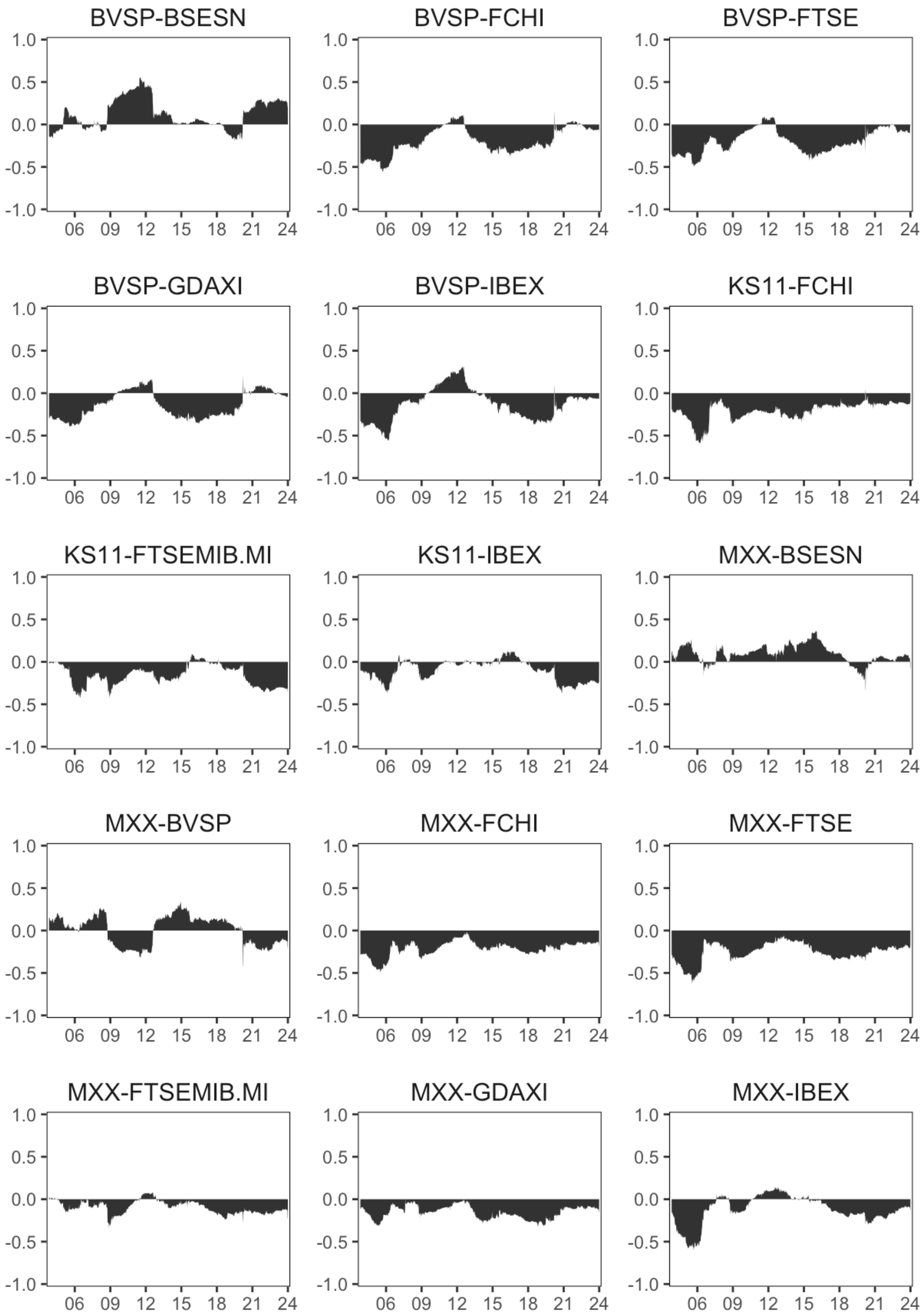


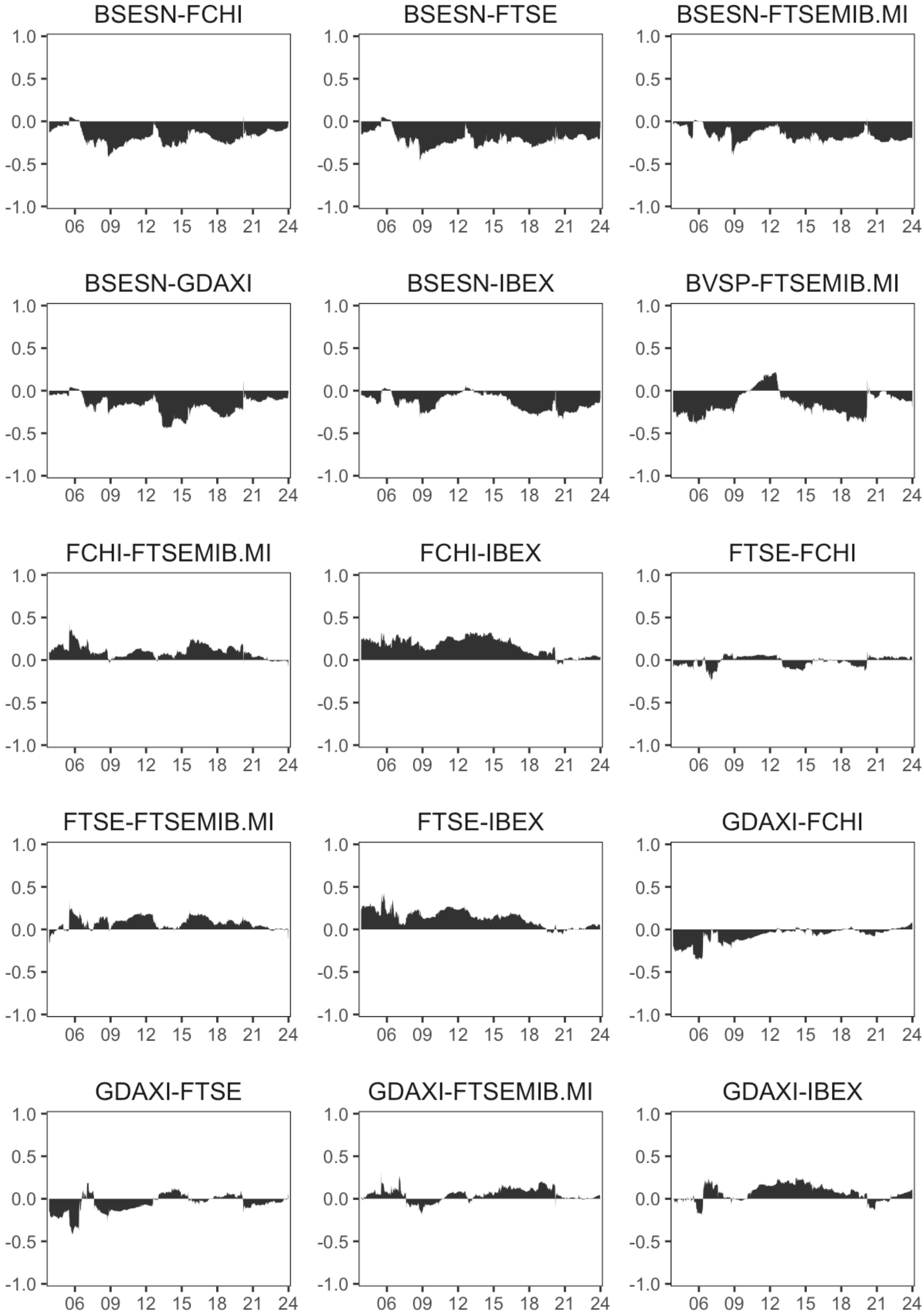
Data source: Yahoo Finance.



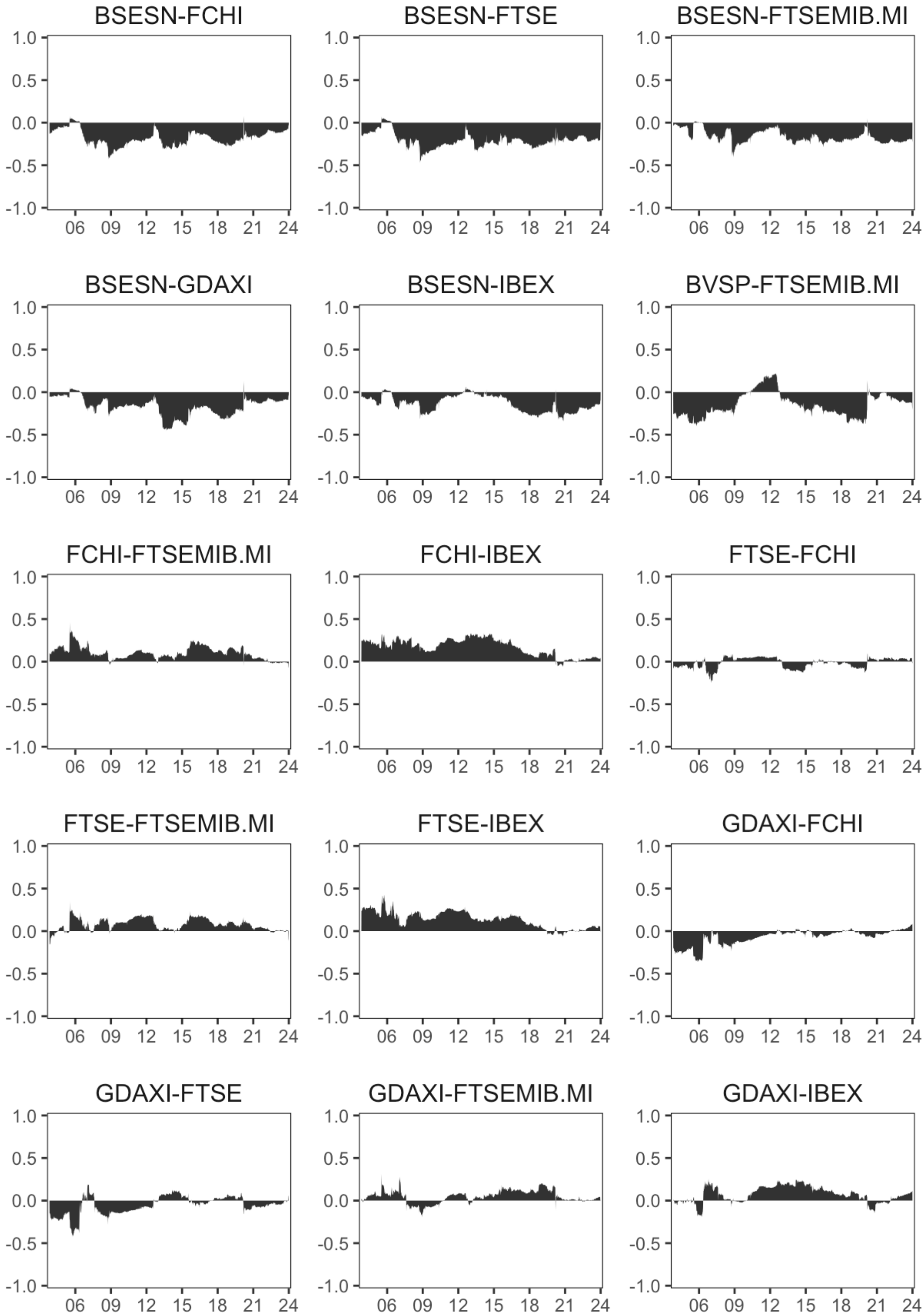
Data source: Yahoo Finance.



Data source: Yahoo Finance.



Data source: Yahoo Finance.



Data source: Yahoo Finance.

5.4 CONCLUSIONS.

- North America has always been a return and volatility spillover transmitter. Yet, the tendency lowers when comparing the S&P 500 (GSPC) with equity indexes of strong economies, such as the French CAC 40 (FCHI) Index, the U.K. FTSE 100 (FTSE) Index, and the German DAX 40 (GDAXI) Index.

  U.S. cross-variance shares also weakned during the COVID-19 crisis, when the S&P 500 (GSPC) was overtaken by weaker indexes. Among them, there is the Brazilian IBOVESPA (BVSP) Index, whose fraction of forecast error variance surpassed the U.S. counterpart for the first time since 2004-01-01.

- Traditionally, Latin America is a net spillover receiver. Yet, when analyzing the transmission with Asian stock market indexes, precisely the Indian S&P SENSEX (BSESN) Index, the Hong Kong Hang Seng Index (HIS), and the Japanese Nikkei 225 (N225), there is no index strongly exceeding the other.

  By examining the period in which the Brazilian IBOVESPA (BVSP) Index experienced a rise in the C. to others, it is evident that the shift began in the mid-2014. Precisely, the inversion coincided with a period of high political instability in Brazil, highlighted by the impeachment of President Rousseff.

- Europe behaves similarly as North America. Since both regions have robust economies, the connectedness between the regions has always been higher-than-average. Hence, depending on the time period that one considers, their stock market indexes tend to become either net transmitters or receivers.

  For instance, analyzing the GFC, it is clear that the contagion occurred from the U.S. to the E.U. From 2008-01-01, in fact, the S&P 500 (GSPC) became a net transmitter in all pairs involving Europe. When examining volatilities, the result is confirmed even with the German DAX 40 (GDAXI) Index.

- Apart from the COVID-19 period, East and South Asian indexes tend to be net spillover receivers. Yet, the Hong Kong Hang Seng Index (HSI) did not became a transmitter even during the 2020 crisis. Hence, by adopting rapid measures to contrast the pandemic, the region acquired quickly a stability.

  Similarly, South Korea did not increase its net directional spillovers only in 2020. It became a net transmitter already in 2015, when the protests against President Park Geun-hye on corruption charges causes political instabilities in the region, lowering investor sentiment and inducing them to sell-offs.

- From 2020, the S&P/ASX 200 Index (AXJO) became the equity index with the highest forecast error variance explained. This trend, reverting the usual behavior of Australian spillovers, could be caused by the recession that the country is facing. Hence, in 2023, its economy reduced by 1% per capita.

6. BANKING NETWORK ANALYSIS.

6.1 DATASET.

The preliminary analysis, considering 14 of the most relevant equity indexes, shed light on the macro-level dynamics of connectedness. Aware of the results achieved throughout *Chapter 5*, we now employ a detailed analysis and quantify the volume of interconnectedness existing among the most capitalized banks of the world.

To start, we examined the list of the world's 100 largest banks drafted by Standard & Poor's Global in 2023. Afterward, we selected a period enabling us to cover the 2008 crisis without sacrificing the majority of the data, spanning from 2008-01-01 to 2024-01-01. Yet, the only banks that were excluded were listed after 2008[52].

Behind the choice of selecting banks by their asset value lies a practical reasoning. Large banks often exhibit (i) high volumes of bilateral transactions, (ii) diversified assets' portfolios, and (iii) active involvement in financial markets. These features, according to Liu, Quiet and Roth (2015), contribute to their high connectedness.

Precisely, scholars believe that the risk of contagion arises from financial markets' participation. Historically, banking sector disruptions were amplified by mark-to-market losses, margin calls, and information spillovers. Over the past 15 years, the bankruptcy of Lehman Brother's in 2008 is probably the most striking example.

Compared to Diebold and Yilmaz *Trans-Atlantic Equity Volatility Connectedness: U.S. and European Financial Institutions* (2016) our study encompasses European, U.S., and Asian banks. Since, according to McKinsey & Co. (2020), Asia accounts for more than one-third of the industry's profits, the region had to be included.

By analyzing the list below (*Figure 29*), it is worth mentioning that China emerges as the dominant player, with a total of 12 banks. The largest institutions are in fact represented by (i) Industrial and Commercial Bank of China (1398.HK), (ii) China Construction Bank. Corp (601939.SS), and (iii) Bank of China Ltd (601988.SS).

While China holds a leading position, it is not the only East-Asian country included in the top three. Despite the 10 U.S. banks securing North America's second place, Japan's 6 banking institutions confirm the region's third position. Hence, Japanese banks have became key partners for global corporations (McKinsey & Co., 2022).

Contrarily, the countries at the bottom of the ranking are Belgium, Austria, Sweden and Norway. With only one institution appearing in the list, they mirror the inferior economic size, global expansion, and technological advancement of the respective countries, especially when compared to countries like China, the U.S., and Japan.

[52] Apart from omitting banks whose data start after 2008-01-01, private banks were excluded as well.

Figure 29. World's 70 largest banks (2008-2024):

Name	*Country*	*Assets*
Industrial and Commerical Bank of China (1398.HK)	China	$5,742 billion
China Construction Bank Corp. (601939.SS)	China	$5,016 billion
Bank of China Ltd. (601988.SS)	China	$4,919 billion
JPMorgan Chase & Co. (JPM)	U.S.	$3,665 billion
Bank of America Corp. (BAC)	U.S.	$3,051 billion
Mitsubishi UFJ Financial Group Inc. (8306.T)	Japan	$2,967 billion
HSBC Holdings PLC (HSBA.L)	U.K.	$2,864 billion
BNP Paribas SA (BNP.PA)	France	$2,849 billion
Crédit Agricole Group (ACA.PA)	France	$2,542 billion
Citigroup Inc. (C)	U.S.	$2,416 billion
SMFG Inc. (8316.T)	Japan	$2,006 billion
Mizuho Financial Group Inc. (8411.T)	Japan	$1,909 billion
Bank of Communications Co. (3328.HK)	China	$1,888 billion
Wells Fargo & Company (WFC)	U.S.	$1,881 billion
Banco Santander SA (SAN.MC)	Spain	$1,853 billion
Barclays PLC (BARC.L)	U.K.	$1,823 billion
UBS Group AG (UBSG.SW)	Switzerland	$1,679 billion
Société Générale SA (GLE.PA)	France	$1,588 billion

Royal Bank of Canada (RY.TO)	Canada	$1,544 billion
The Toronto-Dominion Bank (TD.TO)	Canada	$1,524 billion
China Merchants Bank Co. Ltd (600036.SS)	China	$1,470 billion
Goldman Sachs Group Inc. (GS)	U.S.	$1,441 billion
Deutsche Bank AG (DBK.DE)	Germany	$1,428 billion
Industrial Bank Co. Ltd. (601166.SS)	China	$1,343 billion
China Citic Bank Corp. Ltd. (601998.SS)	China	$1,239 billion
Shanghai Pudong Dev. Bank Co. (600000.SS)	China	$1,184 billion
Morgan Stanley (MS)	U.S.	$1,180 billion
Lloyds Banking Group (LLOY.L)	U.K.	$1,057 billion
China Minsheng Banking Ltd. (600016.SS)	China	$1,051 billion
Intesa Sanpaolo SpA (ISP.MI)	Italy	$1,042 billion
The Bank of Nova Scotia (BNS.TO)	Canada	$1,029 billion
UniCredit SpA (UCG.MI)	Italy	$916 billion
NatWest Group PLC (NWG.L)	U.K.	$867 billion
Bank of Montreal (BMO.TO)	Canada	$859 billion
Commonwealth Bank of Australia (CBA.AX)	Australia	$837 billion
Standard Chartered PLC (STAN.L)	U.K.	$819 billion
Ping An Bank Co. (000001.SZ)	China	$771 billion
Banco Bilbao Vizcaya Arg. SA (BBVA.MC)	Spain	$762 billion
State Bank of India (SBIN.NS)	India	$694 billion

Canadian Imperial Bank of Commerce (CM.TO)	Canada	$691 billion
National Australia Bank Ltd. (NAB.AX)	Australia	$679 billion
U.S. Bancorp (USB)	U.S.	$674 billion
ANZ Group Holdings Limited (ANZ.AX)	Australia	$669 billion
Westpac Banking Corp. (WBC.AX)	Australia	$653 billion
Nordea Bank Abp (NDA-FI.HE)	Finland	$635 billion
CaixaBank SA (CABK.MC)	Spain	$604 billion
KB Financial Group Inc. (105560.KS)	South Korea	$557 billion
PNC Financial Services Group Inc. (PNC)	U.S.	$557 billion
Resona Holdings Inc. (8308.T)	Japan	$557 billion
Truist Financial Corp. (TFC)	U.S.	$555 billion
DBS Group Holdings Ltd. (D05.SI)	Singapore	$554 billion
Danske Bank A/S (DANSKE.CO)	Denmark	$540 billion
Hua Xia Bank Co. (600015.SS)	China	$540 billion
Shinhan Financial Group Ltd. (055550.KS)	South Korea	$537 billion
Sumitomo Mitsui Trust Holdings Inc. (8309.T)	Japan	$516 billion
Commerzbank AG (CBK.DE)	Germany	$510 billion
Bank of Beijing Co. Ltd. (601169.SS)	South Korea	$447 billion
Itau Unibanco Holding SA (ITUB4.SA)	Brazil	$439 billion
Oversea-Chinese Banking Corp. Ltd. (O39.SI)	Singapore	$417 billion

The Bank of New York Mellon Corp. (BK)	U.S.	$405 billion
KBC Group NV (KBC.BR)	Belgium	$380 billion
Banco do Brasil S.A. (BBAS3.SA)	Brazil	$379 billion
United Overseas Bank Limited (U11.SI)	Singapore	$376 billion
Nomura Holdings Inc. (8604.T)	Japan	$373 billion
Erste Group Bank AG (EBS.VI)	Austria	$346 billion
Industrial Bank of Korea (024110.KS)	South Korea	$343 billion
Bank of Ningbo Co. Ltd. (002142.SZ)	China	$343 billion
Banco Bradesco S.A. (BBDC4.SA)	Brazil	$340 billion
Svenska Handelsbanken AB (SHB-A.ST)	Sweden	$331 billion
DNB Bank ASA (DNB.OL)	Norway	$328 billion

Data source: Standard & Poor's Global, 2023.

Just as in *Chapter 5.1*, returns were calculated as the natural logarithmic difference between the weekly adjusted closing prices $r_t = In(P_t) - In(P_{-1})$ on each Friday. Likewise, volatilities were measured with the Garman-Klass estimator, accounting for the highest, lowest, open and closing prices of the stock at the end of the week:

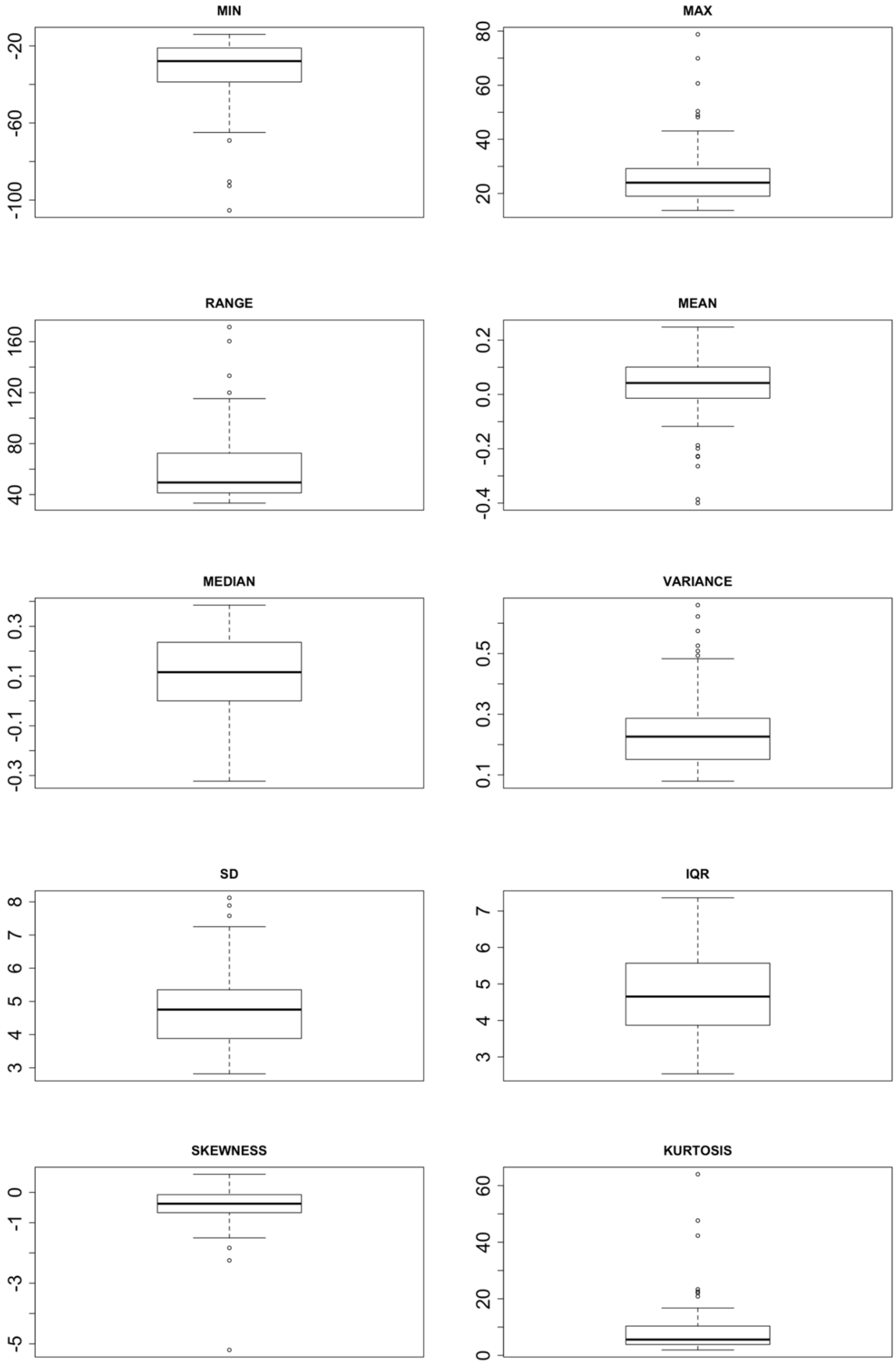
$$\tilde{\sigma}_{GK}{}^2 = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{1}{2}In\left(\frac{P_{it}^{max}}{P_{it}^{min}}\right)\right)^2 - \frac{1}{N}\sum_{i=1}^{N}(2In2-1)\left(In\left(\frac{P_{it}^{close}}{P_{it}^{open}}\right)\right)$$

From 2008-01-01 to 2024-01-01 we recorded 816 returns and 808 volatilities. Yet, 16 and 24 observations were omitted due to data availability issues, mainly related to stock markets' holidays. A detail that becomes extremely relevant if we consider that the sampling data include 21 stock exchanges with different closing days[53].

Examining the stocks' descriptive statistics, returns obey to common stylized facts (*Figure 30*). The main information arising from the box plots is the deviation from normality. Yet, the presence of leptokurtosis and a negative skewness suggests that stocks' return have fatter tails and higher peaks rather than a normal distribution.

[53] Stock exchanges are closed on national public holidays, which significantly vary by country.

Figure 30. Descriptive statistics - Returns (2008-2024):



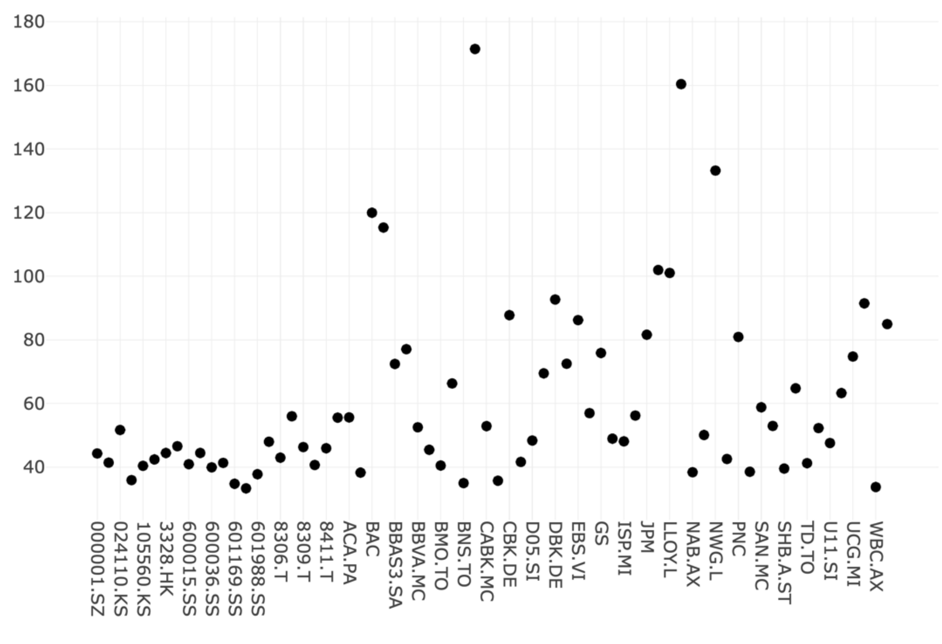
Data source: Yahoo Finance. All data, skewness and kurtosis apart, are in %.

The major difference with respect to *Figure 10* is the narrower range of descriptive statistic values. Since the dataset does no more revolve around equity indexes, but comprises 70 stocks belonging to the financial sector, the data points belonging to the box-plots are more squeezed towards the average, depicted by the black line.

While the inclusion of one sector ensures tighter values, the incorporation of banks resulted in greater fluctuations. Being financials sensitive to economic conditions, market dynamics, leverage usage, and regulatory changes, their instability tends to be higher as well. Yet, the average variance is higher than the one of *Chapter 5.1*.

Breaking down returns, the mean range over which bank stocks oscillate is 60.8%: doubled if compared to the the preliminary analysis value. As illustrated in *Figure 31*, the highest return range pertains to Citigroup (C) (171.43%), closely followed by Morgan Stanley (MS) (160.39%), and NatWest Group (NWG.L) (133.22%).

Figure 31. Return range (2008-2024):



Data source: Yahoo Finance. All tickers reflect the data points on the grid.

The lowest range is instead associated with China Construction Bank (601939.SS) (33.34%), strictly followed by Westpac Banking (WBC.AX) (33.74%) and Bank of Beijing (601169.SS) (34.78%). Since all these banks are listed in Asian-Pacific marketplaces, the trend may be explained by the objectives adopted in the country.

As per BDO Hong Kong (2020), Chinese banks show a high profitability compared to their global counterparts. Their high profits, however, do not lead to high returns on assets. Being the majority of Chinese institutions owned by the State, their main aim is not to maximize profits to shareholders, but to support economic growth.

The Banker International Press Release (2019) declared that the average Return on Assets (ROA) of U.S. banks is 1.2, slighlty higher than China's 0.89. The disparity widens even more when examining the Return on Capital (ROC). In 2019, Chinese banking institutions reached a ROC of only 12, while U.S. stood at almost 14.5.

Shifting the focus towards the descriptive statistics of volatilities (*Figure 32*), data points show a higher mean and median than in the preliminary analysis. Beside the unstable nature of the financial sector, the reason could be that the period analyzed through *Chapter 6.1*, from 2008-01-01 to 2024-01-01, is relatively less stable.

Yet, volatilities still adhere to common facts. Apart from leptokurtosis, the positive skewness suggests that observations are no longer normally distributed. Hence, by considering a dataset that covers the GFC, the 2015 stock market sell-offs, and the outbreak of COVID-19, high volatility values tend to occur more frequently[54].

Analyzing the volatility range, while the average sets at 239.59%, lower and upper bounds exhibit the same trend of *Figure 31*. Still, while the maximum corresponds to an U.K. bank, NatWest Group (NWG.L) (1675.34%), the minimum belongs to an East-Asian bank, precisely Oversea-Chinese Banking Corp. Ltd. (O39.SI).

The gap in the volatility range of Western and Eastern countries could be explained by various factors. First of all, the number of banking institutions controlled by the States. Since the Chinese government aims at ensuring stability, controlling capital flows, and protecting investors, banks operate under a controlled framework.

As a confirm, during 2024 China issued more stringent guidelines to address stock markets' volatility. Under this new regulation, authorities will better control Initial Public Offerings (IPOs), intensify their efforts to fight frauds, and incentivize listed companies to increase payouts (China Securities Regulatory Commission, 2024).

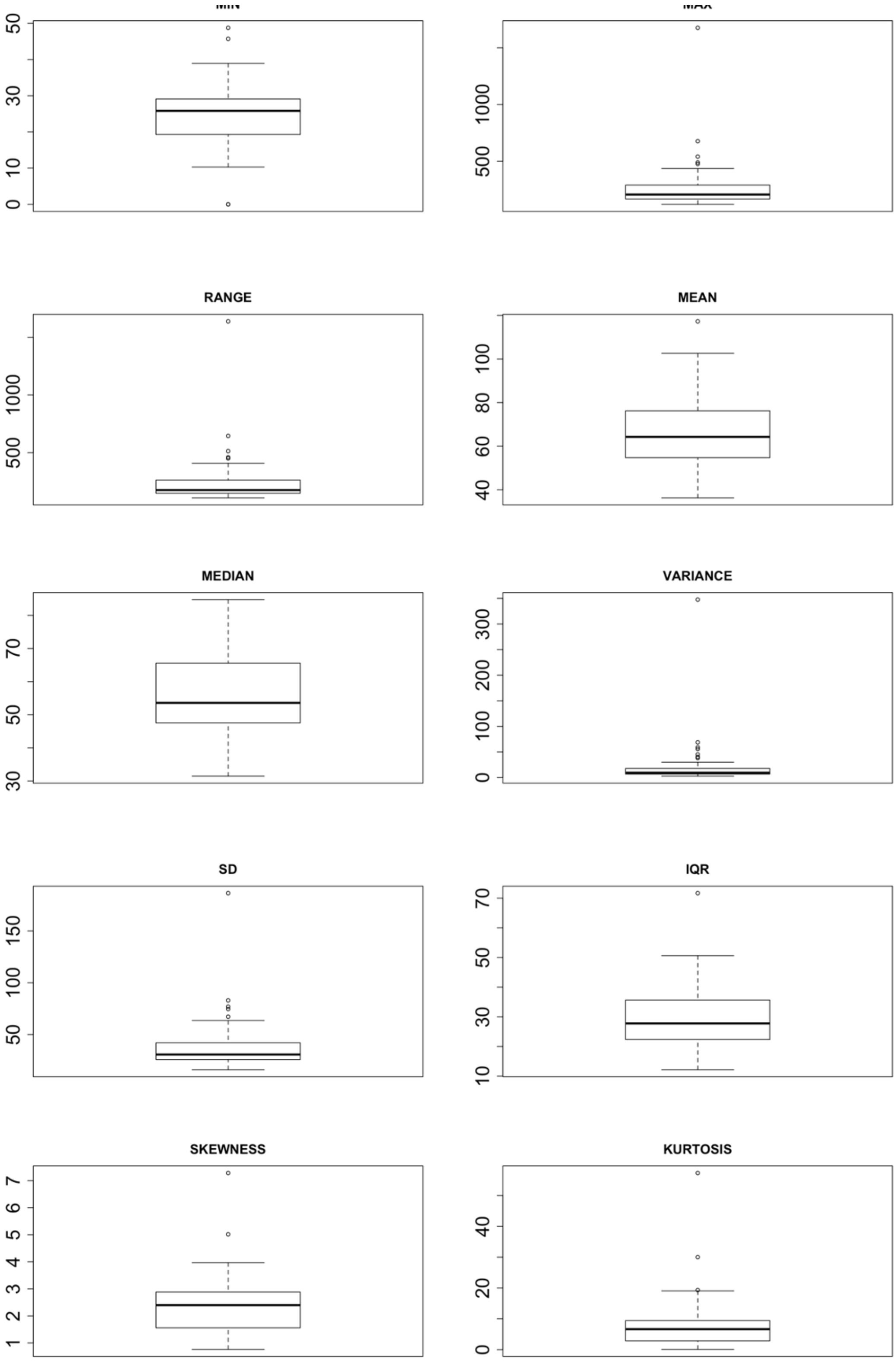
In line with other measures adopted by the Chinese government, the aim is to make the stock market "*safe, regulated, transparent, open, vivid and resilient*" (Li Chao, vice chairman of the CSRC, 2024). Yet, providing a safe and resilient stock market increases the confidence of investors and ensures a less volatile environment.

For model selection, we relied on the Akaike Information Criterion (AIC), leading once more to a $VAR(1)$ in the case of returns. The major difference to *Chapter 5.1* regards in fact volatilities. With a period ranging from 2008-01-01 to 2024-01-01, the AIC does no more suggest a $VAR(4)$ model, but instead a $VAR(10)$ model.

In either case, the Augmented Dickey-Fuller (ADF) test, performed with a 5% and 10% critical values, indicated a strong evidence against the presence of a unit root. By rejecting the null hypothesis, we assumed that the 70 time series did not exhibit any peculiar trend or systematic pattern, treating them as if they are stationary.

[54] As already observed in *Chapter 4.1*, volatility spikes tend to occur as a response to unexpected news.

Figure 32. Descriptive statistics – Volatilities (2008-2024):



Data source: Yahoo Finance. All data, skewness and kurtosis apart, are in %.

6.2 VARIABLE SELECTION.

Before analyzing the interdependence existing among the world's largest banks, it is necessary to address the high-dimensionality of the VAR models. With a dataset containing 70 banks, computational complexity and difficulties in visualizing data might compromise the performance of the analysis, leading to a lower efficiency.

As already observed in *Chapter 4.1*, over the years, the curse of dimensionality has been addressed using various approaches. Yet, the principal methods adopted have been factor models and regularization techniques, such as the Ridge regression, the Lasso, and the Elastic Net, which incorporates the Ridge and the Lasso methods.

After observing the pros and cons of all methods, we omitted factor models, whose interpretation was not as intuitive as shrinkage methods. For a separate reason, and precisely for the lack of shrinkage, we preferred the Lasso, the adaptive Lasso, and the Elastic Net techniques over the traditional Ridge regression (*Chapter 4.2*).

Yet, since none of the previous methods account for lag effects, we considered a variant of the adaptive Lasso, the «*lag-weighted Lasso*». The technique, developed by Park and Sakaori (2013), resembles the former but is suitable to VARs. Weights are in fact determined by both the size of coefficients and the number of lags:

$$\hat{\beta}_{LWlasso} = \arg\min_{\beta}\{\|y_t - x_t\beta\|^2\} + \lambda \sum_{j=0}^{p} \sum_{l=0}^{q_j} \widehat{w}_{j,l}\left|\beta_{j,l}\right|$$

With variable $\widehat{w}_{j,l}$[55]:

$$\widehat{w}_{j,l}^{1} = \frac{1}{[\alpha(1-\alpha)]^{\gamma}}$$

$$\widehat{w}_{j,l}^{2} = \frac{1}{\alpha(1-\alpha)^{l}[|\beta_{j,l}|]^{\gamma}}$$

$$\widehat{w}_{j,l}^{3} = \frac{1}{[\alpha(1-\alpha)^{l}|\beta_{j,l}|]^{\gamma}}.$$

The idea of integrating lag lengths originates from Shrestha (2007), who suggested that as the lag increases, the correlation coefficients between $(Y_t, X_{1,t}, \dots, X_{p,t})$ and $(Y_{t-1}, X_{1,t-1}, \dots, X_{p,t-1})$ lower. In line with the assumption, Shrestha demonstrated that in an autoregressive model *"factor effects reduce as the lag length increases*".

In light of Shrestha's results, Park and Sakaori (2013) expanded the adaptive Lasso to incorporate lag effects. By using these weights, they discovered that "*estimators of variables with small $\alpha(1-\alpha)$ and $\hat{\beta}$, i.e. variables in the distant past and with small effects, are considerably shrunk*", until being removed from the model.

[55] While the type-1 weight reflects only the lag effect, the type-2 and type-3 represent the lag effect and the coefficient size.

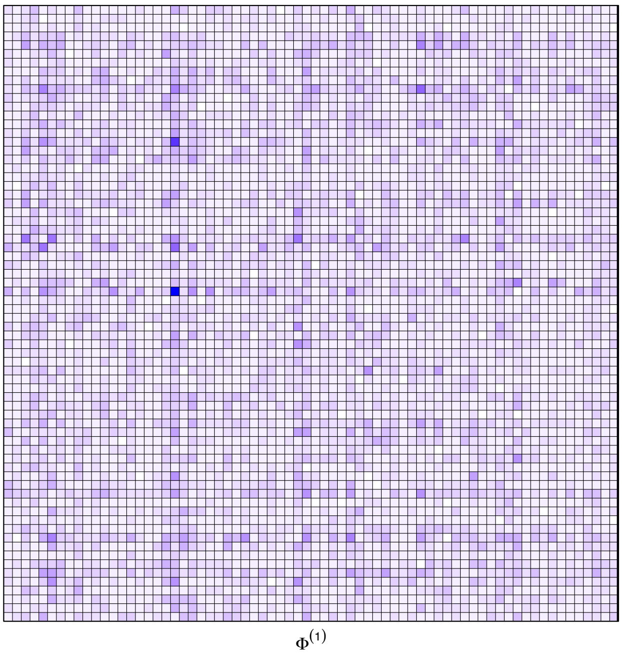
Aware that the lag-weighted Lasso bears a straightforward result, it is necessary to specify the assumptions that we decided to follow. Precisely, the lag order for both returns and volatilities was obtained using the Akaike Information Criterion (AIC). Hence, dimensionality reduction was performed under a $VAR(1)$ and $VAR(10)$.

Given the lag order, the lag-weighted Lasso required to set the depth of the penalty grid and the number of penalty parameters. This involved iterating the model over a range from 50 to 250 for the former, and from 10 to 30 for the latter. The trade-off between complexity and computational effort was represented by 150 and 10.

Starting off with returns, the main requirement of the regularization technique was finding the optimal penalty parameter λ. With our data, the optimal Lambda, hence the Lambda minimizing the Mean Square Forecast Error (MSFE)[56], was chosen by a cross validation procedure, computing the model's performance every time.

Thanks to a grid depth of 150 and 10 penalty parameters, the optimal Lambda was 0.0009, leading to a flexible model but imposing less penalties on the coefficients. Yet, although the in-sample and the out-of-sample loss are 13.4% and 15.1%, the fraction of active coefficients is 99.7%[57], impeding to perform variable selection.

Figure 33. Sparsity pattern – Returns (2008-2024):



Data source: Yahoo Finance.

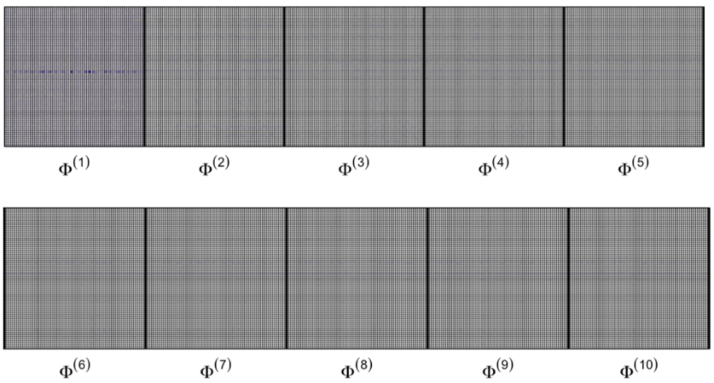
[56] $MSFE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$ with Y_i the observed value at time i, $\hat{Y}_i$ the forecasted value at time i and n the total number of observations.

[57] Lower values are obtained with higher values of the penalty grid.

With volatilities, we reached a similar result. Through the cross-validation process, we found an optimal Lambda of 0.0005, slighlty lower than the value used for the return scenario. The consequence was that across the 10 lags of the VAR, the share of active coefficients (99.9%) made impossible to perform a variable reduction.

To achieve a better outcome we should opt for a penalty grid that allows for greater sparsity. Yet, increasing the depth of the grid and the number of penalty parameters amplifies the computational effort. Given the complexity of carrying out shrinkage methods, we decided to address the high-dimensionality of the model differently.

Figure 34. Sparsity pattern – Volatilities (2008-2024):



Data source: Yahoo Finance.

Since factor models lack interpretability and regularization techniques are not able to select variables, dimensional reduction was performed with a variant of variance thresholding (Otsu, 1979). The method, removing all features with low variability, enabled us to shrink the dataset without sacrificing the model's predictive power.

Precisely, variance thresholding involves calculating the variance of every variable and establishing a discretionary threshold. Any low-variance features, representing variables with a variance below the threshold, are then removed from the database. At the very end, the only predictors selected carry relevant additional information.

However, when applying a variance thresholding to the dataset, East-Asian banks were removed. Given the significant number of Chinese and Japanese stocks in the original list (*Figure 29*), we replaced the variance with the Forecast Error Variance Decomposition (FEVD), omitting all variables with a low contribution to shocks.

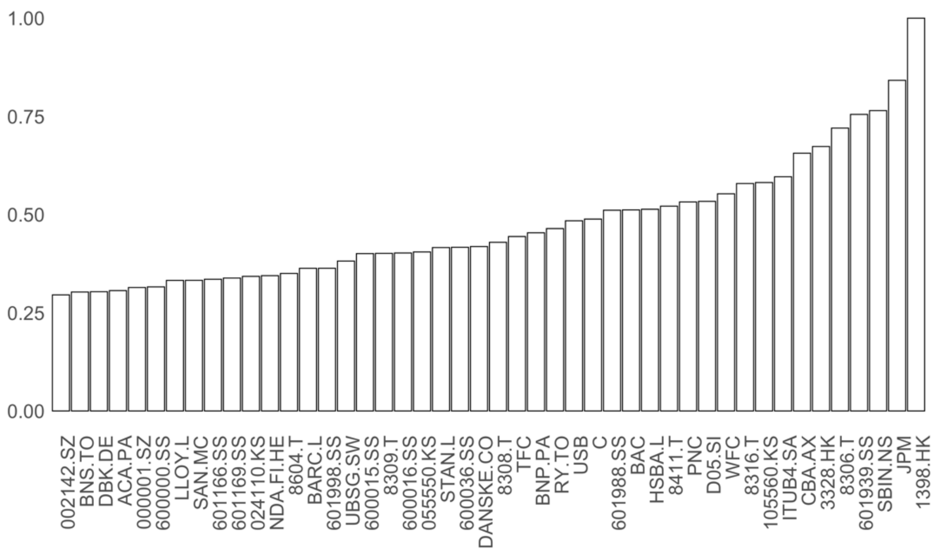
To begin with, we estimated the FEVD with a standard 10-period forecast horizon. Next, we computed the importance matrix, where each column contains the highest forecast error variances in the forecasted period. Yet, to exclude the banks with the lowest significance, feature selection techniques required choosing a threshold[58].

[58] Similarly to variance thresholding, the threshold is discretionary.

As illustrated in *Figure 34*, variable reduction was executed with a 0.30 threshold, and to ensure consistency across datasets, we included only common variables. By observing the plot, it is worth noticing that East-Asian banks are no more excluded, since they do not show high variances, but have significant shock contributions.

Yet, it is worth observing that the FEVD of returns removed only 11 banks. Hence, the majority of exclusions stemmed from the volatility error variances. Although many of these stocks are associated with banks with low asset values, such as DNB Bank ASA (DNB.OL), Goldman Sachs Group Inc. (GS) was excluded as well[59].

Figure 35. FEVD variable selection (2008-2024):



Data source: Yahoo Finance.

The major evidence is that all the stocks chosen by the FEVD thresholding belong to banks with high asset values. In fact, the stocks with the largest % are in the top 3 spots of *Figure 29*: the Industrial and Commerical Bank of China (1398.HK), JP Morgan Chase & Co. (JPM), and China Construction Bank Corp. (601939.SS).

By and large, East-Asia accounts for 50% of the reduced sample. The share, larger than Europe (26%), America (19%), South Asia (2%), and Oceania (2%), sustains the equilibrium of *Figure 29*. Yet, from 2008-01-01 to 2024-01-01, the dataset has been reduced from 70 to 46, significantly increasing the computational efficiency.

With that being said, reducing the number of variables marks the preparatory stage of our connectedness analysis. The static (*Chapter 6.3*) and dynamic (*Chapter 6.4*) spillovers will both be based on the dataset including 46 stocks. Still, the approach remains consistent to Diebold and Yilmaz (2009; 2012) connectivity measures.

[59] The low contribution to shocks could stem from Goldman Sachs risk management strategies.

6.3 STATIC SPILLOVER ANALYSIS.

After addressing the high-dimensionality of the VAR through feature selection, we will analyze return and volatility spillovers among the 46 banks of the sample. Yet, the main difference to *Chapter 5.2* will be the period under analysis, spanning from 2008-01-01 to 2024-01-01, but still including the GFC and the COVID-19 crisis.

The reason why there is no longer a time partition is that we already examined how interdependence varied across volatile periods in *Chapter 5.2*. Since the matter has already been studied in the preliminary analysis, the result would have been highly similar. Hence, to examine the banking network, we chose a single time period.

Based on our assumptions, we modeled return and volatility time series through a $VAR(1)$ and $VAR(10)$ model. Yet, our primary focus remained the spillover index. By employing a connectedness table (*Figure 14*), the metric allowed us to quantify the extent to which spillovers are transmitted across the stocks of the network.

Starting with returns, we chose to illustrate the connectedness table (*Appendix 12*) through a «*directed graph*», whose weights are the entries of the adjacency matrix. Essentially, an adjacency matrix can be defined as a square matrix "*which encodes connection strength of each pair of nodes*" (Kanjilal, Barman, and Kundu, 2021).

While the graph's directed nature enables asymmetric relations between nodes, its weights span from 0.01% to 10.3%. The minimum weight is associated with Bank of China Ltd. (601988.SS) - Crédit Agricole Group (ACA.PA), and the maximum to China Construction Bank Corp. (601939.SS) - Bank of China Ltd. (601988.SS).

At first glance, it is evident that the «*weighted directed graph*» of *Figure 36* exhibits two distinct groups. On one side, there is a prominent cluster comprising European, American, Asian, and Australian banks. On the other side, there is a smaller cluster specifically consisting of Chinese banks, highly connected between each other's.

In the smallest cluster, the most interconnected banks are China Construction Bank Corp. (601939.SS), China Merchants Bank Co. Ltd. (600036.SS), Industrial Bank Co. Ltd. (601166.SS), Shanghai Pudong Development Bank Co. Ltd. (600000.SS), China Minsheng Banking Ltd. (600016.SS), and Hua Xia Bank Co. (600015.SS).

Serving as a bridge between the largest and smallest clusters are the Chinese banks with the highest asset values, namely the Industrial and Commerical Bank of China (1398.HK) and Bank of Communications Co. (3328.HK). Hence, while the former has assets for almost \$5,742 billion, the value of the latter is \$1,888 billion.

As a consequence, despite in the past 20 years the connectedness between Western and Eastern stocks rose (*Chapter 5.2*), China is still far from explaining the forecast error variance of European, American, and Australian returns. Hence, the majority of shocks received from Chinese banks are still transmitted inside the country.

However, the trend does not concern the rest of Asia. Japanese, South-Korean, and Indian banks, such as Mitsubishi UFJ Financial Group Inc. (8306.T), KB Financial Group Inc. (105560.KS), and State Bank of India (SBIN.NS), are in fact collocated in the main cluster, exhibiting a higher interconnectedness than Chinese banks.

Getting back to the matter, the reason why Chinese banks transmit and receive low spillovers from the American and European banking industries could be the market share of foreign banks. In 2023, foreign presence in China's banking sector (1.3%) was inferior to its peers, such as Japan (5.6%) and India (6.4%) (CEIC, 2024).

Yet, although the Chinese government has still a key role in the industry, the recent banking reforms are promoting a market-based approach (RBA, 2021). According to the bulletin, "*while China has become heavily integrated with the global trading system, its integration with capital markets is still at a formative stage*".

The path to integration may be led by the Industrial and Commercial Bank of China (1398.HK). Despite being state-owned, the bank started its international expansion in 2008. With its 428 subsidiaries, it currently operates across 48 countries, and is actively involved in the "Belt and Road" initiative and "Going Global" program.

The connectedness table (*Appendix 12*) clearly demonstrates that the Industrial and Commercial Bank of China (1398.HK) is more connected with Western banks than others. Comparing it to Bank of China Ltd. (601988.SS), the spillovers transmitted to European and American banks were on average 80% lower than the former.

For greater clarity, we can compare the forecast error variance of JP Morgan Chase & Co. (JPM) explained by Bank of China Ltd. (1398.HK) with that of the Industrial and Commercial Bank of China (1398.HK). In fact, cross-variance shares of Bank of China Ltd. (1398.HK) are smaller (0.02%) if compared to the latter (1.27%).

The result does no longer hold when examining the return spillovers transmitted to other East- and South-Asian banks. The Bank of China Ltd. (1398.HK) explains a higher error variance in forecasting China Construction Bank Corp. (601939.SS) returns (9%) than the Industrial and Commercial Bank of China (1398.HK) (3%).

Overall, the first result coming from the analysis is that Chinese banks tend to form a separate cluster. Despite the smaller cluster, the Industrial and Commercial Bank of China (1398.HK) acts as a bridge with the global banking industry, intensifying the global integration of Chinese banks and representing an example for others.

This does not imply that Chinese banks transmit a low amount of return spillovers, but only that return shocks are limited to the East-Asian region. This becomes clear when analyzing the lowest 25-th percentile, since Asian banks transmitted 34% of the return spillovers of Western banks, with China appearing 20% of the times[60].

[60] The lowest 25-th percentile includes return spillovers between 0% and 0.34%.

In line with our thought, the bank with the lowest C. to others is not based in China, but in India. It is in fact the State Bank of India (SBIN.NS), explaining only 31.3% of the forecast error variance in the other 45 banks. Yet, even when accounting for own-variance shares (55.6%), State Bank of India (SBIN.NS) remains the lowest.

The reason why the State Bank of India (SBIN.NS) has the lowest C. to others lies in the Indian region. Even if the bank is the largest public bank of India, the country is still emerging in the global banking industry (IBM, 2022). Hence, the asset value of State Bank of India (SBIN.NS) is lower than that of major European banks[61].

Behind India, the stock with the lowest C. to others is the Commonwealth Bank of Australia (CBA.AX). The bank, in which risk management is playing an important role (CommBank, 2023), constitutes 50% of the sample's cross-variance shares, a % that increases to 67.9% when including the contribution to its own shocks.

Yet, to better comprehend the risk management's impact, we must study the bank's response to Australia's economic slowdown. This includes adopting "*conservative balance sheets*", allowing liquidity excesses, granting a flexible credit pricing, and ensuring compliance with recent financial standards (Commbank, 2023).

The stocks with the highest C. to others including own are instead Bank of America Corp. (BAC) (124.89%), BNP Paribas SA (BNP.PA) (122.10%), and JP Morgan Chase & Co. (JPM) (120.16%). They in fact appear in the central area of the major cluster, representing the most important nodes of the banking network (*Figure 35*).

As illustrated in *Figure 29*, their high spillover transmission could be attributed to their market dominance. The performance of the top-10 stocks in the ranking could in fact significantly impact market stability. Yet, investor's sensitivity to large and highly connected institutions is greater compared to that of peripheral entities.

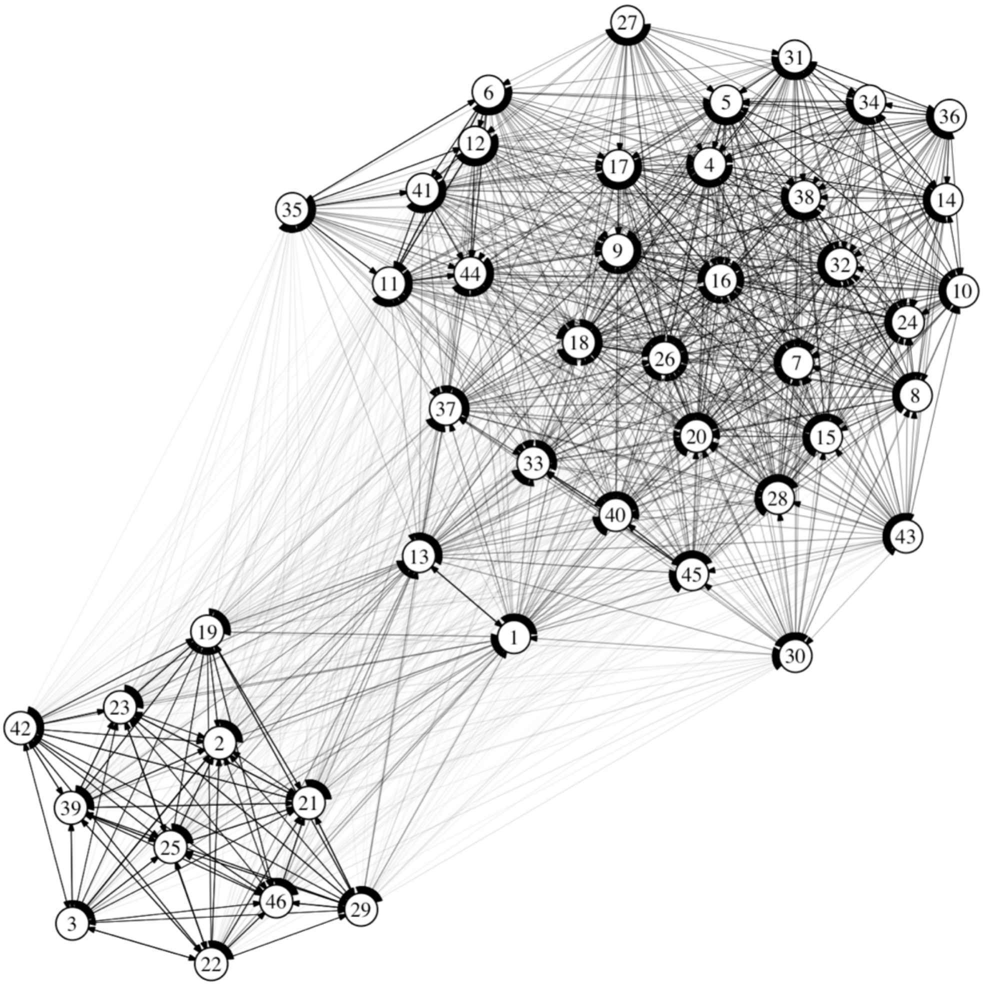
For this reason, S&P Global (2017) declared that Global Systematically Important Banks (G-SIBs), whose size increased compared to that of 2006, should be subject to more stringent requirements. In fact, after the 2023 bank failures U.S. regulators proposed higher capital standards on banks with assets worth over $100 billion.

Currently, capital requirements for $100 billion intermediate companies are set up by fixed ratios and stress tests, such as the CET1 capital ratio requirement of 4.5%, a Stress Capital Buffer (SCB) requirement of minimum 2.5%, and a surcharge for Systematically Important Banks (SIBs), starting at least from 1% (Fed, 2023).

Another reason why North-American and European banks are the highest spillover transmitters could be associated with the GFC. Since the time period of the analysis ranges from 2008-01-01 to 2024-01-01, the database covers both the 2008 housing bubble and its afermath, leading Europe to the 2010 sovereign debt crisis.

[61] The asset value of State Bank of India (SBIN.NS) is $694 billion (*Figure 29*).

Figure 36. Spillover network – Returns (2008-2024):



1398.HK - 1	601939.SS - 2	601988.SS - 3	JPM - 4	BAC - 5
8306.T - 6	HSBA.L - 7	BNP.PA – 8	ACA.PA - 9	C - 10
8316.T - 11	8411.T - 12	3328.HK - 13	WFC - 14	SAN.MC - 15
BARC.L - 16	UBSG.SW - 17	RY.TO - 18	600036.SS - 19	DBK.DE - 20
601166.SS - 21	601998.SS - 22	600000.SS - 23	LLOY.L - 24	600016.SS - 25
BNS.TO - 26	CBA.AX - 27	STAN.L - 28	000001.SZ - 29	SBIN.NS - 30
USB - 31	NDA.FI.HE - 32	105560.KS - 33	PNC - 34	8308.T - 35
TFC - 36	D05.SI - 37	DANSKE.CO - 38	600015.SS - 39	055550.KS - 40
8309.T - 41	601169.SS - 42	ITUB4.SA - 43	8604.T - 44	024110.KS - 45
002142.SZ - 46				

Data source: Yahoo Finance.

Heading to volatility spillovers (*Figure 37*), the main difference with *Figure 36* is the presence of a more interconnected network. To validate the claim, it is possible to compare return and volatility spillover networks with the average node strenght, measuring the strength of the relationships of a node with neighboring nodes.

Although the return and volatility node strength restitutes the same information as the connectedness table, the average node strength reveals a new insight. Precisely, it indicates that nodes of the volatility spillover network have stronger connections (181.79) compared to the nodes of the return spillover network (176.68).

The higher average node strength in the volatility spillover network highlights that from 2008-01-01 to 2024-01-01 major banks became more interconnected in terms of volatility transmission. Hence, because of the GFC, the 2015-2016 stock market sell-off and the 2020 COVID-19 crisis, contagion and systemic risk heightened.

Yet, although the banks transmitting the highest volatility spillovers are still based in Europe and North-America, findings are slighlty different from *Figure 36*. Here, the greatest volatility transmitters are Wells Fargo & Company (WFC) (239.08%), Truist Financial Corp. (TFC) (221.96%), and U.S. Bancorp (USB) (187.02%).

As already mentioned in *Chapter 5.2*, the strong presence of U.S. banks in the top 3 is expained by the high integration of U.S. in global stock markets. Hence, Vidal-Llana, Uribe, and Guillén (2023) declared that "*the country in which a company is listed is the main determinant of its price volatility co-movements in the market*".

A first confirm comes from analyzing the volatility transmission of Wells Fargo & Company (WFC) toward the rest of the sample. By omitting U.S. banks, its average pairwise C. (5.19%) remains considerably high. Precisely, it becomes 6.30% with Oceania, 5.77% with Europe, 5.70% with South-Asia, and 3.45% with East-Asia.

Although the highest spillover transmission belongs to U.S. banks, the majority of European banks is still relevant. In fact, from 2008-01-01 to 2024-01-01, Deutsche Bank AG (DBK.DE) exhibits a C. to others including own of 135.9%, only 19.2% above that of the Swiss investment bank UBS Group AG (UBSG.SW) (116.3%).

What is surprising is that the volatility spillovers of U.K. banks are not just inferior to China, but they are the lowest of the entire sample. Hence, HSBC Holdings PLC (HSBA.L) can explain just 26.1% of the error variance in predicting the returns of the 46 sampled banks, lowering to 12.7% when excluding own-variance shares.

The shift in behavior from the other European banks could be explained by Brexit. As observed by Hill (2015), "*what makes London a gateway for investment across the world into the whole European Union is the single market*". Yet, starting from 2016, the U.K. departed from its biggest market for export of financial services[62].

[62] Although Brexit might be an explanation, the model's accuracy could be another reason.

Shifting to the minor cluster, the main similarity observed with the return spillover network is the presence of Chinese banks. Likewise, the Industrial and Commercial Bank of China (1398.HK) and Bank of Communications Co. (3328.HK) still serve as a bridge between Chinese and America, as well as with European countries.

What is highlighted in contrast to *Figure 36* is the importance of Chinese banks in explaining the forecast error variance of the domestic volatilities. Hereafter, Bank of China Ltd. (601988.SS) is responsible for almost 9.6% of the error variance in forecasting the volatilities of China Construction Bank. Corp (601939.SS).

Yet, Chinese banking institutions still have low cross-variance shares towards U.S. and E.U. banks. Hence, Bank of China Ltd. (601988.SS) accounts for only 0.01% of of the error variance in predicting the volatility of Truist Financial Corp. (TFC), a share that lowers to 0% when considering Royal Bank of Canada (RY.TO).

Similarly, this does not imply that East-Asian banks are among the lowest volatility transmitters, since they are closely intertwined among each other's and they exhibit a high portion of intra-country variance shares. As already mentioned, the smallest C. to others of the sample is associated with HSBC Holdings PLC (HSBA.L).

Upon comparing their own-variance shares, it is clear that all banks headquartered in China account for a larger portion of domestic shocks. As a reference, it is worth mentioning that the maximum domestic variance share of Wells Fargo & Company (WFC) is 8.78%, lower than the 9.6% of Bank of China Ltd. (601988.SS).

Yet, the dynamic analysis of *Chapter 5.3* has already illustrated that during periods of heightened uncertainty and when shocks originating from China are larger, such as during the COVID-19 pandemic, Chinese cross-variance shares tend to increase. A result that has been reached by Lodge, Manu, and Van Robays (2023) as well:

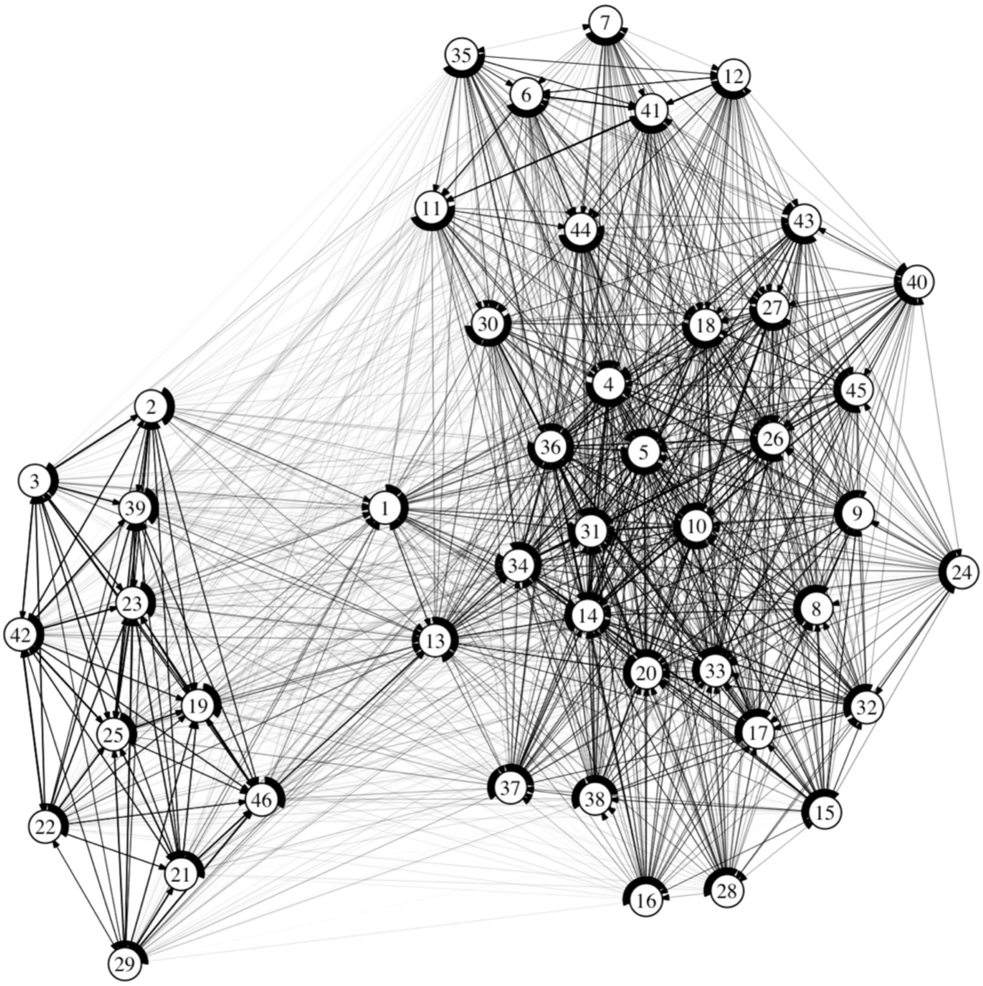
"*Although we find that spillovers of Chinese shocks to global financial markets are contained, they can be reinforced when they hit in a period of heightened volatility and when the shocks are larger in size. So what happens when China gets a cold? Global financial markets sneeze as well*" (Lodge, Manu, and Van Robays, 2023).

Throughout *Chapter 6.2* the results achieved were that (i) Chinese banks constitute a distinct return and volatility spillover cluster, (ii) the trend does not concern other banks based in East-Asia, respectively in South Korea and Japan, and (iii) the high integration between European and American banks is reflected in their spillovers[63].

Although the static analysis led to interesting results, it did not convey information on the dynamic return and volatility spillover networks. Hence, in the same manner as *Chapter 5.3*, we will employ a dynamic connectedness analysis through a rolling window approach and analyze the net directional spillovers by geographical areas.

[63] The list of European banks with which the U.S. have high volatility spillovers excludes the U.K.

Figure 37. Spillover network – Volatilities (2008-2024):



1398.HK - 1	601939.SS - 2	601988.SS - 3	JPM - 4	BAC - 5
8306.T - 6	HSBA.L - 7	BNP.PA – 8	ACA.PA - 9	C - 10
8316.T - 11	8411.T - 12	3328.HK - 13	WFC - 14	SAN.MC - 15
BARC.L - 16	UBSG.SW - 17	RY.TO - 18	600036.SS - 19	DBK.DE - 20
601166.SS - 21	601998.SS - 22	600000.SS - 23	LLOY.L - 24	600016.SS - 25
BNS.TO - 26	CBA.AX - 27	STAN.L - 28	000001.SZ - 29	SBIN.NS - 30
USB - 31	NDA.FI.HE - 32	105560.KS - 33	PNC - 34	8308.T - 35
TFC - 36	D05.SI - 37	DANSKE.CO - 38	600015.SS - 39	055550.KS - 40
8309.T - 41	601169.SS - 42	ITUB4.SA - 43	8604.T - 44	024110.KS - 45
002142.SZ - 46				

Data source: Yahoo Finance.

6.4 DYNAMIC SPILLOVERS.

Given that *Chapter 5.3* already incorporates a dynamic spillover analysis, we chose to continue using a 200-week rolling windows approach but for a more recent time frame. Analyzing the period from 2008-01-01 to 2024-01-01, we can in fact study the aftermath of the GFC without excluding all the banks listed in the early 2000s.

In line with the return spillovers observed across the 14 equity indexes, the growth in spillovers coincides with the 2015 stock-market sell-offs and the outbreak of the COVID-19 crisis (*Figure 38*). However, contrarily to *Figure 22*, there is not a clear distinction between the cycle ending in 2019 and the cycle beginning in 2020.

Figure 38. Total spillovers – Returns (2012-2024):

Data source: Yahoo Finance.

This could be attributed to the 2019 repo crisis. According to the study of Kahn et al. (2023), on September 17, intraday repo rates rose to 300 basis points above the Federal Reserve target. An event that was triggered by different factors, including "*large treasury issuances, tax deadlines, and a lower level of banks' reserves*".

Repo transactions, essentially overnight trades in government securities, play a key role in banks' short-term funding needs. Hence, when banks need higher liquidity, they can sell government securities with an agreement to buy them back later, at a slightly higher price. Yet, the spike in interest rates prevented banks to use them[64].

Another departure from the trend observed in *Figure 22* is the delayed response in return spillovers during the 2020 period. While, following the WHO's declaration, there was an immediate increase in connectivity across stock market indexes, the banking sector manifested substantial spillover effects only from the mid-2020.

[64] When the cost of borrowing increases, repo transactions become less attractive.

The delayed response in bank stocks could be attributed to various factors, first of all the policy intervention, that helped mitigate immediate impacts. Concerns about credit risk and loan quality may have also contributed. Hence, at the beginning of the COVID-19 crisis, there was uncertainty on the extent of future loan defaults[65].

In reference to the 2020 crisis, researchers have identified loan defaults as the main cause of decreasing bank returns (Duan et al., 2021; Foglia et al., 2022). The losses faced by households resulted in fact in an increase in non-performing loans, which in turn diminished the capital, the earnings, and the financial health of banks.

As per Acharya and Steffen (2020), the faster credit line withdrawals worsened the crisis that banks were facing. These outflows provoked a strain on banks' liquidity, reduced their lending ability, and made capital ratios stumble. Yet, the ratios of the top 100 banks remained stable, with an average ratio of 9% (S&P Global, 2021).

The S&P Global highlighted that the Risk-Adjusted Capital (RAC) ratio remained stable because of regulatory restrictions, which decreased dividend payout to grant a higher amount of capital. The delayed response was instead explained throughout policy interventions, which spread the major credit losses over a longer timeframe.

According to Standard & Poor's Global, analysts estimated *"RAC ratios to remain relatively stable, reflecting the gradual recognition of credit losses globally, except in the U.S. and Brazil where the bulk of credit losses have already been recognized, and Australia where banks are returning excess capital*" (S&P Global, 2021).

What further deviates from the total spillovers estimated in *Chapter 5.4* is the range of values. While the return spillovers observed in *Figure 22* span from a minimum of 80% to a maximum of 84%, those of *Figure 38* are higher and wider, oscillating from 82.5% to 91% and with lowest values occurring at the end of 2015.

The reason behind this higher interdependence may be attributed to sector-specific factors. The database of *Chapter 5.1* included 14 equity indexes covering different sectors (e.g. IT, healthcare, industrials), whereas the new data comprised 46 banks characterized by similar characteristics (*Chapter 6.1*) and trends (*Chapter 6.3*).

Another factor contributing to the increase in 2020 spillovers could be the reliance on deposits. As banks finance short and long-term activities using account funds, uncertainty could worsen balance sheets. Hence, when «*run phenomena*» increase, households withdraw their deposits, prompting sell-offs in the stock market.

Alternatively, the 2022 peak could have been triggered by the Ukraine war. At the onset of the conflict, various governments implemented heavy financial sanctions, including the freezing of assets and the exclusion of major Russian banks from the Society for Worldwide Interbank Financial Telecommunication (SWIFT).

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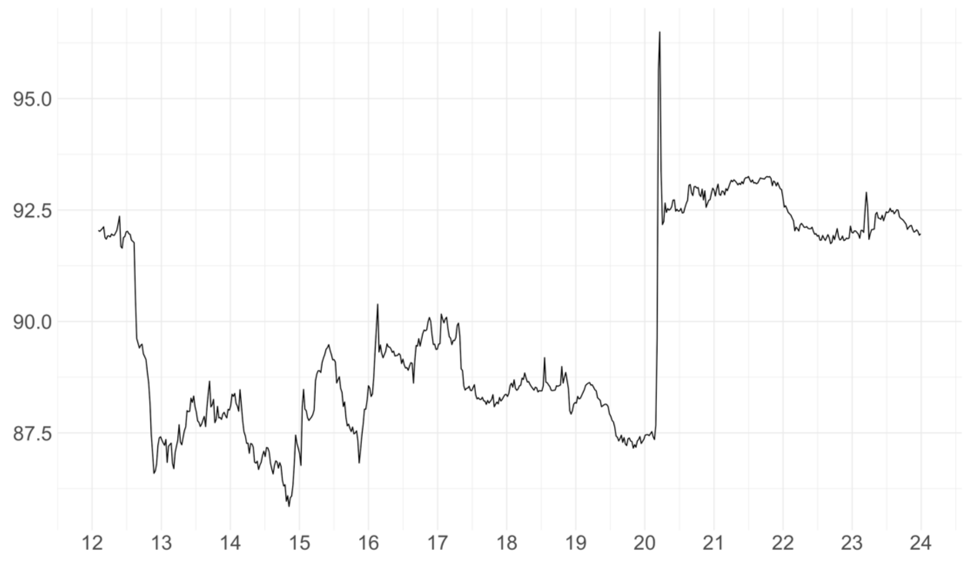
[65] As per S&P Global, the default rate fell to 0.02% in 2020.

Since contagion is more visible through volatility spikes, it is necessary to analyze volatility spillovers (*Figure 39*). At first sight, the major difference with the equity case is the higher range of values, alongside with the presence of more bursts than trends; a result that has been highlighted by Diebold and Yilmaz (2012) as well.

Before understanding why there are fewer trends, it is possible to compare the span of values with *Figure 23*. Although with equities the upper bound was 91%, in the case of banks the highest value is 95%. However, as already mentioned, the higher connectivity stems from the incorporation of stocks belonging to the same sector.

Figure 39. Total spillovers – Volatilities (2012-2024):



Data source: Yahoo Finance.

The reason why there are more spikes than trends could be attributed to the shorter time period, spanning from 2008-01-01 to 2024-01-01; indeed, over long horizons, it is easier to capture trends. Still, by analyzing the various bursts, it is evident that the highest spike (*Figure 39*) coincided with the early-2020 quarantines.

In fact, what differs from *Figure 38* is that the effects of the COVID-19 pandemic were already visible at the beginning of 2020. This may have occurred since stock market investors reacted to the WHO's declarations with fear and uncertainty. Yet, volatility spillovers fell shortly after, stabilizing only in the mid-to-end 2020.

Another distinction lies in the declining return spillovers. By observing volatilities, their reduction is less apparent. Hence, from 2022 onward, volatility spillovers did not decrease but instead settled at 92.5%. Yet, this behavior might be attributed to the nature of volatility, which reacts to unexpected news[66] with sudden spikes.

[66] The sudden reaction to unexpected news was already observed in *Chapter 5.3*.

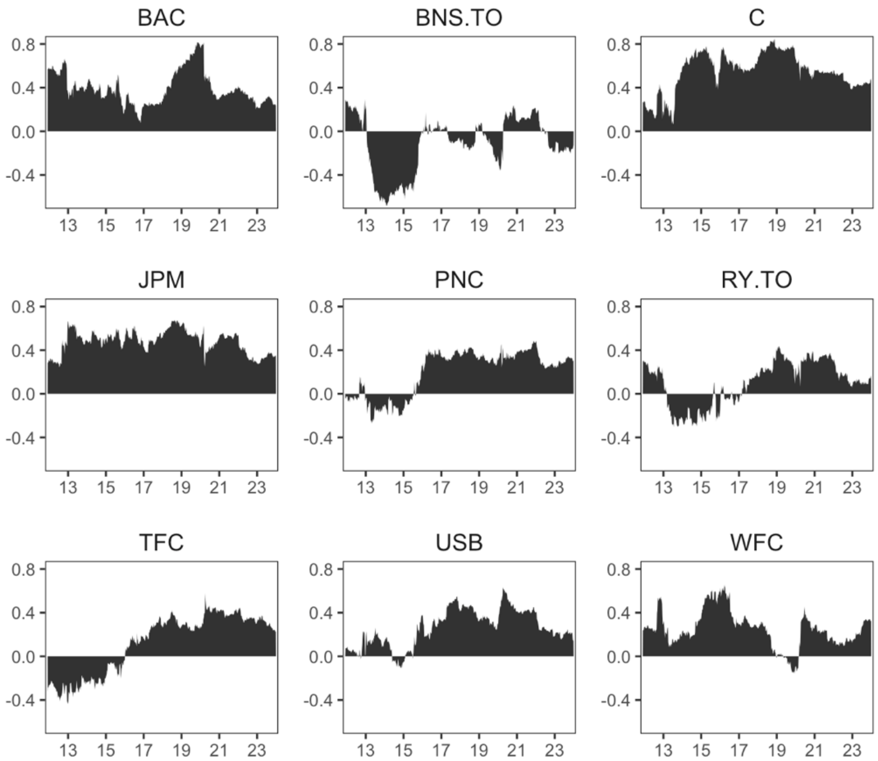
6.5 NET DIRECTIONAL SPILLOVERS - NORTH AMERICA.

Since *Chapter 5.3* revolves around directional spillovers across equity indexes, we already have an idea on how connectedness behaves among countries. Hence, after revising our major results, we won't focus on return and volatility spillovers across regions; instead, we will analyze the transmission of shocks from single banks.

As already seen, the main net spillover transmitters are North America and Europe, which is why we start by analyzing the net return (*Figure 40*) and volatility (*Figure 41*) spillovers of U.S. and Canadian banks. At first glance, this dominance is valid only for the former; however, let us validate this observation by analyzing returns.

While the net directional spillovers of Canada have been variable, U.S. banks have traditionally transmitted more return spillovers than what they have received. With *Figure 40* in mind, it is possible to observe that from 2012-01-01 until 2024-01-01 there are only few periods where U.S. net return spillovers have been negative.

Figure 40. Net directional return spillovers - North America (2012-2024):



Data source: Yahoo Finance.

Among them, the most relevant period ranges from 2012-01-01 to 2016-01-01, and primarily affected Truist Financial Corp. (TFC). By observing the spillover table in *Appendix 13*, it is evident that the main spillovers that the bank received came from other U.S. banks, particularly from the rival U.S. Bancorp (USB) (5.9%).

Yet, to comprehend why it received higher spillovers, it is necessary to mention its third contributor, Wells Fargo & Company (WFC) (4.9%). During 2015, Standard & Poor's downgraded eight of the most important U.S. banks, primarily due to the reduced likelihood of government support in case of future financial crises.

According to Standard & Poor's analysts Plesser and Aurora (2015), the likelihood stemmed from the increased capital requirements set by the Fed. In fact, the central bank removed the "*the uplift based on U.S. government support"* from the ratings of large banks, resulting in downgrades from A+ to A- and from A- to BBB+.

Precisely, the banks subject to the downgrade were Bank of America Corp. (BAC), Bank of New York Mellon (BNY), Citigroup Inc. (C), Goldman Sachs Group Inc. (GS), JP Morgan Chase & Co. (JPM), Wells Fargo & Co. (WFC), Morgan Stanley (MS), and State Street Corp. (STT), four of which are included in the sample[67].

Beside the downgrade of U.S. banks, which may have affected investor sentiment, another element contributing to the increase in return spillovers to Truist Financial Corp. (TFC) is the 2015-2016 stock market sell-off. It is indeed plausible that U.S. banks initially impacted by the trend influenced Truist Financial Corp. (TFC).

The confirmation comes from the plots in *Figure 40*. Starting from 2015, Citigroup Inc. (C) and Wells Fargo & Co. (WFC) experienced a spike in the net transmission of return spillovers. After this period, there was in fact a slowdown, which reversed when the WHO's director declared the SARS-CoV-2 as a health emergency.

What should be highlighted is that in the most recent years, Bank of America Corp. (BAC), Citigroup (C), U.S. Bancorp (USB), Truist Financial Corp. (TFC), and JP Morgan Chase & Co. (JPM), saw a significant decline in return spillovers. For the majority of them, the drop began after the policies set to face the 2020 pandemic.

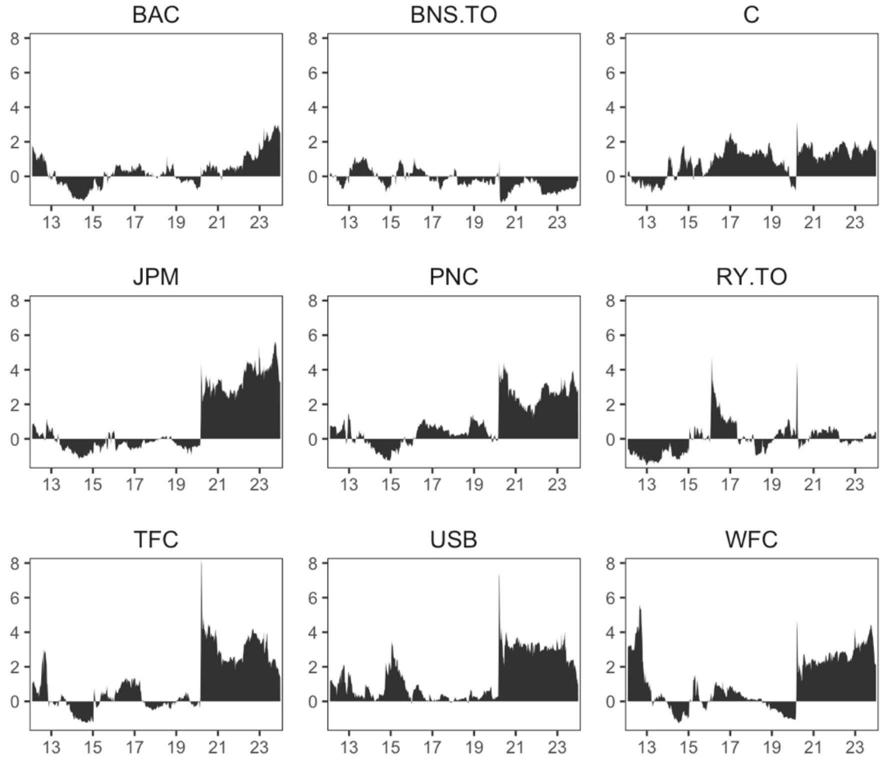
Rather than focusing on why their net directional spillovers are decreasing, it might be more interesting to comprehend the reason for the increasing transmission of Wells Fargo & Co. (WFC). Precisely, in 2022, many analysts downgraded the bank from Buy to Hold due to its low revenue growth (CAGR 2018-2022: -3.9%).

Yet, Canadian banks do not exhibit specific trends. While they are highly impacted by the U.S., with which Canada has high FDIs, return spillovers tend to rely on the bank's size. Hence, the Royal Bank of Canada (RY.TO) transmits higher spillovers than The Bank of Nova Scotia (BNS.TO) because of its higher asset value.

When looking at volatilities (*Figure 41*), outcomes are significantly different from those obtained with returns. From 2012-01-01 to 2024-01-01, U.S. Bancorp (USB) was the only U.S. bank acting as a net transmitter. All other U.S. banks consistently adjusted their net volatility spillovers, doing so until the COVID-19 pandemic.

[67] The banks subject to the highest downgrades were Citigroup Inc. (C) and Bank of America Corp. (BAC).

Figure 41. Net directional volatility spillovers – North America (2012-2024):



Data source: Yahoo Finance.

The first shift, occurring in the majority of banks from 2013-01-01 to 2015-01-01, might have been triggered by the Eurozone sovereign debt crisis. Since E.U. banks were the most affected, they may have transmitted higher spillovers, exceeding the volatility shocks conveyed by other countries, including the U.S. and Canada.

To better comprehend the extent to which a crisis originating in Europe can spread to the U.S., we can analyze the volatility spillovers transmitted to Bank of America Corp. (BAC). Over the last 15 years, on average, every European bank accounted for 3% (*Appendix 13*) of the forecast error variance in predicting its volatilities.

The second cycle, occurring from 2015-01-01 to 2018-01-01, can be explained by the combined effects of the stock market sell-offs and the SWIFT banking hack of 2015-2016. Yet, some of the most affected U.S. banks, including Bank of America Corp. (BAC) and Wells Fargo & Company (WFC), led to higher volatility spikes.

At the onset of the COVID-19 pandemic, most U.S. banks experienced a third shift, after which they became net transmitters. In contrast, Canadian banks did not show the same cycles; while the Euro crisis and the 2020 pandemic did affect its banks, the major shocks occurred in response of domestic crises and declarations[68].

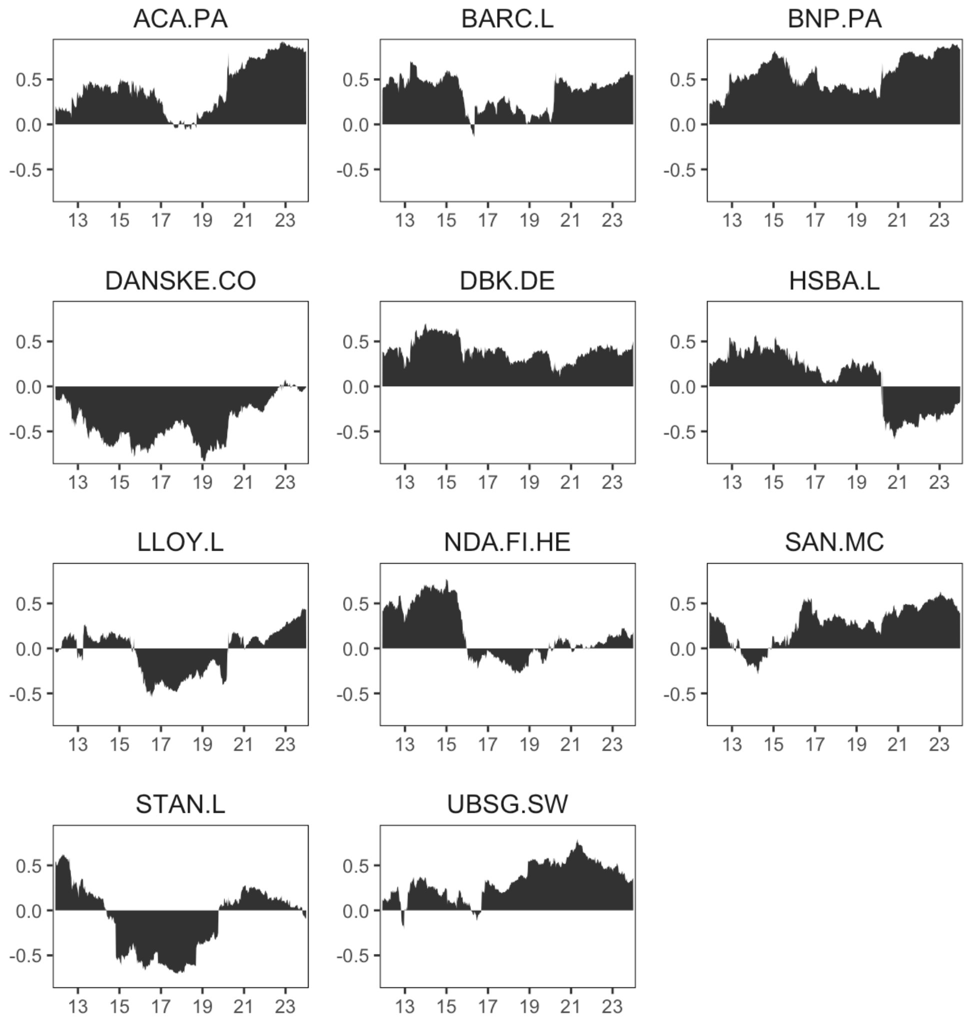
[68] The most relevant is represented by the Canadian Rule Changes (2016), restricting amortization periods.

6.6 NET DIRECTIONAL SPILLOVERS - EUROPE.

In opposition to U.S. returns, where most banks acted as net spillover transmitters, in European countries there is not such a pattern. In *Figure 42*, the behavior varies depending on the region that we consider. Hence, some countries tend to act as net spillover transmitters, while others have historically been net receivers[69].

Precisely, the subset chosen by the FEVD feature selection includes the SIX Swiss Exchange (SW), Euronext Paris (PA), the Copenhagen Stock Exchange (CO), the London Stock Exchange (L), the Helsinki Stock Exchange (FI), the BME Spanish Exchange (MC), and the Deutsche Börse (DE), for a total of 7 countries.

Figure 42. Net directional return spillovers - Europe (2012-2024):



Data source: Yahoo Finance.

[69] When we refer to the net spillover transmission of the U.S., we are only considering returns.

As discussed in *Chapter 5*, the U.K. FTSE 100 (FTSE) Index has historically been a net transmitter. However, this trend holds true only for Barclays PLC (BARC.L), as for more than 4 years, HSBC Holdings PLC (HSBA.L), Lloyds Banking Group (LLOY.L), and Standard Chartered PLC (STAN.L) have behaved as net receivers.

By examining the return spillover table in *Appendix 13*, it is worth mentioning that from 2008-01-01 until 2024-01-01, HSBC Holdings PLC (HSBA.L) explained the highest error variance in predicting Standard Chartered PLC (STAN.L) returns. In fact, when the latter became a net receiver, the former became a net transmitter.

Given that U.K. banks are subject to the same crises, the transmission of spillovers from HSBC Holdings PLC (HSBA.L) to Standard Chartered PLC (STAN.L) could be explained by the bank's magnitude rather than the shock's nature. Hence, HSBC Holdings PLC (HSBA.L) has a higher asset value, approaching $2,864 billion.

However, from 2013-01-01 to 2020-01-01, some shocks have affected only HSBC Holdings PLC (HSBA.L). Hence, during that period, the bank faced different fines related to anti-money laundering failures and manipulation of interest rates. Beside these penalties, the competition from FinTech companies posed another threat.

The shift of the HSBC Holdings PLC (HSBA.L) line in 2020 occurred because all banks from which it received shocks, including Barclays PLC (BARC.L) (3.25%), increased their return spillovers. In fact, Barclays PLC (BARC.L)'s connectedness with European banks is higher than that of HSBC Holdings PLC (HSBA.L).

Heading to France, the results align with *Chapter 5.3*. As shown in *Figure 41*, BNP Paribas SA (BNP.PA) has always been a net return transmitter. While this trend is consistent with French equities, positive values may be attributed to its high market value ($2,849 billion), suggesting that the larger the company, the higher the risk.

Another bank that has transmitted more return spillovers than it has received is the Swiss UBS Group AG (UBSG.SW); its main deviation from the sample lies in the period ranging from 2013-01-01 to 2016-01-01, since the Swiss banking industry was not as heavily impacted by the afermath of the GFC and the Eurozone crisis.

Throughout 2014, the financial stability report of Credit Suisse, part of UBS Group AG, confirmed this resistence. It highlighted that the financial conditions for Swiss banks improved, but also noted that Swiss companies were affected by the fragility of E.U. banks and the "*credit quality of corporates in southern member States*"[70].

By analyzing the most recent time period, major shocks are originating from BNP Paribas SA (BNP.PA), Barclays PLC (BARC.L), and Deutsche Bank (DBK.DE). Currently, they are the only banks whose net directional spillovers are not showing a decreasing trend, either due to their declining profits or misleading outlooks.

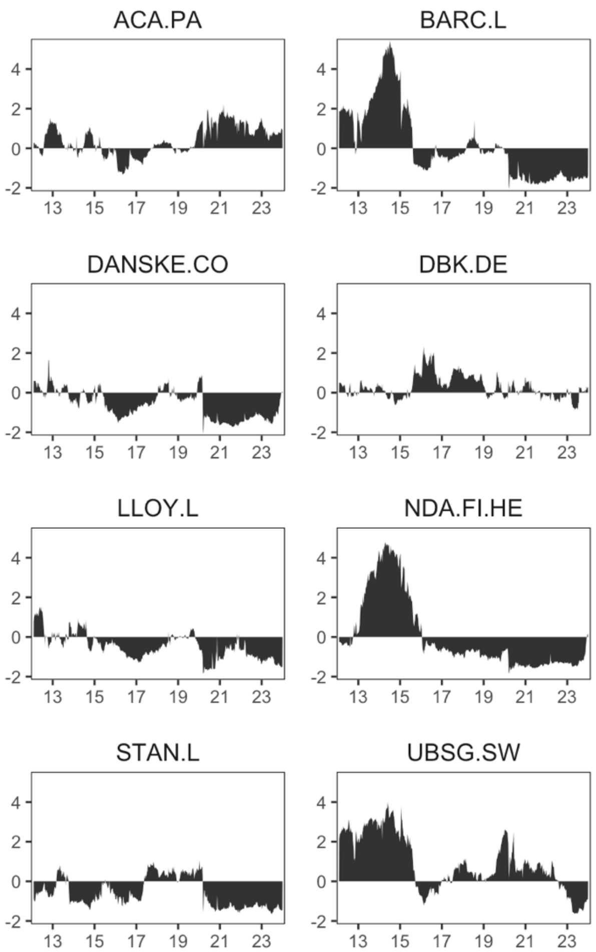
[70] As already discussed in *Chapter 5.3*, the most affected countries were the PIIGS.

Conversely, the most impacted institution by external shocks has traditionally been Danske Bank A/S (DANSKE.CO). Hereafter, the banks sharing the highest shares of its error variance are the Finnish bank Nordea Bank Abp (NDA-FI.HE) (4.1%) and BNP Paribas SA (BNP.PA) (3.2%), exhibiting opposite spillover behaviors.

The interdependence between Danish Danske Bank A/S (DANSKE.CO) and BNP Paribas SA (BNP.PA) may have originated in 2003, when the two banks signed a partnership agreement aimed at expanding their global network. In fact, the project granted to the clients of the former to access all the services of the French bank.

Moving toward volatilities (*Figure 43*), net directional spillovers no longer exhibit increasing or declining trends. Hence, apart from significant economic downturns, such as the Eurozone crisis and the 2015-2016 equity market sell-offs, all banks in the sample display bursts, mostly in response to ECB[71] declarations.

Figure 43. Net directional volatility spillovers - Europe (2012-2024):



Data source: Yahoo Finance.

[71] ECB: European Central Bank.

Here, the main spillover transmitter appears to be BNP Paribas SA (BNP.PA). Yet, this does not imply that all banks of the Paris stock exchange cause more spillovers than they receive. Crédit Agricole Group (ACA.PA) is an example, since it became a net transmitter only after 2020-01-01, in response to the COVID-19 crisis.

Precisely, from 2013-01-01 to 2020-01-01, the line of the bank alternated between positive and negative values. Similar to the U.K. case, these shifts might have been caused by its reaction to the sovereign debt crisis, Basel III regulations, low interest rates, and the rise of FinTech firms, posing a major threat to traditional banks.

The period in which it became a net spillover transmitter was instead characterized by (i) the COVID-19 pandemic, (ii) the compliance to sustainability goals, and (iii) geopolitical tensions. Among the most significant conflicts, there are the trade war between China and U.S., the Ukraine conflict and the recent Palestine tensions.

According to Crédit Agricole Group (2022), "*Each of these conflicts has not only its time frame, but also its areas of uncertainty*". When considering why they could affect banks, *"these various wars are all affecting the structure of the risks we face and our perceptions of them in both time and space*".

The consequences that Crédit Agricole Group (ACA.PA) faced are associated with "*new prohibitions and risk premiums included in prices and interest rates*". Hence, while the 2018 trade war increased volatility and encouraged investors to look for safe-haven assets, in 2022 all Russian banks were banned from the SWIFT.

Back to the matter, both German and Spanish banks serve as net transmitters, with the difference that Germany's main spike occurred one year later. During 2016, in fact, Deutsche Bank AG (DBK.DE) faced various financial difficulties, stemming from its high exposure to risky assets and violations of banking regulations.

On the other hand, Denmark and the U.K. are the primary net spillover recipients. Yet, while Danish banks typically experience volatility shocks due to the country's stable conditions, U.K. banks have a significant international presence. As a result, they can reflect the overall financial health and the global shocks affecting it[72].

Hence, the stock market in which banks are listed is not the sole determining factor. When analyzing U.K. banks, it is evident that not all of them have always been net receivers. Until 2016, Barclays PLC (BARC.L) was a net transmitter and explained the main shocks of Deutsche Bank AG (DBK.DE) and BNP Paribas SA (BNP.PA).

This could be attributed to both the uncertainty generated by the Brexit referendum on the banking industry and the internal activity of Barclays PLC (BARC.L). Yet, in contrast to Lloyds Banking Group (LLOY.L), the bank has a higher exposure to investment banking, as well as to riskier and complex capital markets products.

[72] The reasoning is valid for major banks only, such as Barclays PLC (BARC.L).

6.7 NET DIRECTIONAL SPILLOVERS: EAST ASIA.

Historically, while U.S. banks tend to be net spillover transmitters, the majority of East Asian banks are net spillover receivers. Yet, as already demonstrated through *Chapter 5*, almost all stocks listed on the Tokyo Stock Exchange deviate from such a trend, particularly when considering the period from 2016-01-01 to 2020-01-01.

By analyzing the Japanese banking industry, it is worth observing that in 2016 the Bank of Japan (BOJ) implemented for the first time a negative interest rate policy. Yet, low interest rates reduced the spread between lending rates and funding costs, diminishing the profitability on loans and forcing banks to search for alternatives.

Amongst the alternative activities that permitted Japanese banks to increase profits there were various non-traditional banking activities, such as (i) asset management, (ii) fee-based services, and (iii) overseas lending. Few years later, in 2019, Reuters stated that "*the balance of overseas credit by Japanese banks rose to* $44 *billion*".

However, the behavior does not concern all the banks headquartered in Japan. Yet, from 2008-01-01 to 2024-01-01, Resona Holdings Inc (8308.T) showed a different tendency. Due to its lower asset value, the bank behaved as a net spillover receiver. In fact, it resembled more the spillover trend of Chinese and South Korean banks.

On the contrary, except for East-Asian banks with high asset value, including Bank of Communications Co. (3328.HK) and Industrial Bank Co. (601166.SS), or banks with higher foreign participation, such as Hua Xia Bank Co. (600015.SS), all other stocks tend to receive higher return shocks, primarily during market downturns.

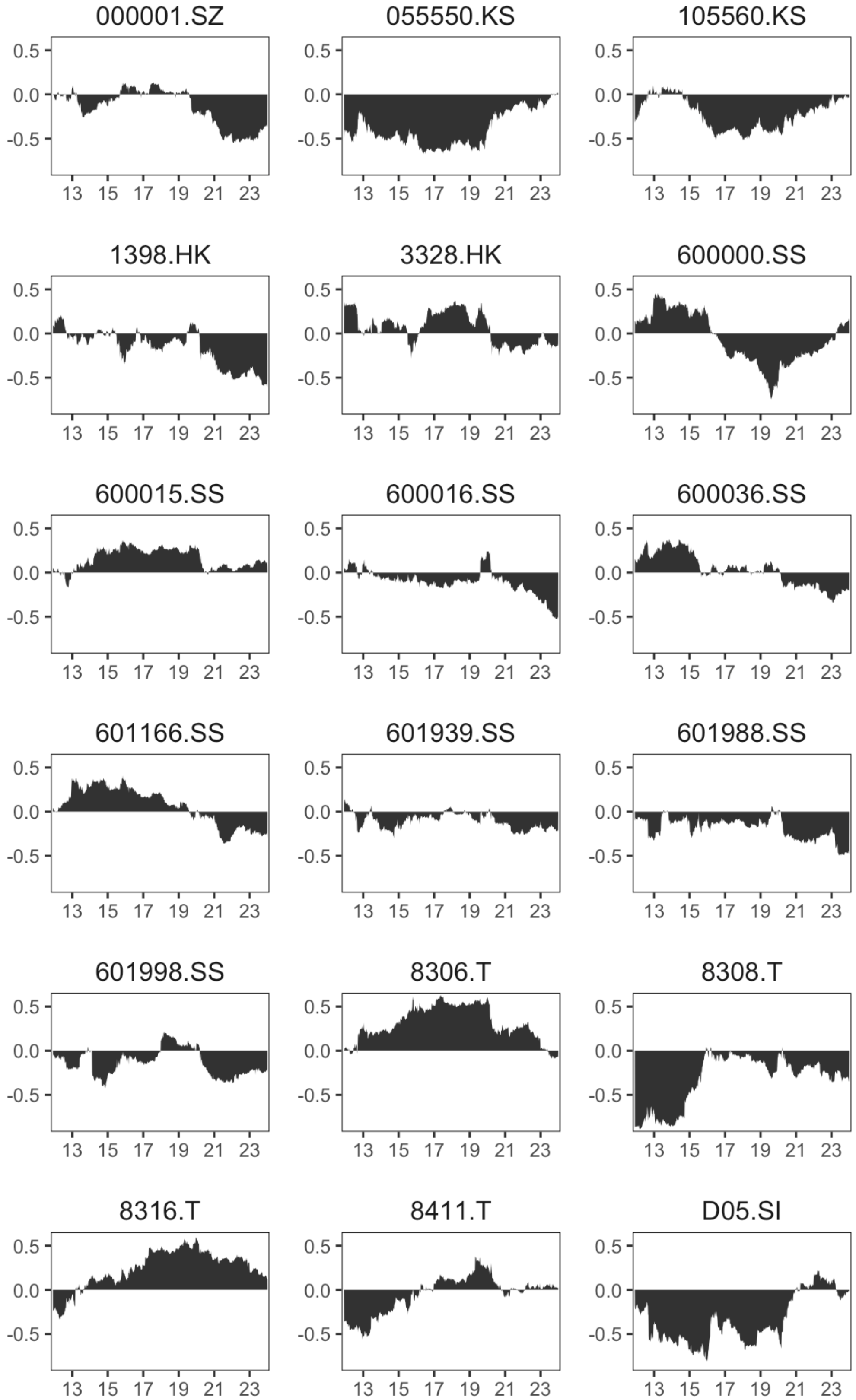
The findings are in line with Chen, Zhong, and Failler (2021), according to which "*China plays the role of a net recipient most of the time*". Although the authors do not investigate the reason why Chinese banks tend to receive more spillovers than what they transmit, we can answer by examining the Chinese banking dynamics.

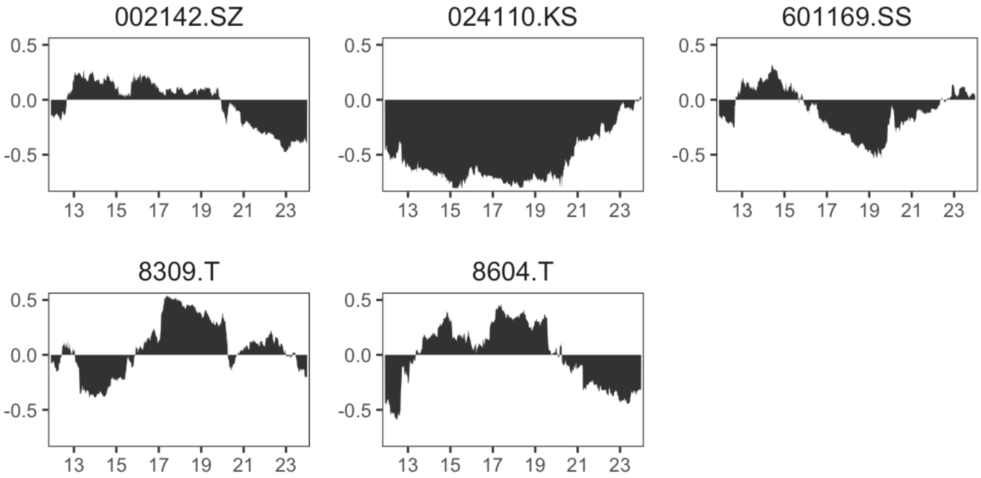
Precisely, East Asian banks often act as financial intermediaries, receiving deposits and allocating the funds to borrowers in the form of loans. Yet, since their stability depends on the performance of their assets, they do not transmit as many shocks as investment banks, but are still subject to sentiment changes (S&P Global, 2024).

A further element that reduces the spillovers transmitted from East-Asia to the rest of the world is the fact that Chinese banks are often state-owned or controlled. Yet, Chinese institutions operate in a highly regulated environment, benefit from access to bailout assistance, and prioritize lending to State-Owned Enterprises (SOEs).

Even if the control of the Chinese government makes banks extremely susceptible to national economic conditions, they do not spread shocks outside of China. Still, they are subject to external shocks, including the sovereign debt crisis of 2011 and the consequences of the COVID-19 pandemic to the E.U. and American markets.

Figure 44. Net directional return spillovers - East Asia (2012-2024):





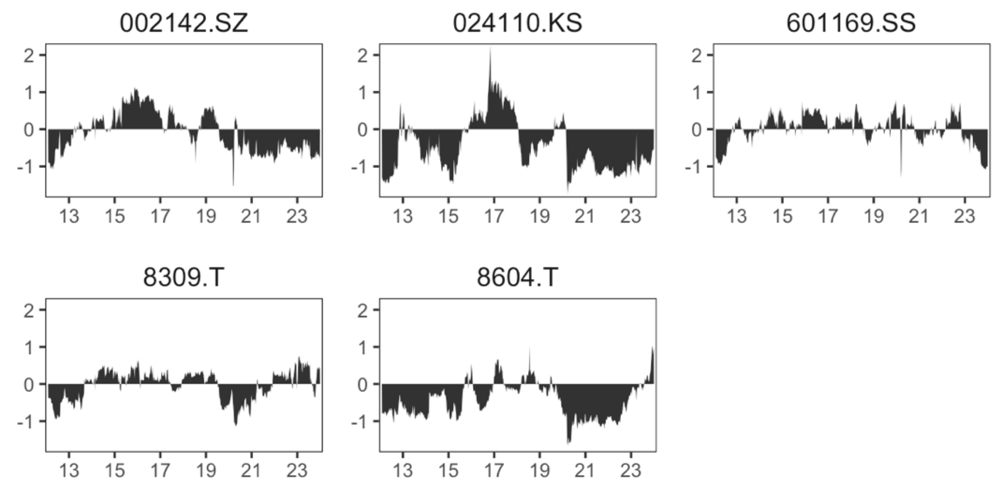
Data source: Yahoo Finance.

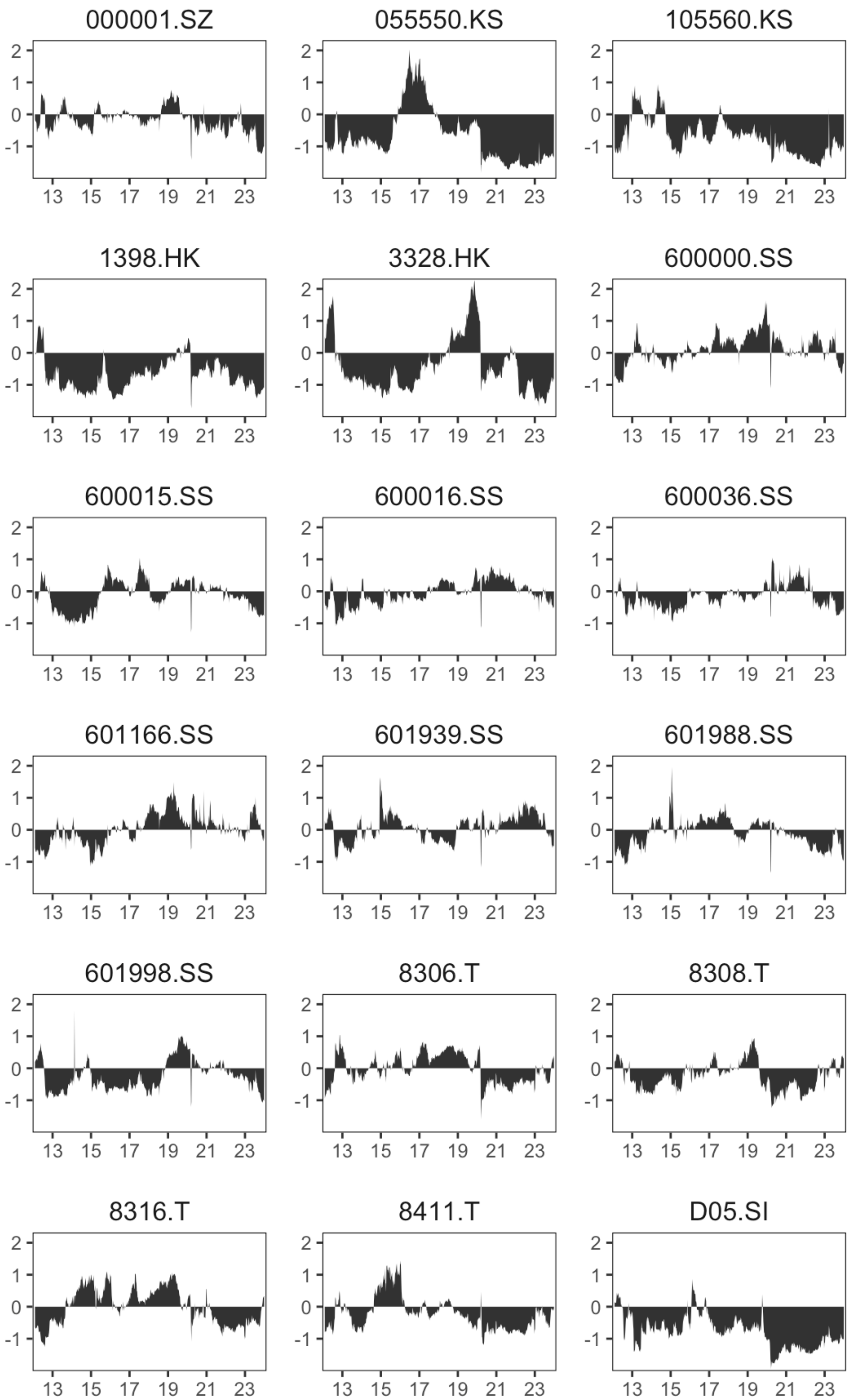
By analyzing return (*Figure 44*) and volatility (*Figure 45*) spillovers, it is clear that net volatility spillovers are lower. As a confirm, while in the previous figure values were constantly negative, with volatilities we reach a higher balance. Such a result, visible with almost all banks, derives from their conservative risk management.

According to Chen et al. (2017), these practices often prioritize stability and capital preservation over high-risk high-reward activities. Hence, Mu (2007) declared that "*although the high credit officials in the head office try to introduce market-based mechanisms in credit allocation, credit officers still rely on traditional systems*".

This does not regard all stocks, since the largest and more integrated Chinese banks continue to receive high shares of volatility spillovers. In fact, from 2013-01-01 to 2024-01-01, the Industrial and Commerical Bank of China (1398.HK) received on average -1% of net directional spillovers, continuing to be a net receiver.

Figure 44. Net directional volatility spillovers - Volatilities (2012-2024):





Data source: Yahoo Finance.

7. SUPERVISED LEARNING.

7.1 DATASET.

After analyzing the dynamic spillovers among the 46 banks selected by the FEVD feature selection, we built a dataset comprising 1.008 observations. While *Chapter 7.2* and *Chapter 7.3* delve into regression models and random forests, *Chapter 7.1* provides insights on the dataset, among which the presence of quarterly data[73].

As one might expect, the dependent variable captures the net directional spillovers transmitted by a stock during a specific quarter. On the other hand, the independent variables, drawn from their income statements, balance sheets and valuations, offer insights on the bank's financial health, market performance, and risk profile[74]:

- The first independent variable is represented by revenues. As revenues indicate the income generated by a bank from its core business activities, the higher the revenues, the more profitable the bank. Yet, banks with higher revenue streams could be more interconnected, but might also be better at absorbing shocks.
- The second independent variable is identified in the Dividend Per Share (DPS). DPS represents the amount of a company's earnings allocated to each share and reflects the return that shareholders receive for each share they own. Hence, the higher the DPS, the greater the bank's stability and the market's confidence.
- The third independent variable is characterized by complex financial products. Precisely, they comprise: (i) collateralized agreements, (ii) reverse REPOs, and (iii) securities borrowed. Yet, what is common among these instruments is their function in facilitating short-term funding and managing banks' liquidity.
- The fourth independent variable is represented by total assets. Being total assets the resources owned and controlled by companies, banks with larger assets are likely to have more relationships with other firms and a larger market influence; in the Diebold & Yilmaz framework, this might result in higher spillovers.
- The fifth independent variable, deposits, serves as the major source of funding, and is used to finance lending activities, invest in securities, and offer financial services. Yet, since deposits increase the liquidity of banks, they can lower the transmission of return and volatility shocks, leading to lower spillovers.
- The sixth independent variable is total debt. Although total debt is included into liabilities, it significantly differs from deposits. High levels of debt could strain cash flows, amplify interest expenses, and reduce flexibility. During crises, this could increase financial vulnerabilities and complicate risk management.

[73] Quarterly scheduling was determined by financial data releases.

[74] All values have been standardized in U.S. dollars.

- The seventh independent variable is identified in the total capital adequacy %. This encompasses various metrics, including the capital adequacy to the Tier 1 and Tier 2. Here, high percentages suggest strong capital positions, amplifying the bank's resilience to shocks and reducing its net spillover transmission.

- The eigth independent variable is characterized by non-performing loans. Non-performing loans denote the portion of loans that are already in default or close to default. Yet, higher levels of non-performing loans could lead to a high credit risk, increasing potential losses and the spillovers that a bank could transmit.

- The ninth independent variable is the Enterprise Value (EV). Being the EV the total value of a company, it provides a measure of the worth of the company to shareholders and debt holders. Since a higher EV indicates stronger confidence in the bank's prospects, it should be inversely correlated with its spillovers.

- The tenth independent variable is the Price-to-Book (P/B) ratio, comparing the company's market value to its book value. Consequently, it indicates how much investors are willing to pay for each dollar of the company's assets. Yet, greater P/B ratios suggest higher investors' confidence and potential overvaluation.

- The eleventh independent variable is the Price-to-Earnings (P/E) ratio, dividing the bank's stock price with earnings. Similarly to the Price-to-Book (P/B) ratio, it indicates how much investors are willing to pay for each dollar of its earnings. Yet, higher P/E ratios suggest that one might expect an earnings' growth.

- The last independent variable is a dummy variable indicating whether the bank pertains to the Western or Eastern part of the world. As *Chapter 6* revealed that East-Asian banks demonstrate lower connectedness with the rest of the sample, we expect the value to be directly correlated with the bank's net spillovers.

All independent variables were sourced from the LSEG Workspace (Refinitiv). As banks publish financial reports, balance sheets, and valuations on a quarterly basis, net return and volatility spillovers have been calculated as the mean of their weekly counterparts, for a total of 731 observations from 01-03-2013 to 01-12-2023[75].

Whenever a missing value occurred, it has been substituted with the average of the preceding 5 quarters, mantaining the bank's financial trends. Yet, when there were no previous data, the missing value was calculated as the constant of the next value; a substitution mechanism that granted to work with a wider and precise dataset.

After analyzing the independent variables, it is worth observing that while *Chapter 7.2* focuses on models with net return spillovers as the dependent variable, *Chapter 7.3* revolves around the volatility counterpart, slightly more difficult to predict.

[75] The time period is the same as in *Chapter 6*.

7.2 NET RETURN SPILLOVERS.

Regressing the net return spillovers on the twelve independent variables[76], results are in line with the expectations of *Chapter 7.1*. Yet, the p-value of three variables, notably complex products, the Price-to-Book ratio (P/B), and the Price-to-Earnings ratio (P/E), is slightly above 5%, meaning that they are not significant (*Figure 45*).

The factors affecting the most net return spillovers are the dummy variable and the net volatility spillovers. While the former underscores the relevance of being listed in a Western country, the importance of the latter stands from its estimation; hence, despite the latter has more bursts, return and volatility spillovers tend to co-move.

Other variables positively impacting net return spillovers are revenues, total assets, and total debt. Although higher revenues and assets indicate that the bank's income streams and holdings rose, they lead to greater interconnectedness. The reason why total debt is positively correlated with return spillovers is instead more intuitive.

Figure 45. Estimates - Linear model (2013-2023):

	Estimate	Std. Error	t value	Pr
(Intercept)	1.665e-01	5.428e-02	3.067e+00	2.199e-03
V.SPILL	1.027e-01	8.333e-03	1.233e+01	2.823e-33
REVENUES	7.134e-09	3.195e-09	2.233e+00	2.569e-02
DPS	-3.868e-02	1.811e-02	-2.135e+00	3.290e-02
COMPLEX.PRODUCTS	2.758e-10	1.468e-10	1.878e+00	6.052e-02
TOTAL.ASSETS	2.740e-10	4.688e-11	5.845e+00	6.247e-09
DEPOSITS	-3.487e-10	5.793e-11	-6.019e+00	2.211e-09
TOTAL.DEBT	6.007e-10	1.022e-10	5.880e+00	5.085e-09
CAPITAL.ADEQUACY	-2.185e-02	3.456e-03	-6.321e+00	3.449e-10
NON.PERFORMING.LOANS	-3.732e-09	1.002e-09	-3.725e+00	2.025e-04
EV	-5.419e-10	8.744e-11	-6.197e+00	7.456e-10
PRICE.TO.BOOK	-5.417e-02	3.867e-02	-1.401e+00	1.614e-01
PRICE.TO.EARNINGS	-9.181e-03	1.463e-02	-6.277e-01	5.303e-01
DUMMY	2.330e-01	2.395e-02	9.731e+00	1.001e-21

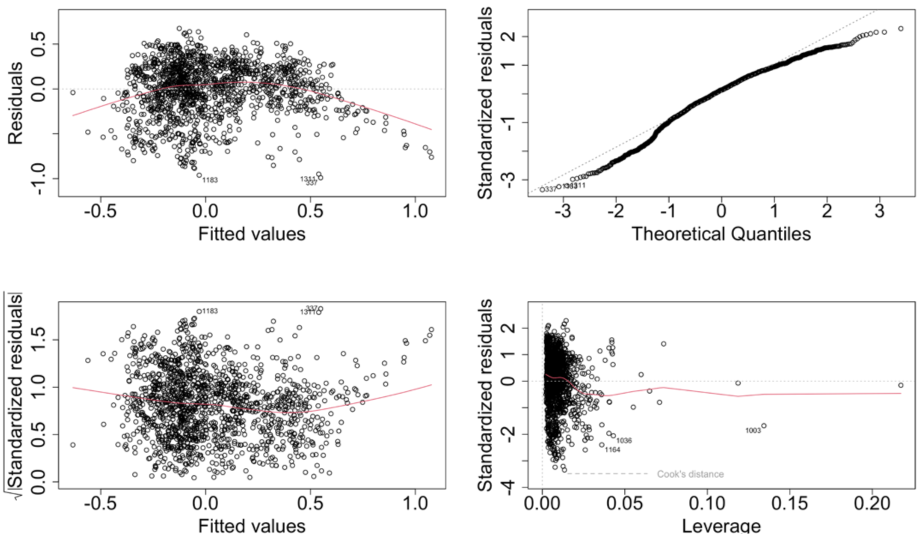
Data source: Refinitiv.

Conversely, the negative coefficients for deposits, capital adequacy, and Enterprise Value (EV) suggest that lower funds, weaker financial health, and negative market sentiment, increase the transmission of return shocks. Generally, all three variables underscore the relevance that banks' stability plays in the escalation of contagion.

[76] Each model has been trained on the 80% of the dataset and tested on the remaining 20%.

The goodness of fit, as suggested by the multiple and adjusted R-squared, indicates that the twelve independent variables explain only about 43% of the variability in net return spillovers (*Figure 46*). However, the regression's low explanatory power gives considerable room for improvement and suggests to employ other models.

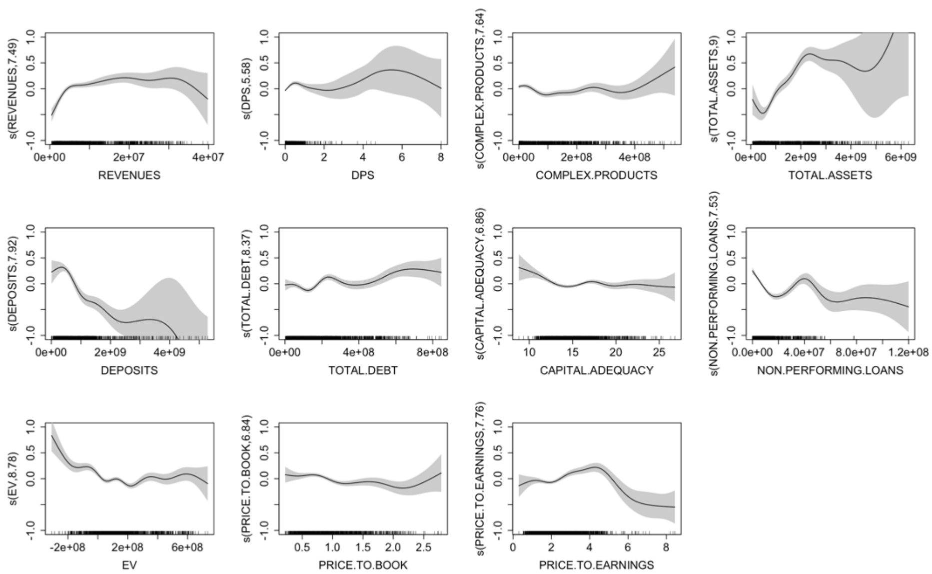
Figure 46. Diagnostics - Linear model (2013-2023):



Data source: Refinitiv.

Despite normally distributed residuals, the "*Residuals vs Fitted plot*" indicates that there might be non-linearity in the data. Hence, we decided to employ a model that could capture non-linear patterns. Precisely, the choice relapsed to an extension of the linear regression, known as Generalized Additive Model (GAM) (*Figure 47*).

Figure 47. Smooth term plot - GAM (2013-2023):



Data source: Refinitiv.

Since Effective Degrees of Freedom (EDF) measure the complexity of the smooth functions, the higher the edf, the more complex the fit to the data. As illustrated in *Figure 47*, the majority of independent variables have non-linear relationships with net return spillovers, meaning that a linear approximation may not be appropriate.

With an EDF of 9.00, 8.78, 8.37, and 7.90, the smooth functions with the strongest non-linear relationships are recognized in total assets, Enterprise Value (EV), total debt, and deposits. Indeed, these values indicate that Generalized Additive Models (GAMs) might offer a better explanation for the variability of net return spillovers.

As shown by the adjusted R-squared (62%) and the Generalized Cross Validation (6.25%), the GAM has a better explanatory power than the linear model. Yet, even though this model has been tested on a large training set ($n = 1.472$) and provides a better fit to the data, we believe that there can still be a margin of improvement.

For this reason, we refined the model by including various interaction effects. Yet, to avoid increasing computational complexity, the only interaction terms taken into account are between total assets, deposits, non-performing loans, Enterprise Value (EV), and Dividend per Share (DPS); here, the variance explained rose to 83%.

Figure 48. Expected Degrees of Freedom (EDF) - GAM (2013-2023):

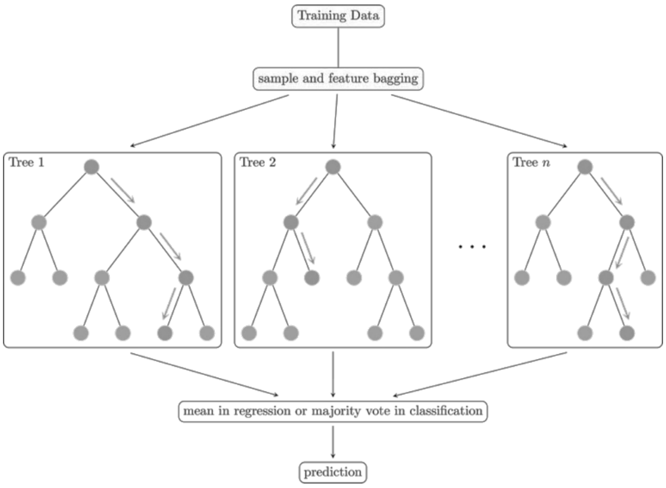
	edf	Ref.df	F	Pr
s(REVENUES)	8.878	8.990	12.5443	0.000e+00
s(DPS)	6.574	7.349	3.9770	3.153e-04
s(COMPLEX.PRODUCTS)	8.165	8.812	3.5192	1.644e-04
s(TOTAL.ASSETS)	8.679	8.937	14.1617	0.000e+00
s(DEPOSITS)	9.000	9.000	8.6141	0.000e+00
s(TOTAL.DEBT)	4.967	6.263	7.7687	0.000e+00
s(CAPITAL.ADEQUACY)	8.097	8.787	3.2259	1.269e-03
s(NON.PERFORMING.LOANS)	8.331	8.637	6.0858	0.000e+00
s(EV)	8.537	8.834	9.5299	0.000e+00
s(PRICE.TO.BOOK)	6.688	7.776	4.6267	1.880e-05
s(PRICE.TO.EARNINGS)	6.336	7.538	5.9995	6.150e-07
ti(TOTAL.ASSETS,DEPOSITS)	15.268	15.451	17.2910	0.000e+00
ti(TOTAL.ASSETS,NON.PERFORMING.LOANS)	13.761	14.475	4.6800	0.000e+00
ti(TOTAL.ASSETS,EV)	14.692	15.190	12.6756	0.000e+00
ti(TOTAL.ASSETS,DPS)	12.583	13.330	3.8421	3.313e-06
ti(DEPOSITS,NON.PERFORMING.LOANS)	15.360	15.582	4.8788	0.000e+00
ti(DEPOSITS,EV)	13.520	14.481	7.6500	0.000e+00
ti(DEPOSITS,DPS)	6.236	7.689	3.2035	8.368e-04
ti(NON.PERFORMING.LOANS,EV)	9.547	10.542	9.2687	0.000e+00
ti(NON.PERFORMING.LOANS,DPS)	1.000	1.000	0.1347	7.137e-01
ti(EV,DPS)	7.426	8.860	2.5042	7.264e-03

Data source: Refinitiv.

Since random forests can capture non-linear relationships, prevent overfitting, and handle interactions, they are often preferred over GAMs. Yet, before analyzing the model's improvement, Misra and Li (2020) defined them as: "*an ensemble method that trains several decision trees in parallel with bootstrapping techniques*".

Precisely, random forests are a machine learning technique that constructs multiple decision trees by dividing the training data. Then, it performs a prediction by taking the weighted average of the individual choices (*Figure 49*). Yet, the result depends on the number of trees that the algorithm employed, in our case equal to 500.

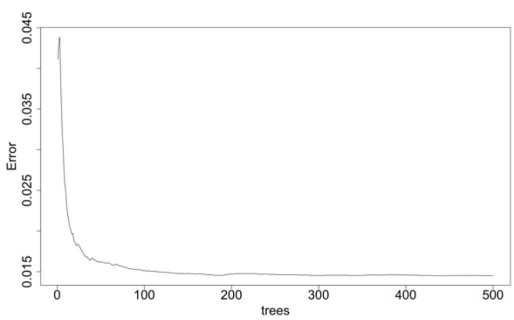
Figure 49. Mechanism - Random forest:



Data source: Janosh Riebesell.

By implementing a random forest, the variance explained increased until 90.63%. Instead, the mean of squared residuals reduced to 1.43%, marking an improvement from the GAM model. However, such high accuracy (Figure 50) does not result in overfitting, since the mean square error is the lowest of all models (1.42%)[77].

Figure 50. Mean square error - Random forest (2013-2023):



Data source: Refinitiv.

[77] While the linear model has a 9.9% MSE, the GAM has a 4% MSE.

7.3 NET VOLATILITY SPILLOVERS.

Considering net volatility spillovers, the variance explained by the linear model is extremely low. Hence, the multiple and adjusted R-squared of the linear regression (*Figure 51*) are 26.87% and 26.22%. Comparing the % to the net return spillovers, net volatility spillovers result not only more complex, but also difficult to predict.

As volatility spillovers historically demonstrated more bursts than trends, the result should not be suprising. Being volatility a measure of risk and uncertainty, it could be influenced by many other factors, like market sentiment and external shocks[78]; the link between return spillovers and profitability, instead, makes the task easier.

Figure 51. Estimates - Linear model (2013-2023):

	Estimate	Std. Error	t value	Pr
(Intercept)	6.930e-01	1.619e-01	4.281e+00	1.979e-05
R.SPILL	9.187e-01	7.454e-02	1.233e+01	2.823e-33
REVENUES	4.095e-09	9.570e-09	4.279e-01	6.688e-01
DPS	2.785e-01	5.376e-02	5.180e+00	2.526e-07
COMPLEX.PRODUCTS	-1.345e-09	4.382e-10	-3.070e+00	2.178e-03
TOTAL.ASSETS	8.621e-11	1.418e-10	6.079e-01	5.433e-01
DEPOSITS	2.102e-10	1.753e-10	1.199e+00	2.306e-01
TOTAL.DEBT	-4.951e-10	3.089e-10	-1.603e+00	1.092e-01
CAPITAL.ADEQUACY	-7.084e-02	1.031e-02	-6.869e+00	9.559e-12
NON.PERFORMING.LOANS	-1.732e-08	2.976e-09	-5.818e+00	7.302e-09
EV	9.326e-10	2.638e-10	3.535e+00	4.202e-04
PRICE.TO.BOOK	1.220e-01	1.157e-01	1.055e+00	2.918e-01
PRICE.TO.EARNINGS	-1.514e-02	4.375e-02	-3.460e-01	7.294e-01
DUMMY	4.679e-01	7.289e-02	6.419e+00	1.845e-10

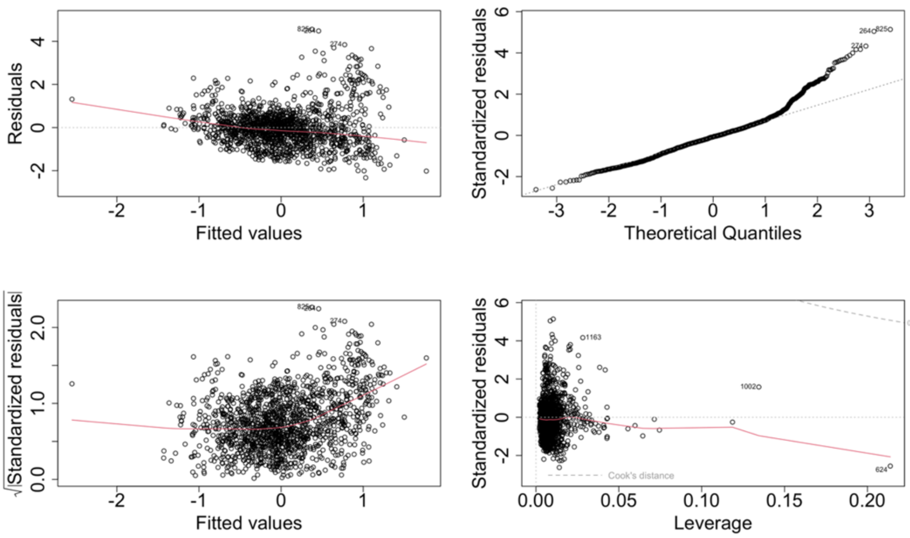
Data source: Refinitiv.

A further confirm comes from the number of non-significant variables. By looking at *Figure 51*, the variables with a higher-than-5% p-value are (i) revenues, (ii) total assets, (iii) deposits, (iv) total debt, (v) the Price-to-Book (P/B), and (vi) the Price-to-Earnings (P/E) ratio, resulting in a higher number compared to *Chapter 7.2*.

However, given the "*Residuals vs Fitted plot*" (*Figure 52*), it could be that a linear model does not accurately capture the relationships between the dependent and the independent variables; an observation that assumes even more relevance when we consider that deviation from normality is more evident than in net return spillovers.

[78] External shocks are extremely difficult to predict (e.g. the COVID-19 pandemic).

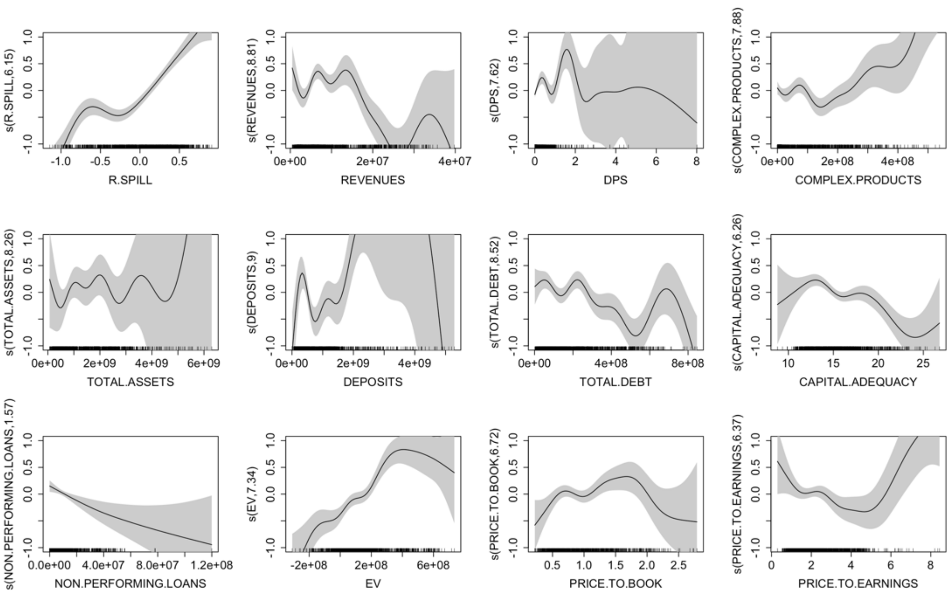
Figure 52. Diagnostics - Linear model (2013-2023):



Data source: Refinitiv.

The smooth term plot of *Figure 53* exhibit several non-linear relationships between the response variable and the predictors. This holds particular importance when we consider deposits[79], revenues, total debt, and total assets. With respect to net return spillovers, confidence intervals are wider, indicating uncertainty.

Figure 53. Smooth term plot - GAM (2013-2023):



Data source: Refinitiv.

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[79] With a 9% EDF, "*deposits*" displays the strongest non-linear relationship with net volatility spillovers.

Incorporating the interaction effects between the variables displaying the lowest p-values or the highest F-values, estimates are in *Figure 54*. Precisely, the interaction terms that we took into account combined net return spillovers, revenues, deposits, total debt, and Enterprise Value (EV), some of which were studied in *Chapter 7.2*.

Figure 54. Expected degrees of freedom - GAM (2013-2023):

	edf	Ref.df	F	Pr
s(R.SPILL)	6.397	7.648	14.0173	0.000e+00
s(REVENUES)	4.211	5.446	0.6165	6.534e-01
s(DPS)	6.618	7.604	2.1392	3.263e-02
s(COMPLEX.PRODUCTS)	8.291	8.846	7.8412	0.000e+00
s(TOTAL.ASSETS)	8.537	8.827	2.5923	6.282e-03
s(DEPOSITS)	6.572	7.496	1.3100	2.068e-01
s(TOTAL.DEBT)	9.000	9.000	6.5611	0.000e+00
s(CAPITAL.ADEQUACY)	1.000	1.000	7.0094	8.207e-03
s(NON.PERFORMING.LOANS)	6.073	7.176	6.0529	8.694e-07
s(EV)	8.478	8.818	5.5852	7.927e-07
s(PRICE.TO.BOOK)	7.413	8.331	4.2874	2.349e-05
s(PRICE.TO.EARNINGS)	7.577	8.475	5.4934	4.775e-07
ti(R.SPILL,DEPOSITS)	6.624	8.242	1.5996	1.176e-01
ti(R.SPILL,EV)	7.653	9.483	3.2723	3.481e-04
ti(R.SPILL,REVENUES)	10.621	11.891	2.7538	1.109e-03
ti(R.SPILL,TOTAL.DEBT)	11.030	12.177	6.7732	0.000e+00
ti(DEPOSITS,EV)	9.192	10.586	5.4687	0.000e+00
ti(DEPOSITS,REVENUES)	12.707	13.341	6.2816	0.000e+00
ti(DEPOSITS,TOTAL.DEBT)	14.895	15.182	7.3733	0.000e+00
ti(EV,REVENUES)	11.213	12.277	9.6207	0.000e+00
ti(EV,TOTAL.DEBT)	14.298	14.651	10.6733	0.000e+00
ti(REVENUES,TOTAL.DEBT)	11.214	12.454	4.4741	8.424e-07

Data source: Refinitiv.

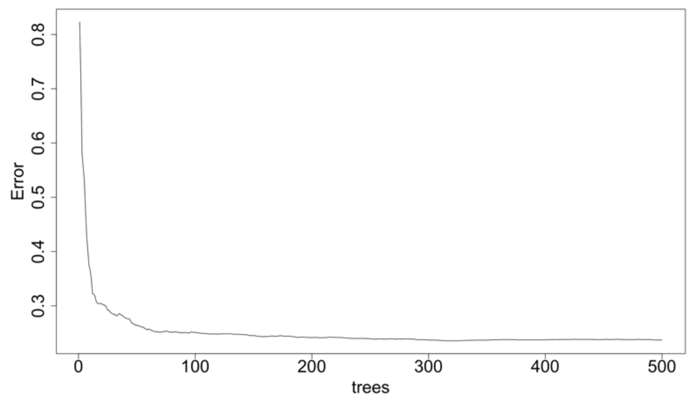
Since the higher the Expected Degree of Freedom (EDF), the more complex the fit to the data, except for capital adequacy, the majority of independent variables have non-linear relationships with net volatility spillovers. However, the term exhibiting the most complex relationship is the interaction between deposits and total debt.

Following the combination between deposits and total debt, the smooth terms with the strongest non-linear relationships are the interaction between Enterprise Value (EV) and total debt (14.30), deposits and revenues (12.71), together with revenues and total debt (11.21); yet, their F-values are lower than that of *Chapter 7.2*.

Apart from noticing that the smooth terms with the highest non-linear relationships are the interaction terms, the model has a better fit than the linear model. Hereafter, the adjusted R-squared reached 70%, lower than that of net return spillovers; once again, this confirms that net volatility spillovers are more difficult to predict.

As already done in *Chapter 7.2*, we could increase the model's accuracy by dealing with a random forest. In such a case, the variance explained increased to 78% and the mean of squared residuals decreased to 23%. Hence, the error rate (*Figure 55*) stops declining after 300 trees, even though the model choose to use 500 trees.

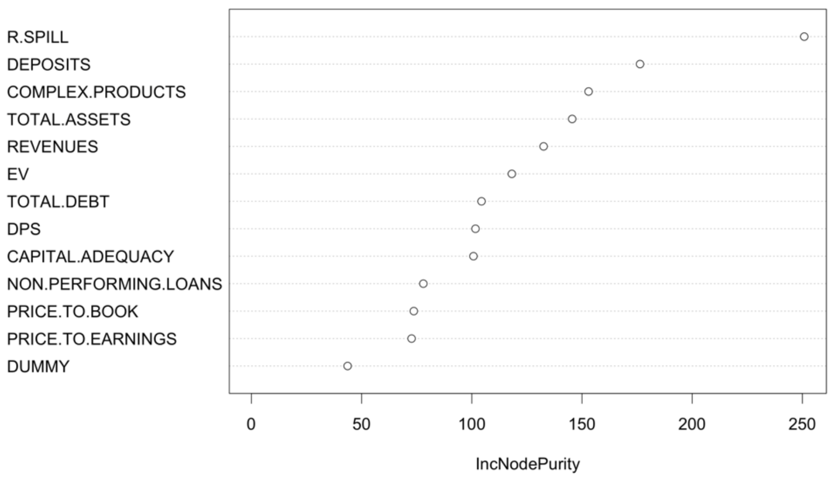
Figure 55. Mean square error - Random forest (2013-2023):



Data source: Refinitiv.

By displaying the importance plot (*Figure 56*), it is worth mentioning that the most important variable remains net return spillovers, strictly followed by deposits. Yet, since net volatility spillovers rise with net return spillovers, this finally proves that whenever there is a shock, contagion occurs with respect to both variables.

Figure 56. Importance plot - Random forest (2013-2023):



Data source: Refinitiv.

CONCLUSIONS.

The primary goal of the research was to analyze the financial spillovers among the world's 14 major equity indexes and the 70 largest banks. By focusing on the time period spanning from 01-01-2004 to 01-01-2024, the study implemented a Diebold and Yilmaz (2009; 2012) approach to their weekly returns and volatilities.

In their 2009 study, "*Measuring financial asset return and volatility spillovers with application to global equity markets*", Diebold and Yilmaz introduced the spillover index, a measure that relies on the Forecast Error Variance Decomposition (FEVD) to quantify the degree of interdependence existing between distinct markets.

Over the years, their framework has been extended to stocks (Diebold and Yilmaz, 2014), government bonds (Demirer et al., 2018), credit default swaps (Greenwood-Nimmo et al., 2019), exchange rates (Bubák et al., 2011), commodity prices (Wang et al., 2018), and, more recently, even cryptocurrencies (Elsayed et al, 2022).

Our major contribution to the existing literature lies in providing both a micro and macro perspective on connectedness; this was accomplished through a preliminary analysis of equity market interdependence, an approach enabling a comprehensive view of systemic risk, which Smaga et al. (2014) recognized as a global threat.

Although the main focus was understanding the propagation of bank's instabilities, equities allowed us to reach interesting results. First, we discovered that during the 2008 crisis, North American and European countries were the most interconnected regions, with the former acting as the main transmitter of volatility spillovers.

In contrast, the stock markets with the lowest transmission were Asian. Hence, the equity indexes with the fewer shocks were the S&P BSE SENSEX Index (BSESN) for returns and the KOSPI Index (KS11) for volatilities. Yet, the result stressed the financial isolation of Asian countries from Western equity markets.

Unlike the 2008 banking crisis, the sovereign debt crisis was associated with lower spillovers. From 01-01-2009 to 01-01-2015, PIIGS equity indexes displayed large own-variance shares, but low interdependence; this was particularly evident in the case of the Portuguese PSI 20 Index (PSI20), exhibiting the lowest share.

Heading to the COVID-19 crisis, despite the pandemic originated in East Asia, the region's impacts on U.S. and E.U. equity markets were quite limited. From 01-01-2019 to 01-01-2023, return and volatility spillovers have been lower than expected, probably due to the strategies implemented by Hong Kong and South Korea.

Yet, since the country that suffered the most the COVID-19 was India, we reached an interesting result. As already demonstrated by Capelle-Blancard and Desroziers (2020), indexes of structurally fragile economies received more shocks than those of countries with robust economic stability and strong financial systems.

By employing a rolling-window approach, the study also shed light on the dynamic nature of equity markets. Here, the primary finding was that while Western equities act as net spillover transmitters, Eastern stock markets tend to be receivers; yet, the result was even confirmed by the analysis of the global banking network.

While extending the research to the world's largest banks, the study addressed the high-dimensionality of the Vector Autoregressions (VARs) through FEVD feature selection. Precisely, what the global banking network highlighted was the presence of two distinct clusters, respectively comprising Western and Chinese banks.

As a confirm, although the high asset value of Industrial and Commercial Bank of China (1398.HK) and Bank of Communications Co. (3328.HK) allows these banks to act as a bridge between the two clusters, Chinese banks tend to be isolated. Yet, the reason behind their exclusion could be related to the government's policy.

Being the majority of banking institutions owned or controlled by the government, Chinese banks operate under a controlled framework. The Chinese State influences their risk management practices and strategic decisions, leading banks to prioritize national economic policies instead of profitability and shareholder value.

To be more precise, we have to consider the rolling-window analysis, highlighting significant spillover bursts during the 2015 stock market sell-off, the 2019 crisis in the Repo market, and the COVID-19 pandemic. Yet, even when considering banks, U.S. and Chinese stocks respectively act as net transmitters and receivers.

Still, as the spillover behavior of European banks was influenced by various factors (e.g. country, size, share of foreign assets) we decided to use a regression approach to identify which variables affected bank spillovers. Here, the only non-significant variables have been the Price-to-Book (P/B) and Price-to-Equity (P/E) ratio.

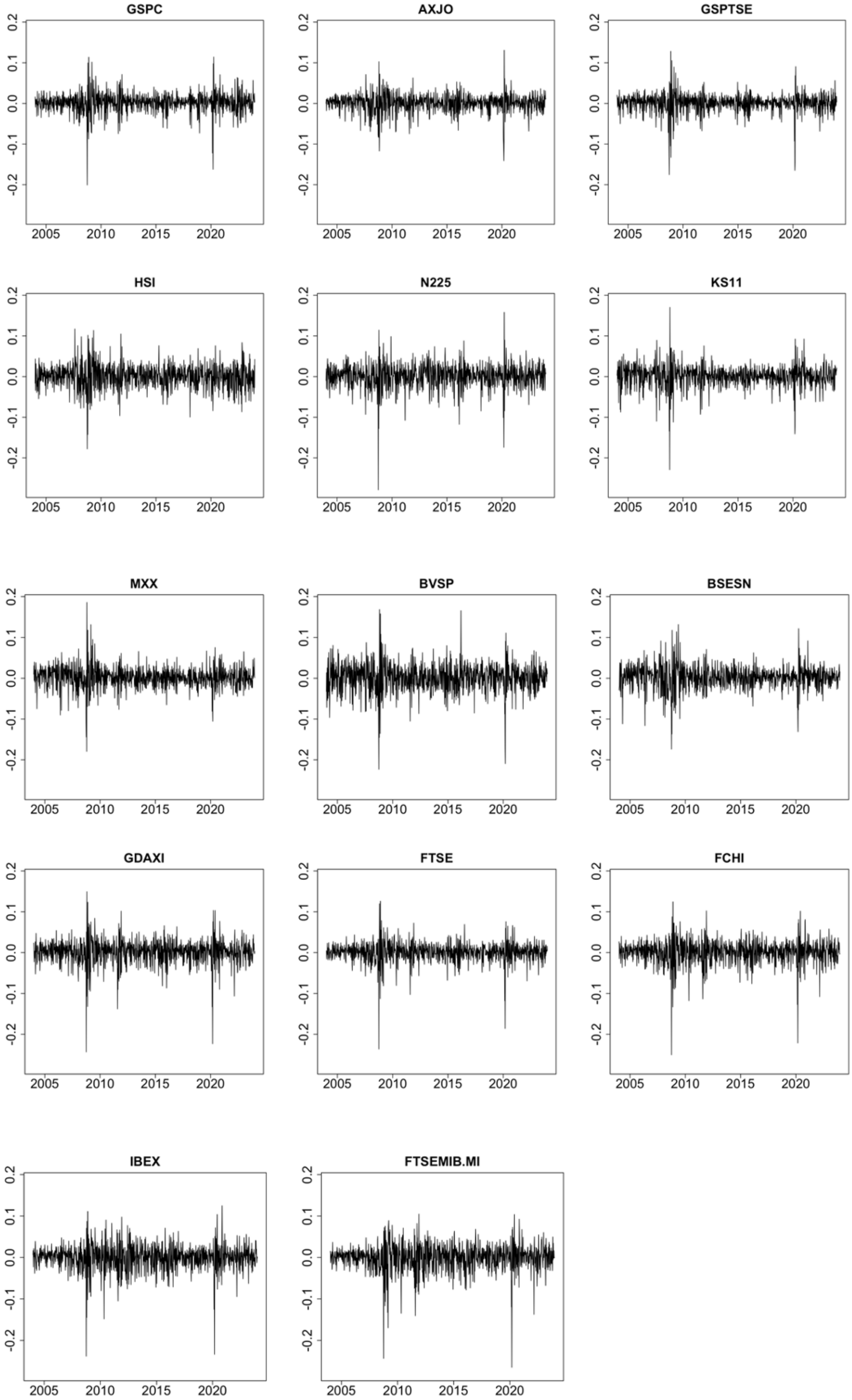
On the contrary, the most important variables have been the dummy variable and total revenues. Hence, both the presence of a Western bank and high profits could increase banks' connectedness; as previously observed, both European and North-American banks are associated with higher return and volatility spillovers.

In either case, the "*Residuals vs Fitted plot*" indicated the presence of various non-linear relationships. As a consequence, we considered supervised learning models able to account for complex relationships. More precisely, the models we chose to analyze were the Generalized Additive Model (GAM) and the random forest.

Since random forests significantly improved the explanatory power of the models, reaching 90% and 78% of the variance explained, we believe that future research should refine these models by considering other independent variables. We do find macroeconomic and sentiment-related variables great examples to explore.

APPENDIX

Appendix 1. Time series - Returns (2004-2024):



Data source: Yahoo Finance.

Appendix 2. Descriptive statistics - Returns (2004-2024)[80]:

	MIN	MAX	RANGE	MEAN	MEDIAN	VARIANCE	SD	IQR	SKEWNESS	KURTOSIS
GSPC	-20.08	11.42	31.51	0.14	0.26	0.06	2.45	2.38	-0.95	8.67
AXJO	-14.12	13.08	27.20	0.08	0.28	0.05	2.23	2.27	-0.74	5.26
GSPTSE	-17.54	12.82	30.36	0.09	0.31	0.05	2.29	2.14	-1.43	11.13
HSI	-17.82	11.72	29.53	0.02	0.26	0.09	2.93	3.73	-0.30	2.47
N225	-27.88	15.82	43.70	0.11	0.26	0.09	2.96	3.21	-1.15	10.00
KS11	-22.93	17.03	39.96	0.11	0.30	0.07	2.73	2.71	-0.96	8.41
MXX	-17.93	18.58	36.51	0.18	0.23	0.07	2.65	2.94	-0.21	6.35
BVSP	-22.32	16.84	39.17	0.16	0.39	0.12	3.48	4.13	-0.54	4.78
BSESN	-17.38	13.17	30.55	0.24	0.42	0.08	2.83	3.12	-0.49	4.07
GDAXI	-24.35	14.94	39.29	0.14	0.39	0.09	2.96	3.05	-1.21	9.63
FTSE	-23.63	12.58	36.21	0.05	0.20	0.06	2.38	2.46	-1.54	15.38
FCHI	-25.05	12.43	37.48	0.07	0.30	0.08	2.88	3.01	-1.38	10.20
IBEX	-23.83	12.48	36.31	0.03	0.34	0.10	3.09	3.26	-1.14	7.77
FTSEMIB.MI	-26.52	10.47	37.00	0.01	0.33	0.10	3.23	3.46	-1.47	8.98

Data source: Yahoo Finance. All data, skewness and kurtosis apart, are in %.

Appendix 3. Descriptive statistics - Volatilities (2004-2024):

	MIN	MAX	RANGE	MEAN	MEDIAN	VARIANCE	SD	IQR	SKEWNESS	KURTOSIS
GSPC	0.49	23.73	23.24	2.81	2.26	0.04	2.06	1.81	3.52	21.15
AXJO	0.60	18.34	17.74	2.60	2.14	0.03	1.74	1.50	3.46	19.47
GSPTSE	0.52	19.82	19.30	2.63	2.08	0.04	2.04	1.62	4.00	23.78
HSI	0.71	28.45	27.74	3.56	3.04	0.05	2.24	1.99	3.51	22.80
N225	0.44	24.33	23.90	3.32	2.87	0.04	2.11	1.80	4.02	27.67
KS11	0.57	24.39	23.82	3.16	2.61	0.05	2.18	1.79	4.05	26.93
MXX	0.84	20.32	19.47	3.28	2.80	0.04	1.95	1.76	2.91	14.36
BVSP	0.82	34.22	33.40	4.62	4.02	0.08	2.79	2.39	4.06	27.76
BSESN	0.71	23.50	22.80	3.47	2.84	0.06	2.44	1.98	3.51	19.02
GDAXI	0.56	22.88	22.31	3.49	2.97	0.05	2.19	2.00	3.16	16.48
FTSE	0.71	20.38	19.67	2.88	2.38	0.04	1.96	1.73	3.38	18.60
FCHI	0.74	21.56	20.82	3.44	2.87	0.05	2.17	2.16	2.76	12.94
IBEX	0.71	20.95	20.24	3.75	3.23	0.05	2.27	2.32	2.53	11.13
FTSEMIB.MI	0.56	28.97	28.41	3.86	3.32	0.06	2.43	2.46	2.84	16.11

Data source: Yahoo Finance. All data, skewness and kurtosis apart, are in %.

[80] The interquartile range (IQR), indicating the difference between the 75th and 25th percentile of a dataset, represents the spread of the middle 50%:
$IQR = 03 - Q1$

Appendix 4. Spillover table - Returns (2004-2009)[81]:

	GSPC	AXJO	GSPTSE	HSI	N225	KS11	MXX	BVSP	BSESN	GDAXI	FTSE	FCHI	IBEX	FTSEMIB.MI	C. from others
GSPC	11.88	5.83	7.13	3.88	6.16	4.59	7.30	6.72	3.72	8.77	8.79	8.82	8.20	8.21	88.12
AXJO	7.81	15.89	7.15	5.75	6.83	5.54	7.35	6.54	3.79	6.36	7.46	6.77	6.05	6.70	84.11
GSPTSE	8.22	6.15	13.68	4.82	6.04	4.48	5.73	8.00	4.17	7.34	8.57	8.32	6.59	7.86	86.32
HSI	5.66	6.18	5.83	16.54	7.38	7.96	5.73	6.58	6.21	6.30	6.64	6.20	6.26	6.52	83.46
N225	6.83	6.00	6.15	6.17	13.89	7.47	5.99	5.98	4.08	7.75	7.37	7.63	6.76	7.92	86.11
KS11	5.70	5.46	5.07	7.69	8.76	16.48	6.68	6.80	5.66	7.14	6.21	6.06	6.15	6.14	83.52
MXX	8.60	6.42	5.86	4.75	6.14	5.88	14.20	8.08	3.76	7.69	7.02	6.78	7.83	6.98	85.80
BVSP	7.59	5.60	7.94	5.43	6.10	5.99	7.94	14.06	4.35	7.30	7.14	6.98	7.07	6.50	85.94
BSESN	6.09	4.75	5.75	7.08	5.43	6.40	5.22	6.05	18.44	7.45	6.62	6.75	6.75	7.22	81.56
GDAXI	7.82	4.54	5.68	4.27	6.44	5.23	5.82	5.71	4.51	11.62	9.20	10.20	9.60	9.35	88.38
FTSE	8.01	5.33	6.76	4.54	6.06	4.62	5.52	5.75	4.00	9.31	11.59	10.25	9.01	9.25	88.41
FCHI	7.90	4.82	6.39	4.21	6.33	4.44	5.22	5.47	4.08	10.14	10.10	11.67	9.22	9.99	88.33
IBEX	7.48	4.62	5.10	4.58	5.87	4.66	6.17	5.68	4.50	9.94	9.18	9.81	12.97	9.43	87.03
FTSEMIB.MI	7.60	4.94	6.37	4.58	6.71	4.51	5.49	5.12	4.58	9.44	9.42	10.32	9.10	11.81	88.19
C. to others (spillover)	95.33	70.64	81.19	67.76	84.26	71.76	80.16	82.49	57.41	104.93	103.76	104.91	98.60	102.08	86.09
C. to others including own	107.21	86.53	94.87	84.30	98.14	88.24	94.36	96.55	75.85	116.56	115.34	116.58	111.57	113.89	1400.00

Data source: Yahoo Finance.

Appendix 5. Spillover table - Volatilities (2004-2009):

	GSPC	AXJO	GSPTSE	HSI	N225	KS11	MXX	BVSP	BSESN	GDAXI	FTSE	FCHI	IBEX	FTSEMIB.MI	C. from others
GSPC	13.60	6.79	9.10	5.95	4.52	1.85	4.50	6.14	2.01	6.95	10.51	10.19	7.57	10.32	86.40
AXJO	10.52	13.56	8.14	6.78	4.76	1.95	5.88	4.03	3.20	5.63	10.50	9.12	7.24	8.69	86.44
GSPTSE	12.52	7.27	12.68	4.48	4.41	1.64	4.42	6.02	2.18	6.87	9.67	10.02	7.52	10.29	87.32
HSI	10.88	7.03	7.20	11.41	4.92	3.18	5.29	5.82	3.57	5.58	10.52	9.21	6.66	8.73	88.59
N225	11.04	5.47	7.70	5.39	10.60	3.56	5.15	6.23	3.03	7.32	9.50	9.42	6.03	9.56	89.40
KS11	11.73	3.28	8.68	5.28	6.51	10.00	4.32	6.78	3.10	7.43	8.66	9.18	5.73	9.30	90.00
MXX	10.61	5.70	10.53	5.06	5.07	3.23	10.88	5.72	2.96	7.24	9.25	9.43	6.03	8.30	89.12
BVSP	11.31	4.80	9.65	4.62	4.94	3.29	5.37	14.06	1.83	6.28	9.01	9.40	6.07	9.37	85.94
BSESN	8.64	4.57	8.71	5.89	5.19	3.88	5.36	4.24	14.36	6.81	8.53	9.12	6.73	7.97	85.64
GDAXI	11.09	5.43	7.80	4.66	6.01	2.70	4.67	5.38	2.37	10.09	10.13	10.99	8.28	10.40	89.91
FTSE	11.09	7.24	8.47	5.87	4.52	2.23	4.95	5.19	2.82	7.01	11.88	10.61	7.90	10.23	88.12
FCHI	11.09	6.70	8.39	4.75	4.83	2.08	4.39	5.06	2.67	8.19	10.79	11.79	8.48	10.79	88.21
IBEX	10.43	7.18	7.29	4.50	5.22	2.23	4.40	4.63	2.74	8.37	10.44	11.20	11.07	10.30	88.93
FTSEMIB.MI	11.28	7.08	8.44	4.85	4.97	2.07	4.41	5.31	2.59	7.62	10.46	10.68	8.20	12.05	87.95
C. to others (spillover)	142.23	78.54	110.11	68.08	65.86	33.88	63.12	70.54	35.09	91.29	127.97	128.56	92.44	124.26	88.00
C. to others including own	155.83	92.10	122.79	79.49	76.47	43.88	74.00	84.61	49.45	101.38	139.85	140.35	103.51	136.30	1400.00

Data source: Yahoo Finance.

[81] The theoretical reference to the connectedness table is represented in Figure 14.

Appendix 6. Spillover table - Returns (2009-2015):

	GSPC	AXJO	GSPTSE	HSI	N225	KS11	MXX	BVSP	BSESN	GDAXI	FTSE	FCHI	IBEX	FTSEMIB.MI	ISEQ	FTSEA.AT	PSI20	C. from others
GSPC	11.46	5.96	7.73	4.47	3.96	4.13	6.40	4.85	3.26	8.00	8.64	8.33	5.79	6.72	6.34	2.59	1.37	88.54
AXJO	7.50	14.60	7.63	5.34	4.27	4.96	5.38	4.21	3.41	6.29	8.29	7.38	4.32	5.48	5.92	2.45	2.56	85.40
GSPTSE	8.37	6.46	12.50	5.44	3.40	5.01	6.06	6.03	4.19	6.47	8.06	7.27	4.94	6.11	5.82	2.32	1.55	87.50
HSI	6.22	5.86	6.80	15.43	5.46	7.52	5.81	6.42	6.29	5.43	6.44	5.94	3.59	4.47	3.95	2.90	1.46	84.57
N225	6.93	5.76	5.22	6.71	19.05	5.75	3.84	3.18	4.34	6.39	6.59	6.91	4.30	5.32	5.36	3.27	1.07	80.95
KS11	5.89	5.56	6.42	7.74	4.84	15.96	5.39	6.01	5.45	6.57	6.33	6.41	3.85	4.56	5.33	2.21	1.48	84.04
MXX	8.40	5.49	7.22	5.57	2.96	5.04	15.15	6.56	3.90	7.16	7.39	7.08	4.30	5.57	5.12	2.10	1.00	84.85
BVSP	6.64	4.64	7.54	6.37	2.57	5.92	6.88	15.76	4.66	6.48	6.96	7.25	4.85	5.39	4.69	2.26	1.15	84.24
BSESN	5.66	4.60	6.58	7.87	4.37	6.65	5.01	5.71	19.42	5.68	6.21	5.55	3.91	4.95	4.01	2.47	1.33	80.58
GDAXI	8.08	5.01	6.04	3.96	3.75	4.72	5.52	4.77	3.33	11.61	8.59	9.82	6.43	7.61	6.98	2.86	0.91	88.39
FTSE	8.32	6.36	7.09	4.49	3.72	4.28	5.32	4.87	3.47	8.16	11.05	8.96	5.68	6.93	6.80	2.84	1.65	88.95
FCHI	7.69	5.35	6.19	3.97	3.76	4.17	4.96	4.89	3.01	8.97	8.63	10.62	7.60	8.42	7.03	3.10	1.62	89.38
IBEX	6.91	4.13	5.43	3.20	3.15	3.41	3.85	4.31	2.80	7.71	7.21	10.00	14.05	11.10	6.28	4.66	1.79	85.95
FTSEMIB.MI	7.12	4.65	5.90	3.43	3.41	3.49	4.35	4.18	3.11	8.02	7.67	9.70	9.71	12.23	6.79	4.36	1.89	87.77
ISEQ	7.52	5.51	6.30	3.31	3.68	4.42	4.61	4.04	2.78	8.16	8.34	8.96	6.02	7.54	13.60	3.41	1.78	86.40
FTSEA.AT	5.34	4.05	4.55	4.13	3.85	3.33	3.24	3.55	2.97	5.65	5.92	6.79	7.76	8.25	5.77	23.04	1.80	76.96
PSI20	4.20	5.88	5.39	2.00	1.72	2.06	2.23	2.38	1.66	2.53	4.72	5.25	4.46	5.21	5.36	2.14	42.81	57.19
C. to others (spillover)	110.79	85.29	102.05	78.00	58.88	74.87	78.85	75.95	58.64	107.69	115.98	121.59	87.50	103.65	91.56	45.94	24.41	83.63
C. to others including own	122.25	99.89	114.55	93.43	77.94	90.84	93.99	91.71	78.06	119.29	127.03	132.21	101.55	115.88	105.17	68.98	67.22	1700.00

Data source: Yahoo Finance.

Appendix 7. Spillover table - Volatilities (2009-2015):

	GSPC	AXJO	GSPTSE	HSI	N225	KS11	MXX	BVSP	BSESN	GDAXI	FTSE	FCHI	IBEX	FTSEA.AT	ISEQ	FTSEMIB.MI	PSI20	C. from others
GSPC	14.54	5.78	8.37	3.18	1.57	5.20	5.80	3.83	1.29	7.50	9.29	8.19	4.72	7.04	6.92	0.91	5.85	85.46
AXJO	9.13	14.42	7.37	4.40	2.30	4.83	6.29	3.48	1.75	6.71	8.14	6.96	3.89	6.51	6.45	0.90	6.46	85.58
GSPTSE	10.67	6.01	16.73	5.10	1.49	6.06	5.20	3.79	1.94	7.33	8.23	6.34	3.36	6.08	6.81	0.58	4.29	83.27
HSI	6.94	5.90	6.85	18.54	2.12	8.10	6.94	3.99	2.52	7.05	8.01	4.87	2.01	4.38	5.42	1.21	5.16	81.46
N225	6.51	6.33	5.35	3.72	34.07	3.87	5.84	3.03	1.34	6.06	6.77	4.96	1.68	2.99	4.57	0.96	1.96	65.93
KS11	8.54	5.48	6.70	5.99	1.71	18.42	4.94	3.39	2.41	7.71	8.37	6.04	2.53	6.85	5.59	0.34	4.99	81.58
MXX	9.05	6.19	6.54	5.81	2.91	4.86	18.08	5.58	2.34	6.28	7.25	5.69	2.64	5.07	6.67	0.56	4.47	81.92
BVSP	7.53	4.60	5.24	4.47	1.81	3.54	6.83	20.32	1.29	5.15	6.79	5.74	2.98	5.27	8.52	1.92	7.99	79.68
BSESN	5.63	3.67	8.14	8.61	1.57	7.47	6.96	2.74	30.32	3.20	4.42	1.84	0.86	4.71	6.68	0.54	2.65	69.68
GDAXI	7.78	4.92	5.99	3.73	1.81	5.20	4.33	2.98	1.13	13.50	9.20	10.92	4.79	8.79	5.85	1.08	8.00	86.50
FTSE	9.77	5.25	6.52	4.00	1.99	5.61	5.11	3.27	1.52	8.28	12.85	9.24	4.53	6.61	6.88	0.96	7.61	87.15
FCHI	8.38	4.48	5.29	3.11	1.60	4.08	4.33	2.90	1.13	9.81	9.38	13.42	7.45	9.59	6.15	1.21	7.70	86.58
IBEX	7.36	3.92	3.96	2.60	1.17	3.21	3.46	2.30	1.44	6.57	6.79	10.93	18.65	12.69	4.91	1.74	8.31	81.35
FTSEA.AT	8.41	3.73	5.34	2.31	1.03	3.92	3.79	2.98	1.87	7.75	7.17	9.75	9.18	17.68	5.76	1.58	7.75	82.32
ISEQ	8.45	5.71	5.62	3.60	2.05	4.73	5.44	4.92	2.43	4.84	7.95	6.83	3.50	6.00	21.74	1.59	4.59	78.26
FTSEMIB.MI	2.48	1.63	2.12	1.76	2.14	1.13	0.90	1.82	2.96	0.82	2.20	1.85	2.97	3.70	3.60	61.84	6.08	38.16
PSI20	2.42	2.06	1.63	1.91	2.52	1.87	1.54	2.18	1.52	2.21	2.95	3.16	2.56	3.89	1.85	2.70	63.05	36.95
C. to others (spillover)	119.06	75.68	91.03	64.30	29.78	73.68	77.70	53.19	28.87	97.27	112.91	103.30	59.64	100.16	92.63	18.77	93.85	75.99
C. to others including own	133.60	90.10	107.76	82.84	63.85	92.11	95.78	73.51	59.19	110.78	125.76	116.72	78.28	117.85	114.37	80.61	156.90	1700.00

Data source: Yahoo Finance.

Appendix 8. Spillover table - Returns (2019-2023):

	GSPC	AXJO	GSPTSE	HSI	N225	KS11	MXX	BVSP	BSESN	GDAXI	FTSE	FCHI	IBEX	FTSEMIB.MI	C. from others
GSPC	15.10	7.94	10.95	1.81	5.97	6.69	5.20	5.16	5.13	8.05	7.11	7.71	6.14	7.05	84.90
AXJO	6.91	14.72	8.13	1.95	7.69	5.90	3.90	4.95	4.47	8.63	8.46	8.65	7.45	8.20	85.28
GSPTSE	9.28	8.71	13.03	1.96	6.12	6.84	5.39	5.22	5.16	7.90	8.07	7.66	7.00	7.66	86.97
HSI	3.40	4.21	4.51	28.01	6.19	8.05	3.44	3.88	6.12	6.61	6.01	6.96	5.30	7.31	71.99
N225	5.98	8.01	6.86	3.36	15.20	8.31	3.00	3.53	4.86	8.95	7.44	9.07	7.15	8.27	84.80
KS11	6.68	6.91	8.18	4.29	8.41	14.99	5.47	4.85	5.12	7.74	6.84	7.44	6.04	7.04	85.01
MXX	6.47	5.64	8.08	2.26	3.91	6.99	18.71	5.89	5.39	6.80	7.46	7.12	8.09	7.18	81.29
BVSP	6.37	8.08	7.56	2.91	4.56	5.95	5.69	18.64	6.05	6.77	7.38	6.56	6.56	6.92	81.36
BSESN	6.12	6.43	7.51	4.09	5.82	6.12	5.13	5.74	17.92	7.20	6.41	7.37	7.02	7.12	82.08
GDAXI	6.10	7.00	6.63	2.66	6.79	5.81	4.20	3.73	4.65	12.30	8.80	11.06	9.56	10.72	87.70
FTSE	5.96	7.34	7.60	2.64	6.16	5.65	5.02	4.58	4.38	9.32	13.01	9.93	9.20	9.19	86.99
FCHI	5.91	6.77	6.42	2.74	6.78	5.47	4.35	3.64	4.72	10.92	9.26	12.16	10.09	10.77	87.84
IBEX	5.10	6.51	6.38	2.11	5.83	4.92	5.40	3.69	4.77	10.43	9.44	11.14	13.46	10.82	86.54
FTSEMIB.MI	5.25	6.67	6.31	2.82	6.24	5.20	4.37	3.47	4.59	11.19	9.00	11.42	10.36	13.10	86.90
C. to others (spillover)	79.54	90.21	95.12	35.60	80.47	81.91	60.56	58.33	65.42	110.51	101.68	112.09	99.96	108.26	84.26
C. to others including own	94.64	104.93	108.15	63.60	95.67	96.89	79.27	76.97	83.34	122.81	114.69	124.25	113.42	121.36	1400.00

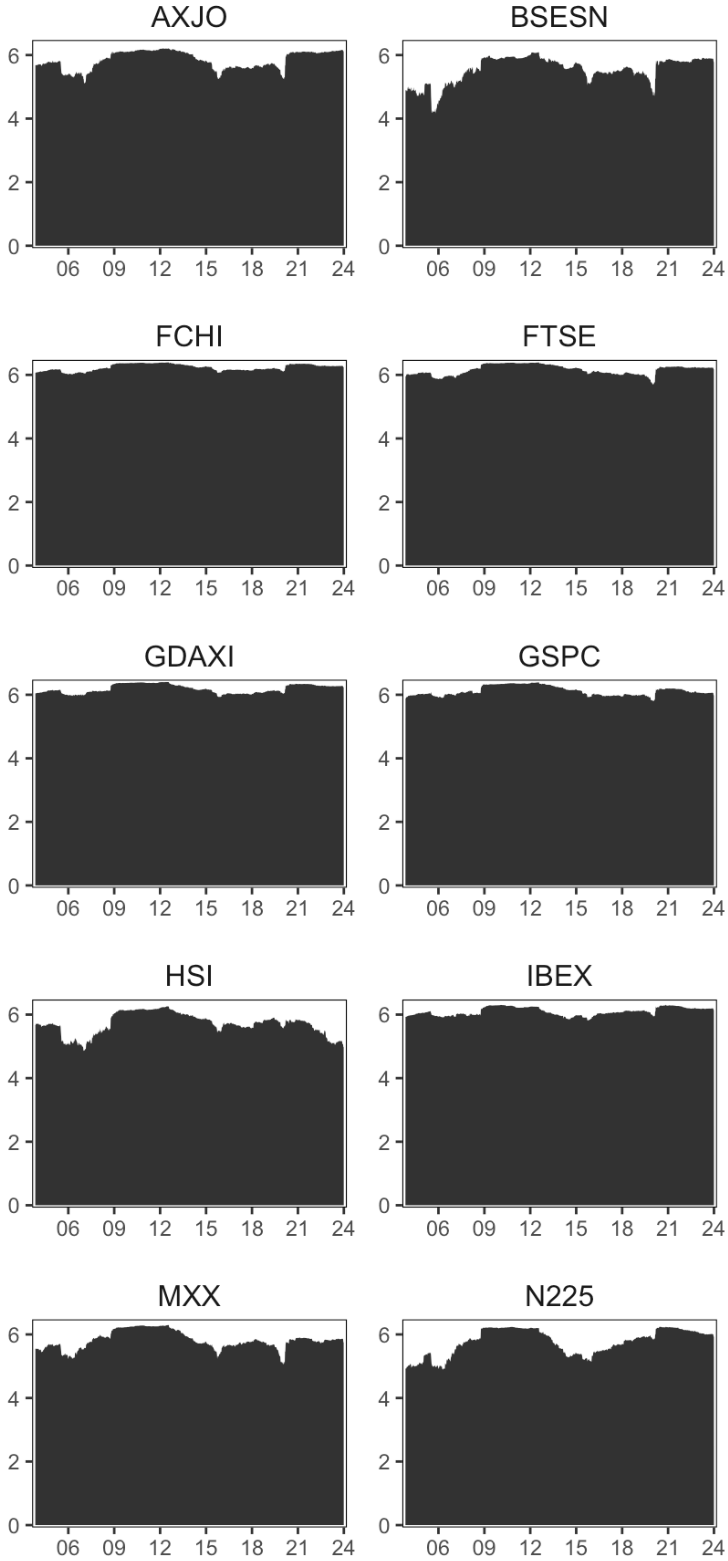
Data source: Yahoo Finance.

Appendix 9. Spillover table - Volatilities (2019-2023):

	GSPC	AXJO	GSPTSE	HSI	N225	KS11	MXX	BVSP	BSESN	GDAXI	FTSE	FCHI	IBEX	FTSEMIB.MI	C. from others
GSPC	12.41	11.36	11.40	1.48	5.33	4.29	7.67	6.12	3.36	8.07	9.41	7.54	5.52	6.05	87.59
AXJO	7.16	18.11	9.06	0.84	6.40	4.34	6.35	8.34	4.00	5.81	10.93	6.16	6.44	6.07	81.89
GSPTSE	9.09	13.25	11.84	1.27	6.35	4.38	6.66	8.04	4.01	6.57	9.86	6.31	6.19	6.20	88.16
HSI	5.46	6.68	6.17	19.06	4.90	5.32	6.61	5.15	3.24	7.83	6.39	7.03	8.45	7.70	80.94
N225	5.79	11.93	9.12	1.54	12.07	5.32	5.62	7.79	5.61	6.20	8.66	5.97	6.99	7.41	87.93
KS11	4.76	13.79	8.01	2.19	7.12	12.07	6.49	9.48	4.96	4.31	9.10	4.64	6.34	6.76	87.93
MXX	8.01	11.36	8.48	1.88	4.15	4.13	16.17	5.93	3.41	6.57	10.84	6.88	6.60	5.61	83.83
BVSP	6.58	13.81	9.06	1.71	6.40	4.94	5.98	13.68	3.91	5.26	10.57	5.47	6.18	6.44	86.32
BSESN	6.16	13.98	8.44	1.29	6.55	5.19	6.72	7.87	8.91	5.57	9.20	6.14	6.90	7.07	91.09
GDAXI	8.43	11.18	7.93	0.61	4.57	3.38	7.73	4.10	3.57	11.86	9.80	10.33	8.11	8.39	88.14
FTSE	7.16	12.40	7.97	0.47	4.60	3.50	7.35	5.68	3.54	8.25	13.76	8.79	9.10	7.41	86.24
FCHI	8.08	10.63	7.32	0.74	4.11	3.05	7.24	3.87	3.68	10.92	10.34	11.93	9.49	8.61	88.07
IBEX	6.30	10.70	6.50	0.44	4.02	3.35	7.17	4.18	3.72	9.61	10.81	10.84	13.02	9.34	86.98
FTSEMIB.MI	7.15	10.68	7.52	0.72	4.96	4.17	6.59	4.96	4.31	9.66	9.70	9.70	9.24	10.65	89.35
C. to others (spillover)	90.12	151.77	106.97	15.18	69.45	55.38	88.19	81.50	51.31	94.62	125.58	95.78	95.55	93.05	86.75
C. to others including own	102.53	169.87	118.81	34.24	81.52	67.45	104.36	95.18	60.22	106.48	139.35	107.72	108.57	103.70	1400.00

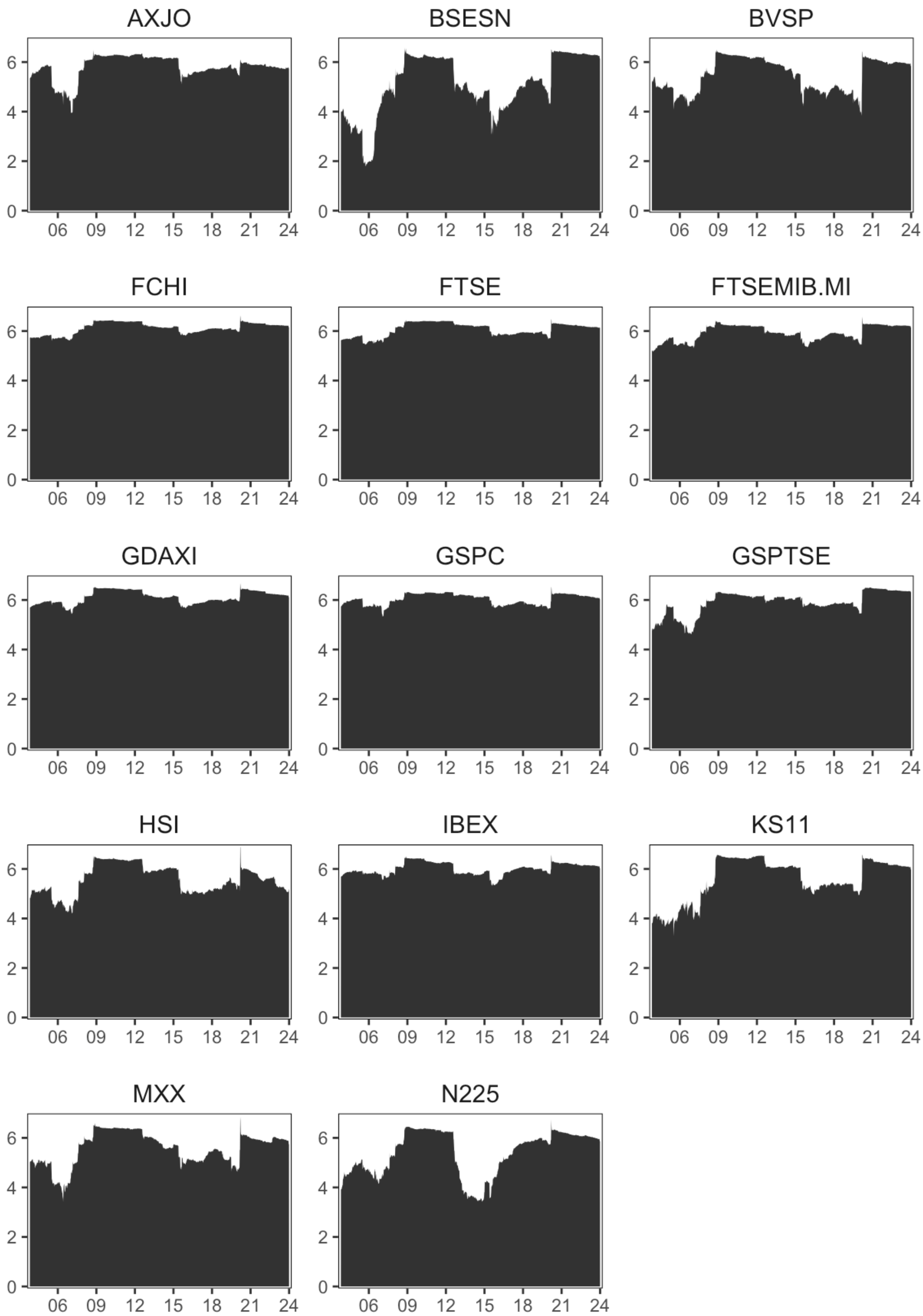
Data source: Yahoo Finance.

Appendix 10. Directional spillovers *TO* 14 markets - Returns (2004-2024):



Data source: Yahoo Finance.

Appendix 11. Directional spillovers *TO* 14 markets - Volatilities (2004-2024):



Data source: Yahoo Finance.

Appendix 12.1. Spillover table - Returns (2008-2024):

	1398.HK	601939.SS	601988.SS	JPM	BAC	8306.T	HSBA.L	BNP.PA	ACA.PA	C	8316.T	8411.T	3328.HK	WFC	SAN.MC	BARC.L
1398.HK	12.92	3.05	2.02	1.98	1.94	1.23	2.44	1.64	1.65	1.96	1.21	1.00	8.80	1.26	1.78	1.86
601939.SS	3.16	13.34	9.10	0.39	0.29	0.48	0.35	0.23	0.32	0.28	0.40	0.27	3.23	0.09	0.42	0.24
601988.SS	2.38	10.34	15.20	0.23	0.10	0.25	0.19	0.13	0.25	0.11	0.21	0.16	2.83	0.07	0.25	0.14
JPM	1.27	0.14	0.02	8.55	5.44	1.76	3.46	3.42	3.38	5.38	1.60	1.14	1.22	5.63	2.97	2.65
BAC	1.20	0.16	0.03	5.23	8.01	2.06	3.31	3.31	3.00	5.47	1.73	1.70	1.28	5.44	2.67	3.52
8306.T	0.96	0.39	0.19	2.09	2.58	9.98	1.85	2.33	2.29	2.02	8.12	7.26	1.31	2.26	2.04	2.62
HSBA.L	1.82	0.18	0.05	3.83	3.93	1.84	9.59	4.12	3.87	3.30	1.64	1.55	1.82	3.62	3.79	3.61
BNP.PA	1.03	0.08	0.03	3.39	3.47	1.92	3.57	8.29	5.76	3.17	1.89	1.51	1.24	3.05	4.90	4.13
ACA.PA	1.02	0.07	0.01	3.55	3.33	2.00	3.55	6.12	8.82	3.32	1.92	1.66	1.10	3.00	5.00	4.12
C	1.31	0.14	0.05	5.51	5.90	1.74	2.97	3.30	3.28	8.66	1.71	1.37	1.35	4.93	2.92	3.39
8316.T	0.99	0.32	0.13	2.01	2.32	8.52	1.75	2.42	2.33	2.10	10.43	7.85	1.55	1.95	2.16	2.76
8411.T	0.90	0.24	0.14	1.58	2.47	8.27	1.84	2.11	2.16	1.81	8.51	11.33	1.44	1.97	2.03	2.83
3328.HK	7.53	2.65	2.07	1.61	1.77	1.46	2.12	1.69	1.52	1.75	1.63	1.38	11.08	1.18	2.05	2.05
WFC	0.82	0.07	0.03	5.71	5.69	1.92	3.20	3.07	2.86	4.82	1.57	1.45	0.91	8.52	2.74	3.04
SAN.MC	1.20	0.23	0.10	3.15	2.94	1.78	3.48	5.20	4.98	2.97	1.79	1.53	1.61	2.89	8.79	3.69
BARC.L	1.24	0.14	0.08	2.73	3.94	2.22	3.25	4.25	3.99	3.48	2.20	2.10	1.56	3.17	3.59	8.58
UBSG.SW	1.11	0.24	0.11	3.30	3.68	2.25	3.34	4.10	4.40	3.94	2.19	1.94	1.37	3.04	3.83	3.86
RY.TO	1.37	0.30	0.23	3.56	3.89	2.07	2.38	3.52	3.01	3.63	1.81	1.65	1.68	3.67	2.92	3.63
600036.SS	2.84	6.53	5.13	0.48	0.31	0.63	0.48	0.45	0.50	0.35	0.66	0.55	3.41	0.11	0.58	0.45
DBK.DE	1.44	0.22	0.17	3.00	3.43	2.18	3.05	4.66	4.63	3.06	1.84	1.81	1.63	2.99	4.48	4.11
601166.SS	2.23	6.35	5.37	0.31	0.18	0.39	0.25	0.34	0.43	0.19	0.39	0.29	2.99	0.05	0.55	0.29
601998.SS	2.17	7.11	7.68	0.21	0.17	0.32	0.25	0.20	0.33	0.18	0.28	0.23	2.83	0.06	0.35	0.25
600000.SS	2.17	6.29	5.72	0.37	0.20	0.49	0.17	0.22	0.34	0.19	0.51	0.39	2.99	0.06	0.30	0.32
LLOY.L	1.10	0.07	0.03	3.08	3.91	1.68	3.42	4.01	4.23	3.43	1.68	1.67	1.34	3.48	4.06	6.05
600016.SS	1.98	7.53	7.05	0.38	0.25	0.33	0.31	0.26	0.44	0.25	0.36	0.21	2.68	0.12	0.40	0.28
BNS.TO	1.37	0.38	0.24	3.64	3.60	1.88	2.55	3.08	2.65	3.51	1.74	1.44	1.71	3.71	3.01	3.06
CBA.AX	0.85	0.28	0.15	3.12	2.68	1.87	2.06	3.08	2.90	3.04	1.74	1.59	1.08	3.04	3.05	2.67
STAN.L	1.88	0.30	0.16	3.02	3.23	1.46	4.55	3.65	3.44	3.06	1.36	1.51	2.20	3.12	4.15	3.35
000001.SZ	2.24	6.57	5.36	0.28	0.20	0.34	0.28	0.23	0.35	0.18	0.31	0.25	2.55	0.07	0.41	0.19
SBIN.NS	2.69	0.46	0.35	2.06	1.97	1.57	2.43	2.68	2.15	1.81	1.15	1.03	3.09	2.28	3.12	2.76
USB	0.84	0.04	0.02	5.53	4.87	1.69	3.26	3.36	2.75	3.87	1.55	1.27	0.98	6.19	2.64	3.26
NDA.FI.HE	1.16	0.09	0.10	2.81	3.24	2.26	3.11	4.47	4.15	3.21	1.87	1.93	1.50	3.06	3.95	4.01
105560.KS	2.05	0.38	0.24	2.36	2.49	2.34	2.13	2.76	2.80	2.35	2.29	2.00	2.50	2.37	2.67	2.93
PNC	0.79	0.06	0.00	5.77	5.42	1.65	3.45	3.59	2.83	4.67	1.44	1.13	0.88	6.11	2.61	3.03
8308.T	0.87	0.42	0.33	1.33	1.39	8.50	1.84	1.99	1.75	0.81	8.24	7.93	1.35	1.41	1.85	2.12
TFC	0.78	0.06	0.05	5.25	5.30	1.98	3.01	3.25	3.12	4.00	1.63	1.56	0.85	5.88	2.76	2.99
D05.SI	2.54	0.78	0.45	2.34	2.76	2.46	2.88	2.96	2.63	2.43	2.25	1.98	2.94	2.14	2.92	2.56
DANSKE.CO	0.74	0.14	0.09	2.63	3.50	1.86	2.96	4.30	3.84	3.34	1.70	1.82	1.33	3.02	3.88	4.14
600015.SS	2.03	7.27	7.15	0.31	0.18	0.31	0.18	0.16	0.31	0.15	0.33	0.25	2.79	0.10	0.33	0.20
055550.KS	2.18	0.46	0.22	2.23	2.29	2.33	2.26	2.65	2.63	2.11	2.15	1.66	2.23	2.21	2.78	2.77
8309.T	1.45	0.34	0.14	2.36	2.73	7.17	2.28	2.08	2.19	2.33	6.62	6.10	1.69	2.39	2.39	2.30
601169.SS	2.07	6.76	6.45	0.36	0.13	0.31	0.17	0.24	0.43	0.27	0.39	0.15	2.71	0.06	0.37	0.13
ITUB4.SA	2.44	0.20	0.22	3.44	3.07	1.46	2.65	2.94	2.78	3.85	1.40	1.23	2.59	2.82	3.72	3.18
8604.T	1.48	0.42	0.16	2.45	2.92	6.58	2.01	2.65	2.41	2.49	6.42	6.13	1.71	2.11	2.22	2.35
024110.KS	2.20	0.38	0.19	2.39	2.61	2.03	2.03	2.29	2.33	2.36	2.17	1.99	3.15	2.05	2.95	2.37
002142.SZ	2.05	6.38	6.07	0.23	0.16	0.38	0.24	0.26	0.34	0.17	0.38	0.25	2.53	0.07	0.39	0.26
C. to others (spillover)	77.93	85.00	73.69	111.61	116.87	98.21	97.34	113.80	108.72	107.16	92.95	83.85	94.54	108.32	108.95	110.53
C. to others including own	90.85	98.34	88.89	120.16	124.89	108.19	106.94	122.10	117.54	115.82	103.38	95.19	105.62	116.84	117.74	119.11

Data source: Yahoo Finance.

Appendix 12.2. Spillover table - Returns (2008-2024):

	UBSG.SW	RY.TO	600036.SS	DBK.DE	601166.SS	601998.SS	600000.SS	LLOY.L	600016.SS	BNS.TO	CBA.AX	STAN.L	000001.SZ	SBIN.NS	USB
1398.HK	1.60	1.82	2.98	2.15	2.37	1.95	2.18	1.44	1.90	1.77	0.65	2.45	2.15	1.35	1.19
601939.SS	0.33	0.38	7.02	0.38	6.83	6.56	6.39	0.18	7.50	0.46	0.19	0.46	6.40	0.28	0.08
601988.SS	0.07	0.36	6.18	0.35	6.50	8.02	6.49	0.11	7.89	0.39	0.10	0.33	5.84	0.29	0.07
JPM	3.05	3.19	0.17	2.86	0.12	0.07	0.12	2.59	0.15	3.22	1.55	2.45	0.13	0.60	5.19
BAC	3.26	3.36	0.17	3.17	0.11	0.08	0.13	2.80	0.13	2.98	1.25	2.52	0.13	0.61	4.36
8306.T	2.44	2.26	0.52	2.51	0.32	0.24	0.39	1.74	0.27	1.93	1.13	1.47	0.24	0.66	1.87
HSBA.L	3.52	2.47	0.21	3.32	0.15	0.13	0.09	3.23	0.19	2.53	1.18	4.27	0.15	0.87	3.39
BNP.PA	3.77	3.15	0.19	4.47	0.13	0.09	0.07	3.35	0.09	2.64	1.60	3.01	0.08	0.86	3.07
ACA.PA	4.36	2.84	0.13	4.74	0.08	0.09	0.07	3.74	0.06	2.40	1.53	3.03	0.03	0.69	2.69
C	3.72	3.32	0.20	3.06	0.09	0.11	0.11	2.87	0.15	3.06	1.64	2.51	0.14	0.57	3.70
8316.T	2.53	2.07	0.52	2.25	0.30	0.19	0.40	1.85	0.29	1.88	1.09	1.51	0.20	0.48	1.80
8411.T	2.50	2.10	0.50	2.41	0.26	0.19	0.35	1.92	0.20	1.72	1.07	1.80	0.18	0.50	1.65
3328.HK	1.70	1.96	3.08	2.10	2.70	2.17	2.56	1.48	2.21	1.91	0.70	2.43	2.08	1.40	1.18
WFC	2.81	3.35	0.11	2.85	0.07	0.05	0.08	2.87	0.10	3.30	1.48	2.52	0.11	0.73	5.81
SAN.MC	3.74	2.81	0.33	4.53	0.26	0.18	0.17	3.61	0.19	2.75	1.59	3.59	0.18	0.97	2.59
BARC.L	3.65	3.36	0.22	4.11	0.14	0.13	0.16	5.11	0.09	2.69	1.35	2.83	0.09	0.95	3.11
UBSG.SW	9.07	2.78	0.28	4.34	0.18	0.18	0.11	3.18	0.19	2.34	1.92	3.17	0.14	0.65	2.44
RY.TO	2.79	9.34	0.48	3.16	0.33	0.35	0.32	3.10	0.27	5.75	2.01	2.62	0.34	0.96	3.43
600036.SS	0.48	0.56	12.27	0.62	7.74	5.17	7.40	0.30	6.43	0.66	0.15	0.74	7.30	0.45	0.22
DBK.DE	4.18	3.07	0.35	8.73	0.25	0.25	0.19	2.80	0.25	2.66	1.30	3.17	0.17	1.03	2.60
601166.SS	0.36	0.38	7.75	0.43	12.26	6.17	8.58	0.20	7.11	0.50	0.22	0.62	8.15	0.36	0.09
601998.SS	0.27	0.46	6.03	0.46	7.20	14.42	6.58	0.16	7.54	0.33	0.24	0.35	6.48	0.18	0.06
600000.SS	0.23	0.43	7.85	0.32	9.01	5.96	12.95	0.16	7.29	0.48	0.11	0.34	7.80	0.33	0.12
LLOY.L	3.62	3.29	0.15	3.26	0.10	0.09	0.07	9.89	0.05	2.79	1.36	2.97	0.05	0.66	3.72
600016.SS	0.30	0.37	6.96	0.49	7.66	6.97	7.46	0.14	13.41	0.42	0.16	0.55	7.19	0.28	0.11
BNS.TO	2.48	6.04	0.54	2.88	0.34	0.27	0.32	2.74	0.29	9.75	2.34	2.87	0.34	0.97	3.65
CBA.AX	3.60	3.68	0.36	2.62	0.47	0.31	0.19	2.38	0.25	4.02	17.14	2.81	0.29	0.89	2.76
STAN.L	3.58	2.91	0.54	3.65	0.37	0.21	0.24	3.01	0.37	3.05	1.66	10.15	0.28	1.13	2.47
000001.SZ	0.27	0.43	8.01	0.39	8.89	6.11	8.07	0.11	7.32	0.48	0.16	0.44	13.51	0.35	0.11
SBIN.NS	2.00	2.49	0.87	3.06	0.69	0.27	0.66	1.84	0.44	2.45	1.62	2.81	0.63	24.29	1.75
USB	2.42	3.40	0.12	2.67	0.07	0.05	0.09	3.38	0.09	3.57	1.46	2.18	0.09	0.63	9.36
NDA.FI.HE	3.96	3.20	0.21	4.56	0.16	0.17	0.11	3.41	0.12	2.86	1.48	2.96	0.08	0.73	2.66
105560.KS	2.27	2.32	0.87	2.86	0.56	0.35	0.49	2.45	0.26	2.58	1.13	2.34	0.40	0.86	2.19
PNC	2.75	3.26	0.09	2.60	0.07	0.05	0.06	3.01	0.09	3.37	1.53	2.38	0.08	0.64	6.37
8308.T	1.78	1.46	0.67	2.09	0.40	0.33	0.54	1.49	0.29	1.41	1.01	1.57	0.23	0.47	1.47
TFC	2.96	3.02	0.08	2.65	0.07	0.05	0.06	2.88	0.07	2.90	1.44	2.41	0.09	0.73	6.64
D05.SI	2.99	2.20	1.17	3.06	0.95	0.60	0.77	2.17	0.63	2.49	1.93	3.32	0.70	1.30	1.86
DANSKE.CO	4.16	3.23	0.25	3.95	0.20	0.20	0.17	3.19	0.13	2.84	1.48	3.37	0.19	0.90	2.45
600015.SS	0.20	0.43	7.40	0.30	7.45	7.45	8.15	0.15	8.29	0.38	0.14	0.33	7.08	0.37	0.10
055550.KS	2.24	2.41	0.72	2.61	0.56	0.19	0.42	2.57	0.22	2.52	1.52	2.14	0.39	0.88	2.24
8309.T	2.65	2.04	0.35	2.43	0.21	0.23	0.25	1.95	0.19	1.84	1.27	1.69	0.13	0.63	2.15
601169.SS	0.23	0.40	6.78	0.31	8.37	7.09	8.11	0.12	7.20	0.40	0.12	0.36	6.61	0.19	0.03
ITUB4.SA	2.49	3.01	0.52	2.87	0.25	0.26	0.21	2.67	0.25	3.59	1.32	3.50	0.19	1.05	2.49
8604.T	2.51	2.33	0.57	2.53	0.35	0.24	0.40	1.64	0.33	1.98	1.30	1.50	0.28	0.55	1.80
024110.KS	2.56	1.80	0.79	2.62	0.48	0.20	0.47	2.06	0.32	2.48	1.34	2.82	0.26	0.90	1.78
002142.SZ	0.25	0.43	7.34	0.34	8.00	7.37	6.44	0.13	6.29	0.46	0.14	0.39	8.42	0.41	0.14
C. to others (spillover)	103.62	100.62	90.63	109.41	91.82	77.41	86.70	92.32	83.94	97.21	49.95	93.87	82.50	31.30	99.65
C. to others including own	112.68	109.95	102.90	118.14	104.09	91.82	99.65	102.20	97.35	106.96	67.09	104.02	96.01	55.59	109.01

Data source: Yahoo Finance.

Appendix 12.3. Spillover table - Returns (2008-2024):

	NDA.FI.HE	105560.KS	PNC	8308.T	TFC	D05.SI	DANSKE.CO	600015.SS	055550.KS	8309.T	601169.SS	ITUB4.SA	8604.T	024110.KS	002142.SZ
1398.HK	1.66	2.09	1.11	0.62	0.98	2.73	0.86	2.06	2.10	1.63	1.93	2.06	1.57	2.05	1.84
601939.SS	0.14	0.44	0.16	0.26	0.05	0.90	0.12	7.61	0.43	0.39	6.41	0.36	0.47	0.40	5.81
601988.SS	0.17	0.29	0.10	0.21	0.02	0.57	0.07	8.42	0.23	0.17	6.99	0.45	0.20	0.18	6.14
JPM	2.55	1.61	5.43	0.65	4.36	1.58	1.98	0.09	1.32	1.81	0.08	1.87	1.67	1.41	0.09
BAC	2.79	1.51	4.85	0.69	4.34	1.80	2.55	0.12	1.20	1.96	0.06	1.55	1.90	1.41	0.09
8306.T	2.48	1.89	1.82	5.04	2.02	2.17	1.66	0.27	1.77	6.41	0.21	0.85	5.41	1.45	0.27
HSBA.L	3.30	1.57	3.62	1.08	2.86	2.27	2.58	0.12	1.50	2.04	0.06	1.62	1.59	1.38	0.13
BNP.PA	4.08	1.74	3.29	0.99	2.77	1.93	3.23	0.07	1.55	1.54	0.06	1.59	1.78	1.26	0.11
ACA.PA	3.98	1.79	2.72	0.93	2.83	1.69	3.06	0.06	1.53	1.72	0.05	1.59	1.70	1.21	0.05
C	3.05	1.63	4.49	0.44	3.48	1.75	2.61	0.08	1.24	1.81	0.11	2.12	1.76	1.52	0.13
8316.T	2.15	1.86	1.66	5.12	1.74	2.09	1.62	0.29	1.75	6.23	0.23	0.91	5.50	1.64	0.26
8411.T	2.42	1.64	1.44	5.36	1.82	1.99	1.86	0.26	1.49	6.24	0.11	0.86	5.70	1.64	0.20
3328.HK	1.83	2.17	1.05	0.87	0.90	2.73	1.33	2.44	1.80	1.66	2.16	1.84	1.56	2.50	1.96
WFC	2.83	1.65	5.74	0.75	4.97	1.51	2.30	0.09	1.33	1.84	0.05	1.53	1.46	1.22	0.10
SAN.MC	3.79	1.75	2.52	0.97	2.47	2.04	3.08	0.22	1.63	1.90	0.17	2.12	1.58	1.76	0.20
BARC.L	3.79	1.83	2.82	1.12	2.64	1.73	3.20	0.12	1.60	1.76	0.03	1.72	1.62	1.38	0.13
UBSG.SW	3.98	1.46	2.74	0.99	2.74	2.18	3.47	0.15	1.29	2.19	0.08	1.49	1.85	1.57	0.15
RY.TO	3.27	1.83	3.36	0.79	2.82	1.73	2.73	0.33	1.65	1.65	0.25	1.72	1.77	1.25	0.31
600036.SS	0.31	0.91	0.27	0.44	0.10	1.27	0.29	7.22	0.68	0.39	6.07	0.43	0.63	0.76	6.27
DBK.DE	4.38	1.83	2.46	1.07	2.37	2.14	3.15	0.18	1.56	1.90	0.15	1.65	1.73	1.53	0.18
601166.SS	0.23	0.58	0.16	0.29	0.04	1.01	0.31	7.33	0.52	0.24	7.45	0.33	0.38	0.48	6.82
601998.SS	0.23	0.43	0.09	0.25	0.02	0.73	0.20	8.50	0.19	0.26	7.43	0.40	0.33	0.24	7.35
600000.SS	0.17	0.47	0.17	0.32	0.03	0.80	0.25	8.45	0.40	0.27	7.62	0.27	0.43	0.45	5.79
LLOY.L	3.72	1.62	3.27	0.86	3.02	1.59	2.85	0.11	1.59	1.73	0.03	1.72	1.37	1.19	0.05
600016.SS	0.20	0.30	0.18	0.17	0.03	0.75	0.23	8.72	0.22	0.20	6.90	0.38	0.39	0.33	5.74
BNS.TO	3.07	2.04	3.55	0.77	2.79	2.04	2.56	0.33	1.73	1.55	0.24	2.26	1.58	1.74	0.36
CBA.AX	2.65	1.49	2.85	1.17	2.59	2.68	2.28	0.23	1.91	1.95	0.15	1.50	1.83	1.57	0.18
STAN.L	3.31	1.65	2.68	0.95	2.47	2.80	3.12	0.26	1.31	1.53	0.22	2.32	1.19	1.89	0.24
000001.SZ	0.19	0.46	0.13	0.20	0.05	0.84	0.25	7.59	0.39	0.17	6.47	0.24	0.38	0.31	7.87
SBIN.NS	2.02	1.76	1.71	0.71	1.88	2.73	1.99	0.73	1.69	1.56	0.35	1.78	1.11	1.83	0.69
USB	2.63	1.69	6.35	0.78	5.99	1.40	1.99	0.09	1.48	1.78	0.03	1.44	1.35	1.15	0.11
NDA.FI.HE	9.10	1.87	2.90	1.15	2.40	1.97	4.08	0.14	1.64	1.79	0.09	1.84	1.81	1.53	0.09
105560.KS	2.64	12.60	1.90	0.96	1.53	2.45	2.23	0.44	6.73	1.84	0.38	1.81	1.93	5.40	0.57
PNC	2.91	1.41	9.32	0.65	5.39	1.54	2.13	0.10	1.26	1.59	0.04	1.40	1.32	1.06	0.09
8308.T	2.14	1.31	1.30	16.76	1.55	2.00	1.30	0.43	1.58	7.32	0.29	0.70	4.10	1.48	0.41
TFC	2.53	1.20	5.94	0.94	9.77	1.56	2.14	0.05	1.24	1.92	0.04	1.29	1.62	1.16	0.07
D05.SI	2.68	2.29	2.02	1.41	1.91	11.84	2.65	0.59	1.73	2.19	0.70	1.59	1.80	2.77	0.66
DANSKE.CO	4.96	1.76	2.62	0.88	2.43	2.45	11.05	0.13	1.50	1.47	0.05	1.36	1.44	1.78	0.12
600015.SS	0.18	0.46	0.15	0.20	0.04	0.62	0.12	12.70	0.32	0.19	7.48	0.32	0.26	0.28	6.41
055550.KS	2.53	7.18	1.90	1.07	1.80	2.07	2.15	0.34	13.63	2.02	0.25	1.70	1.99	6.20	0.39
8309.T	2.18	1.61	1.92	4.88	2.13	2.05	1.45	0.19	1.74	11.09	0.12	0.90	5.04	1.92	0.21
601169.SS	0.16	0.42	0.11	0.22	0.01	0.81	0.09	8.22	0.25	0.16	13.89	0.48	0.30	0.23	7.34
ITUB4.SA	3.12	2.23	2.43	0.66	1.94	1.87	1.98	0.26	1.84	1.28	0.32	15.49	1.32	2.43	0.17
8604.T	2.41	1.84	1.75	2.98	2.02	1.95	1.60	0.25	1.83	5.56	0.25	0.99	12.14	1.37	0.24
024110.KS	2.35	6.02	1.66	1.20	1.70	3.19	2.38	0.31	6.41	2.38	0.23	2.26	1.54	13.81	0.20
002142.SZ	0.15	0.66	0.12	0.39	0.07	0.83	0.17	7.40	0.40	0.26	7.71	0.27	0.29	0.20	14.37
C. to others (spillover)	102.30	74.24	99.51	52.45	90.10	79.53	82.23	91.40	67.56	86.44	80.11	57.87	76.51	66.53	76.62
C. to others including own	111.40	86.84	108.83	69.22	99.87	91.36	93.28	104.10	81.19	97.53	94.00	73.36	88.66	80.34	90.98

Data source: Yahoo Finance.

Appendix 13.1. Spillover table - Volatilities (2008-2024):

	1398.HK	601939.SS	601988.SS	JPM	BAC	8306.T	HSBA.L	BNP.PA	ACA.PA	C	8316.T	8411.T	3328.HK	WFC	SAN.MC	BARC.L
1398.HK	6.66	2.22	1.99	4.27	4.81	0.27	0.09	2.14	1.29	4.46	0.74	0.64	5.53	5.45	1.61	1.17
601939.SS	3.30	14.30	9.60	0.65	1.51	0.69	0.21	0.03	0.03	0.89	0.22	0.37	2.30	1.36	0.05	0.20
601988.SS	1.86	8.13	13.54	0.32	0.95	0.77	0.10	0.02	0.09	0.25	0.28	0.47	3.27	0.84	0.06	0.15
JPM	2.11	0.21	0.08	6.91	4.78	0.44	0.10	2.44	2.55	5.63	0.57	0.83	2.77	7.93	2.46	0.61
BAC	1.54	0.11	0.05	5.74	8.80	0.20	0.22	2.22	2.67	5.78	0.30	0.47	2.70	8.78	2.19	1.10
8306.T	1.00	0.03	0.07	2.85	3.51	8.51	0.99	1.79	2.35	4.01	5.99	5.73	2.48	3.60	1.02	0.93
HSBA.L	0.14	0.19	1.80	2.08	4.60	0.72	13.33	3.70	3.10	1.66	0.38	0.75	0.86	5.10	2.29	0.81
BNP.PA	0.84	0.21	0.30	4.23	5.30	0.52	0.45	6.78	5.51	4.00	0.47	1.11	1.67	5.58	5.08	1.38
ACA.PA	0.73	0.29	0.30	4.03	4.24	0.52	0.32	5.47	7.65	4.12	0.54	0.95	1.05	5.71	4.78	1.00
C	1.51	0.15	0.04	5.25	5.97	0.33	0.03	1.94	2.36	6.63	0.49	0.53	2.57	8.48	1.81	0.93
8316.T	1.54	0.07	0.03	3.20	4.04	5.29	0.46	1.59	2.38	4.57	6.47	4.89	3.04	3.78	1.13	1.06
8411.T	1.13	0.02	0.05	3.61	3.78	4.68	0.78	2.00	2.72	4.04	4.25	5.92	2.98	4.31	1.21	1.19
3328.HK	3.21	1.39	1.12	4.76	4.32	0.24	0.05	2.59	1.92	4.64	0.30	0.42	6.97	6.64	1.91	0.84
WFC	1.72	0.24	0.04	5.95	6.37	0.23	0.06	1.98	2.05	5.46	0.33	0.38	2.90	9.95	1.74	0.64
SAN.MC	0.76	0.07	0.09	5.10	3.61	0.27	0.38	5.95	5.99	4.02	0.37	1.05	1.23	5.79	8.74	1.56
BARC.L	1.65	0.03	0.08	4.99	4.78	1.04	0.64	3.19	3.36	4.99	1.36	1.35	2.08	6.37	3.31	3.60
UBSG.SW	1.03	0.05	0.09	5.69	5.32	0.45	0.21	3.48	2.86	5.30	0.73	1.01	2.24	7.04	3.06	1.21
RY.TO	1.07	0.02	0.00	4.52	4.64	0.36	0.09	2.60	2.99	4.62	0.29	0.48	2.62	7.09	1.64	0.23
600036.SS	2.43	6.12	5.87	1.20	1.32	0.41	0.12	0.23	0.10	1.06	0.18	0.16	3.39	2.14	0.08	0.10
DBK.DE	0.75	0.06	0.16	5.06	6.03	0.49	0.29	3.50	3.08	5.49	0.51	0.72	2.00	7.28	3.08	1.43
601166.SS	1.94	6.41	5.53	0.94	1.01	0.16	0.17	0.24	0.06	1.34	0.36	0.07	3.37	1.85	0.08	0.23
601998.SS	1.58	4.14	7.45	0.40	0.23	0.20	0.03	0.47	0.10	0.28	0.17	0.05	4.04	0.43	0.36	0.40
600000.SS	1.59	4.96	6.47	0.78	1.22	0.75	0.18	0.16	0.14	0.71	0.17	0.34	3.09	1.79	0.13	0.60
LLOY.L	0.14	1.03	0.42	4.74	2.00	0.29	1.30	1.80	2.99	3.01	0.45	0.61	0.30	4.19	2.27	2.36
600016.SS	1.93	4.65	6.45	0.88	1.00	0.10	0.05	0.18	0.12	0.59	0.42	0.09	3.35	1.27	0.06	0.70
BNS.TO	0.86	0.02	0.02	4.58	4.27	0.43	0.17	2.86	3.13	4.24	0.40	0.60	2.51	6.80	1.81	0.29
CBA.AX	1.43	0.02	0.05	4.65	3.60	0.77	0.18	2.53	3.10	4.73	0.90	1.19	2.05	6.30	1.71	0.22
STAN.L	1.04	0.13	0.14	4.75	5.19	1.19	1.18	1.63	1.72	5.39	1.14	2.35	2.15	5.67	1.56	1.25
000001.SZ	2.16	4.59	4.46	0.57	0.91	0.05	0.05	0.45	0.06	0.85	0.51	0.07	3.10	1.86	0.10	0.43
SBIN.NS	2.80	0.17	0.11	3.32	4.00	1.39	0.53	2.63	2.45	3.18	1.62	1.21	2.54	5.70	2.42	0.87
USB	1.75	0.11	0.04	5.72	5.94	0.19	0.04	2.01	2.06	4.90	0.34	0.56	3.17	8.61	1.49	0.71
NDA.FI.HE	0.77	0.05	0.12	5.06	5.80	0.19	0.19	4.10	3.16	4.86	0.19	0.34	2.32	7.30	3.57	0.73
105560.KS	1.05	0.04	0.10	4.18	4.11	0.43	0.04	2.82	2.60	4.76	0.48	0.42	2.27	6.87	2.40	0.96
PNC	1.72	0.18	0.03	5.71	6.12	0.21	0.08	2.01	2.00	5.63	0.40	0.39	2.95	8.36	1.56	0.52
8308.T	0.93	0.09	0.12	4.46	5.39	4.59	0.53	1.84	1.81	3.99	4.76	4.28	2.64	4.67	1.00	1.13
TFC	1.82	0.06	0.01	5.38	5.05	0.35	0.08	2.23	2.23	4.52	0.58	0.80	2.83	7.89	1.37	0.60
D05.SI	1.54	0.23	0.04	3.67	5.48	0.20	0.21	2.95	3.00	4.20	0.33	0.27	2.94	7.22	2.13	0.63
DANSKE.CO	0.84	0.08	0.18	6.11	5.30	0.12	0.35	2.88	4.11	5.25	0.40	0.19	1.50	7.05	3.41	0.70
600015.SS	1.13	6.27	7.14	0.42	1.12	0.65	0.08	0.28	0.05	0.31	0.26	0.35	3.53	1.21	0.18	0.26
055550.KS	1.31	0.02	0.04	3.70	3.86	0.63	0.07	3.24	2.86	4.45	0.59	0.52	2.27	6.49	2.09	0.82
8309.T	1.33	0.04	0.04	3.54	3.94	5.07	0.60	1.82	2.52	4.42	4.44	4.02	2.95	4.10	1.31	0.89
601169.SS	0.88	5.89	7.99	0.51	0.68	1.22	0.33	0.14	0.09	0.55	0.29	0.49	1.95	0.83	0.34	0.66
ITUB4.SA	0.99	0.03	0.12	4.55	3.79	0.49	0.06	2.49	3.59	4.61	0.90	0.88	1.58	6.06	2.43	0.60
8604.T	1.76	0.20	0.04	3.47	5.49	3.02	0.51	2.22	3.69	5.13	2.84	2.67	3.15	4.77	1.78	1.08
024110.KS	1.30	0.01	0.01	3.65	4.25	0.86	0.07	3.13	2.86	4.38	0.69	0.56	2.24	6.62	2.19	0.68
002142.SZ	1.77	4.87	5.74	0.65	0.97	0.56	0.08	0.77	0.29	1.04	0.16	0.07	4.32	1.92	0.52	0.17
C. to others (spillover)	64.66	63.92	74.64	159.90	170.61	42.02	12.74	94.80	98.19	162.37	42.09	45.71	116.76	229.14	76.76	35.04
C. to others including own	71.31	78.22	88.18	166.80	179.40	50.53	26.07	101.58	105.84	169.00	48.57	51.63	123.73	239.08	85.50	38.64

Data source: Yahoo Finance.

Appendix 13.2. Spillover table - Volatilities (2008-2024):

	UBSG.SW	RY.TO	600036.SS	DBK.DE	601166.SS	601998.SS	600000.SS	LLOY.L	600016.SS	BNS.TO	CBA.AX	STAN.L	000001.SZ	SBIN.NS	USB
1398.HK	3.22	1.62	1.20	3.08	2.00	1.67	1.56	0.62	1.84	2.07	2.31	1.10	1.23	0.82	4.66
601939.SS	0.08	0.16	6.29	1.48	5.58	4.17	5.75	1.11	8.02	0.15	0.13	0.33	3.35	0.33	0.89
601988.SS	0.10	0.10	5.53	0.94	5.59	6.91	7.34	0.34	7.81	0.02	0.06	0.56	3.09	0.24	1.10
JPM	2.94	4.57	0.22	3.69	0.33	0.27	0.52	0.73	0.42	5.20	3.80	0.75	0.16	1.44	6.31
BAC	4.83	3.60	0.11	4.08	0.24	0.09	0.34	1.13	0.37	4.45	3.07	1.69	0.07	1.27	6.77
8306.T	2.12	4.31	0.02	2.32	0.22	0.07	0.41	0.73	0.49	3.64	1.01	0.76	0.08	1.47	2.89
HSBA.L	2.96	4.43	0.45	2.25	0.33	1.40	0.64	1.04	0.91	4.24	3.67	1.69	0.70	1.57	1.99
BNP.PA	4.75	2.54	0.44	6.34	0.03	0.09	0.04	0.90	0.07	3.61	3.70	1.08	0.11	0.70	4.06
ACA.PA	4.66	3.33	0.49	6.10	0.04	0.03	0.02	0.87	0.05	4.23	3.82	1.01	0.27	0.80	3.84
C	3.67	5.34	0.07	3.68	0.38	0.12	0.29	1.42	0.33	5.76	3.15	1.24	0.10	1.37	6.26
8316.T	2.15	3.49	0.15	2.28	0.68	0.30	1.23	0.62	1.06	3.50	1.63	0.47	0.44	0.96	4.03
8411.T	2.18	4.74	0.05	2.15	0.21	0.07	0.70	0.76	0.42	4.08	2.28	0.80	0.08	1.30	3.87
3328.HK	3.62	2.73	0.73	4.62	1.21	1.52	1.07	0.96	1.25	3.15	2.53	1.15	0.54	0.85	5.17
WFC	3.27	4.28	0.21	3.45	0.39	0.22	0.48	0.89	0.56	5.10	3.54	0.94	0.12	1.69	7.30
SAN.MC	4.65	3.64	0.08	5.29	0.07	0.28	0.05	0.85	0.05	4.41	2.33	0.68	0.05	1.14	4.14
BARC.L	4.01	3.59	0.09	3.63	0.19	0.15	0.16	0.91	0.05	5.06	3.08	0.77	0.07	1.75	5.16
UBSG.SW	5.70	3.57	0.19	5.15	0.06	0.26	0.16	0.86	0.14	4.78	3.47	0.84	0.11	0.63	5.50
RY.TO	2.58	8.19	0.02	3.19	0.04	0.00	0.28	0.53	0.22	7.15	5.12	0.70	0.06	2.05	5.72
600036.SS	0.07	0.22	9.96	0.85	7.07	4.76	7.79	0.15	8.25	0.19	0.55	0.30	5.49	0.49	1.39
DBK.DE	4.62	4.07	0.29	7.66	0.01	0.11	0.04	0.92	0.06	4.54	2.82	1.32	0.13	0.82	4.79
601166.SS	0.11	0.08	6.50	0.57	12.01	5.16	7.43	0.06	8.40	0.07	0.22	0.20	5.76	0.32	1.61
601998.SS	0.25	0.16	4.76	1.06	5.87	15.37	7.86	0.10	9.13	0.05	0.06	0.31	4.09	0.38	0.58
600000.SS	0.12	0.14	5.42	0.61	7.53	6.06	11.88	0.05	9.46	0.14	0.45	0.20	4.48	0.45	1.79
LLOY.L	3.56	3.84	0.70	2.10	0.09	0.22	0.07	17.81	0.30	4.13	4.03	1.47	0.09	1.77	3.40
600016.SS	0.23	0.03	6.23	0.62	7.16	6.45	9.35	0.09	13.29	0.04	0.12	0.39	5.69	0.33	0.99
BNS.TO	2.38	7.37	0.03	3.33	0.01	0.01	0.23	0.70	0.11	7.74	5.50	0.60	0.07	1.98	5.71
CBA.AX	1.52	5.44	0.05	3.33	0.02	0.12	0.28	0.27	0.07	6.27	8.55	0.15	0.07	1.17	5.13
STAN.L	5.45	5.45	0.12	3.24	0.52	0.46	0.03	3.16	0.15	3.69	0.54	13.18	0.06	1.02	4.32
000001.SZ	0.07	0.01	7.16	0.83	9.04	4.53	7.63	0.03	8.84	0.04	0.17	0.12	10.17	0.58	1.35
SBIN.NS	2.07	4.41	0.10	2.07	0.39	0.15	0.46	0.46	0.22	4.98	3.54	0.63	0.23	6.51	4.47
USB	2.90	4.66	0.12	2.99	0.23	0.12	0.52	0.64	0.44	5.64	4.22	0.65	0.08	1.22	8.44
NDA.FI.HE	5.34	3.90	0.15	5.49	0.14	0.32	0.13	1.32	0.17	3.51	2.35	1.25	0.06	0.86	4.71
105560.KS	3.03	5.26	0.12	3.37	0.04	0.02	0.03	1.21	0.02	6.20	3.23	0.81	0.04	1.32	4.84
PNC	3.06	4.68	0.13	2.79	0.34	0.19	0.56	0.90	0.44	5.28	3.87	0.82	0.10	1.37	7.07
8308.T	1.96	3.62	0.12	2.33	0.55	0.34	0.71	0.60	0.65	3.23	1.48	1.25	0.10	1.03	4.19
TFC	2.09	4.36	0.05	2.76	0.13	0.02	0.48	0.32	0.23	5.85	5.22	0.30	0.04	1.32	7.42
D05.SI	2.03	5.00	0.13	3.95	0.27	0.20	0.52	0.27	0.82	4.66	3.98	0.48	0.16	2.59	4.38
DANSKE.CO	4.02	2.68	0.27	3.45	0.22	0.21	0.13	0.72	0.10	3.31	2.49	0.11	0.05	0.88	5.67
600015.SS	0.10	0.18	6.10	0.83	6.26	6.22	8.18	0.41	8.85	0.18	0.14	0.51	4.86	0.41	0.48
055550.KS	2.44	4.69	0.10	2.88	0.05	0.02	0.10	1.51	0.03	6.28	4.57	0.58	0.02	1.29	5.10
8309.T	2.19	4.69	0.06	2.34	0.49	0.16	0.83	1.16	0.77	3.67	1.54	0.74	0.14	1.30	3.74
601169.SS	0.28	0.05	5.02	0.96	6.63	8.72	8.44	0.19	9.70	0.09	0.07	0.19	3.98	0.20	0.51
ITUB4.SA	2.80	5.81	0.20	2.58	0.03	0.01	0.05	1.12	0.05	6.16	4.42	0.53	0.05	2.09	4.79
8604.T	3.38	5.22	0.05	4.57	0.16	0.04	0.59	0.39	0.35	3.56	2.06	1.28	0.04	1.75	4.27
024110.KS	2.57	5.86	0.10	3.45	0.08	0.05	0.08	0.72	0.01	6.55	3.21	0.65	0.02	1.58	4.58
002142.SZ	0.16	0.31	6.32	1.25	6.85	4.54	6.35	0.08	5.61	0.17	1.26	0.15	5.01	0.48	1.61
C. to others (spillover)	110.58	148.23	66.73	128.33	77.76	66.83	89.90	32.82	97.29	159.09	110.79	32.54	51.54	49.38	178.57
C. to others including own	116.28	156.41	76.69	135.99	89.77	82.20	101.78	50.63	110.58	166.83	119.34	45.72	61.71	55.89	187.02

Data source: Yahoo Finance.

Appendix 13.3. Spillover table - Volatilities (2008-2024):

	NDA.FI.HE	105560.KS	PNC	8308.T	TFC	D05.SI	DANSKE.CO	600015.SS	055550.KS	8309.T	601169.SS	ITUB4.SA	8604.T	024110.KS	002142.SZ
1398.HK	2.36	0.92	3.35	1.02	4.12	1.87	1.83	0.89	1.65	0.60	2.10	1.57	0.51	2.32	2.57
601939.SS	0.25	1.22	0.70	0.56	1.25	1.45	0.32	4.78	0.12	0.36	7.98	0.65	0.75	0.04	6.03
601988.SS	0.04	0.98	1.14	0.15	1.47	0.62	0.28	7.54	0.07	0.53	8.59	0.55	0.91	0.07	6.19
JPM	1.79	1.47	5.65	0.27	7.40	1.57	1.49	0.18	0.97	0.74	0.40	2.61	1.04	2.02	0.66
BAC	2.23	0.97	5.31	0.18	6.68	1.71	1.40	0.18	0.67	0.48	0.18	1.58	1.02	1.91	0.50
8306.T	1.50	0.66	2.53	3.39	2.85	0.98	1.88	0.54	1.28	8.96	0.02	2.39	5.10	2.29	0.21
HSBA.L	2.56	2.42	1.23	0.38	3.46	1.64	1.75	0.55	1.24	1.52	1.39	3.87	3.96	4.23	0.06
BNP.PA	3.84	2.00	4.00	0.24	5.44	1.24	2.27	0.07	0.96	0.67	0.02	2.09	1.74	3.19	0.33
ACA.PA	3.38	2.66	3.45	0.26	4.71	1.20	2.79	0.02	1.36	0.81	0.01	2.72	1.63	3.65	0.07
C	1.84	1.98	5.39	0.25	6.35	2.03	1.15	0.10	1.39	0.68	0.22	2.25	0.80	2.95	0.41
8316.T	0.99	0.59	3.74	2.48	3.87	0.94	2.75	0.86	1.50	6.59	0.39	2.54	3.58	2.15	0.49
8411.T	1.48	1.02	3.45	2.17	4.34	1.17	2.48	0.52	1.50	5.54	0.10	3.03	3.99	2.39	0.45
3328.HK	3.25	1.21	3.79	0.67	4.43	1.89	2.06	0.82	1.01	0.41	1.43	1.60	0.36	2.69	1.97
WFC	1.79	1.29	6.00	0.23	7.80	1.81	1.26	0.25	0.76	0.62	0.28	2.10	0.84	1.86	0.64
SAN.MC	4.05	1.86	4.44	0.13	4.70	1.47	2.69	0.13	0.41	0.45	0.34	2.73	1.06	2.35	0.52
BARC.L	2.06	1.82	4.54	0.67	6.09	1.16	1.41	0.03	1.14	1.10	0.14	3.33	1.91	2.86	0.27
UBSG.SW	3.16	1.53	5.39	0.25	8.29	1.04	2.06	0.11	0.70	0.69	0.27	2.29	1.02	1.86	0.16
RY.TO	1.76	2.47	4.79	0.12	7.84	2.12	1.58	0.19	1.44	0.89	0.07	2.74	1.25	3.26	0.34
600036.SS	0.16	0.25	2.06	0.12	1.54	2.30	0.88	5.10	0.13	0.14	6.68	0.05	0.40	0.11	7.63
DBK.DE	3.20	2.25	4.72	0.21	6.41	1.26	1.35	0.07	0.88	0.80	0.04	1.93	1.45	3.12	0.18
601166.SS	0.28	0.58	2.32	0.50	1.71	1.45	0.63	4.87	0.22	0.10	6.26	0.13	0.29	0.15	8.24
601998.SS	0.20	1.90	0.92	0.11	0.45	0.81	0.81	7.33	0.25	0.15	10.09	0.27	0.69	0.08	5.55
600000.SS	0.17	0.96	1.86	0.15	1.88	1.72	1.25	6.03	0.12	0.24	7.96	0.05	0.56	0.12	5.06
LLOY.L	6.21	3.25	3.68	0.46	2.83	0.33	1.05	0.37	1.58	0.66	0.22	2.71	0.76	4.35	0.08
600016.SS	0.14	1.20	1.17	0.41	1.10	1.69	1.00	6.71	0.09	0.26	8.15	0.03	0.22	0.13	4.83
BNS.TO	1.69	2.87	4.53	0.21	7.44	2.08	1.64	0.13	1.56	0.90	0.04	3.11	1.28	3.54	0.24
CBA.AX	1.08	2.68	4.11	0.13	7.79	1.77	2.08	0.13	2.50	1.73	0.06	3.78	2.33	3.57	0.37
STAN.L	2.78	0.48	4.67	1.32	4.42	0.49	0.08	0.12	0.15	1.73	0.15	1.84	2.45	1.22	0.25
000001.SZ	0.22	0.32	2.44	0.16	1.78	1.92	1.37	5.32	0.19	0.13	5.67	0.06	0.10	0.16	9.36
SBIN.NS	2.33	1.49	3.88	1.04	7.07	1.56	2.38	0.47	1.45	2.13	0.20	3.34	3.06	3.28	0.73
USB	1.42	1.26	6.22	0.13	10.02	1.43	1.78	0.35	0.68	0.60	0.22	2.01	0.77	1.94	0.68
NDA.FI.HE	7.23	1.77	5.18	0.08	5.96	1.41	3.20	0.33	0.43	0.36	0.07	1.88	0.65	2.55	0.46
105560.KS	2.84	6.26	4.20	0.62	4.99	2.16	1.17	0.02	2.96	0.99	0.05	4.33	1.09	5.11	0.12
PNC	1.67	1.47	6.87	0.13	8.67	1.68	1.95	0.28	0.83	0.61	0.22	2.45	0.98	2.18	0.57
8308.T	1.34	0.69	4.33	5.12	4.50	0.57	2.33	0.79	0.78	6.15	0.13	1.99	3.98	2.40	0.51
TFC	1.10	1.39	6.32	0.16	12.32	1.38	2.11	0.32	0.78	0.92	0.09	2.56	1.28	2.23	0.63
D05.SI	2.48	2.30	4.12	0.24	6.06	5.76	3.21	0.69	1.38	0.88	0.17	2.78	1.08	3.45	0.92
DANSKE.CO	4.26	1.81	4.71	0.10	5.58	1.31	12.27	0.42	0.50	0.53	0.03	2.68	0.39	2.44	0.19
600015.SS	0.33	1.28	0.87	0.12	0.62	1.01	1.22	10.78	0.03	0.27	8.70	0.29	0.59	0.20	6.71
055550.KS	1.92	5.08	4.10	0.46	5.25	1.78	1.47	0.02	5.09	1.12	0.03	4.34	1.25	5.30	0.17
8309.T	1.37	0.63	3.64	2.29	3.90	0.88	2.24	0.72	1.37	7.99	0.16	2.60	4.61	2.37	0.39
601169.SS	0.19	1.22	1.07	0.17	0.38	0.89	0.43	7.33	0.06	0.59	13.40	0.19	1.03	0.06	5.12
ITUB4.SA	2.13	3.39	4.27	0.43	6.20	2.25	2.41	0.02	2.12	1.04	0.02	7.38	1.82	2.64	0.06
8604.T	1.50	0.40	3.87	1.33	4.68	0.96	2.37	0.72	1.08	4.32	0.23	1.71	5.04	1.99	0.26
024110.KS	2.65	3.82	4.23	0.86	5.16	1.25	1.85	0.08	2.64	1.53	0.08	3.31	1.52	7.73	0.23
002142.SZ	0.38	0.57	2.15	0.18	2.18	1.62	1.66	5.29	0.23	0.15	6.50	0.07	0.36	0.35	14.24
C. to others (spillover)	82.36	72.37	164.52	25.54	209.63	63.86	75.36	71.82	43.16	60.67	86.17	91.10	66.47	97.11	81.42
C. to others including own	89.59	78.63	171.40	30.66	221.96	69.63	87.63	82.60	48.25	68.66	99.57	98.48	71.51	104.83	95.66

Data source: Yahoo Finance.

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