Hacettepe University Graduate School Of Social Sciences

Department of Economics

ON THE CONTAGION OF FINANCIAL RISK

Burak Sencer ATASOY

Ph.D. Dissertation

Ankara, 2023

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The jury finds that Burak Sencer ATASOY has on the date of 12/30/2022 successfully passed the defense examination and approves his Ph. D. Dissertation titled “On the Contagion of Financial Risk”.

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Burak Sencer ATASOY

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ETİK BEYAN

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ABSTRACT

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The global financial system has become highly interconnected over the past few decades and financial shocks have propagated faster, causing systemic events to occur more frequently. This dissertation examines systemic risk contagion through two linked chapters, each contributing to different strands of the literature. In the first chapter, I construct a contagion test, based on time varying Granger causality and dynamic conditional correlation approaches. Using the test on the systemic risk contributions of international banks, I identify several contagion episodes during the period 2004-2021, particularly concentrated during the four periods of turmoil. I then analyze systemic risk spillovers across international banks following extreme adverse and beneficial shocks, identify the main risk transmitters, and scrutinize changes in network topology during the four contagion episodes. The results reveal that the main transmitters of systemic risk differ not only across magnitudes and directions of shocks, but also across crisis periods. In the second chapter, I investigate the determinants of systemic risk contagion based on tail behavior, taking into account time-variation, slope heterogeneity and endogeneity. Using explanatory variables derived from banks' balance sheets representing size, profitability, capital adequacy, credit quality, leverage, and funding structure I find that determinants of systemic risk contagion change over time, differ in each crisis episode, and no single factor drives contagion persistently. I show that some determinants gradually lose their influence on the propagation of shocks, while others are effective only during a single period of turmoil. The results also show significant heterogeneity across banks, and I do not detect significant clustering at either the national or regional level. The findings reveal that static surveillance methods may fail to capture the factors that propagate systemic risk. In light of my findings, I propose a holistic systemic risk surveillance model that uses high-frequency data and incorporates several risk factors simultaneously.

Keywords

Contagion , Systemic Risk , Banking , Spillovers , Tail Risk, Causality , Correlations

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ABBREVIATIONS

AB/BB	: The Arellano-Bover/Blundell-Bond Dynamic Panel GMM Estimator
CCEMG	: Common Correlated Effects Mean Group Estimator
CDS	: Credit Default Swap
DCC-GARCH	: Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity
DY	: Diebold and Yilmaz
ESDC	: European Sovereign Debt Crisis
ESM	: European Stability Mechanism
FIs	: Financial Institutions
FSB	: Financial Stability Board's
GFC	: Global Financial Crisis
GFEVD	: Generalized Forecast Error Variance Decomposition
G-SIBs	: Global Systemically Important Banks
LA-VAR	: Lag Augmented Vector Autoregression
LGD	: Loss Given Default
MES	: Marginal Expected Shortfall
NPL	: Non-performing loans
PCA	: Principal Component Analysis
QC	: Quantile Connectedness
REGC	: Recursive Evolving-Window Granger Causality
ROA	: Return on Assets
SIFIs	: Systemically Important Financial Institutions
TARP	: Troubled Assets Relief Program
TBTF	: Too Big to Fail
TCI	: Total Connectedness Index
TITF	: Too Interconnected to Fail
TSITF	: Too Systematically Important to Fail
TVGC	: Time Varying Granger Causality
TVP-VAR	: Time-varying Vector Autoregressions with Stochastic Volatility

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INTRODUCTION

Systemic risk and contagion have become popular topics in the literature since the 2008 Global Financial Crisis (GFC). Although both concepts were analyzed long before the GFC, they have received renewed attention, especially after the collapse of Lehman Brothers. Often regarded as the hallmark of the GFC, Lehman's bankruptcy revealed the weakness of the financial system, created panic, and overturned market confidence. Indeed, prior to the 2008 crisis, many studies focusing on systemic risk highlighted the dangers associated with elevated systemic risk and warned policymakers against an upcoming financial catastrophe[1]. Nevertheless, the crisis emerged despite these wake-up calls. The shattering effects of the 2008 crisis revived interest in systemic risk and underscored the need for effective measurement and supervision of systemic events. It became clear that the interconnectedness of financial institutions was not only a virtue, but also a threat to the system's stability.

Systemic risk does not have a universally recognized definition. A crisis could be called systemic if many institutions fail together, or a failure spreads to the entire system (Acharya, 2009). During systemic events, asset and liability co-movements between financial institutions are apt to be higher or lower than levels implied by fundamentals. Systemic events may emerge from two sources. First, there may be an adverse shock affecting all agents in the system, such as a sudden decline in gross domestic product, a surge in unemployment, or a fluctuation in interest rates/exchange rates. This type of risk arises as a result of common exposure to shocks. Second, there may be a spread of individual adverse financial conditions. Since financial networks are highly interconnected, the failure of one economic agent may spread to the entire system and create a widespread crisis. Thus, as systemic risk threatens the stability of the entire economy, identifying the institutions that contribute the most to systemic risk - Systemically Important Financial Institutions (SIFIs) that are Too Big To Fail (TBTF) – has become one of the focal points of the literature.

Another concept that has become popular during recent decades is interconnectedness. The way of risk transmission has changed significantly since the 2000s and both speed

[1] De Nicolo and Kwast (2002), Danielsson (2003), Lehar (2005), *inter alia*.

and magnitude of shocks have surged due to increased economic integration, globalization, technological advancement, prevalence of online financial transactions and electronic trading. Notwithstanding the benefits, increased interconnectedness and deeper integration have several adverse effects such as extremely volatile capital flows and liquidity as well as quick propagation of crises. Countries or financial institutions - that could find ample liquidity during tranquil times under high levels of economic and financial integration- may face severe liquidity constraints during turbulent times, since liquidity dries out rapidly as a consequence of financial openness and integration. Considering the interconnected nature of economic agents, this may easily turn into a widespread crisis. Similarly, during fluctuant times, an institution may fail to fulfill its obligations to its creditors and face default. If the creditor has inadequate capital to cover the losses caused by the failure, it may default too. Depending on the level of interconnectedness in the system and strength of balance sheets, this distortion may create a domino effect and cause a major financial collapse. Since financial and real sectors are also interconnected, the real economy may also be affected and cause a widespread economic crisis. Hence, given this mechanism, in addition to TBTF concept, the concept of Too Interconnected To Fail (TITF) has gained prominence since 2008.

The description of the SIFIs by the Financial Stability Board (2010) is "*financial institutions whose disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity*". Accordingly, there are two methodologies for identifying SIFIs. The first methodology is built on balance sheet data of financial institutions to structurally model asset and liability qualities. However, this methodology is mostly limited to the use of financial regulators, as detailed financial statements are generally not publicly available. The second methodology employs publicly available market data such as market returns, stock volatility, or Credit Default Swap (CDS) spreads to infer interdependencies without knowing the cross-positioning of institutions. It could be argued that policymakers were blindsided by the failures during the 2008 crisis and had to bailout the failing SIFIs to maintain the stability of the financial system. Even though this resolution saved the day, it also exacerbated systemic risk - as it induced excessive leverage in anticipation of future bailouts. To prevent moral hazard, policymakers have begun to pay special attention to detecting systemic events at an early stage and aim to implement the necessary policies to contain a systemic crisis. This mechanism involves not only close scrutiny of financial institutions, but also the discovery of contagion mechanisms.

However, analyzing contagion mechanisms is not an easy task because, like systemic risk, there is no universally recognized definition of contagion. The literature mostly explains contagion by sudden increase in co-movements that cannot be explained by the usual linkages and fundamentals. While early studies used basic procedures such as comparing correlations before and after certain events, more sophisticated methodologies as well as different concepts such as connectedness, spillovers and interdependence have been introduced in subsequent years. Nevertheless, the concept of contagion remains controversial in the literature. Some studies argue that linkages between financial agents are always present, and they only imply contagion if there is an increased dependence between two markets, and no dependence prior to the shock. Others argue that the difference between the concepts of spillovers, interconnectedness or contagion is semantic, and if the magnitude of the co-movement is higher than the scholar's expectations, it could be called contagion. Therefore, distinguishing between the usual interdependence of economic agents and contagious effects is a delicate matter.

The literature includes a plethora of studies examining systemic risk, the determinants of systemic risk, and contagion, however studies analyzing the determinants of systemic risk contagion are relatively few. In this dissertation, I aim to construct a new contagion metric and examine the determinants of systemic risk contagion. Rather than investigating why systemic events occur, I focus on how systemic shocks are transmitted. While acknowledging the challenge of bringing together two controversial concepts in the literature, I think that achieving this ambitious goal is an excellent opportunity to conclude the Ph.D. process. Accordingly, the dissertation consists of two linked chapters, each contributing to a different strand of the literature.

The first chapter of the dissertation consists of two parts. In the first part, I build a new systemic risk contagion test, based on time varying Granger causality and dynamic conditional correlation approaches using data of 36 of the world's 50 largest banks from 13 countries covering the period 2004Q2-2021Q3. In this respect, I first calculate systemic risk contributions of the 36 banks employing the Marginal Expected Shortfall

(MES) methodology (Acharya et al., 2017; Brownlees and Engle, 2017). Following several studies in the literature, I define financial contagion as "*extreme co-movements that cannot be explained with usual linkages and fundamentals*". Since using bank-level data generates too many correlation series, I employ Principal Component Analysis (PCA) for dimensionality reduction and to ensure that each major region (US, Europe, UK, Japan, Canada) is represented by a single component. To measure time varying co-movements, I adopt the DCC-GARCH methodology of Engle (2002) and mark periods when the dynamic conditional correlation between the two series exceeds trend by two standard deviations. Then, I employ the time-varying Granger causality methodology (Phillips et al., 2015a, 2015b; Shi et al., 2018, 2020) to test whether extreme jumps in correlations indicate a contagious movement, and I mark periods when the causality test statistic exceeds critical value at 5%, suggesting a statistically significant causal relationship between systemic risk contributions. Finally, I match periods with extreme jumps in correlations with time periods where the causality test statistic is statistically significant. The contagion metric takes the value "1" if there is a match, and "0" otherwise. Thus, this approach, combining correlation with causality, not only provides a robust contagion test, but also a time-varying, directional contagion indicator. Employing the new contagion metric, I identify contagion episodes and the direction of contagion across countries over the sample period.

I find that there are several episodes of contagion, particularly concentrated during four crisis periods, and that both uni-directional and bi-directional contagion are evident. The contagion episodes have different durations and the net transmitters and receivers of systemic risk differ significantly in each. I find that the US is the epicenter of financial stress transmission during the GFC, and spread of systemic risk from the US to other regions occurs about a year before Lehman's collapse, just as the US yield curve is inverted. During the European Sovereign Debt Crisis (ESDC), Europe and the UK are at the forefront, transmitting risks to United States and Canada at different times for different durations. This indicates that contagious effects during the ESDC spread beyond Europe's borders, belying the name of the crisis. Interconnectedness during the 2014-2017 period is higher compared to the other crisis periods due to abundance of notable systemic events such as the Russian crisis, Brexit, the FED's tapering plan, and stock market crash in China. Consequently, the contagion mechanism during this period is more complex compared to other crisis periods and bi-directional causality is detected between US-Canada, US-UK, US-Japan, UK-Europe, Canada-Europe, Canada-Japan.

Finally, despite fundamental differences between Covid-19 crisis period with other crisis periods, contagion dynamics are similar to those observed during the 2014-2017 turbulence period and bi-directional contagion appears to be quite widespread. During the Covid-19 pandemic, I identify bi-directional contagion between US-Canada, US-UK, US-Europe, Canada-Europe, UK-Canada and uni-directional contagion from UK to Europe, from Europe to Japan, and from Japan to US, while Japan appears to remain outside of the systemic risk transmission mechanism.

In the second part of the first chapter, I examine systemic risk spillovers across 36 banks, identify the largest transmitters of systemic risk, and analyze changes in network topology during the four contagion episodes that are identified in the first part of the chapter (the GFC, the ESDC, the 2014-2017 turmoil period, and the Covid-19 pandemic). Since the MES series are leptokurtic and fat tailed, I focus on tail events and aim to find the main transmitters of systemic risk after extreme shocks. In line with this objective, I employ the Quantile Connectedness (QC) methodology (Ando et al., 2022), which enables gauging pairwise spillovers after system-wide extreme adverse and beneficial shocks. Instead of examining an average shock's effects on the network topology as in Diebold and Yilmaz (2012, 2014), the QC methodology allows analyzing "the effect of idiosyncratic shocks from one bank to the other as the shock size varies" and calculates connectedness measures for each percentile. To utilize the valuable information contained in each percentile, I compute systemic risk connectedness measures at the 1st, 10th, 50th, 90th, and 99th percentiles to represent the effects of extremely beneficial, beneficial, average, adverse, and extremely adverse shocks, respectively. I then identify the largest transmitters of systemic risk and examine network topology of risk propagation during the four crisis episodes. Accordingly, the main systemic risk transmitters differ not only across percentiles, but also across crisis periods. This result supports my findings in the first part, reiterating that each period of turmoil has different characteristics.

In the second chapter of the dissertation, I investigate the determinants of systemic risk contagion. The literature highlights idiosyncratic features in explaining risk transmission and emphasizes the importance of time variation and non-linearity in systemic risk analysis. Following the literature and considering my findings in the first chapter, I follow a time-varying approach that takes into account endogeneity and uses bank-level balance sheet data representing size, profitability, capital adequacy, credit quality, leverage, and funding structure. Similar to the second part of the first chapter, I measure systemic risk by MES. However, since the contagion metric I derive in the first chapter yields a bilateral binary variable, I cannot use it as a dependent variable while using unilateral balance sheet data. Thus, I construct a new contagion metric by defining systemic risk contagion as "*extreme amplification of spillover effects that cannot be explained by usual linkages and fundamentals*". In this respect, I follow the QC methodology to calculate spillovers from one bank to other banks (TO Spillovers) at the 90th percentile and set the condition for contagion as "exceeding the trend by two standard deviations". I then sum each bank's excess TO spillovers to other banks to find their aggregated excess TO spillovers, which I call their overall contribution to systemic risk contagion. In the next step, using the aggregated excess TO spillovers as dependent variable, I investigate how idiosyncratic characteristics of banks affect systemic risk contagion. In this respect, I use the Arellano-Bover/Blundell-Bond dynamic panel GMM estimator (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998), the Common Correlated Effects Mean Group estimator (Pesaran, 2006; Chudik and Pesaran, 2015; Neal, 2015) and the Time-varying Vector Autoregressions (Primiceri, 2005; Nakajima, 2011). These methodologies not only have properties to deal with endogeneity but also have unique features complementing each other. Accordingly, the panel GMM model allows me to perform sub-period analysis to scrutinize the dynamics of the four distinct crisis periods I identify in Chapter 1, the Common Correlated Effects Mean Group estimator has properties to consider cross-section dependence and slope-homogeneity, and the TVP-VAR model takes into account time variation in the parameters.

According to my findings, the determinants of contagion differ during each crisis episode and that no factor persistently drives contagion. Instead, I find that some determinants gradually lose their influence on the propagation of shocks, while others are effective only during a single period of turmoil. The results also show significant heterogeneity across banks, and I do not detect clustering at the national or regional level. The findings of the second chapter reveal that systemic risk determinants change over time, and static surveillance methods may not identify the factors propagating systemic risk. Since the main drivers of risk transmission differ in each period of turmoil, a combination of risk factors, instead of addressing a single factor, may establish a more holistic regulatory approach.

CHAPTER 1: A NOVEL CONTAGION TEST AND THE MAIN TRANSMITTERS OF SYSTEMIC RISK

1.1. INTRODUCTION

Since the pioneering study of King and Wadhwani (1990), scholars have examined how shocks are transmitted. The transmission of shocks is often referred to as contagion and is broadly defined as the spread of financial shocks through increased co-movements. The concept of contagion was first used to define risk propagation between Asian countries during 1997 Thai currency crisis, followed by 1998 Russian crisis and 1999 Brazilian crises. However, it became an important subject in the literature when the turmoil in the United States housing sector led to the Global Financial Crisis (GFC) in 2008, one of the most severe economic crises since the Great Depression.

The concept of systemic risk also gained popularity during the GFC. The bankruptcy of Lehman Brothers fueled the fears of a systemic collapse and shifted attention from the individual risks of financial institutions (FIs) to systemic risk. The GFC highlighted the roles of size and interconnectedness in risk transmission and paved the way to financial sector reforms based on the Too Big To Fail (TBTF) phenomenon. Recognizing that the failure of large interconnected FIs would threaten the financial system's stability, policymakers provided financial support to bail out troubled FIs. To hinder the further build-up of risk, they also introduced new measures, including higher loss absorbency, better resolution framework, and more intensive regulatory oversight for Systematically Important Financial Institutions (SIFIs). Following the GFC, the European Sovereign Debt Crisis (ESDC) emerged in Greece in 2010 showed that small but highly interconnected countries can also create contagion, channeling the discussions towards the Too Interconnected To Fail (TITF) concept. Indeed, interconnectedness across financial institutions has elevated since the 1990s and the global financial system has become highly interdependent. As technology has advanced and financial markets have globalized, FIs have easily created contractual obligations with other financial institutions around the world, leading to increased bilateral risks. In this environment, crises have become more frequent, and risks have propagated through various channels such as stock market returns, capital flows, bank lending, and trade.

In this study, I examine systemic risk contagion and detect the largest systemic risk transmitters among 36 of the world's 50 largest banks from 13 countries covering the period 2004Q2-2021Q3. The study consists of two parts. In the first part, I construct a new contagion test following a three-step procedure. First, I compute the systemic risk contributions of banks using the MES methodology (Acharya et al., 2017; Brownlees and Engle, 2017). Second, I employ principal component analysis (PCA) to reduce dimension of the data and to ensure that each major region (US, Europe, UK, Japan, Canada) is represented by a single component. Third, I construct a novel measure of contagion which combines dynamic conditional correlations with time varying causality. In this respect, I employ the DCC-GARCH (Engle, 2002) and time varying Granger causality (Phillips et al.; 2015a, 2015b; Shi et al.; 2018, 2020) methodologies to detect the contagion periods during 2004-2021. In the second part of the study, I use the quantile connectedness methodology by Ando et al. (2022) and compute systemic risk connectedness measures at the 1^{st}, 10^{th}, 50^{th}, 90^{th}, and 99^{th} percentiles to represent the effects of extremely beneficial, beneficial, average, adverse, and extremely adverse shocks, respectively. I then identify the largest systemic risk transmitters and examine the network topology of systemic risk for the four crisis episodes.

The study is organized as follows. Section 1.2 summarizes the literature on systemic risk and contagion. Section 1.3 presents the data and methodology. Section 1.4 provides information on the derivation of the contagion test. Section 1.5 discusses the contagion events identified in Section 1.4. Section 1.6 identifies the main transmitters of systemic risk over the sample period. Section 1.7 concludes.

1.2. LITERATURE REVIEW

Prior to the Thai crisis in 1997, studies on propagation of financial shocks across countries were scarce. Following King and Wadhwani (1990), early studies mostly use correlation analysis to model financial contagion (Lee and Kim, 1993; Calvo and Reinhart, 1996; Masih and Masih, 1997; Baig and Goldfajn, 1999; Ghosh et al., 1999). These studies focus on the co-movements in turbulent and tranquil times, defining contagion as a sudden rise in correlations. Despite providing important insights into how markets behave during normal and crisis times, studies using correlations are criticized for yielding biased results due to heteroskedasticity, omitted variables and surged volatility (Boyer et al., 1999; Forbes and Rigobon, 2002; Billio and Pelizzon, 2003), and for employing contagion tests that are highly dependent on the selection of window (Billio and Pelizzon, 2003). Moreover, periods of crisis usually involve fewer observations and the power of contagion tests based on comparisons between crisis and non-crisis periods is relatively low (Dungey and Zhumabekova, 2001). As pointed out in Forbes and Rigobon (2002), examining contagion by taking into consideration the upward bias during crisis periods provides conflicting results with earlier studies, since the use of bias-adjusted data provides limited evidence in favor of contagion. The authors also emphasize the difference between “interdependence” and “contagion” concepts, arguing that interconnections between financial institutions do not necessarily connotate contagion. In the following years, the co-movement approach remains popular with studies using Forbes and Rigobon (2002)’s adjusted correlation coefficients (Dungey and Zhumabekova, 2001; Billio and Pelizzon, 2003), higher order of moments (Fry et al.; 2010, Fry-McKibbin and Hsiao, 2018; Fry-McKibbin et al., 2019), and various contagion tests (Favero and Giavazzi, 2002; Bae et al. 2003; Dungey et al., 2005). However, contagion tests based on co-movements yield contradictory results as they differ significantly in terms of data treatment, econometric issues, and the effects of common shocks.

Another strand of the literature employs ARCH-GARCH type of models to examine variance-covariance propagation between stock markets. Starting with Hamao et al. (1990), studies focusing on volatility spillovers mostly define contagion as excess correlation in model residuals and constitute an important part of the literature (Theodossiou and Lee, 1993; Susmel and Engle, 1994; Koutmos and Booth, 1995; Edwards, 1998; Ng, 2000; Alper and Yilmaz, 2004; Kenourgios and Dimitriou, 2014; Hemche et al., 2016). These studies proliferate after the introduction of the DCC-GARCH (Engle, 2002), accounting for upward bias due to surged volatility and heteroskedasticity. Many studies (Chiang et al., 2007; Baumöhl and Lyócsa, 2014; Moore and Wang, 2014; Kenourgios, 2014; Mollah et al., 2016; Bonga-Bonga, 2018) employ the DCC-GARCH methodology and its variants to analyze financial risk propagation through time-varying conditional correlations. Another pioneering study in the volatility spillovers literature is Diebold and Yilmaz (2009), in which the authors investigate return and volatility spillovers by measuring connectedness based on the decomposition of the forecast error variance. Along with the DCC-GARCH methodology developed by Engle (2002), the Diebold and Yilmaz (DY) approach is one of the most widely used methodologies for modelling financial contagion (Claeys and Vasicek; 2014; Fernández-Rodríguez et al., 2016; *inter* *alia*). The DY approach is further enhanced by Diebold and Yilmaz (2012, 2014), while Baruník and Křehlík (2018) introduce a measure of connectedness that takes into account heterogeneous frequency responses to shocks.

In line with surged interconnectedness, network analysis has also become increasingly popular in the financial contagion literature since the 2000s. Allen and Gale (2000) are the first to provide a comprehensive analysis of contagion through direct linkages in financial systems, concluding that contagion does not occur when the network is complete because the adverse shock is debilitated, but the system becomes more fragile when the network is incomplete. Following Allen and Gale (2000), several studies examine financial contagion using centrality measures and comparing the network topology before and after a crisis period (Chinazzi et al., 2013; Brunetti et al., 2019; Bonaccolto et al., 2019; Zhu et al., 2018; Billio et al., 2021), while others examine network topology over time and identify the main transmitters of risk (Elliott et al., 2014; Langfield et al.; 2014; Hautsch et al., 2015; di Iasio et al., 2013; Silva et al., 2017). Recent studies focus on the dynamic nature of networks and analyze financial contagion through time-varying network topology (Battiston et al., 2012; Blasques et al., 2018; Brownlees et al., 2021; Franch et al., 2022). Another strand analyzes risk spillovers and financial interconnectedness employing causality tests (Bodart and Candelon, 2009; Hong et al., 2009; Billio et al., 2012; Chen et al., 2014; Gomez-Puig and Sosvilla-Rivero, 2013; Gomez-Puig and Sosvilla-Rivero, 2014; Balboa et al., 2015) and causality networks (Billio et al., 2012; Lee and Yang, 2014; Billio et al., 2016; Wang et al., 2017; Papana et al., 2017; Corsi et al., 2018).

The literature distinguishes between the effects of common risks that are irrelevant of a country's idiosyncratic exposures (Caporale et al., 2005) and idiosyncratic risks that make countries more vulnerable to contagious effects (Forbes and Chinn, 2004). However, the findings related to these two effects are hardly concurrent, mixed at best. Some authors argue that common shocks are more effective in creating contagion (Ballester et al., 2016; De Grauwe and Ji, 2013; Chiarella et al., 2015), while others find evidence in favor of idiosyncratic shocks (Hilscher and Nosbusch, 2010; Grinis, 2015) or both types (Claessens et al., 2001; Dungey and Gajurel; 2014). Nevertheless, both common and idiosyncratic risks might lead to systemic crises depending on the level of interconnectedness and bilateral exposures between FIs. As noted by (Acemoglu et al., 2015), interconnectedness provides beneficial diversification during tranquil times, but it also tends to amplify the propagation of large shocks and might turn individual risks into systemic events during turbulent periods. In line with elevated interconnectedness, systemic risk, first examined during the 1990s, becomes prominent after the GFC, and many studies address systemic risk within interconnectedness and contagion frameworks (Lee, 2013; Georg, 2013; Paltalidis et al., 2015; Ding et al., 2017; Constantin et al., 2018). A strand of the literature establish market-based metrics to measure systemic risk (Allen et al., 2012; Billio et al., 2012; Girardi and Ergun, 2013; Banulescu and Dumitrescu, 2015; Adrian and Brunnermeier, 2016; Acharya et al., 2017), while others focus on the systemic risk determinants (Adrian and Shin, 2010; López-Espinosa et al., 2013; Weiß et al., 2014; Thakor, 2014; Laeven et al., 2016; Fiala and Havranek, 2017; Varotto and Zhao, 2018).

The empirical literature on financial contagion could also be categorized in terms of the data and methodologies used. In this respect, studies examine the roles of exchange rates (Celik, 2012; Dimitriou and Kenourgios, 2013; Loaiza Maya et al., 2015), bond yields (Favero and Giavazzi, 2002; Gomez-Puig and Sosvilla-Rivero, 2014; Cronin et al., 2016; Arghyrou and Kontonikas, 2012), CDS spreads (Guo et al., 2011; Beirne and Fratzscher, 2013), CDOs (Longstaff, 2010), house prices (Anderson et al., 2015; Teng et al., 2017), oil prices (Gómez-Puig and Sosvilla-Rivero, 2016; Khaled et al., 2018), cryptocurrencies (Koutmos, 2018; Bouri et at., 2021; Shahzad et al., 2021; Caporale et al., 2021), and stock market returns (Kenourgios et al., 2011; Wang et al., 2017; Shen et al., 2015; Boubaker et al., 2016). The authors employ various methodologies such as VAR-VECM (Samarakoon, 2011; Ang and Longstaff, 2013; Sui and Sun, 2016; Koutmos, 2018), minimal spanning and hierarchical trees (He and Chen, 2016), regime switching models (Ang and Bekaert, 2002; Guo et al., 2011; Kenourgios et al., 2011; Cronin et al., 2016), copulas (Aloui et al., 2012; Philippas and Siriopoulos, 2013; Samitas and Tsakalos, 2013; BenSaïda, 2018), wavelet-based models (Rua and Nunes, 2009; Aloui and Hkiri, 2014; Dewandaru et al., 2016), logit-probit models (Luchtenberg and Vu, 2015; Dungey and Gajurel, 2015), state space estimators (Khan and Park, 2009; Shen et al., 2015; Piccotti, 2017), smooth transition models (Chelley-Steeley, 2005; Lahrech and Sylwester, 2011; Allegret et al., 2017), extreme value theory (Poon et al., 2004; Longin and Solnik, 2001; Straetmans, and Chaudhry, 2015), agent based models (Tedeschi et al., 2012; Halaj, 2018), spatial methods (Blasques et al., 2016; Calabrese et al., 2017), jump processes (Aït-Sahalia et al., 2015; Jawadi et al., 2015; Zhang et al., 2022), and quantile regression (Caporin et al., 2018; Siebenbrunner and Sigmund, 2019).

While the concept of contagion remained controversial in the literature as studies diverge significantly on its definition, scope, and determinants; contagion's affinity with some concepts such as interconnectedness, bilateral exposures, and systemic risk has come to the fore. It is also observed that the literature includes a plethora of studies examining the concepts of systemic risk and contagion, but relatively few studies focusing on systemic risk contagion. In this study, I aim to contribute to the literature by constructing a new contagion test, identifying the main systemic risk transmitting financial institutions at the global level, and examining the network topology of systemic risk spillovers.

1.3. DATA AND METHODOLOGY

To examine systemic risk contagion, I employ data of 36 of the world's 50 largest banks from 13 countries in terms of total assets, covering the 2004Q2-2021Q3 period. As of September 2021, the sum of total assets and market capitalization in the sample are $47.8 trillion and $3.2 trillion, respectively. Table 1 denotes asset size and market capitalization of the banks.

The contagion analysis consists of two parts. First, I build a novel systemic risk contagion test, based on time varying Granger causality and dynamic conditional correlation approaches. To do so, I first calculate systemic risk contributions of the 36 banks employing the Marginal Expected Shortfall (MES) methodology. Then, I employ principal component analysis (PCA) for dimensionality reduction and to ensure that each major region (US, Europe, UK, Japan, Canada) is represented by a single component. Finally, I define systemic risk contagion and build the time varying contagion metric. In the second part, I examine systemic risk spillovers across 36 banks, identify the main systemic risk transmitters, and analyze changes in network topology over the four crisis periods.

Table 1. Asset Size and Market Capitalization of Banks

	Institution	Origin	Total Assets (US$ Billion)	Market Cap (US$ Billion)
1	JP Morgan	U.S.	3,744	489
2	Mitsubishi	Japan	3,408	80
3	HSBC	U.K.	2,715	114
4	Bank of America	U.S.	2,434	357
5	BNP Paribas	France	2,429	77
6	Credit Agricole	France	2,257	40
7	Sumitomo Mitsui	Japan	1,955	49
8	Citi	U.S.	1,951	142
9	Wells Fargo	U.S.	1,928	191
10	Mizuho	Japan	1,875	36
11	Banco Santander	Spain	1,703	63
12	Societe Generale	France	1,522	25
13	Barclays	U.K.	1,510	43
14	Deutsche Bank	Germany	1,456	26
15	Goldman Sachs	U.S.	1,200	133
16	Royal Bank of Canada	Canada	1,116	140
17	Lloyds	U.K.	1,104	44
18	Toronto-Dominion	Canada	1,102	118
19	Intesa Sanpaolo	Italy	1,058	55
20	ING	Netherlands	1,001	57
21	UBS	Switzerland	972	59
22	UniCredit	Italy	960	30
23	Morgan Stanley	U.S.	895	178
24	Scotia Bank	Canada	873	74
25	Credit Suisse	Switzerland	813	27
26	BBVA	Spain	782	44
27	Bank of Montreal	Canada	665	62
28	Nordea Bank	Finland	623	22
29	Danske Bank	Denmark	565	15
30	U.S. Bancorp	U.S.	554	88
31	CIBC	Canada	496	51
32	Commerzbank	Germany	478	9
33	Truist Financial	U.S.	473	78
34	PNC	U.S.	410	83
35	Capital One	U.S.	390	72
36	BNY Mellon	U.S.	382	45
TOTAL			**47,800**	**3,217**

Source: Bloomberg

I gauge systemic risk by using the Marginal Expected Shortfall (MES) methodology introduced by Acharya et al. (2017) and advanced by Brownlees and Engle (2017). The MES is a market-based metric that gauges an economic agent's marginal contribution to the systemic risk. The agent's contribution to the overall risk of the financial system rises with the value of MES. As shown in Figure 1, the MES jumps significantly during crisis periods and succeeds in capturing the financial stress in the system.

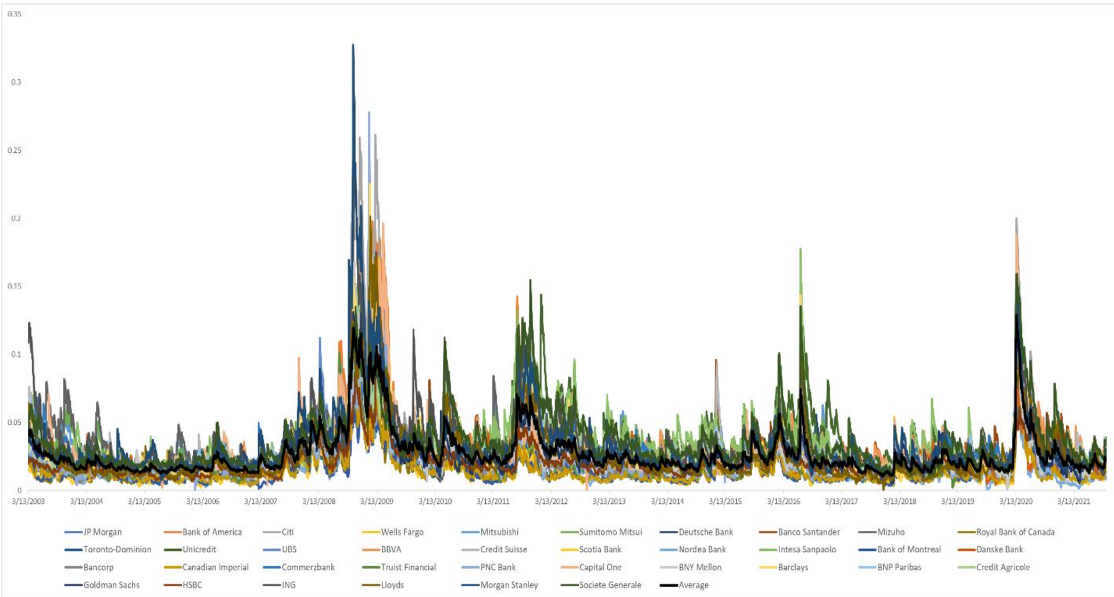

Figure 1. Systemic Risk Measured by Marginal Expected Shortfall

1.4. DEFINING SYSTEMIC RISK CONTAGION

Following several studies in the literature, I define financial contagion as "*extreme co-movements that cannot be explained with usual linkages and fundamentals*" and employ correlations to gauge co-movements. However, since the data set includes 36 banks, correlation analysis yields a large number of correlation series that are difficult to interpret. In this respect, I employ principal component analysis for dimensionality reduction while retaining the information provided by the data and ensuring that each major region (US, Europe, UK, Japan, Canada) is represented by a single component. The first principal components successfully represent each region, with variance explained by each component at 91.7%, 83.7%, 93.3%, 95.2%, and 95.9% for the US, Europe, the UK, Japan, and Canada, respectively. Hence, instead of examining correlations between systemic risk contributions of banks, I examine correlations across five regions to make inference.

1.4.1. Dynamic Conditional Correlations

To gauge co-movements, I adopt the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) approach introduced by Engle (2002) which yields time-varying conditional correlations between systemic risk contributions of financial institutions. The DCC-GARCH model takes into account heteroskedasticity, and provides more accurate estimates than traditional GARCH models (Engle, 2002).

Let $y_t = [y_{1t}, y_{2t}]'$ be a 2x1 vector including the data when of $y_t|\Omega_{t-1} \sim N(0, H_t)$. The reduced form Vector Autoregressions below shows the conditional mean equations:

$$A(L)y_t = \varepsilon_t \tag{1}$$

where $\varepsilon_t = [\varepsilon_{1t}, \varepsilon_{2t}]'$ is the innovations vector, $A(L)$ is the lag operator matrix and $\varepsilon_t \sim N(0, H_t)$, *t*=1,2,….,T. The conditional variance covariance matrix of the standard errors is $H_t = D_t R_t D_t$, where $D_t = diag\{\sqrt{h_{it}}\}$ denotes standard deviations acquired from the GARCH model and $R_t = [\rho_{ij}]_t$ for i,j=1,2 is a correlation-matrix of conditional-correlations. h_{it} shows the standard deviations in D_t while the matrix R_t depicts the DCC-GARCH process.

$$h_{it} = \gamma_i + \sum_{p=1}^{P_i} \alpha_{ip} \varepsilon^2{}_{it-p} + \sum_{q=1}^{Q_i} \beta_{iq} h_{iq-q} \quad , \quad \forall_i = 1,2 \tag{2}$$

$$R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1} \tag{3}$$

where $Q_t = (1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n)\,\bar{Q} + \sum_{m=1}^{M} a_m (\varepsilon_{t-m} \varepsilon'{}_{t-m}) + \sum_{n=1}^{N} b_n Q_{t-n}$, $\bar{Q}$ is the time invariant variance covariance matrix acquired by the estimation of equation (2), and $\overline{Q_t}$ represents the square root of the diagonal elements of Q_t.

Finally, the conditional correlation is denoted by $\rho_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}}$ and the parameters of the DCC-GARCH process are gauged by maximization of the log likelihood function in equation 4.

$$L = -\frac{1}{2}\sum_{t=1}^{T} n[log(2\pi)] + 2log|D_t| + {y_t}'{D_t}^{-1}{D_t}^{-1}y_t - {\varepsilon_t}'\varepsilon_t + log|R_t| + {\varepsilon_t}'{R_t}^{-1}\varepsilon_t \qquad (4)$$

The dynamic conditional correlations between systemic risk contributions of five regions are shown in Appendix 1. Before progressing to build the contagion metric, two points are worth mentioning. First, as shown in Appendix 1, correlations of MES between US-Canada, Europe-Canada and UK-Canada show a clear upward trend over the sample period, whereas the correlations between the US-UK exhibit only a mild increase. This emphasizes that the systemic risk interconnectedness of the Canadian banking sector has increased over the years. Second, the length of time that correlations remain above trend varies significantly. Correlations between systemic risk contributions of US-Canada, US-UK, Canada-UK, Canada-Europe remain above the confidence intervals for longer periods and return to the trend slower. Other correlations, on the other hand, exhibit sharper jumps and return to their trends faster. The sharpness in the jumps is more evident in Japan’s correlations with other regions.

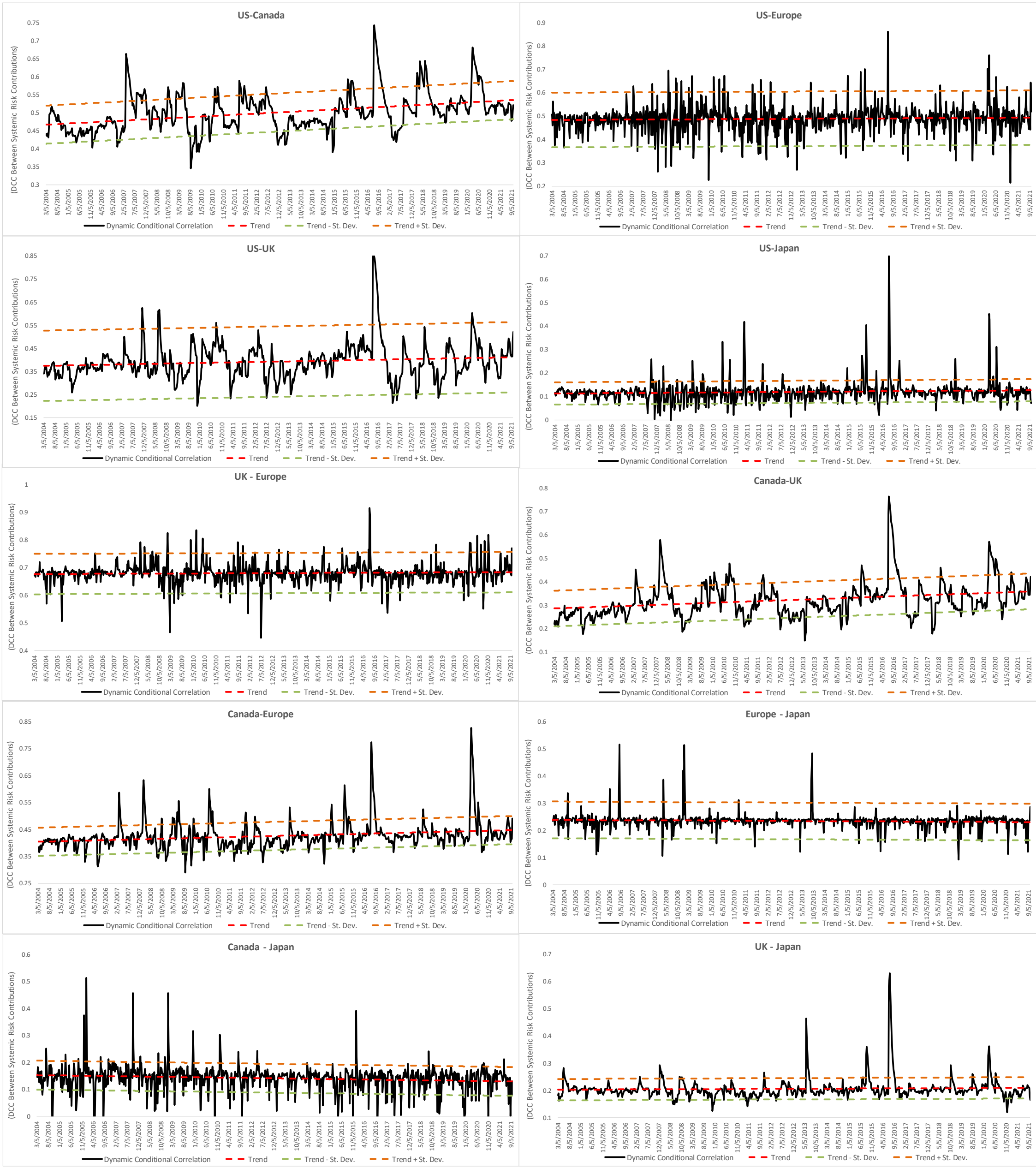

Figure 2. Dynamic Conditional Correlations

1.4.2. Time Varying Granger Causality

Notwithstanding time varying correlations incorporate valuable information regarding financial contagion, they lack two important aspects: (1) They tell us little about the causal relationship between two systemic risk series. The systemic risk contributions of two FIs may react similarly to a common shock, resulting in a common movement despite the absence of a contagious effect. In other words, as the famous quote puts it, "*correlation* *does not imply causation*". (2) Correlations do not provide information on the direction of the contagion. Even if there really is contagion, there is no way to find out which financial institution is contagious by examining the correlation structure.

To address these shortcomings and test whether extreme jumps in correlations actually infer a contagious movement, I employ the time varying Granger causality (TVGC) methodology (Phillips et al., 2015a, 2015b; Shi et al., 2018, 2020). Time TVGC methodology has several advantages over the conventional Granger Causality approach (Granger, 1969). First, it takes into account time variation and precisely captures changes in causal direction between variables. In this way, it provides a useful tool for detecting the starting and ending points of causal events. Second, since the methodology builds on the Lag Augmented Vector Autoregression (LA-VAR) model[2], it can be used with non-stationary data. Therefore, it does not require the data to be differenced or detrended. Finally, rather than arbitrarily selecting a time period, this methodology allows for a data-driven examination of causal relationships and therefore avoids false inferences.

The Lag Augmented Vector Autoregression model with the highest order of integration d is exhibited below:

$$y_t = \gamma_0 + \gamma_1 t + \sum_{i=1}^{k} J_i y_{t-i} + \sum_{j=k+1}^{k+d} J_j y_{t-j} + \varepsilon_t \tag{5}$$

where y_t is a vector with n-dimensions, k is the lag-order, t is the time trend, $J_{k+1} = \cdots = J_{k+d} = 0$ and, and ε_t is the error term. The equation could be altered as follows:

$$y_t = \Gamma\tau_t + \Phi x_t + \Psi z_t + \varepsilon_t \tag{6}$$

where

$$\Gamma = (\gamma_0, \gamma_1)_{n\times(q+1)} \tag{7}$$

$$\tau_t = (1, t)'_{2\times1} \tag{8}$$

[2] See Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996).

$$x_t = \left(y'_{t-1}, \dots, y'_{t-k}\right)'_{nk\times 1} \tag{9}$$

$$z_t = \left(y'_{t-k-1}, \dots, y'_{t-k-d}\right)'_{nd\times 1} \tag{10}$$

$$\Phi = (J_1, \dots, J_k)_{n\times nk} \tag{11}$$

$$\Psi = (J_{k+1}, \dots, J_{k+d})_{n\times nd}. \tag{12}$$

The null hypothesis below tests the non-causality:

$$H_0 : \; R_\phi = 0 \tag{13}$$

R represents a $m \times n^2 k$ matrix with restrictions on $\phi = vec(\Phi)$ using vectorization of rows. Since the components of the coefficient matrix with d-lagged vectors (Ψ) are zero, Ψ is omitted.

Then the Wald test is defined as follows subject to the restrictions placed by the null hypothesis:

$$W = \left(R\hat{\phi}\right)' \left[R\left\{\hat{\Sigma}_\varepsilon \otimes (X'QX)^{-1}\right\}R'\right]^{-1} R\hat{\phi} \tag{14}$$

where $\hat{\Phi}$ = the OLS estimator, $\hat{\phi} = vec\left(\hat{\Phi}\right)$, $\otimes$ = Kronecker product, and $\hat{\Sigma}_\varepsilon = \frac{1}{T}\hat{\varepsilon}'\hat{\varepsilon}$. The Wald statistic has m number of restrictions and follows the asymptotic null distribution of χ^2_m.

The time varying Granger causality methodology offers three approaches. Among them, I choose the recursive evolving-window Granger causality (REGC) test due to its higher power in finite samples (Shi et al., 2020). The REGC test gauges Wald-statistics for every possible sub-samples of the data. Hence, the test generates Wald test statistics for every observation in the sample except for the first one. Let $f_w = f_2 - f_1$, where f_1 and f_2 are the startpoints and endpoints of the sample, respectively. The Wald-statistic gauged from this sub-sample is represented by $W_{f_1}^{f_2}$. Assume $\tau_1 = [f_1 T]$, $\tau_2 = [f_2 T]$, $\tau_w = [f_w T]$, where $\tau_0 = [f_0 T]$ shows the minimum number of observations necessary to build a Vector Autoregression and T denotes the total number of observations. The recursive-evolving-window methodology possesses endpoint of the regression $\tau_2 = \{\tau_0, \dots, T\}$, while its startpoint τ_1 varies from 1 to $\tau_2 - \tau_0 + 1$. Therefore, the procedure covers all possible values. The test yields Wald-statistics $\{W_{f_1,f_2}\}_{f_2=f}^{f_1\in[0,f_2-f_0]}$ for each observation in the sample. The supremum of the Wald-statistics yields the test statistic below:

$$SW_f(f_0) = \sup_{f_2 = f, f_1 \in [0, f_2 - f_0]} \{W_{f_1,f_2}\} \tag{15}$$

which is used to make inference on Granger noncausality for the observation $[fT]$.

The time-varying Granger causality series for systemic risk contributions across the five regions are shown in Figure 3. Similar to dynamic conditional correlations, the time-varying Granger causality plots show sharp increases in some periods, suggesting contagion effects.

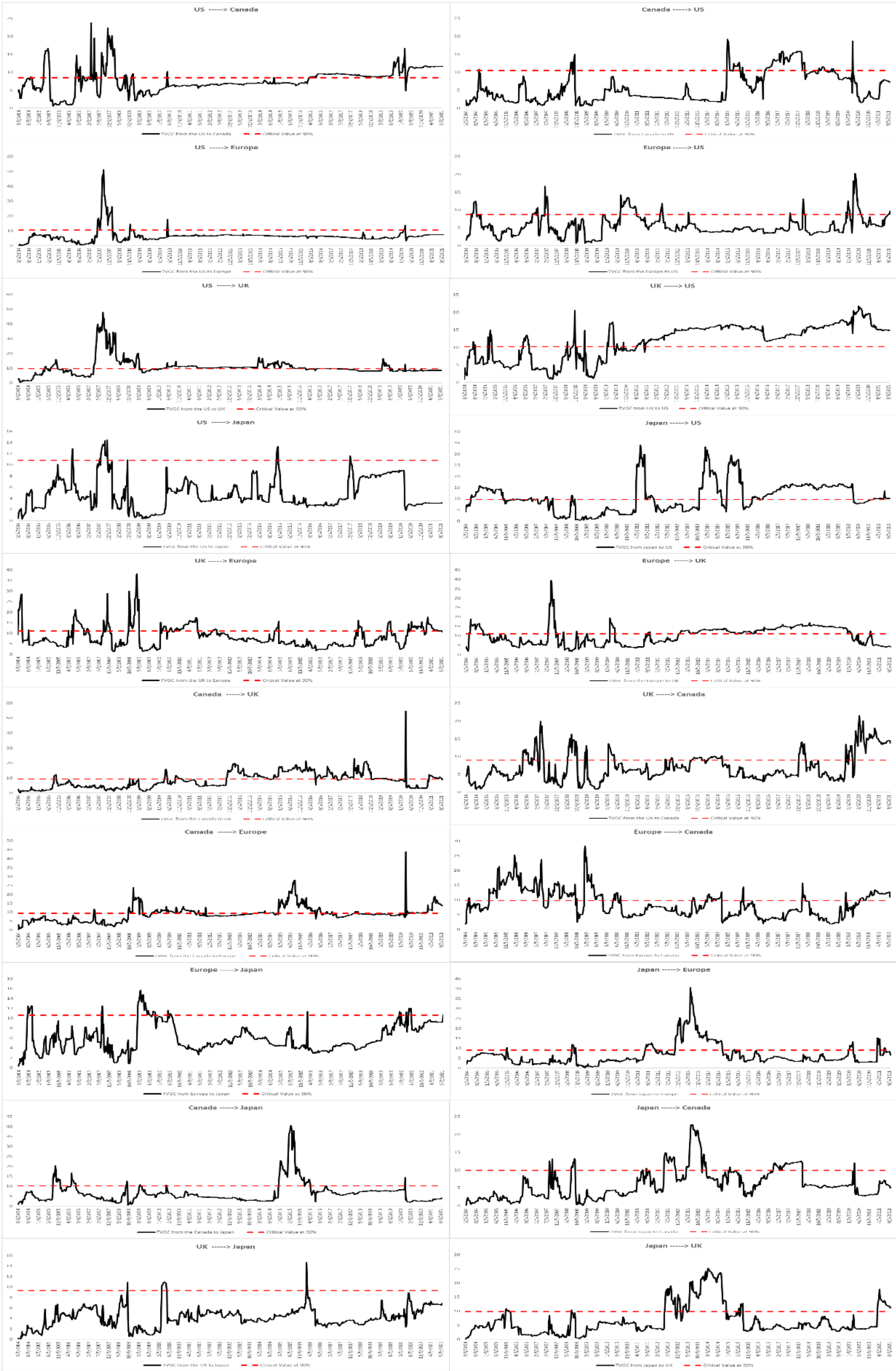

Figure 3. Time-varying Granger Causality Graphs

1.4.3. Building the Contagion Metric

Let $\rho_{12,t}$ be the conditional correlation between two series at time t, and $\tilde{\rho}_{12,t}$ and σ show trend and standard deviations of conditional correlations over the sample period, respectively. If the dynamic correlation at time t is more than two standard deviations from the trend, the co-movement at time t is called "extreme increase in correlations" and denoted by a dummy variable as follows:

$$C_t = \begin{cases} 1 & if \quad \rho_{12,t} > \tilde{\rho}_{12,t} + 2\sigma \\ 0 & otherwise \end{cases} \tag{16}$$

Similarly, after computing the time varying causality series between the systemic risk contributions of the five regions, I mark periods when causality test statistic (SW_f) exceeds critical value at 5% ($SW_f(f_0)^{5\%}$), which indicates a statistically significant causal relationship between the systemic risk contributions[3].

$$GC_t = \begin{cases} 1 & if \quad SW_f(f_0) \geq SW_f(f_0)^{5\%} \\ 0 & otherwise \end{cases} \tag{17}$$

Then, to construct the contagion metric, I match periods with extreme increases in correlations with time periods where the causality test statistic is statistically significant. The contagion metric takes the value "1" if there is a match, and "0" otherwise.

$$Contagion_t = \begin{cases} 1 & if \quad GC_t = C_t \\ 0 & otherwise \end{cases} \tag{18}$$

Thus, this approach, combining correlation and causality not only provides a robust test of contagion, but also a time-varying, directional contagion indicator. As far as I know, the only methodology that combines correlation and causality in interconnectedness analysis is Lu et al. (2014), in which the authors use dynamic correlations and time-varying causality to examine the direction of spillovers in crude oil markets. The methodology Lu et al. (2014) employs is a popular approach and used by many studies in the literature (Jammazi et al. 2017; Kanda et al. 2018; Sibande et al. 2019; Zhang et

[3] Data are aggregated weekly to avoid potential problems related to time-zone differences. Since MES series are stationary at levels, the order of integration is set to zero. The estimation is performed with heteroskedasticity-consistent standard errors, initial estimation window of 52 weeks, and a linear trend. The lag lengths in the VAR, varies between 1 and 2, is set by Schwarz Information Criterion.

al. 2021). Even though interconnectedness metrics proposed in this study and Lu et al. (2014) are similar in combining correlations with causality, they differ in two ways. First, causality series in Lu et al. (2014) are calculated using the methodology proposed by Hong (2001). As shown in Caporin and Costola (2022), the critical values adopted by Lu et al. (2014) causes type I errors due to the non-standard distribution of the metric. The authors emphasize that replicating the analysis in Lu et al. (2014) under simulated critical values yields significantly different results on causal relationships. I, on the other hand, adopt the causality methodology introduced by Phillips et al. (2015a, 2015b) and Shi et al. (2018, 2020), which uses bootstrapped critical values and enables employing recursive evolving window approach. Thus, causal relationships I obtain are more reliable compared to Lu et al. (2014). Second, while Lu et al. (2014) consider spillovers based on strengthening of causal links between two series, I distinguish between spillovers and contagion by defining spillovers as "excessive increases in correlations". Hence, rather than providing a spillover analysis, I propose a contagion test.

1.5. CONTAGION EPISODES

Figure 4 denotes contagion episodes calculated by combining causality and correlation data for five regions. Consistent with many studies that identify bi-directional contagion in the literature (Luchtenberg and Vu, 2015; Wang et al., 2019; Lin et al., 2019; Aye et al., 2022), I observe bi-directional contagion in some periods. To illustrate this phenomenon, I employ a 100% stacked column graph. Accordingly, there are several contagion episodes particularly concentrated over four crisis periods (The GFC, the ESDC, 2014-2017 Turmoil, and Covid-19 Crisis) and both uni-directional and bi-directional contagion are evident. These episodes are shown in Table 2. I denote the identified contagion episodes, crisis periods, and some of the notable systemic events in an aggregated contagion graph in Figure 5.

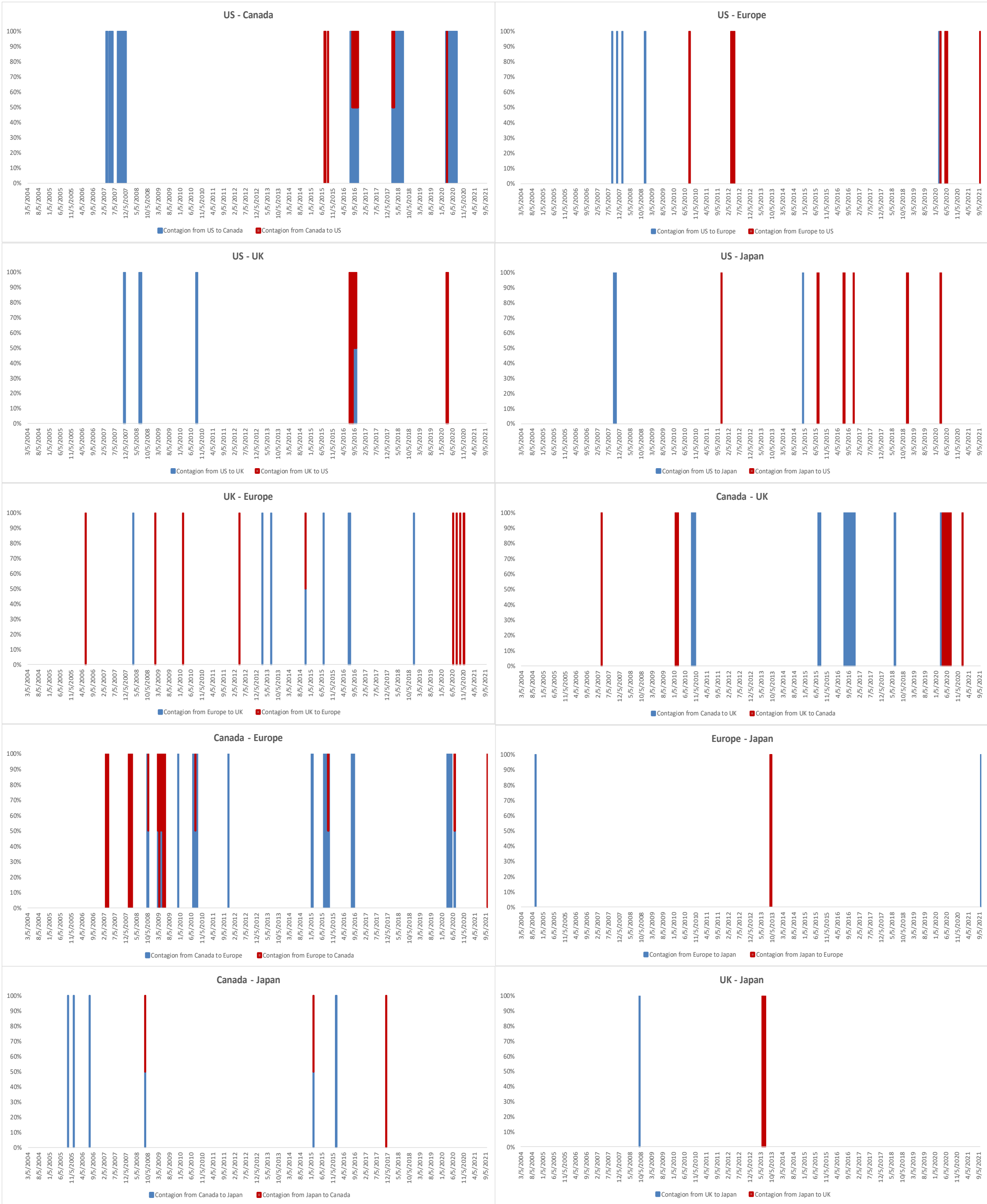

Figure 4. Contagion Episodes During 2004-2021

During the GFC the United States is at the epicenter of the risk transmission, propagating systemic risk to Canada, the UK, Europe, and Japan. This is to be expected, since the GFC first emerged in the US and intensified with the Lehman Collapse in September 2008. The Lehman Collapse is indeed a remarkable contagious event as evident in most panels of Figure 4. However, while the collapse of Lehman Brothers is generally recognized as the hallmark of the GFC, the contagious effects are first felt in March 2007. In 2007, the US starts to propagate systemic risk to Canada in the first quarter, to Japan in the second quarter, and to Europe in the third quarter. Thus, the spread of systemic risk from the US to other regions occurs about a year before Lehman's collapse, precisely when the US yield curve is inverted. During the GFC, the US and Canada are the main transmitters and receivers of systemic risk, respectively. Contagion between these two countries is stronger, more persistent, and longer lasting than contagion between other regions. This may be due to the fact that the US and Canada are neighbors, and their banking sectors are more interdependent than in other regions. Finally, the UK is also estimated to be a net recipient of systemic risk from Europe and the US during the GFC.

Table 2. Direction of Contagion

GFC	ESDC	2014-2017 Turmoil	Covid-19 Pandemic
US -----> Canada, UK, Europe, Japan	US -----> UK	US <-----> Canada	US <-----> Canada
Europe -----> UK, Canada	Europe -----> US	Canada <-----> Europe	US <-----> UK
Japan -----> Canada	Canada <-----> Europe	Canada <-----> Japan	US <-----> Europe
	UK -----> Europe	UK <-----> Europe	Canada <-----> Europe
	UK <-----> Canada	US <-----> UK	UK -----> Europe
	Japan -----> US	Japan <-----> US	UK <-----> Canada
			Europe -----> Japan
			Japan -----> US

Source: Author’s calculations

The ESDC emerged right after the GFC in peripheral Europe and spread to core European countries and as well as to the UK. Despite affecting other continents to some extent, the ESDC is generally regarded as a crisis mainly contained within continental Europe and the UK. This could be seen in Table 2 and Figure 4, where Europe and the UK are clearly at the center of the contagion mechanism, transmitting risks to US and Canada over different time periods. Surprisingly, the US banks are net recipients of systemic risk during the ESDC, while Canadian banks are found to be in a bi-directional contagion relationship between European and British banks. No contagion is detected between US and Canada during the ESDC period.

The 2014-2017 period includes several noteworthy events such as the Russian crisis, Brexit, the FED’s tapering plan, and the stock market crash in China. In this period, interconnectedness is higher, and the contagion mechanism is more complex than in other crisis periods. Accordingly, bi-directional contagion is detected between US-Canada, US-UK, US-Japan, UK-Europe, Canada-Europe, Canada-Japan, while no contagion is detected between United States-Europe, UK-Japan, Europe-Japan, and UK-Canada.

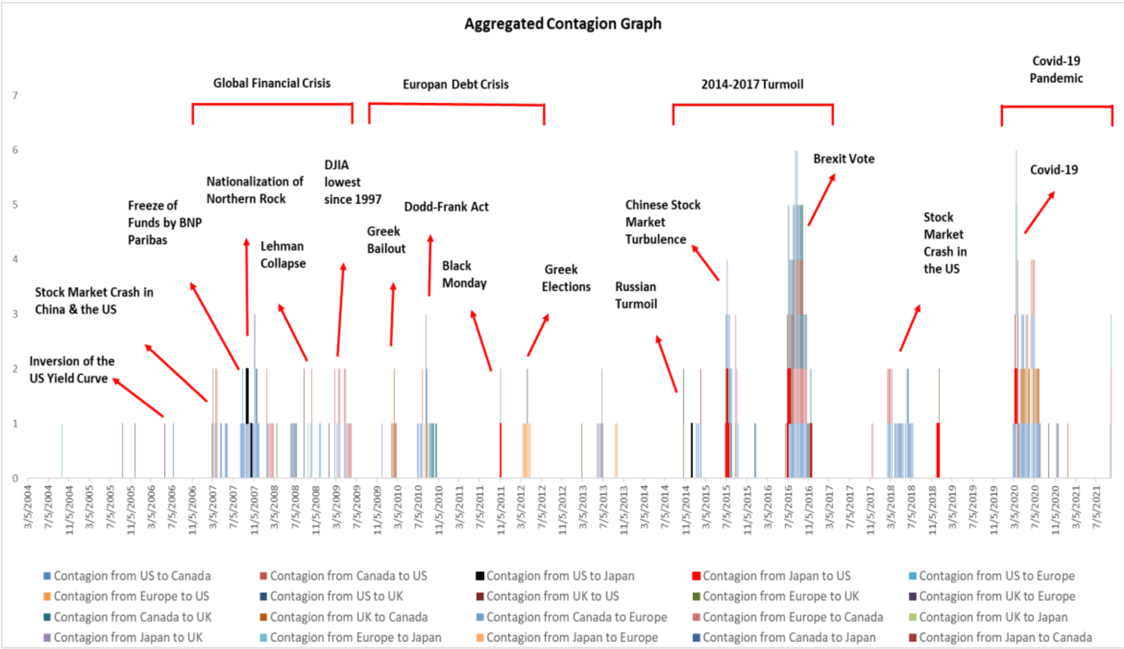

Figure 5. Aggregated Contagion Graph

Source: Author's calculations

Covid-19 crisis is fundamentally different from the other three crisis episodes. It emerged in the real sector, rapidly spread to financial sector, and created a widespread chaos within a few weeks. Its effects were exacerbated by lockdowns and disruption of supply chains. Recovery of the financial markets were also swift, broadly materialized in line with vaccine development efforts. But despite these differences, the contagion dynamics I find during the Covid-19 period are similar to those I observe during the 2014-2017 turbulence period, as bi-directional contagion appears to be quite widespread. Accordingly, I detect bi-directional contagion between US-Canada, US-UK, US-Europe, Canada-Europe, UK-Canada and uni-directional contagion from UK to Europe, from Europe to Japan, and from Japan to US. Japan appears to remain outside of the systemic risk transmission mechanism during the Covid-19 pandemic as no contagion is found between Japan-Europe, Japan-UK, and Japan-Canada.

Tables 2-3 and Figures 4-5 reveal important findings. First, the US is estimated to be a net transmitter of shocks during the GFC but the net receiver during the ESDC. This could be explained by the full compliance of the US banks with the measures taken by the authorities to curb risk appetite, reduce leverage, and improve financial ratios. As banks become more resilient, the entire US financial system also becomes less prone to receiving systemic risk from other countries. Nevertheless, the US returns to the epicenter of the contagion mechanism starting from 2014. Second, Canada's involvement in systemic risk transmission becomes more pronounced after 2014, with Canada transmitting systemic risk to United States, Europe, and the UK during 2014-2016 turmoil and Covid-19 pandemic periods. Canada's increased interconnectedness between the US and Europe, evident in dynamic conditional correlations, could be behind this finding. Third, contagion episodes originated in Japan has distinct features compared to contagion in other regions. These episodes tend to be short-lived, and correlations usually return to their trend within a week after making extreme jumps.

Table 3. List of Contagion Episodes

US -----> Canada
03/01/2007 - 5/28/2007
08/17/2007 - 12/07/2007
07/08/2016 - 10/21/2016
02/16/2018 - 07/13/2018
03/06/2020 - 07/31/2020

Canada -----> US
07/06/2015 - 07/27/2015
08/24/2015 - 08/31/2015
08/05/2016 - 10/21/2016
02/16/2018 - 03/09/2018
03/20/2020 - 04/03/2020

Japan -----> UK
05/31/2013 - 07/12/2013

Europe-----> US
08/13/2010 - 08/25/2010
03/16/2012 - 04/25/2012
03/20/2020 - 03/25/2020
05/22/2020 - 05/29/2020
06/19/2020 - 06/24/2020
09/24/2021 - 09/29/2021

Europe-----> Canada
03/02/2007 - 04/06/2007
01/18/2008 - 03/07/2008
10/10/2008 - 10/16/2008
02/27/2009 - 04/03/2009
04/24/2009 - 06/12/2009
07/30/2010 - 08/06/2010
08/28/2015 - 09/09/2015
06/26/2020 - 07/08/2020
09/23/2021 - 9/30/2021

US -----> UK
11/23/2007 - 11/30/2007
06/13/2008 - 07/18/2008
08/20/2010 - 09/03/2010
08/19/2016 - 10/07/2016
03/27/2020 - 04/03/2020

Canada -----> UK
09/10/2010 - 10/29/2010
07/10/2015 - 08/14/2015
07/08/2016 - 12/02/2016
06/08/2018 - 06/22/2018
03/20/2020 - 04/02/2020

UK -----> Japan
09/19/2008 - 09/25/2008

UK -----> Europe
05/26/2006 - 06/02/2006
01/23/2009 - 01/28/2009
02/12/2010 - 02/18/2010
04/13/2012 - 04/20/2012
10/24/2014 - 10/30/2014
06/19/2020 - 06/23/2020
08/07/2020 - 08/14/2020
09/25/2020 - 09/30/2020
11/13/2020 - 11/26/2020

Japan -----> Canada
08/29/2008 - 09/05/2008
09/13/2013 - 09/19/2013
02/06/2015 - 02/13/2015
11/17/2017 - 11/21/2017

US -----> Europe
08/31/2007 - 09/05/2007
11/09/2007 - 11/15/2007
01/18/2008 - 01/25/2008
11/28/2008 - 12/11/2008
02/28/2020 - 03/06/2020

Europe-----> UK
03/21/2008 - 03/25/2008
3/1/2013 - 03/08/2013
06/28/2013 - 07/04/2013
10/24/2014 - 10/29/2014
07/03/2015 - 07/09/2015
06/17/2016 - 07/15/2016
12/14/2018 - 12/19/2018

Canada -----> Europe
10/03/2008 - 10/16/2008
02/27/2009 - 04/02/2009
04/24/2009 - 05/05/2009
12/04/2009 - 12/08/2009
07/02/2010 - 09/03/2010
11/04/2011 - 11/10/2011
01/09/2015 - 01/30/2015
07/03/2015 - 8/14/2015
08/28/2015 - 09/18/2015
07/22/2016 - 09/02/2016
03/20/2020 - 04/03/2020
04/17/2020 - 05/20/2020
06/26/2020 - 07/07/2020
09/23/2021 - 9/29/2021

Japan -----> Europe
09/13/2013 - 10/02/2013

US -----> Japan
09/21/2007 - 10/01/2007
10/19/2007 - 10/23/2007
12/12/2014 - 12/19/2014

Europe-----> Japan
09/24/2004 - 09/30/2004
09/23/2021 - 9/28/2021

Japan -----> US
11/04/2011 - 11/11/2011
07/03/2015 - 07/17/2015
07/01/2016 - 07/19/2016
11/18/2016 - 11/22/2016
12/07/2018 - 12/17/2018
03/13/2020 - 03/26/2020

UK-----> Canada
03/30/2007 - 04/05/2007
01/29/2010 - 03/03/2010
04/10/2020 - 08/07/2020
01/15/2021 - 01/19/2021

Canada -----> Japan
09/16/2005 - 09/22/2005
12/02/2005 - 12/06/2005
07/14/2006 - 07/20/2006
08/29/2008 - 09/05/2008
02/06/2015 - 02/12/2015
12/18/2015 - 01/02/2016

UK -----> US
07/01/2016 - 10/07/2016
03/13/2020 - 04/10/2020

1.6. THE MAIN TRANSMITTERS OF SYSTEMIC RISK

The previous section provides valuable insights into how systemic risk spreads over the sample period and identifies contagion episodes. However, since the data are aggregated by PCA, the contagion analysis ignores the heterogeneity of the dataset and neglects important idiosyncratic features of the banks. The dataset is indeed heterogeneous; it includes 36 banks from 13 countries, with total assets ranging from $382bn to $3,744bn. The banks in the sample differ not only in size, but also in capital adequacy, leverage, profitability, etc. Thus, while the first principal components explain, on average, about 90 percent of the total variance, the remaining 10 percent still contains valuable insights into the unique features of the banks. By examining the data set at the bank-level, I aim to find out which banks are more involved in systemic risk transmission during the four crisis periods I identify in the previous section.

Preliminary analysis of the data shows that the MES series are leptokurtic and fat-tailed (Table 4), which means that they are more likely to contain extreme events than data following a normal distribution. This leads me to focus on tail events and examine the risk transmission mechanism after extreme shocks. For this purpose, I employ the Quantile Connectedness (QC) methodology (Ando et al., 2022) which allows computing the pairwise spillovers after system-wide extreme adverse and beneficial shocks[4]. Rather than examining an average shock's effects as in Diebold and Yilmaz (2012, 2014), the QC allows to analyze "*the impact of idiosyncratic shocks from one bank to another as the shock size varies*". The QC offers a flexible approach by running vector autoregressions for each percentile and capturing changes in network topology after systemic shocks, that are known to be less frequent and larger (Ando et al., 2022). Using systemic risk contributions of 36 banks as input, the QC approach not only gauges the total connectedness in the system, but also yields TO, FROM, and NET directional spillovers across 36 banks at the τ^{th} conditional quantile[5].

[4] See Appendix 2.

[5] FROM Spillovers: Directional spillover effects from all banks to the i^{th} bank, TO Spillovers: Directional spillover effects from the i^{th} bank to all banks, NET Spillovers for the i^{th} bank = TO Spillovers - FROM Spillovers.

Table 4. Descriptive Statistics

	Mean	Skewness	Kurtosis	Jarque-Bera Test
JP Morgan	0.027	3.027***	10.433***	29347.114***
Bank of America	0.031	3.206***	11.106***	33172.760***
Citi	0.032	3.555***	14.971***	55405.091***
Wells Fargo	0.026	3.142***	11.088***	32763.610***
Mitsubishi	0.028	2.099***	6.843***	12999.599***
Sumitomo Mitsui	0.027	2.254***	7.879***	16620.532***
Deutsche Bank	0.03	2.317***	6.919***	13988.355***
Banco Santander	0.034	2.142***	6.560***	12383.292***
Mizuho	0.027	2.297***	8.289***	18115.512***
Royal Bank of Canada	0.015	4.141***	23.724***	127357.766***
Toronto-Dominion	0.015	4.239***	26.400***	155083.318***
Unicredit	0.038	1.649***	3.356***	4467.088***
UBS	0.028	2.711***	9.551***	24332.114***
BBVA	0.033	2.022***	5.674***	9791.763***
Credit Suisse	0.029	3.057***	12.953***	41384.281***
Scotia Bank	0.014	4.256***	25.489***	145661.817***
Nordea Bank	0.022	2.057***	5.029***	8514.977***
Intesa Sanpaolo	0.036	2.166***	6.292***	11772.363***
Bank of Montreal	0.014	4.854***	36.718***	290956.589***
Danske Bank	0.023	2.611***	10.565***	28011.563***
Bancorp	0.023	3.040***	10.288***	28807.070***
Canadian Imperial	0.015	4.436***	28.362***	178138.110***
Commerzbank	0.032	2.241***	6.670***	13024.045***
Truist Financial	0.025	3.006***	10.897***	31244.986***
PNC Bank	0.025	4.157***	24.440***	134425.388***
Capital One	0.031	3.282***	12.676***	41102.533***
BNY Mellon	0.026	3.846***	19.525***	88830.814***
Barclays	0.031	2.773***	10.504***	28458.407***
BNP Paribas	0.033	2.075***	4.770***	8063.045***
Credit Agricole	0.032	1.998***	4.650***	7581.342***
Goldman Sachs	0.027	2.969***	10.433***	29066.116***
HSBC	0.021	2.831***	11.417***	32759.523***
ING	0.036	3.084***	13.389***	43832.298***
Lloyds	0.027	2.902***	11.191***	32056.361***
Morgan Stanley	0.033	4.289***	25.765***	148741.409***
Societe Generale	0.037	2.098***	5.051***	8696.008***

Source: Author's calculations. *** Implies rejection of the null hypothesis at 1% significance level.

Figure 6 exhibits the total connectedness index (TCI) at the 10th, 50th and 90th percentiles. As seen in Figure 6, the TCI varies significantly for each percentile. The TCI at the median is 89.4 on average and oscillates between 75 and 95 across the sample, while the TCIs at the 10th and 90th percentiles are 93.5 and 94.1 on average, respectively. Hence, to utilize the valuable information contained in each percentile, I examine systemic risk connectedness measures for different percentiles, and in this context, I choose the 1st, 10th, 50th, 90th, and 99th percentiles to represent the effects of extremely beneficial, beneficial, average, adverse, and extremely adverse shocks, respectively. Beneficial shocks are defined as news, events, or policies that are expected to have detrimental impact on systemic risk such as accommodative monetary policy or TBTF subsidies. However, while beneficial shocks are expected to have a stabilizing role, they may also exacerbate systemic risk through moral hazard and search for yield. In line with the literature that recognizes both surged connectedness under adverse financial conditions (Ang and Bekaert, 2002; Ando et al., 2022; *inter alia*) and strong spillover effects after given shocks at both tails (Jorion and Zhang, 2007; Londono, 2019), I find that TCI is strong in both tails and higher after adverse shocks.

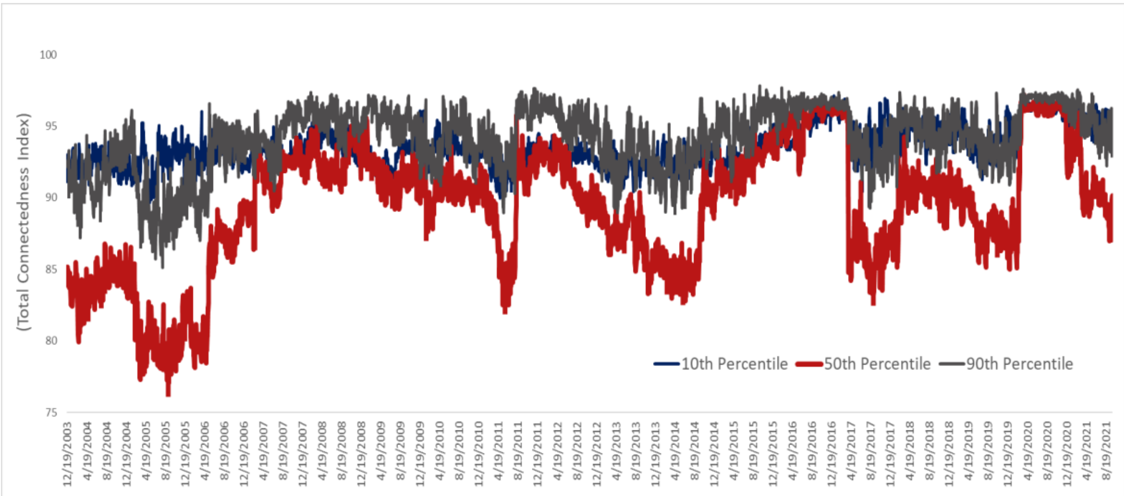

Figure 6. Total Connectedness Index at Different Percentiles

Source: Author's calculations. Window length and forecast horizon are set 250 days and 5 trading days, respectively.

1.6.1. Systemic Risk Spillovers at Different Percentiles

The discussion in Section 1.5 shows that each crisis period has different dynamics and a country that spreads systemic risk in one period may be a recipient of systemic risk in another. Based on this finding, I calculate the TO, FROM, and NET spillovers at the 1st,

10^{th}, 50^{th}, 90^{th}, and 99^{th} percentiles for 36 banks during the GFC, ESDC, 2014-2017 turmoil, and Covid-19 pandemic periods. In this way, I aim to identify the main transmitters of systemic risk and investigate the network topology during four contagion episodes[6]. Table 5 summarizes the main transmitters of systemic at the 1^{st}, 10^{th}, 50^{th}, 90^{th}, and 99^{th} percentiles risk for each crisis period[7]. As evident in Table 5, the main systemic risk transmitters differ not only across percentiles, but also across crisis periods. This result supports my findings in section 1.5, reiterating that each period of turmoil has different characteristics.

Table 5. Main Transmitters of Systemic Risk

Full Sample					
	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
1^{st} Percentile	Bancorp	BBVA	Banco Santander	Bank of America	JP Morgan
10^{th} Percentile	HSBC	Barclays	Commerzbank	Lloyds	Deutsche Bank
50^{th} Percentile	Barclays	Scotia Bank	JP Morgan	Bank of America	Banco Santander
90^{th} Percentile	Banco Santander	Unicredit	HSBC	Credit Agricole	Deutsche Bank
99^{th} Percentile	Unicredit	HSBC	Banco Santander	Credit Agricole	Toronto-Dominion
The GFC					
	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
1^{st} Percentile	Deutsche Bank	Banco Santander	Credit Agricole	Intesa Sanpaolo	Mitsubishi
10^{th} Percentile	Wells Fargo	BBVA	Banco Santander	Citi	Bank of America
50^{th} Percentile	Wells Fargo	Truist Financial	Citi	Bank of America	Goldman Sachs
90^{th} Percentile	JP Morgan	Goldman Sachs	Citi	BBVA	Credit Suisse
99^{th} Percentile	Citi	Banco Santander	JP Morgan	BBVA	Commerzbank
The ESDC					
	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
1^{st} Percentile	Scotia Bank	PNC Bank	Wells Fargo	Truist Financial	Morgan Stanley
10^{th} Percentile	Deutsche Bank	Citi	Scotia Bank	Societe Generale	ING
50^{th} Percentile	Banco Santander	Societe Generale	Toronto-Dominion	Bank of America	Scotia Bank
90^{th} Percentile	BBVA	Bancorp	HSBC	Nordea Bank	Barclays
99^{th} Percentile	Danske Bank	BNP Paribas	BBVA	HSBC	JP Morgan
2014-2017 Turmoil					
	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
1^{st} Percentile	Credit Agricole	Deutsche Bank	Commerzbank	UBS	Banco Santander
10^{th} Percentile	Banco Santander	BBVA	Unicredit	ING	Intesa Sanpaolo
50^{th} Percentile	JP Morgan	Morgan Stanley	BNP Paribas	Banco Santander	BBVA
90^{th} Percentile	HSBC	Unicredit	Sumitomo Mitsui	Nordea Bank	UBS
99^{th} Percentile	Lloyds	Bancorp	Goldman Sachs	Barclays	BNP Paribas
Covid-19 Pandemic					
	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
1^{st} Percentile	Intesa Sanpaolo	UBS	Canadian Imperial	Wells Fargo	Bank of America
10^{th} Percentile	UBS	Intesa Sanpaolo	Canadian Imperial	Nordea Bank	Wells Fargo
50^{th} Percentile	UBS	Credit Suisse	BNP Paribas	Deutsche Bank	Barclays
90^{th} Percentile	HSBC	Scotia Bank	Toronto-Dominion	Credit Agricole	Mizuho
99^{th} Percentile	BBVA	Wells Fargo	Bancorp	Mizuho	BNP Paribas

[6] I obtain spillover tables by examining the effects of systemic shocks at the five selected percentiles over the four crisis periods. The tables are built by decomposing the GFEVD "for variable i coming from shocks to variable j, for all i and j". The ij^{th} entry shows the estimated contribution to the bank i's GFEVD from innovations to bank j. The tables are omitted to save space. They are available upon request.

[7] The table should read as follows: The 1^{st} and 10^{th} percentiles show spillovers after large beneficial shocks, 90^{st} and 99^{th} percentiles show spillovers after large adverse shocks, and 50^{th} percentile shows spillovers after median shocks.

1.6.1.1. The GFC

The GFC originated in the US mortgage market and propagated to the financial and real sectors, respectively. Due to the origin of the GFC, I find large US banks such as JP Morgan, Citi, Goldman Sachs, and Wells Fargo, to be the main transmitters of systemic risk at high percentiles during the GFC, in line with my expectations. JP Morgan's role during the GFC could be particularly focused on. JP Morgan acquired Bear Stearns and Washington Mutual in 2008, making it the world's largest bank by market capitalization. However, by doing so, it also acquired billions of USD worth of troubled assets. Thus, in addition to its massive balance sheet, JP Morgan's acquisition of troubled assets may be another factor influencing its involvement in systemic risk transmission at high percentiles by making it more connected to other financial institutions. However, it’s also worth emphasizing that the US banks also dominate risk transmission in lower percentiles. Accordingly, Wells Fargo and Citi are the first and fourth largest transmitters of beneficial spillovers at the 10th percentile, respectively, while US banks rank in the top five at the median. This shows that the GFC carries the US label in every aspect. Also, the role of European banks during the GFC should not be underestimated. Some European banks, especially Spanish banks, are also among the top transmitters of systemic risk at the 90th and 99th percentiles. This shows that some of the European banks are quickly integrated into the shock propagation network during the GFC, either because of the fragility or interconnectedness of banks. This finding is congruent with Section 1.5, where I detect unidirectional contagion from Europe to the UK and Canada. Finally, four of the top five transmitters at the 1st percentile are European banks, implying European banks are more prone to transmit risks after beneficial shocks during the GFC.

Figure 7 shows the systemic risk spillover networks during the GFC. Accordingly, two important points stand out. First, there is a significant difference between the spillover networks of large beneficial and large adverse shocks. While JP Morgan is the epicenter of the network at the 90th percentile and unquestionably dominates it, there is no such bank in the spillover network at the 10th percentile. Second, the spillover networks at the 10th and 50th percentiles show explicit clusters, but the networks in the remaining percentiles are dispersed.

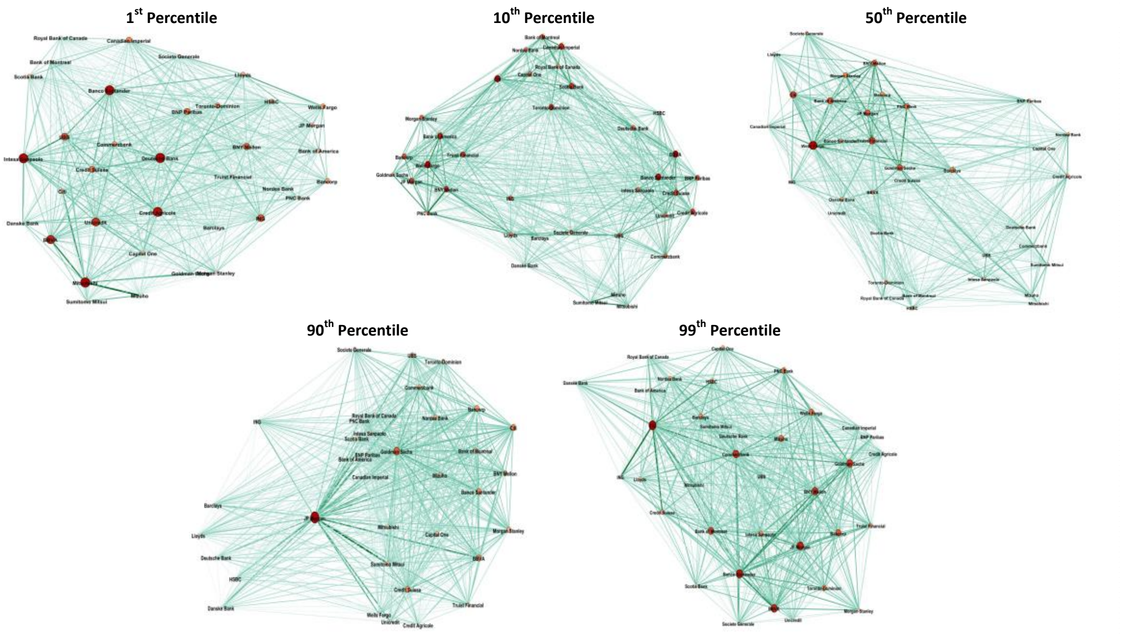

Figure 7. Systemic Risk Spillover Networks During the Global Financial Crisis

1.6.1.2. The ESDC

The ESDC originated in Europe and was effective between 2009-2012. It should therefore not be surprising that European banks dominate the table of main systemic risk transmitters during the ESDC, just as US banks do during the GFC. Table 5 denotes that BBVA is the largest and third larger transmitter of systemic risk at the 90th and 99th percentiles, respectively. Although BBVA is not among the largest banks, it is highly interconnected. Due to its interconnectedness, it was among the Financial Stability Board's (FSB) global systemically important banks (G-SIBs) between 2011-2013. Similar to BBVA, BNP Paribas, Barclays, HSBC, and Nordea, which are identified as the top risk transmitters during the ESDC according to Table 5, were also listed as G-SIBs by the FSB during 2011-2013. Hence, my findings are in line with the FSB's classification, highlighting the importance of higher loss absorption requirements imposed on systematically important banks under the Basel framework. In addition, Table 5 provides surprising findings. Accordingly, Danske Bank is the largest risk transmitter at the 99th percentile during the ESDC, while Bancorp is the second largest risk transmitter at the 90th percentile. These two banks are among the smallest in the sample and neither of them has ever been on the FSB's G-SIB list. This finding points out that despite being among the smallest banks in the sample, both Danske Bank's and Bancorp's vulnerability to large adverse shocks, as well as their strong linkages with other banks, make them important transmitters of systemic risk during the ESDC.

Figure 8 exhibits the systemic risk spillover network during the ESDC. Although they represent different crisis periods and the banks' positions in risk transmission differ, the spillover networks during the ESDC and GFC show similarities. Accordingly, there are signs of clustering among banks at the 10th and 50th percentiles, a single bank (BBVA) dominates the network at the 90th percentile, and there is no dominant bank at the 10th percentile. Figure 8 also provides distinguishing features on systemic risk transmission during the ESDC. It confirms the high interconnectedness of Danske Bank and Bancorp at the 90th and 99th percentiles and their pivotal position in the network. This finding once again emphasizes the inadequacy of focusing on the effects of average shocks in systemic risk analysis, as the important positions of these two banks in systemic risk transmission network are not visible after average or median shocks. Finally, the list of transmitters at the median and lower percentiles is heterogeneous, including banks from the US, Spain, Canada, France, the Netherlands, and Germany.

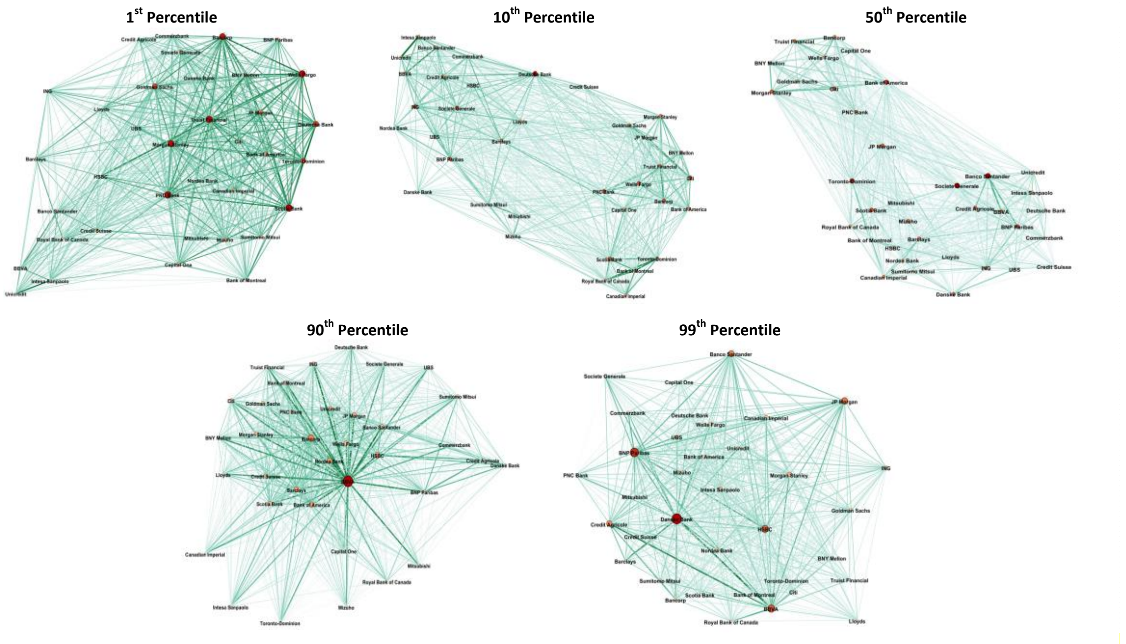

Figure 8. Systemic Risk Spillovers Network During the European Sovereign Debt Crisis

1.6.1.3. 2014-2017 Turmoil

Unlike the GFC and the ESDC, the period of turmoil from 2014 to 2017 did not emerge from a single theme. This period was characterized by a succession of adverse shocks, including the oil shock, Russia's annexation of Crimea, the Chinese stock market turmoil, the Brazilian economic crisis, and the Brexit process. The adverse effects of these shocks not only had different impacts in many countries, but also overlapped, creating a self-feeding spillover mechanism. These events seem to lead to a notable surge in the total connectedness, especially at the median or higher percentiles, as shown in Table 5 and Figure 6. The surged interconnectedness during 2014-2017 is in line with my findings in section 1.5 in which I identify more contagion episodes compared to the other three crisis periods. According to Table 5, the two British banks, HSBC and Lloyds, are the largest transmitters of systemic risk at the 90th and 99th percentiles, respectively. Moreover, Barclays is also estimated to be the fourth largest transmitter of systemic risk at the 99th percentile. Since all the British banks in my sample are estimated to be at the center of systemic risk transmission following large adverse shocks during 2014-2017 points out to the importance of the Brexit process as a systemic event. Brexit reveals the exposures of other banks to British banks and demonstrates the importance of the Brexit process not only for Europe but also for the world. However, the effects of the other adverse shocks should not be underestimated as they contribute significantly to the heterogeneity in Table 5. Bancorp, which is found to be the second largest transmitter of risk at the 90th percentile during the ESDC, is estimated to be the second largest transmitter of systemic risk at the 99th percentile during the 2014-2017 turmoil period. This finding shows that Bancorp has maintained its pivotal role in systemic risk propagation since the ESDC, despite its limited asset size. Table 5 identifies UniCredit, Sumitomo Mitsui, Nordea, BNP Paribas, and UBS as the other main transmitters of systemic risk at the 90th and 99th percentiles, all of which were also on the FSB's G-SIB list during 2014-2017. Table 5 includes two Japanese banks and eight banks from five European countries at the 1st and 10th percentiles, showing that the heterogeneity among the main transmitters of systemic risk is also present after large beneficial shocks. In addition, the two US banks (JP Morgan and Morgan Stanley) are estimated to be the largest transmitters of systemic risk after median shocks. Finally, BBVA and Santander, which are among the largest transmitters of systemic risk after large adverse shocks during the ESDC, are estimated to be the largest transmitters of systemic risk after large beneficial shocks at the 10th percentile during the period 2014-2017. This reversal could be a consequence of the Spanish bailout, which provided €41.3 billion to the Spanish banks through the European Stability Mechanism (ESM) during the ESDC. Although this policy was implemented to prevent bank failures and reduce systemic risk, it may have led Spanish banks to spread systemic risk through different channels.

Figure 9 shows the systemic risk network during the period 2014-2017. The centrality of HSBC and Lloyds in spillover networks following large adverse shocks as well as the size of the nodes, an indicator of their total NET spillovers, distinguishes them from other banks. The clustering observed at the 10th and 50th percentiles in the systemic risk networks during the GFC and ESDC seems to be valid only for Canadian banks in the 2014-2017 period. Finally, the following bilateral relationships stand out in the 2014-2017 period: Wells Fargo's connectedness with Mizuho and Mitsubishi at the 1st percentile, HSBC's connectedness with UniCredit and Nordea at the 90th percentile, and Credit Agricole's connectedness with HSBC and UBS at the 99th percentile.

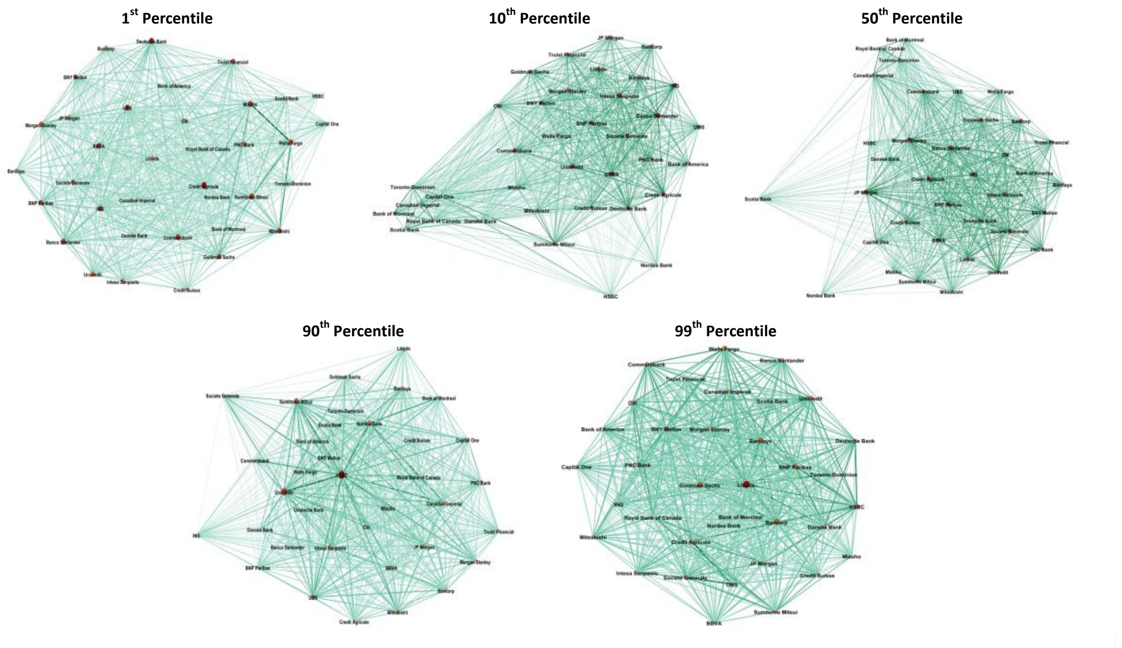

Figure 9. Systemic Risk Spillovers Network During the 2014-2017 Turmoil Period

1.6.1.4. Covid-19 Pandemic

The Covid-19 crisis originated in the real sector and threatened the banking sector through demand. It represented a unique period with negative effects on the real economy, such as mass layoffs, supply chain disruptions and lockdowns, as well as financial market distress. As evident in Figure 1, systemic risk propagated faster during the Covid-19 crisis compared to the previous crisis periods. After skyrocketing, systemic risk, measured by MES, peaked within weeks, and returned to pre-crisis levels in two quarters. In response to the Covid-19 crisis, policymakers introduced various forbearance measures to support bank capital, lending, and profitability, such as releasing regulatory capital buffers, reducing risk-asset weights, delaying non-performing loans (NPL) classifications, and restricting dividend distributions. Table 5 shows that, in contrast to the GFC, ESDC and the 2014-2017 turmoil periods, no single bank or region is dominant in risk transmission at the high percentiles. HSBC and BBVA are estimated to be the largest systemic risk transmitters during Covid-19 period at the 90th and 99th percentiles, respectively. HSBC, which is consistently estimated to be among the top 5 transmitters at the 90th and 99th percentiles since the ESDC, and BBVA, which is among the top 5 transmitters at the 99th percentile during the GFC and ESDC, represent two different aspects of risk transmission. In this context, the role of HSBC, the third largest bank in the sample, shows the effect of asset size in risk transmission, while the role of BBVA, a medium-sized bank, shows the effect of interconnectedness. The involvement of Canadian banks in risk transmission during this period supports my findings in Section 1.5. Finally, Bancorp is again among the largest transmitters at the 99th percentile, while Wells Fargo, BNP Paribas, Credit Agricole and Mizuho stand out as other important transmitters.

Figure 10 emphasizes the pivotal positions of Intesa Sanpaolo, UBS, Canadian Imperial, and Wells Fargo in the systemic risk spillover networks after extremely beneficial shocks. Accordingly, these banks rank among four out of the five largest transmitters at both the 1st and 10th percentiles. This finding might reflect the effects of global ultra-loose monetary policy during the Covid-19 pandemic as well as other forbearance measures by governments and regulatory bodies. The figure also shows that clustering is possible only after the median shocks.

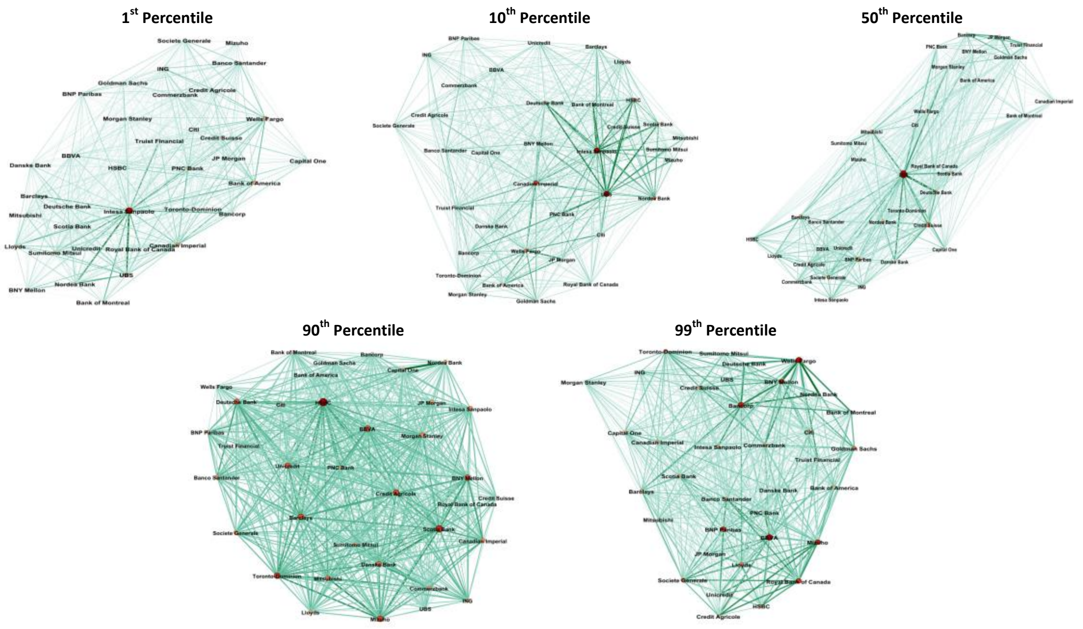

Figure 10. Systemic Risk Spillovers Network During the Covid Pandemic

1.6.1.5. Full Sample

Over the full sample period 2004-2021, European banks are estimated to be the main transmitters of systemic risk after extremely adverse shocks, except for the GFC period. This makes sense, since the sample period includes both major global crises affecting the whole world and large adverse shocks such as the Greek bailout and the Brexit process, whose effects are mostly limited in Europe. Moreover, the European region, which includes 14 banks from 8 countries, has a more heterogeneous structure compared to other regions and highlights banks' idiosyncratic characteristics more prominently. For instance, while the systemic risk spillovers of banks from European countries such as Banco Santander and BBVA are higher during the ESDC period, British banks are found to be the largest transmitters of systemic risk during the Brexit period of 2014-2017. This is also evident in Figure 1, as the individual systemic risk contributions of European banks peak at different times during the sample period, suggesting that some banks deviate from the group and reflect the idiosyncratic features of each bank.

UniCredit, Banco Santander, HSBC, and Credit Agricole stand out as the largest transmitters of systemic risk at the 90th and 99th percentiles over the full sample period.

While Barclays, Scotia Bank, JP Morgan, Bank of America, and Banco Santander are the five banks that propagate most systemic risk after median shocks, the 10th and 1st percentiles are dominated by the UK-German banks and by the Spanish-US banks, respectively. It should be noted that the full sample covers tranquil periods as well as tumultuous periods. Since spillovers are present during both good and bad times, but intensify during crisis periods (Rigobon, 2019), full sample analysis presents insight on interconnectedness, rather than contagion. In this sense, regardless of whether they create contagion or not, the above-mentioned banks could be considered as the most interconnected banks over the entire sample period. Finally, systemic risk spillovers network over the full sample period highlights the central position of the European and British banks. Similar to crisis periods, clustering is possible only at the median.

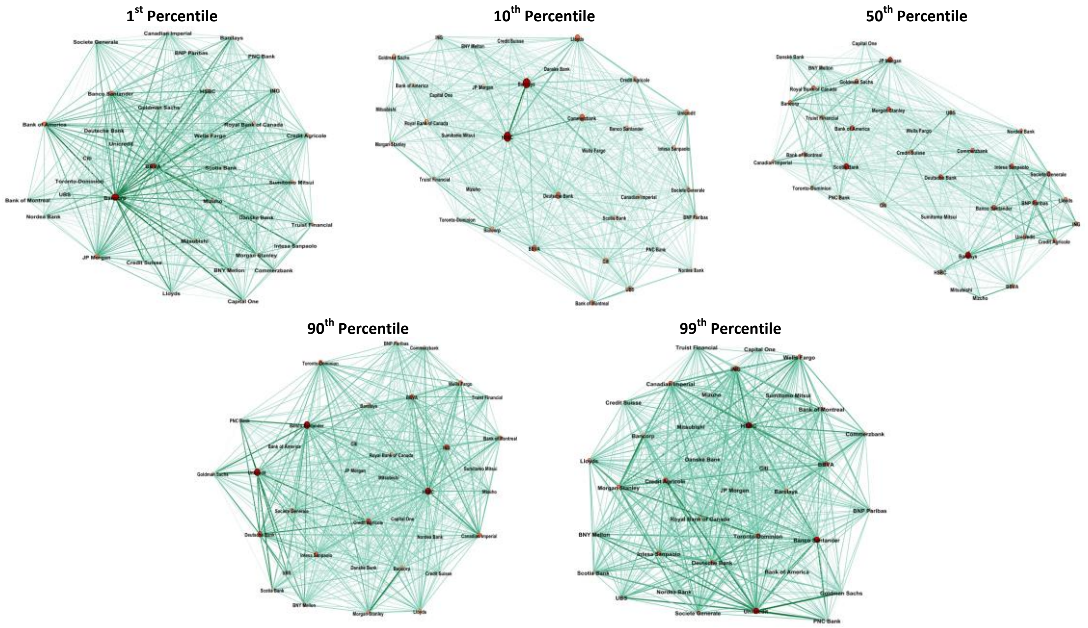

Figure 11. Systemic Risk Spillovers Network During the Full Sample Period

1.7. CONCLUSION

This study examines systemic risk contagion using data from 36 of the world's 50 largest banks. I follow a two-step procedure. First, I construct a new contagion test by incorporating time-varying causality and correlations, then I use the new contagion measure to identify contagion events over the period 2004-2021 and determine the direction of contagion. Second, given that the risk transmission mechanism differs according to the magnitude of financial shocks and whether they are adverse or beneficial, I employ the QC methodology developed by Ando et al. (2022), which allows the calculation of systemic risk connectedness measures at the 1st, 10th, 50th, 90th, and 99th percentiles to represent the effects of extremely beneficial, beneficial, average, adverse, and extremely adverse shocks, respectively. I then identify the largest transmitters of systemic risk and scrutinize the network topology of systemic risk spillovers during the four crisis periods. The newly developed contagion test identifies various contagion episodes, mostly occurring during four major distress periods: The GFC, the ESDC, 2014-2017, and the Covid-19 Pandemic. The test also provides evidence on both uni-directional and bi-directional contagion and implies that net transmitters and receivers of systemic risk differ significantly in each contagion period.

I find that the US is the epicenter of systemic risk during the GFC, and the spread of systemic risk from the US to other regions occurs about a year before Lehman's collapse, just as the US yield curve is inverted. This finding indicates that the crisis was signaled long before Lehman’s collapse and policymakers could have mitigated the adverse effects of the GFC by taking necessary measures. During the GFC, the US banks not only dominated systemic risk transmission at the median and higher percentiles but were also among the largest transmitters at the 1st and 10th percentiles. This shows that the GFC carries the US label in all respects. On the other hand, the contagion test detects uni-directional contagion from Europe to the UK and Canada during the GFC. European banks, especially Spanish banks, are among the top transmitters of systemic risk at the 90th and 99th percentiles, and four of the five largest systemic risk transmitters at the 1st percentile are European banks. This points out that European banks are quickly integrated into the shock propagation network during the GFC, either because of their fragility or interconnectedness. It could also be inferred that European banks transmit systemic risk after large adverse and beneficial shocks rather than average or median shocks during the GFC. Finally, Canada and the UK are net recipients of systemic risk during the GFC, while Japan transmits systemic risk to Canada. During the GFC, the spillover networks at the 10th and 50th percentiles show explicit clustering, but the networks in the remaining percentiles are dispersed.

During the ESDC, Europe and the UK are at the forefront, transmitting risks to United States and Canada at different times for different durations. Although being a medium-sized bank, BBVA is the largest and third larger transmitter of systemic risk at the 90th and 99th percentiles, respectively, due to its high interconnectedness. BNP Paribas, Barclays, HSBC, and Nordea are identified as the other largest risk transmitters during the ESDC, all of which, including BBVA, were listed as G-SIBs by the FSB during 2011-2013. Hence, my findings are in line with the FSB’s classification, highlighting the importance of higher loss absorption requirements imposed on systematically important banks under the Basel framework. Nevertheless, two small banks, Danske Bank and Bancorp, are estimated to be among the largest transmitters of systemic risk at the 90th and 99th percentiles. The fact that these banks have never been on the FSB's G-SIBs list, emphasizes that despite being among the smallest banks in the sample, both Danske Bank’s and Bancorp’s vulnerability to large adverse shocks, as well as their strong linkages with other banks, make them important transmitters during the ESDC. Surprisingly, while US banks are net recipients during the ESDC, Canadian banks are found to be in a bi-directional contagion relationship with European and British banks. No contagion is detected between US and Canada during the ESDC period. Finally, the systemic risk spillover networks during the ESDC and GFC are similar; both networks show signs of clustering among banks at the 10th and 50th percentiles, are dominated by a single bank at the 90th percentile and contain no dominant bank at the 10th percentile.

The 2014-2017 period includes several adverse shocks that led to increased interconnectedness and made the period significantly different from the GFC, ESDC and Covid-19 pandemic periods. During 2014-2017, bi-directional contagion is detected between US-Canada, US-UK, US-Japan, UK-Europe, Canada-Europe, Canada-Japan while no contagion is detected between United States-Europe, UK-Japan, Europe-Japan, and UK-Canada. British banks are at the epicenter of the risk transmission at the 90th and 99th percentiles, most likely due to the Brexit process. During 2014-2017, there is considerable heterogeneity among transmitters, as a result of a variety of shocks, each with its own specific nature. In addition to Bancorp, which has maintained its central role in risk transmission since the ESDC, UniCredit, Sumitomo Mitsui, Nordea, BNP Paribas and UBS are identified as the largest systemic risk transmitters at the 90th and 99th percentiles, all of which also appeared on the FSB's G-SIB list during 2014-2017. Similarly, risk transmission after median shocks and large beneficial shocks is also heterogeneous. Unlike the GFC and ESDC, the clustering observed in the systemic risk spillover networks at the 10th and 50th percentiles is found to apply only to Canadian banks over the 2014-2017 period.

Finally, despite the main differences between the Covid-19 pandemic and other crisis periods, the contagion test using aggregated data points to contagion dynamics similar to those observed in the 2014-2017 turbulence period, as bidirectional contagion appears to be quite common. However, bank-level interconnectedness reveals that no single bank or region dominates the risk transmission at the 90th and 99th percentiles, in contrast to the GFC, ESDC and 2014-2017 turbulence periods. HSBC and BBVA are estimated to be the largest systemic risk transmitters during Covid-19 at the 90th and 99th percentiles, respectively. In this context, the role of HSBC, the third largest bank in the sample, shows the effect of asset size in risk transmission, while the role of BBVA, a medium-sized bank, shows the effect of interconnectedness. In addition to Canadian banks, Bancorp, Wells Fargo, BNP Paribas, Credit Agricole and Mizuho are the other significant systemic risk transmitters in this period. Finally, Intesa Sanpaolo, UBS, Canadian Imperial, and Wells Fargo play pivotal positions in the systemic risk spillover networks after extremely beneficial shocks, as they are among four of the five largest transmitters at both the 1st and 10th percentiles.

Over the full sample period 2004-2021, European banks are the main overall transmitters of systemic risk after extremely adverse shocks, with the exception of the GFC period. This finding is due both to the heterogeneity of the European sample and the abundance of adverse shocks whose effects are mostly confined to Europe, such as the Greek bailout and the Brexit process. UniCredit, Banco Santander, HSBC, and Credit Agricole stand out as the largest transmitters of systemic risk at the 90th and 99th percentiles over the full sample period. Barclays, Scotia Bank, JP Morgan, Bank of America, and Banco Santander are the five banks that propagate most systemic risk after median shocks, while the 1st and 10th percentiles are dominated by British-German and Spanish-US banks, respectively. It should be noted that the full sample covers tranquil periods as well as tumultuous periods. Since “spillovers are present in both good and bad times, but intensify during crisis periods” (Rigobon, 2019), the full sample analysis provides insights on interconnectedness rather than contagion. In this sense, regardless of whether they generate contagion or not, the banks mentioned above could be considered the most interconnected during 2004-2021.

The findings of this study suggest that the systemic risk transmission during crisis periods differs not only in terms of the magnitude and direction of shocks but also in terms of their speed. Hence, they emphasize the inadequacy of focusing on the effects of average shocks in systemic risk analysis, as systemic shocks tend to be larger. The findings also show that each contagion episode and turmoil period have different characteristics. For instance, while contagion between US-Canada and Canada-UK are stronger, more persistent, and longer lasting than contagion between other regions, contagion episodes originating in Japan tend to be short-lived, usually end within a week. Examining the network topology also provides valuable insights as systemic risk propagation networks differ in parallel with the variation of shocks across percentiles. Accordingly, banks show a very clear clustering behavior after median shocks during the GFC, ESDC, and Covid-19 periods, whereas no clustering among banks is observed for large adverse shocks during any of the four crisis periods. This suggests that, after large adverse shocks, regional and regulatory factors become less influential and idiosyncratic features kick in.

This study offers a novel contagion test combining time varying causality and correlations. Since the results show significant variations according to the period analyzed, it draws attention to the importance of using methods that take into account time-variation and non-linearity. It also highlights the advantages of employing connectedness measures that consider tail behavior in systemic risk modelling. The scope of this paper could be widened by expanding regional coverage to include banks from more countries such as Australia, Mexico, China, India, Russia, South Africa, and Brazil. Moreover, the network topology could be examined in more detail, employing more sophisticated community detection measures and spatial tools. Finally, the determinants of systemic risk contagion could be investigated by taking into account the idiosyncratic characteristics of banks other than size, considering that some banks spread more systemic risk than banks with larger asset size or market capitalization.

CHAPTER 2: DETERMINANTS OF SYSTEMIC RISK CONTAGION

2.1. INTRODUCTION

The global financial system has become highly interconnected over the past few decades. Following the financial liberalization in many countries during the 1980s, financial shocks propagated faster, causing financial crises to occur more frequently. The Tequila Crisis (1994), Asian Flu (1997), Russian Default (1998), Global Financial Crisis (2008), and European Sovereign Debt Crisis (2010) demonstrated that a turmoil in one country could quickly spread to other countries due to increased interdependence in the global financial system. In line with rapid shock transmission and surged incidences, the number of studies analyzing the transmission of shocks has proliferated in recent years. The literature has drawn an analogy between the economy and epidemics, calling the rapid transmission of financial shocks "contagion".

Contagion has had various definitions since its introduction to the financial economics literature during the 90s. It could be roughly described as the spread of disturbances between countries through co-movements in financial market instruments (Claessens et al., 2001). Other definitions are a significant increase in cross-market linkages after a shock to one country (Forbes and Rigobon, 2002), co-movements that cannot be explained by economic fundamentals (Masson, 1999), excess co-movements (Pindyck and Rotemberg, 1990), unexplained turmoil in financial markets (Sachs et al., 1996), the influence of extreme events such as jumps or outliers (Favero and Giavazzi, 2002), and strong correlations that exceed expectations (Edwards, 2000; Bekaert et al., 2005). Despite these voluminous attempts, there is no universally accepted definition of financial contagion.

While the level of financial risk of a firm or an investment portfolio could be gauged by several methodologies such as the Value at Risk (Leavens, 1945; Markowitz, 1952; Roy, 1952) and the Expected Shortfall (Basel Committee on Banking Supervision, 2013), these methodologies do not represent the risk of the financial system as a whole. As risks tend to spread among institutions in times of financial stress and ultimately threaten the entire financial system, more attention has been paid to systemic risk rather than the individual risk of financial institutions. Systemic risk was first analyzed during the 1990s

(Folkerts-Landau, 1990; Davis, 1995; Loretan, 1996; Rochet and Tirole, 1996; Angelini et al, 1996; Darby, 1997), but studies examining systemic risk proliferated after the Global Financial Crisis (GFC). Following the GFC, the outbreak of the 2010 European Sovereign Debt Crisis (ESDC) fueled the discussions on systemic risk further.

This study explores the determinants of systemic risk contagion using bank-level data. Instead of investigating systemic events, I focus on how systemic shocks transmit. Following the systemic risk literature, I use explanatory variables derived from balance sheets of banks representing size, profitability, capital adequacy, credit quality, leverage, and funding structure. As systemic shocks are known to be less frequent and usually more significant, I use excess adverse systemic risk spillovers at the 90th percentile as the dependent variable. My sample period spanning almost two decades allows me to analyze sub-periods and scrutinize the dynamics of four distinct crisis periods: The GFC, ESDC, 2014-2017 turmoil, and the Covid-19 pandemic. I follow a three-step procedure in the empirical analysis. First, I calculate the systemic risk contributions of banks by employing the Marginal Expected Shortfall (MES) methodology introduced by Acharya et al. (2017). Second, I compute a systemic risk contagion metric, excess systemic risk spillovers at the 90th percentile, through the quantile connectedness approach (Ando et al., 2022). Finally, I examine the determinants of systemic risk contagion by employing the Arellano-Bover/Blundell-Bond dynamic panel GMM (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998), Common Correlated Effects Mean Group (Pesaran, 2006; Chudik and Pesaran, 2015; Neal, 2015), and Time-varying Vector Autoregressions (Primiceri, 2005; Nakajima, 2011) methodologies. To my knowledge, this is the first study that examines the determinants of systemic risk contagion based on its tail behavior while taking time variation into account, slope heterogeneity, and endogeneity. In this respect, I aim to fill the gap in the literature. The study is organized as follows. Section 2 provides a literature review on systemic risk, contagion, and its potential determinants. Section 3 presents data and methodology. Section 4 discusses the results of the empirical analysis. Section 5 concludes and provides policy implications.

2.2. LITERATURE REVIEW

2.2.1. Systemic Risk

Systemic risk has been extensively investigated in the literature, yet there is no consensus on its definition. Adrian and Brunnermeier (2016) define systemic risk as “the risk that institutional distress spreads widely and distorts the supply of credit and capital to the real economy”. Patro et al. (2013) acknowledge systemic risk as “a situation in which the entire financial system is simultaneously stressed, with an ensuing credit and liquidity crisis”. According to the Bank for International Settlements (1994), systemic risk is “the failure of a participant to meet its contractual obligations may, in turn, cause other participants to default with a chain reaction leading to broader financial difficulties”. The European Central Bank adopts a similar definition by expressing systemic risk as “the possibility of an institution failing to honor its obligations, prompting the same failure on the part of other participants and eventually jeopardizing the stability of the financial system” (European Central Bank, 2009). Different definitions, however, share some common points, such as increased uncertainty, exposure, vulnerability, malfunctioning, and bankruptcy.

Since the definition of systemic risk is vague, the majority of the studies in the literature focus on defining an accurate measure of systemic risk. These metrics include the Delta Conditional Value at Risk by Adrian and Brunnermeier (2016), Alternative Delta Conditional Value at Risk by Girardi and Ergun (2013), Marginal Expected Shortfall by Acharya et al. (2017), Distress Insurance Premium by Huang et al. (2009, 2012), Systemic Risk Measure by Brownlees and Engle (2017), Component Expected Shortfall by Banulescu and Dumitrescu (2015), CATFIN by Allen et al. (2012), and PCAS by Billio et al. (2012). These distinct methodologies meet on common ground since they aim to capture potential systemic crises by measuring the increase in tail co-movements.

2.2.2. Determinants of Systemic Risk

Determinants of systemic risk have been a hot topic in the literature, especially after the GFC. In this section, I review the determinants of systemic risk, with particular emphasis on balance sheet indicators reflecting idiosyncratic features of financial institutions.

2.2.2.1. Bank Size

Bank size is often positively associated with systemic risk[8] (De Jonghe, 2010; Drehmann and Tarashev, 2011; Hovakimian et al., 2012; Vallascas and Keasey, 2012; Pais and Stork, 2013; Anginer et al., 2014; Sedunov, 2016; Laeven et al., 2016; Black et al., 2016; Varotto and Zhao, 2018; Duan et al., 2021; Altunbas et al., 2022). According to this view, large banks tend to create higher systemic risk for two reasons. First, banks with large total assets are more likely to have lower capital and net stable funding ratios while having higher exposure to risky activities (Laeven et al., 2016). Second, large banks take excessive risk by relying on TBTF subsidies (Financial Stability Board, 2010; Farhi and Tirole, 2012; Gandhi and Lustig, 2015; Chaudron, 2018; Dávila and Walther, 2020). Knowing that a bank has a high probability of bailing out due to its size, lenders might ignore the bank's credit risk and provide funding at lower rates. This mechanism is an example of a moral hazard, and excessive risk-taking behavior could eventually contribute to systemic risk. However, government subsidies to large banks do not necessarily intensify systemic risk. Berger et al. (2020) show that the Troubled Assets Relief Program (TARP) in the U.S. has been successful in decreasing systemic risk contributions of banks, particularly for larger banks. Similarly, as Cordella and Yeyati (2003) argue, bailout programs reduce bank risk by creating a risk extenuating value effect that dominates the moral hazard issue[9]. Finally, according to another view on the connection between systemic risk and bank size, large banks are less vulnerable to macroeconomic and liquidity risks thanks to their operational diversity and capital reserves (Boyd et al., 2004; Rahman et al., 2022). Although most studies consider the rising systemic risk with size, some underline the advantages and benefits coming concomitant with larger asset size and assert that there might be a negative relationship between systemic risk and bank size (Knaup and Wagner, 2012).

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[8] Total assets are among the main determinants of systemic risk in both the Dodd-Frank Act and the Basel Criteria.

[9] The nexus between government support and moral hazard is extensively investigated in the literature. Elyasiani et al. (2014) find that the TARP program lowered the liquidity risk but boosted credit risk as banks enhanced their lending to risky borrowers by providing funding from core deposits. Duchin and Sosyura (2014) reach the same conclusion and emphasize that default risk of bailed-out banks surge despite improved regulatory capital ratios. Black and Hazelwood (2013) argue that degree of risk taking differed by bank size for TARP recipients, and larger banks became riskier. A similar conclusion is reached by Dávila and Walther (2020), that is, large banks under government support tend to take on more leverage, become riskier, and raise the magnitude of government bailouts. Antzoulatos and Tsoumas (2014) assert that government support induces moral hazard when a country's institutions and regulatory framework are weak.

2.2.2.2. Capital Adequacy

Capital could be addressed as the “lifeblood” of distressed financial systems. Past crises have demonstrated that capital shortfall is a significant risk factor and systemic risk occurs when the financial sector is undercapitalized (Acharya et al., 2013). It is no surprise that the literature is dominated by studies that emphasize the necessity of having adequate capital buffers to prevent systemic risk (De Jonghe, 2010; Vallascas and Keasey, 2012; Laeven et al., 2016; Nistor and Ongena, 2020; Berger et al., 2020; Duan et al., 2021). These studies proliferated after the GFC, in line with regulatory reforms that strengthened the banks' balance sheets through reduced leverage and elevated capital buffers. Regulatory reforms such as the Dodd-Frank Act and Basel III imposed stricter regulations on SIFIs to address TBTF, Too Systematically Important To Fail (TSITF), and moral hazard concerns[10]. Nevertheless, optimal levels of capital buffers, both for banks and the financial system, are still being debated in the literature after more than a decade since the occurrence of the GFC (Dagher et al. 2016). Supporters of high capital buffers highlight the shortcomings of excessive leverage, the risks it brings, and the negative externalities it creates (Admati and Hellwig, 2014). They emphasize the safeguarding role of large capital buffers against extreme shocks (Altunbas et al., 2022, De Jonghe, 2010) since well-capitalized banks are less prone to information contagion (Acharya and Yorulmazer, 2008) and less inclined to take excessive risks (Gambacorta and Mistrulli, 2004). Others point out the delicate trade-off between financial soundness and lending activity arguing that setting capital buffers too high would increase the cost of funding, hamper economic growth, and promote unregulated financial intermediaries (Dagher et al. 2016).

2.2.2.3. Profitability

Profitability is often regarded as an important determinant of systemic risk and is usually measured by Return on assets (ROA). ROA shows the profitability of a company compared to its total assets and could affect systemic risk in three ways. First, the share of non-interest income in total income could promote ROA but also drives systemic risk since non-interest income generating activities are often deemed riskier (Demirguc-Kunt

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[10] Despite the success of recapitalizations in reducing systemic risk (Nistor and Ongena, 2020; Berger et al., 2020), policymakers prefer preventing the emergence of systemic events through capital regulations since recapitalizations are costly and have severe adverse effects on real economy.

and Huizinga, 2010; Knaup and Wagner, 2012; Williams, 2016; Rahman et al., 2022). Second, by promoting prudence and providing additional buffers, profits could calm banks' risk-taking behavior, and both banks' idiosyncratic risks and systemic risk contribution could be expected to decline (Lehar, 2005; Xu et al., 2019). However, this mechanism might not work when interest rates are very low. The third channel emerges under prolonged low interest rate periods, during which investors might look out for risky assets offering high yields, leading to the “search for yield” phenomenon (Dell’Ariccia and Marquez, 2013; Brunnermeier, 2001; Dell’Ariccia et al., 2011; Adrian and Shin, 2010; Buch et al., 2014). This tendency amplifies, and interest rate risk deepens if the managers have ambitious targets for rate of return (Rajan, 2006; Colletaz et al, 2018).

2.2.2.4. Funding Structure

Banks primarily provide funding from retail (customer) deposits and wholesale funding. Retail deposits constitute the most common type of funding for many banks since they provide stable and low-cost financing. Retail deposits are often regarded as “sluggish” or “sticky” since they rely on a local customer base, provide protection by deposit guarantee schemes, and are less sensitive to fluctuations in interest rates (Huang and Ratnovski, 2011). On the other hand, wholesale funding is provided by large institutional investors, is more sensitive to interest rates, unstable, and tends to be riskier as it creates maturity mismatch for banks (Demirguc-Kunt and Huizinga, 2010; López-Espinosa et al., 2013). Furthermore, financial institutions (FIs) that depend on short-term funding through the wholesale market are more interconnected to other banks, which makes them vulnerable to market conditions (López-Espinosa et al., 2012). A strand of the literature shows that liquidity risk increases in line with the share of wholesale funding in total funding and emphasizes too much reliance on short-term borrowing could create a systemic crisis, just like during the GFC[11] (Brunnermeier and Oehmke, 2013; Cornett et al., 2011; Diamond and Rajan, 2009; Raddatz, 2010; Damar et al., 2013; Xu et al., 2019). However, high reliance on deposit funding could also contribute to systemic risk through deposit insurance systems[12] since these systems could create moral hazard under weak institutions[13] (Acharya, 2009; Demirguc-Kunt and Detragiache, 1997; Calomiris and

[11] Gorton and Metrick (2012) identify the GFC as a bank run emerged in the securitized banking system.
[12] See Anginer and Demirguc-Kunt (2018) for economic costs and benefits of deposit insurance.
[13] Since deposit insurance systems provide depositors protection against bank insolvencies and reduce the probability of bank runs, they could also contribute to financial stability (Gropp and Vesala, 2004; DeLong and Saunders, 2011; Hovakimian et al., 2012).

Chen, 2018; Bostandzic and Weiß, 2018; Hoque et al., 2015; Calomiris and Jaremski, 2016; Calomiris and Chen, 2018). Several studies emphasize that adverse effects related to a moral hazard could be offset by having good institutions and a better regulatory framework (Angkinand, 2009; Demirguç-Kunt and Detragiache, 2002; Cull et al., 2004; Anginer et al.; 2014; Angkinand and Wihlborg, 2010).

2.2.2.5. Credit Quality

NPLs depress banks' profitability and hamper new lending, eventually slowing down economies by impairing their financial intermediation role. Banks are required to allocate “loan loss reserves” to cover potential insolvencies for bad and good loans that may become uncollectible in the future (Walter, 1991). These buffers enable banks to cover expected loan losses without deteriorating their capital structure. The ratio of loan loss reserves to non-performing loans is called “NPL Coverage Ratio”, and the uncovered portion of the NPLs constitutes an important indicator for the credit risk of banks[14]. Inadequate loan loss provisioning could damage a bank's profitability and deplete its capital (Arner et al., 2021). Wong et al. (2011) identify inadequate loan-loss provisions as the primary driver of systemic risk in Hong Kong and conclude that loan loss reserves could be used to lower systemic risk. Nevertheless, it should be noted that loan loss reserves are prone to manipulation in accrual accounting (Wahlen, 1994; Alali and Jaggi, 2011), and managers tend to exploit these reserves to meet their targets (Laeven and Majnoni, 2003; Beatty and Liao, 2014) as well as to perform income smoothing (Lobo and Yang, 2001; Kilic et al., 2013; Morris et al., 2016) and capital management (Anandarajan et al., 2007; Curcio and Hasan, 2015). Moreover, loan loss provisioning is procyclical (Wong et al., 2011, Huizinga and Laeven, 2019), and banks tend to have more loan loss provisions during times of political uncertainty (Ng et al., 2020).

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[14] Loan loss principles differ significantly among banks throughout the world. In Europe, large banks have a tendency to have smaller NPL coverage compared to small and mid-size banks (Alessi et al. (2021), while the loan loss reserves of US banks have been more volatile and higher than that of EU banks due to differences in accounting standards (European Banking Authority, 2021). NPL coverage ratios tend to be higher under high share of deposit funding, well-developed NPL secondary markets, robust growth environment, tighter supervision, and very low asset quality (Alessi et al., 2019). The tendency of using discretionary loan loss reserves has elevated since the adoption of Basel III regulatory framework (Jutasompakorn et al., 2021).

2.2.2.6. Leverage

Financial leverage reflects the trade-off between the cost of equity and the advantages of debt financing (Bussière et al., 2020). Excessive leverage increases the financial risk (Thurner, 2011), and hence, it is listed among the main reasons behind financial instability episodes and banking crises, including the GFC (Thurner, 2011; Miele and Sales, 2011; Schularick and Taylor, 2012; Thakor, 2014; Papanikolaou and Wolff, 2014). According to this view, financial institutions with high leverage ratios tend to involve in riskier lending activities, create more volatility, and contribute more to systemic risk compared to their low-leveraged counterparts (Shleifer and Vishny, 2010; Adrian and Shin, 2010; Acharya et al., 2013; Hovakimian et al., 2012; Acharya and Thakor, 2016; Brunnermeier et al., 2020; Xu et al., 2019; Duan et al., 2021). Thus, a strand of the literature argues that highly levered banks should hold more capital to promote financial stability and prevent future crises (Kuzubas et al., 2016; Valencia, 2014, Acosta-Smith et al., 2020).

Financial leverage could also be affected by changes in asset prices through the value of equity. When the value of equity surges due to increased asset prices, a bank's leverage ratio decreases. Then, it may be possible for the bank to increase leverage by increasing its non-equity liabilities and then expanding lending (Adrian and Shin, 2010). This mechanism implies a positive relation between leverage and balance sheet size, which is called "leverage procyclicality" (Kalemli-Ozcan et al., 2012; Damar et al., 2013; Beccalli et al.; 2015; Aymanns and Farmer; 2015; Cincinelli et al.; 2021). Leverage procyclicality is often associated positively with wholesale funding since quick access to market-based funds, such as institutional deposits and repos enable FIs to adjust leverage ratios rapidly (Damar et al., 2013). Acquiring short-term debt through the wholesale market and funding high-risk borrowers -a widely used policy before the GFC- increases the systemic risk (Adrian and Shin, 2010). Nevertheless, in line with banks' increased preference to use customer deposits over wholesale funding since the GFC, leverage procyclicality declined during the last decade.

Finally, the literature highlights that deleveraging has a negative impact on financial stability when agents simultaneously sell assets to meet regulatory standards, especially during downturns when markets are illiquid (Brunnermeier and Pedersen, 2009). These instabilities include contagion (Geanakoplos, 2010; Kuzubas et al., 2016; Acharya and

Thakor, 2016), increased volatility (Adrian and Shin, 2010; Aymanns and Farmer; 2015), fire sales (Acharya and Viswanathan, 2011), elevated systemic risk (Tasca et al., 2014; Poledna et al., 2014; Papanikolaou and Wolff, 2015; Phelan, 2016; Aymanns et al., 2016), and market failure (Thurner et al., 2012).

2.2.2.7. Other Determinants

A strand of the literature associates the bank's ownership structure with its financial risk contribution. State-owned and politically connected banks are often found to have less default risk than private ones since they enjoy stronger government protection and implicit bail-out guarantee (Faccio et al., 2006; Acharya and Kulkarni 2012). In turn, public banks could have higher operational risk as a result of excessive risk-taking brought by government ownership (Boubakri et al., 2020). Some studies argue that since foreign and multinational banks operating in multiple countries diversify risks better, they contribute less to systemic risk than local banks (Fiala and Havranek, 2017; Faia et al., 2019). Moreover, non-traditional and off-balance sheet financial activities (López-Espinosa et al., 2013; Karim et al., 2013; Calmès and Théoret, 2013; Sedunov, 2016), regulatory regime and financial structure (Weiß et al., 2014; Qin and Zhou, 2019) are suggested as important drivers of systemic risk.

2.2.3. Contagion

King and Wadhwani (1990)'s seminal paper is among the earliest studies on financial contagion. The authors define contagion as "a significant increase in correlations of asset returns" and examine the stock market crash in 1987. In general, early studies on financial contagion involve examining whether bad news, such as an announcement of a bank failure, affects other banks negatively. If the result confirms the adverse effect, the authors conclude that there is a contagious effect (Acharya and Yorulmazer, 2008).

Many scholars distinguish the propagation of financial risks through "interconnectedness" and "contagion" concepts. Interconnectedness refers to the complex relationships between economic units arising from financial transactions and obligations. Contagion, on the other hand, corresponds to "a strong propagation of failures from one institution, market, or system to another" (De Bandt and Hartmann, 2000). It could be argued that interconnectedness and contagion overlap and interact in various ways (Scott, 2014). However, the concept of financial contagion remains controversial in the literature. Forbes and Rigobon (2002) posit that linkages between financial agents do not necessarily imply contagion. They stress that contagion exists only if there is an increased dependence between two markets, with no dependence prior to the shock. The authors refer to this phenomenon as “interdependence” or “spillovers” rather than contagion. However, the authors also imply that the difference between the concepts of spillover and contagion is semantic. Rigobon (2019) presents two aspects to distinguish between spillover and contagion concepts. First, if the magnitude of the co-movement is higher than the scholar’s expectations, it could be called contagion. Second, while spillovers are present during both tranquil and tumultuous periods, contagion appears to be more significant during crises. Again, as the work of Forbes and Rigobon (2002) suggests, the difference is hardly discernible. Regardless of the adopted concept, interdependence, spillover, or contagion, researchers pay great attention to the topic, especially after three crises in 1997, 1998, and 2008.

The literature implies various types of contagion. The first type is the usual interdependence of the markets, where shocks are transmitted between financial agents through real and financial linkages. This interdependence is referred to as “fundamentals-based contagion” and could occur during both tranquil and tumultuous periods (Calvo and Reinhart, 1996). The second type of contagion is called “shift” contagion and indicates extreme co-movements that cannot be explained with usual linkages and fundamentals (Forbes and Rigobon, 2002). Shift contagion implies co-movements “driven by change in the structural transmission of shocks across countries rather than temporary changes in the size of underlying shocks” (Gravelle et al., 2006). It usually launches and recedes rapidly (Ait-Sahalïa et al., 2015) and results in a financial crisis involving a sharp decline in economic sentiment, financial panic, and bank runs (Kleimeier and Sander, 2003). The third type of contagion is “pure” contagion, which reflects excess contagion in turbulent times that cannot be explained by market fundamentals or common shocks (Flavin and Panopoulou, 2010). Pure contagion asserts shocks are triggered by a shift in idiosyncratic market sentiment (Gómez-Puig and Sosvilla-Rivero, 2016). However, distinguishing between contagion types is difficult as the transmission of shocks is complex and encompasses several features (Grinis, 2015). As shown in (Gómez-Puig and Sosvilla-Rivero, 2016), pure and fundamentals-based contagion can also coexist.

2.2.4. Systemic Risk Contagion

There is a plethora of studies examining the drivers of systemic risk, but studies scrutinizing the determinants of systemic risk contagion are relatively few. Some studies employ idiosyncratic features of financial institutions as potential determinants of systemic risk contagion. Among these, López-Espinosa et al. (2012) employ CoVaR spillovers to identify the main drivers of systemic contagion during 2001-2009. They find short-term wholesale funding as the main determinant of systemic contagion between 22 large international banks. The authors assert neither size nor leverage plays an important role in systemic shock propagation. López-Espinosa et al. (2013) reach a similar finding, concluding that unstable funding is the main driver of systemic risk between 2001 and 2010. In a recent study analyzing data from 116 European banks, Zedda and Cannas (2020) do not refer size among the major drivers of systemic risk contagion. Instead, capital adequacy and interbank exposures could be used to explain contagious effects. Souza et al. (2015) indicate that size is important in explaining systemic contagion only when FIs have vulnerable lenders. They also show that financial institutions are prone to contagion when their exposure/capital ratio is low. On the other hand, Weiß and Muhlnickel (2014) and Siebenbrunner et al. (2017) denote that size is the primary determinant of systemic risk contribution for insurers in the United States and banks in Austria.

Interbank exposures stand out as another prominent determinant of systemic risk propagation. Allen and Gale (2000) show that the conversion of interbank spillovers to contagion essentially depends on the "*completeness of the structure of interregional claims*" and the network structure of that market. Carrying out simulations for the German banking sector, Memmel and Sachs (2013) find that interbank exposure distribution among banks, along with capital adequacy and average *loss given default* (LGD), is an important determinant of interbank contagion. Degryse and Nguyen (2007) run stress tests for the Belgian financial system and assert that interbank exposures have immense potential to create a systemic crisis depending on the interbank market structure, capital adequacy, internationalization level of assets, and effectiveness of regulations. In their study, focusing on the network structure of the financial system, Nier et al. (2007)

conclude that net worth, size of interbank liabilities, interbank connectivity, and concentration level of the financial system affect systemic risk contagion. Gai and Kapadia (2010) reach a similar finding and assert capital and bank connectivity are important determinants of contagion. Finally, Sachs (2014) stresses that contagious effects mitigate in a system with a lower LGD and interbank claims but a higher capital level.

Some studies use network theory to examine systemic risk contagion. Using Austrian banking sector data, Elsinger et al. (2006) exhibit that contagion is a rare phenomenon, and systemic risk mostly originates in correlated portfolio exposures. Lee (2013) highlights that both direct and indirect liquidity shortages could turn into systemic events due to balance sheet interconnectedness and fire sales. In another study, Markose et al. (2012) analyze systemic risk contagion through concentration in bilateral CDS exposures of banks. They identify J.P. Morgan as the most interconnected bank, followed by large European banks. The authors suggest a progressive systemic tax based on banks' interconnectedness to preserve the stability of the system. Hautsch et al. (2015) define realized systemic risk betas and assess the importance of international banks by employing the LASSO. Wang et al. (2018) show that systemic risk contagion is mainly caused by direct credit and liquidity exposures in China. Caccioli et al. (2014) examine the stability of the financial system by focusing on common asset holdings of financial institutions. The authors build a model that amplifies shocks through diversification, crowding, and leverage. While asset diversification promotes stability, too much diversification could amplify contagion. Elliott et al. (2014), Aymanns and Georg (2015), Paltalidis et al. (2015), Härdle et al. (2016), Verma et al. (2019), Chen et al. (2019), Zhang et al. (2020) are some of the other studies that employ network theory to scrutinize systemic risk connectedness and contagion.

2.2.5. Summary

The literature emphasizes the importance of idiosyncratic features in explaining systemic risk. While various features such as size, capital adequacy and leverage are identified as substantial drivers of systemic risk, there are differences among the findings. In some studies, a feature identified as the most substantial determinant of systemic risk does not have any effect on systemic risk in others. I observe two reasons behind this divergence. First, the effects of idiosyncratic features depend on many factors such as the institutional structure, the stringency of regulations or the presence of moral hazard. For example, a feature that is expected to contribute to financial stability may create or propagate systemic risk under weak institutions. This implies that applying the same analysis under strong institutions and a better regulatory framework might yield different results. Second, there is considerable time variation and non-linearity in the findings. A feature found to be a substantial driver of systemic risk at one point in time might be found to lose its effectiveness over time or to have no effect at all at another period. This makes sense as macroeconomic conditions, regulations and vulnerabilities change from time to time and financial institutions need to adapt quickly to the "new normal". Indeed, the deleveraging, increased preference for deposit funding, and shift away from off-balance sheet activities since the GFC illustrate how banks have changed their risk management. During this transition, the drivers of systemic risk might also have changed over time, leading to conflicting findings in the literature.

The inconsistency of the findings and the fact that they vary across the periods examined emphasize the importance of applying a holistic and time-varying approach to systemic risk modeling and lead us to use methods that meet these needs. Moreover, given the heterogeneity across financial institutions and the benefits of using bank-level data, I use bank-level data rather than aggregated data to examine systemic risk contagion at the international level. Therefore, I derive several explanatory variables representing idiosyncratic characteristics from banks' balance sheets and investigate how their impact on systemic risk contagion changes over time.

2.3. DATA AND METHODOLOGY

2.3.1. Data

I use data from 27 of the world’s 50 largest banks covering the period 2004Q2-2021Q3 to model systemic risk contagion. Banks are selected based on their balance sheet size, market capitalization, and data availability. As of September 2021, total assets and market capitalization in my sample are $33.2 trillion and $2.5 trillion, respectively. Names, market values, and total assets of the banks are exhibited in Table 6.

As discussed in the previous section, I use several suggested variables derived from balance sheets of banks representing size (Total Assets), profitability (Return on Assets), capital (Tier 1 Capital Ratio), credit quality (Non-performing Loan Coverage Ratio), leverage (Assets/Equity), and funding structure (Deposit/Assets). In addition to idiosyncratic features of banks, I also employ variables representing global liquidity (Global Liquidity/GDP)[15] and global economic activity (Global Industrial Production Volume) to control for observed common shocks. The descriptive statistics, definitions, and data sources of variables are shown in Table 7.

2.3.2. Marginal Expected Shortfall (MES)

To gauge systemic risk, I employ Marginal Expected Shortfall (MES)[16] methodology introduced by Acharya et al. (2017) and advanced by Brownlees and Engle (2017). The MES "measures a firm's expected equity loss when the market falls below a certain threshold over a given horizon and predicts the contribution of an institution i to systemic risk as measured by the expected shortfall of the system" (Benoit et al., 2013).

The systemic risk calculated with the MES methodology is denoted in Figure 12. Accordingly, the MES captures not only large-scale crises such as the GFC, ESDC and Covid-19, but also milder shocks such as the Russian Crisis in 2014-2015 and the Brexit process in 2016. It also highlights the heterogeneity among banks, as some significantly diverge from the average in turbulent times.

[15] Since the GFC, banks have chosen to invest in ultra-safe instruments such as short-dated treasury securities or central bank reverse repo facilities, rather than lending to borrowers or investing in stock markets. To prevent this phenomenon, the ECB as well as central banks of Switzerland, Denmark, Sweden, and Japan have adopted negative deposit rates since 2008. As the "parked" money in central banks does not really "flow" in the system, I employ the sum of total international claims/global GDP as an indicant of global liquidity.

[16] See Appendix 1.

Table 6. Banks in the Sample

	Institution	Origin	Total Assets (US$ Billion)	Market Cap (US$ Billion)
1	J.P. Morgan	U.S.	3,744	489
2	Mitsubishi	Japan	3,408	80
3	Bank of America	U.S.	2,434	357
4	Sumitomo Mitsui	Japan	1,955	49
5	Citi	U.S.	1,951	142
6	Wells Fargo	U.S.	1,928	191
7	Mizuho	Japan	1,875	36
8	Banco Santander	Spain	1,703	63
9	Deutsche Bank	Germany	1,456	26
10	Royal Bank of Canada	Canada	1,116	140
11	Toronto-Dominion	Canada	1,102	118
12	Intesa Sanpaolo	Italy	1,058	55
13	UBS	Switzerland	972	59
14	UniCredit	Italy	960	30
15	Scotia Bank	Canada	873	74
16	Credit Suisse	Switzerland	813	27
17	BBVA	Spain	782	44
18	Bank of Montreal	Canada	665	62
19	Nordea Bank	Finland	623	22
20	Danske Bank	Denmark	565	15
21	U.S. Bancorp	U.S.	554	88
22	CIBC	Canada	496	51
23	Commerzbank	Germany	478	9
24	Truist Financial	U.S.	473	78
25	PNC	U.S.	410	83
26	Capital One	U.S.	390	72
27	BNY Mellon	U.S.	382	45
TOTAL			**33,166**	**2,508**

Source: Bloomberg

Table 7. Variable Definitions and Data Sources

Variable Name	Obs	Mean	Std. Dev.	Min	Max	Definition	Representing Feature	Data Source
Return on Assets	1,890	0.66	0.59	-1.59	3.38	Net Income/Average Total Assets	Profitability	Bloomberg
Tier 1 Ratio	1,890	12.11	3.13	5.34	22.70	Tier 1 Risk-Based Capital Ratio (%)	Capital Adequacy	Bloomberg
Deposits/Total Assets	1,890	53.57	15.68	17.81	81.72	Deposits/Total Assets	Funding Structure	Bloomberg
Total Assets	1,890	-1.70	1.37	-3.41	2.90	Normalized Total Assets	Size	Bloomberg
NPL Coverage Ratio	1,890	1.60	2.38	0.15	26.32	Loan Loss Reserves / Non-performing Loans	Credit Quality	Bloomberg
Assets/Equity	1,890	17.24	8.27	5.63	98.30	Assets/Shareholder's Equity	Leverage	Bloomberg
Global Liquidity	1,890	47.54	6.68	39.43	66.76	Sum of international claims/GDP	Global Liquidity	Bank for International Settlements
Global Economic Activity	1,890	108.44	12.63	86.29	128.95	Global Industrial Production Index	Global Economic Activity	CPB Netherlands Bureau for Economic Policy Analysis

Note: Historical stock prices and market capitalization data are obtained from Bloomberg.

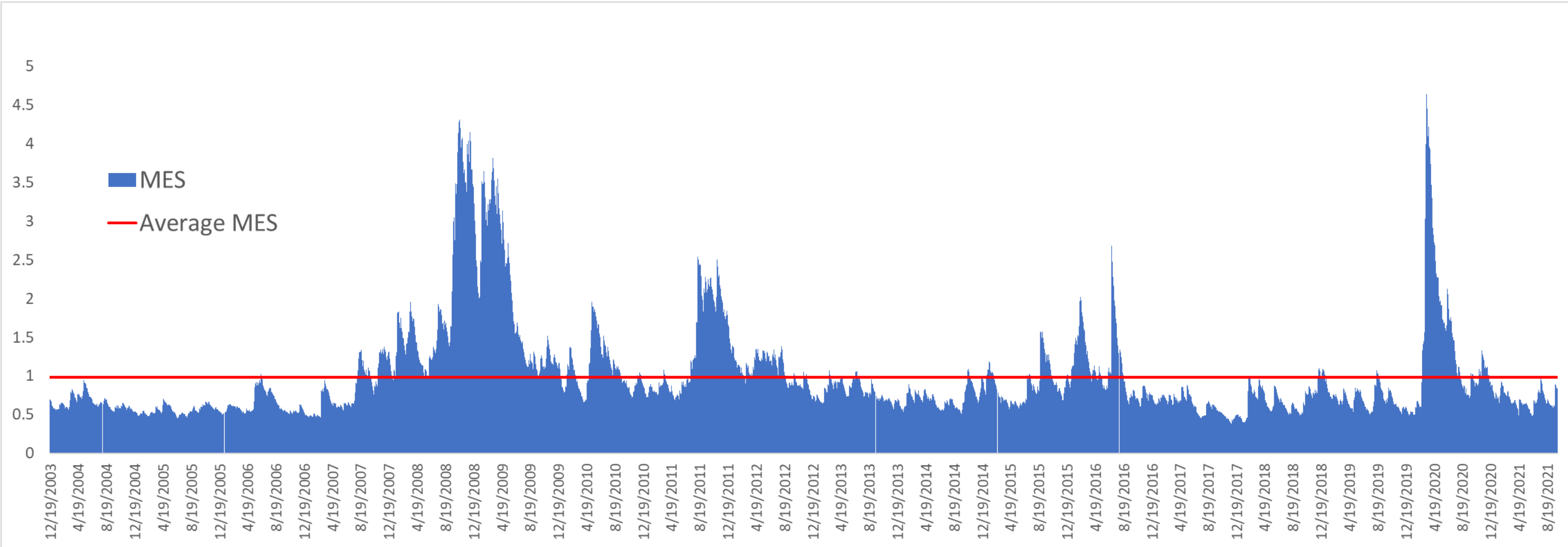

Figure 12. Marginal Expected Shortfall (MES)

Source: Author's calculations

Summary statistics exhibited in Table 8 indicate MES data are positively skewed, non-normal, and leptokurtic. Therefore, I focus on tail movements rather than the conditional mean or median.

Table 8. Descriptive Statistics of MES

	Mean	Skewness	Kurtosis	J-B
JP Morgan	0.027	3.027***	10.433***	29347.114***
Bank of America	0.031	3.206***	11.106***	33172.760***
Citi	0.032	3.555***	14.971***	55405.091***
Wells Fargo	0.026	3.142***	11.088***	32763.610***
Mitsubishi	0.028	2.099***	6.843***	12999.599***
Sumitomo Mitsui	0.027	2.254***	7.879***	16620.532***
Deutsche Bank	0.03	2.317***	6.919***	13988.355***
Banco Santander	0.034	2.142***	6.560***	12383.292***
Mizuho	0.027	2.297***	8.289***	18115.512***
Royal Bank of Canada	0.015	4.141***	23.724***	127357.766***
Toronto-Dominion	0.015	4.239***	26.400***	155083.318***
UniCredit	0.038	1.649***	3.356***	4467.088***
UBS	0.028	2.711***	9.551***	24332.114***
BBVA	0.033	2.022***	5.674***	9791.763***
Credit Suisse	0.029	3.057***	12.953***	41384.281***
Scotia Bank	0.014	4.256***	25.489***	145661.817***
Nordea Bank	0.022	2.057***	5.029***	8514.977***
Intesa Sanpaolo	0.036	2.166***	6.292***	11772.363***
Bank of Montreal	0.014	4.854***	36.718***	290956.589***
Danske Bank	0.023	2.611***	10.565***	28011.563***
Bancorp	0.023	3.040***	10.288***	28807.070***
Canadian Imperial	0.015	4.436***	28.362***	178138.110***
Commerzbank	0.032	2.241***	6.670***	13024.045***
Truist Financial	0.025	3.006***	10.897***	31244.986***
PNC Bank	0.025	4.157***	24.440***	134425.388***
Capital One	0.031	3.282***	12.676***	41102.533***
BNY Mellon	0.026	3.846***	19.525***	88830.814***

Descriptive statistics for the return series. Rejection of the null hypothesis at 1% significance level is indicated with ***. J-B is the Jarque-Bera statistic for normality

2.3.3. Quantile Connectedness Approach

To build my contagion metric, I employ the quantile connectedness methodology introduced by Ando et al. (2022) that advances the VAR based connectedness approach of Diebold and Yilmaz (2012, 2014). The Diebold and Yilmaz (DY) approach allows estimating the average topology of the network when an average shock hits the financial system. Nevertheless, DY approach might fall short of gauging the outcome of systemic shocks since systemic shocks are less frequent, usually larger, and propagate differently than average shocks (Ando et al., 2022). Quantile connectedness methodology captures the variation in network topology by running quantile vector autoregressions and calculating pairwise spillovers when extreme adverse and beneficial shocks affect the system. In this respect, rather than finding out "*how much of the future uncertainty associated with variable i can be attributed to shocks coming from variable j*?", I aim to capture "*how much of the future uncertainty associated with variable i can be attributed to idiosyncratic shocks coming from variable j as the shock size varies*?" (Ando et al., 2022). Employing systemic risk contributions of 27 banks, I obtain four important connectedness measures at the τ^{th} conditional quantile: (1) total connectedness among banks, (2) directional spillover effects from all banks to the i^{th}bank (FROM Spillovers), (3) directional spillover effects from the i^{th}bank to all banks (TO Spillovers), and (4) NET Spillovers for the i^{th}bank (TO Spillovers - FROM Spillovers)[17].

Figure 13 denotes the percentile variation of the total connectedness index. While the middle of the figure shows average shocks, the left and right sides show large beneficial and large adverse shocks, respectively[18]. The connectedness index hovers around 90 when average shocks hit the system around the median, but it reaches 95 when large adverse shocks kick in. It shows that more substantial spillovers are generally present in the right tail, indicating the magnitude of spillovers increases with size of adverse shocks. As systemic shocks are known to be less frequent and usually larger, I opt for higher percentiles to build my systemic risk contagion variable.

[17] See Appendix 2 for more information on Quantile Connectedness methodology.

[18] The announcement of a massive asset purchase program by the FED acts as a large beneficial systemic shock since this policy is implemented to decrease systemic risk. Failure of highly interconnected international banks, on the other hand, is an example for a large adverse shock, as it is most likely to drive systemic risk worldwide.

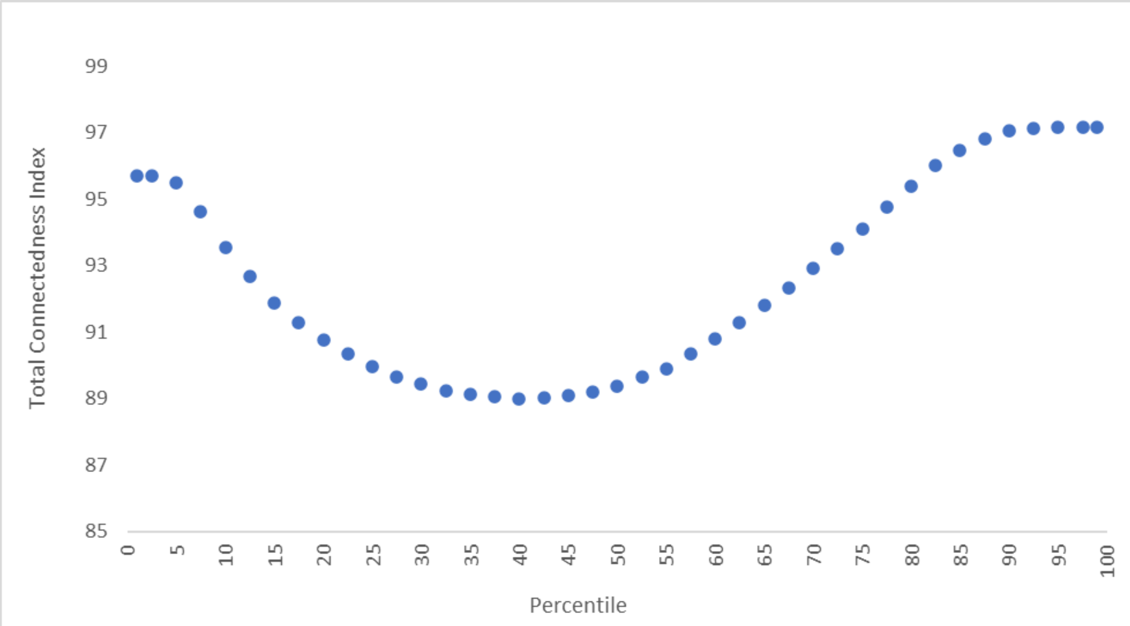

Figure 13. Percentile Variation of Total Connectedness Index

Source: Author's calculations

To detect the effects of large adverse shocks, τ is taken as 90 and connectedness measures at the 90th percentile are calculated [19]. Figure 14 shows the total spillover index computed during the sample period. As seen in Figure 14, there has been a significant surge in spillovers during some periods. Some of these increases are persistent, sometimes taking years for spillovers to revert to their long-term average. Combining Figures 12 and 14, I identify four crisis periods based on calculated systemic risk and aggregated spillover measures: The GFC, ESDC, 2014-2017 Turmoil, and the Covid-19 Pandemic[20].

Together with total spillovers, I calculate NET and TO spillovers for 27 banks at the 90th percentile, denoted in Figures 15 and 16, respectively. NET and TO spillover effects indicate significant time-variation and heterogeneity, differentiating considerably even among banks operating in the same country. The differences in systemic risk propagation among banks that are exposed to the same shocks lead us to examine the idiosyncratic features of banks.

[19] The total spillover index reaches a plateau around the 90th percentile but bank-level TO spillovers exhibit higher volatility in higher percentiles. Thus, we adopt τ as 90 to avoid extreme bank-level volatility in spillovers.
[20] See Appendix 3 for elaboration on crisis periods.

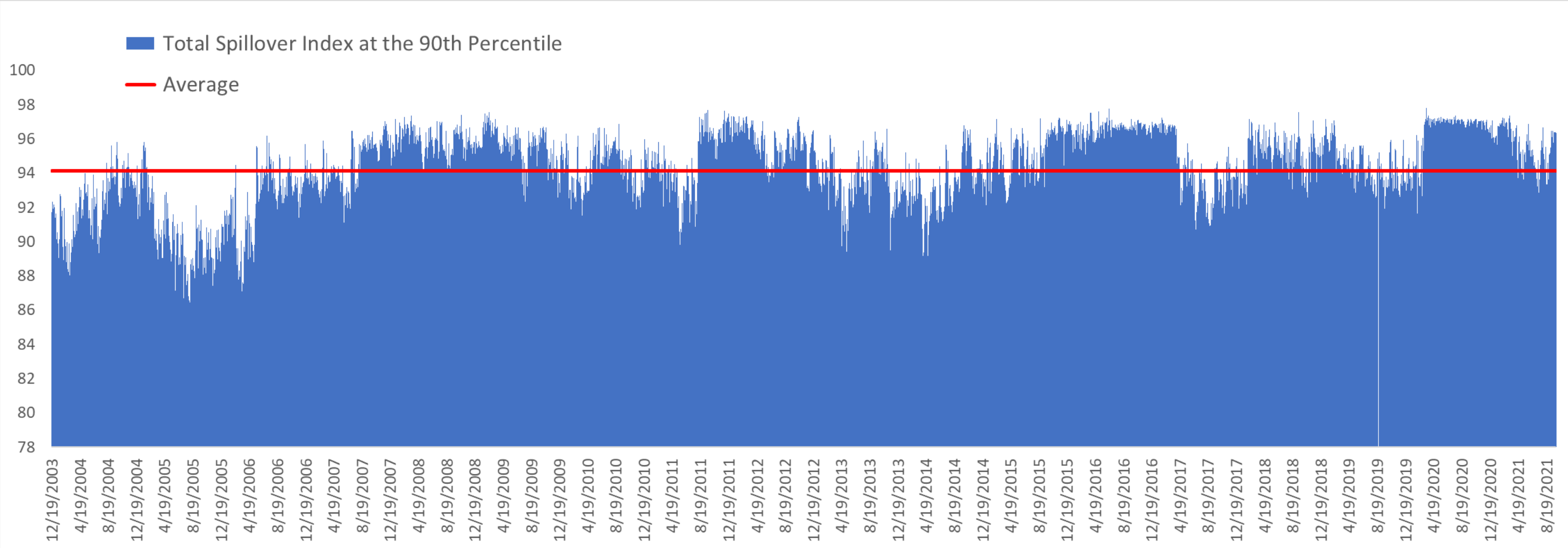

Figure 14. Total Spillover Index at the 90th Percentile

Source: Author’s calculations

2.3.4. The Definition of Systemic Risk Contagion

Following Forbes and Rigobon (2002) I define systemic risk contagion as "*extreme amplification of spillover effects that cannot be explained with usual linkages and fundamentals*". In this context, I adopt the view that systemic risk spillovers between financial institutions are always present but become contagious if they meet certain conditions. In other words, I see an increase in spillovers necessary but not sufficient for systemic risk contagion (Alter and Beyer, 2014).

I set "TO Spillovers" at the 90th percentile as the variable of interest and the condition for contagion as "exceeding the trend by two standard deviations". In this respect, first, I calculate TO Spillovers of each bank to other banks. Then, to gauge excess spillovers of each bank to other banks, I calculate the fraction of TO spillovers that exceed the trend by more than 2 standard deviations for each bank. Finally, I sum up each bank's excess TO spillovers to other banks to find their aggregated excess TO spillovers, which I call their overall contribution to systemic risk contagion.

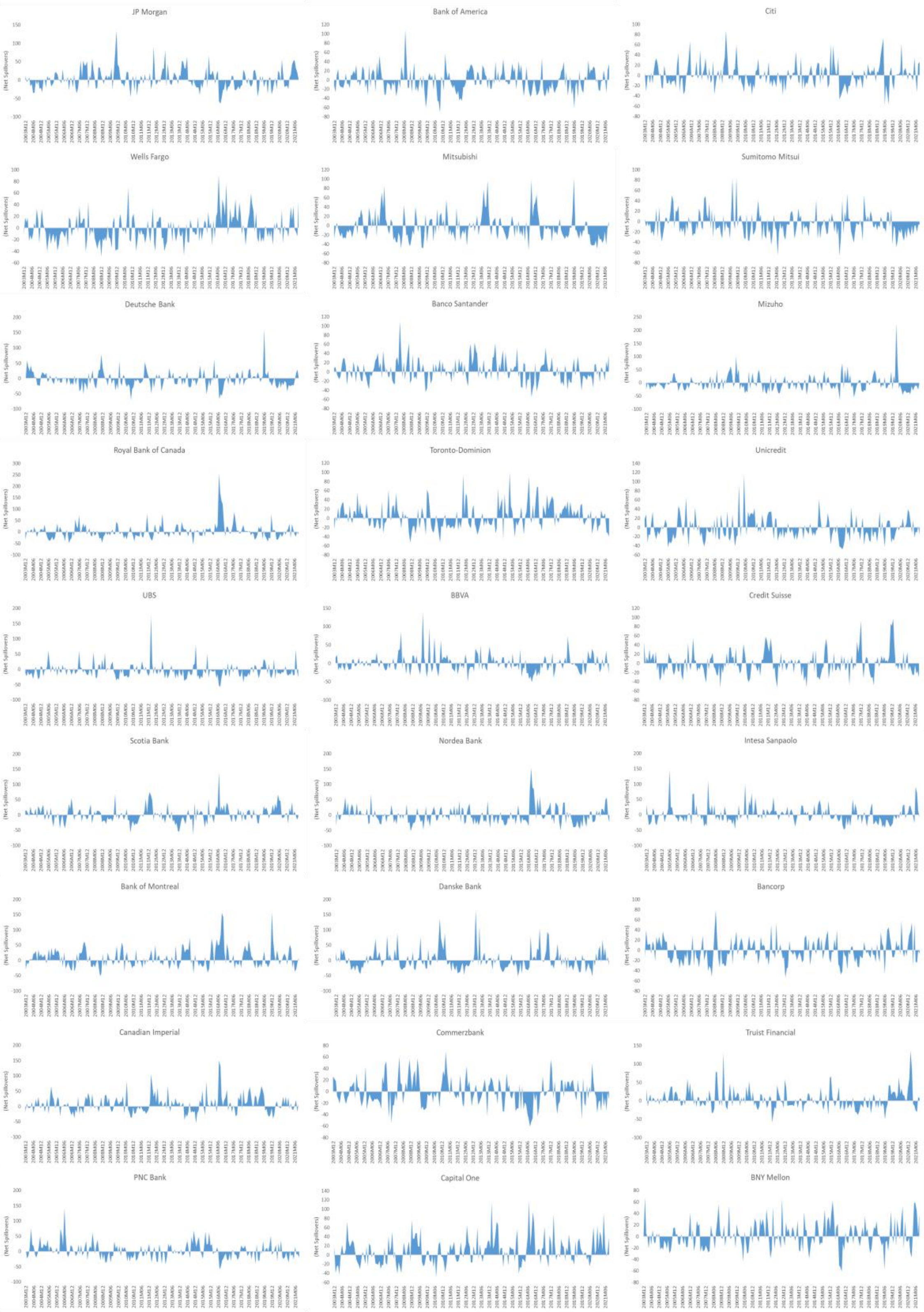

Figure 15. Net Spillovers at the 90th Percentile

Source: Author's calculations

Figure 16. TO Spillovers at the 90th Percentile

Source: Author’s calculations

2.4. EMPIRICAL ANALYSIS

Kleinow and Moreira (2016) show that banks' systemic risk sensitivity and contributions differ significantly during tumultuous and tranquil times. They stress that factors that promote financial stability under certain conditions might exacerbate systemic risk under different circumstances. Similarly, Weiß et al. (2014) argue that determinants of systemic risk "are often unique to each crisis", and their prominence changes in each crisis period. So, if the significance and effectiveness of determinants depend on the period examined, policies to fight against systemic risk might also need to vary by the conjuncture (Moore and Zhou, 2012). Many studies indicate that, in addition to systemic risk, contagion also shows significant regional disparity (Bae et al, 2003; Afonso et al., 2015) and time variation (Degryse and Nguyen, 2007). As Acemoglu et al. (2015) note, financial contagion has phase transition characteristics; interconnections between FIs that contribute to financial stability might increase systemic risk beyond a certain point. Finally, the literature also emphasizes the importance of dealing with reverse causality and endogeneity in systemic risk analysis since leaving these issues unresolved provides biased and inconsistent parameter estimates (Hodula et al., 2021; Ahrend and Goujard, 2012; Bostandzic et al., 2022; Béreau et al., 2022).

In the light of the findings above, I employ three estimators:

a. The Arellano-Bover/Blundell-Bond dynamic panel GMM estimator (AB/BB)
b. Common Correlated Effects Mean Group (CCEMG) Estimator
c. Time-varying Vector Autoregressions with Stochastic Volatility (TVP-VAR)

These estimators not only possess properties to deal with endogeneity but also have unique features complementing each other. Accordingly, the panel GMM model allows us to perform sub-period analysis, the CCEMG estimator deals with cross section dependence and slope heterogeneity, and the TVP-VAR model takes into account time variation in parameters.

I follow a three-step procedure in the empirical analysis. First, I calculate the systemic risk contributions of banks by employing the MES methodology[21]. Second, I compute my

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[21] Following Acharya et al. (2017), the expected shortfall level is set 5%.

systemic risk contagion metric, excess systemic risk spillovers at the 90th percentile, through quantile connectedness approach. Finally, I examine the determinants of systemic risk contagion by employing the panel GMM, CCEMG, and TVP-VAR models.

2.4.1. The Arellano-Bover/Blundell-Bond Panel GMM Estimator

Following Xu et al. (2019), I employ the AB/BB dynamic system GMM estimator due to persistence in systemic risk. The AB/BB panel GMM estimator is designed for large N small T panels, which allows me to examine crisis periods (GFC, ESDC, 2014-2017 Turmoil, and Covid-19) separately. However, unlike Xu et al. (2019), I consider endogeneity since there might be reverse causality between some of the variables. The GMM estimator deals with endogeneity, takes into account the unobserved bank-specific effects, and solves the autocorrelation problem. The details on the panel GMM methodology are given in Appendix 4.

Following Bond (2002), I compare the coefficients of lagged dependent variables of the Fixed Effects, OLS, difference GMM, and system GMM estimators. I conclude that the difference GMM estimator yields downward biased results due to weak instrumentation and decide to employ the two-step system GMM estimator with the standard error correction by Windmeijer (2005)[22]. The findings of the Arellano-Bover/Blundell-Bond 2-step System GMM Estimator are presented in sub-sections between 2.4.1.1 - 2.4.1.6 for each explanatory variable.

2.4.1.1. Bank Size

Bank size is found to be an important driver of systemic risk transmission since larger banks propagated more systemic risk during the GFC and ESDC. This result reflects larger banks' excessive risk-taking behavior and their possible reliance on TBTF subsidies. In addition, the coefficient of total assets during the GFC is estimated to be almost two times larger than in the ESDC, indicating a stronger size effect during the GFC. The positive effect of total assets on systemic risk is congruent with many studies (Laeven et al., 2016; Duan et al., 2021; Altunbas et al., 2022). However, this tendency changes dramatically after the ESDC. Accordingly, the coefficient of the total assets is

[22] These results of the 1-step and difference GMM models are available upon request from the authors.

found to be insignificant during the 2014-2017 turmoil period but negative and significant during the Covid-19 crisis. This significant turnaround could be the result of regulatory reforms such as the Basel III, which imposed stricter regulations on SIFIs[23]. So, it is possible to argue that size-related risks of large banks were trimmed by surged capital adequacy and limited speculative trading, which had an alleviating effect on systemic risk contagion[24]. Large banks may also have benefited from their operational diversification and improved hedging mechanisms compared to smaller banks (Boyd et al., 2004; Knaup and Wagner, 2012; Rahman et al., 2022), helping them reduce their contribution to systemic risk during the Covid-19 pandemic.

[23] The Financial Stability Board (FSB) has announced the list of global systemically important banks (G-SIBs) to address "too big to fail" and "too systematically important to fail" concerns since 2011. G-SIBs are subject to higher common equity tier 1 capital ratio requirements set by The Basel Committee.

[24] Tier 1 Risk-Based Capital and Total Risk-Based Capital Ratios of J.P. Morgan were 8.3% and 12.5% prior to the GFC, respectively. These ratios rose to 10.2% and 13.9% at the end of GFC sub-period and kept increasing further. As of third quarter of 2021, the aforementioned ratios stand at 15.8% and 16.9% while the newly introduced Common Equity Tier 1 Ratio is at 12.9%.

Table 9. Determinants of Systemic Risk Contagion During the GFC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged Excess TO Spillovers	0.5706***	0.5641***	0.5966***	0.5728***	0.5488***	0.5692***	0.5540***	0.5583***
	(0.0605)	(0.0608)	(0.0689)	(0.0624)	(0.0703)	(0.0697)	(0.0642)	(0.0653)
Return on Assets	-0.0066	-0.1697	-0.0165	-0.0057	-0.0095	-0.0080	-0.0135	-0.0114
	(0.0128)	(0.1076)	(0.0246)	(0.0135)	(0.0136)	(0.0192)	(0.0146)	(0.0149)
Tier 1 Ratio	-0.0537***	-0.0575***	-0.0470*	-0.0544***	-0.0491***	-0.0553***	-0.0516***	-0.0514***
	(0.0142)	(0.0138)	(0.0241)	(0.0142)	(0.0152)	(0.0139)	(0.0139)	(0.0140)
Deposit/Assets	0.0004	0.0003	0.0004	0.0005	0.0002	0.0003	0.0003	0.0003
	(0.0008)	(0.0008)	(0.0009)	(0.0010)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Total Assets (TA)	0.1387***	0.1289***	0.1314**	0.1435***	0.1436***	0.1375***	0.1427***	0.1421***
	(0.0459)	(0.0499)	(0.0575)	(0.0458)	(0.0412)	(0.0472)	(0.0445)	(0.0453)
NPL Coverage Ratio	-0.1998***	-0.1932***	-0.1532***	-0.2019***	-0.1903***	-0.1966***	-0.1867***	-0.1856***
	(0.0280)	(0.0268)	(0.0340)	(0.0284)	(0.0282)	(0.0286)	(0.0281)	(0.0283)
Total Assets/Equity	0.0044**	0.0050**	0.0047**	0.0043*	0.0036	0.0050**	0.0040*	0.0041*
	(0.0022)	(0.0022)	(0.0023)	(0.0022)	(0.0023)	(0.0023)	(0.0021)	(0.0021)
Global Liquidity	0.0014	-0.0047	-0.0001	0.0015	0.0017	0.0017	-0.0040	0.0016
	(0.0035)	(0.0048)	(0.0038)	(0.0036)	(0.0036)	(0.0035)	(0.0049)	(0.0036)
Global Economic Activity	-0.4108***	-0.4223***	-0.4128***	-0.4116***	-0.4295***	-0.4123***	-0.4543***	-0.4382***
	(0.0625)	(0.0610)	(0.0879)	(0.0638)	(0.0708)	(0.0739)	(0.0711)	(0.0741)
TA * Return on Assets		0.0125						

		(0.0082)						
TA * Tier 1 Ratio			-0.0009					
			(0.0011)					
TA * Deposit/Assets				-0.0000				
				(0.0000)				
TA * NPL Coverage Ratio					0.0011			
					(0.0008)			
TA * Total Assets/Equity						-0.0000		
						(0.0001)		
TA* Global Liquidity							-0.0001	
							(0.0001)	
TA * Global Economic Activity								-0.0010
								(0.0011)
# of observations	216	216	216	216	216	216	216	216
# of groups	27	27	27	27	27	27	27	27
# of instruments	25	26	26	26	26	26	26	26
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen p-value	0.28	0.29	0.22	0.27	0.25	0.27	0.27	0.27
Sargan p-value	0.20	0.20	0.12	0.20	0.18	0.19	0.17	0.17
AR(2) p-value	0.19	0.20	0.28	0.19	0.19	0.19	0.20	0.20

Windmeijer (2005) corrected robust standard errors in parentheses. The dependent variable is excess TO Spillovers at the 90^{th} Percentile. The table also includes time dummies, number of groups, number of instruments, Hansen and Sargan over-identification tests, and AR(2) test of the error terms. *, **, and *** denote statistically significant coefficient at the 10%, 5% and 1% levels, respectively. As a result of the CIPS unit root test of Pesaran (2007), Total Assets and Global Economic Activity variables are used after first-differencing. Due to endogeneity concerns, the following variables are instrumented with their own lags up to four quarters: Tier 1 Ratio, NPL Coverage Ratio, Assets/Equity.

Table 10. Determinants of Systemic Risk Contagion During the ESDC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged Excess TO Spillovers	0.7763***	0.6979***	0.6466***	0.6626***	0.7845***	0.7375***	0.7267***	0.8189***
	(0.2435)	(0.2449)	(0.2125)	(0.2419)	(0.2426)	(0.2574)	(0.2583)	(0.2238)
Return on Assets	-0.1046*	-6.1802**	-0.1238*	-0.1097*	-0.1009*	-0.1357*	-0.0248	-0.1212*
	(0.0611)	(2.5462)	(0.0636)	(0.0646)	(0.0613)	(0.0717)	(0.0556)	(0.0695)
Tier 1 Ratio	-0.0688***	-0.0788***	-0.0798***	-0.0705**	-0.0682**	-0.0674**	-0.0431*	-0.0857***
	(0.0255)	(0.0261)	(0.0294)	(0.0292)	(0.0283)	(0.0294)	(0.0249)	(0.0287)
Deposit/Assets	-0.0028*	-0.0029	-0.0011	-0.1850	-0.0028*	-0.0020	-0.0010	-0.0012
	(0.0016)	(0.0021)	(0.0025)	(0.2566)	(0.0016)	(0.0019)	(0.0027)	(0.0020)
Total Assets (TA)	0.0747***	0.0776***	0.0656**	0.0827***	0.0736	0.0663**	0.0868***	-0.0153
	(0.0282)	(0.0257)	(0.0297)	(0.0285)	(0.0452)	(0.0280)	(0.0310)	(0.0345)
NPL Coverage Ratio	-0.1940**	-0.0409	-0.1922**	-0.1874**	0.1689	-0.1558**	0.1026	0.0431
	(0.0895)	(0.1165)	(0.0838)	(0.0799)	(0.4826)	(0.0726)	(0.0963)	(0.0927)
Total Assets/Equity	-0.0088	-0.0177**	-0.0052	-0.0109	-0.0090	-0.0060	-0.0052	-0.0065
	(0.0079)	(0.0080)	(0.0111)	(0.0078)	(0.0081)	(0.0086)	(0.0069)	(0.0062)
Global Liquidity	-0.0077	-0.0085	-0.0049	0.0071	-0.0076	-0.0052	-0.4786*	-0.1410**
	(0.0108)	(0.0133)	(0.0157)	(0.0146)	(0.0121)	(0.0115)	(0.2552)	(0.0583)
Global Economic Activity	-0.4265**	-0.2989	-0.5665**	-0.5514**	-0.4216**	-0.4570**	-0.4156*	-0.2972
	(0.2103)	(0.2290)	(0.2497)	(0.2249)	(0.2144)	(0.2066)	(0.2337)	(0.2125)
TA * Return on Assets		0.4506**						

		(0.1878)						
TA * Tier 1 Ratio			0.0022					
			(0.0033)					
TA * Deposit/Assets				0.0136				
				(0.0190)				
TA * NPL Coverage Ratio					0.0004			
					(0.0339)			
TA * Total Assets/Equity						-0.0013		
						(0.0010)		
TA* Global Liquidity							0.0331*	
							(0.0182)	
TA * Global Economic Activity								6.8868**
								(3.0740)
# of observations	297	297	297	297	297	297	297	297
# of groups	27	27	27	27	27	27	27	27
# of instruments	26	27	27	27	27	27	27	27
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen p-value	0.28	0.59	0.32	0.28	0.18	0.31	0.14	0.55
Sargan p-value	0.55	0.67	0.35	0.46	0.42	0.57	0.79	0.68
AR(2) p-value	0.17	0.18	0.25	0.22	0.17	0.17	0.14	0.15

Windmeijer (2005) corrected robust standard errors in parentheses. The dependent variable is excess TO Spillovers at the 90^{th} Percentile. The table also includes time dummies, number of groups, number of instruments, Hansen and Sargan over-identification tests, and AR(2) test of the error terms. *, **, and *** denote statistically significant coefficient at the 10%, 5% and 1% levels, respectively. As a result of the CIPS unit root test of Pesaran (2007), Total Assets and Global Economic Activity variables are used after first-differencing. Due to endogeneity concerns, the following variables are instrumented with their own lags up to four quarters: Tier 1 Ratio, NPL Coverage Ratio, Assets/Equity.

Table 11. Determinants of Systemic Risk Contagion During the 2014-2017 Turmoil

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged Excess TO Spillovers	0.4435***	0.4334***	0.4617***	0.4521***	0.4070***	0.4185***	0.4506***	0.4648***
	(0.1111)	(0.1438)	(0.1422)	(0.1357)	(0.1416)	(0.1227)	(0.1385)	(0.1439)
Return on Assets	0.0284	0.0608	0.0405	0.0446	0.0398	0.0201	0.0410	0.0792
	(0.0360)	(0.0473)	(0.0450)	(0.0412)	(0.0433)	(0.0551)	(0.0439)	(0.0759)
Tier 1 Ratio	-0.0740	-0.0435	-0.0717	-0.0598	-0.0534	-0.0341	-0.0655	-0.0227
	(0.0586)	(0.0810)	(0.0782)	(0.0739)	(0.0710)	(0.0523)	(0.0759)	(0.0679)
Deposit/Assets	-0.0162***	-0.0182***	-0.0176***	-0.0182***	-0.0169***	-0.0168***	-0.0177***	-0.0173***
	(0.0050)	(0.0051)	(0.0045)	(0.0049)	(0.0050)	(0.0038)	(0.0047)	(0.0041)
Total Assets (TA)	-0.3250	-0.5250*	-0.5428*	-0.5658**	-0.4957	-0.6956	-0.5358*	-1.4568**
	(0.2104)	(0.2734)	(0.3144)	(0.2771)	(0.3036)	(0.8040)	(0.3015)	(0.7102)
NPL Coverage Ratio	-0.1652***	-0.1337***	-0.1702***	-0.1568***	-0.1379***	-0.1602***	-0.1658***	-0.0996**
	(0.0478)	(0.0502)	(0.0492)	(0.0504)	(0.0491)	(0.0415)	(0.0491)	(0.0507)
Total Assets/Equity	0.0638**	0.0735**	0.0619**	0.0675**	0.0730**	0.0663**	0.0631**	0.0750*
	(0.0296)	(0.0345)	(0.0276)	(0.0309)	(0.0356)	(0.0293)	(0.0285)	(0.0383)
Global Liquidity	0.0239	0.0094	-0.0048	-0.0016	-0.0052	0.0103	-0.0035	-0.0234
	(0.0225)	(0.0269)	(0.0113)	(0.0102)	(0.0116)	(0.0287)	(0.0107)	(0.0362)
Global Economic Activity	-0.3791**	0.3567	-0.3617*	-0.3558*	-0.3788*	-0.4007**	-0.3701*	0.3124
	(0.1826)	(0.2235)	(0.1915)	(0.2010)	(0.2159)	(0.1668)	(0.1931)	(0.2064)
TA * Return on Assets		0.9388*						
		(0.5613)						

TA * Tier 1 Ratio			0.0346					
			(0.0236)					
TA * Deposit/Assets				0.0089				
				(0.0055)				
TA * NPL Coverage Ratio					0.7555			
					(0.6621)			
TA * Total Assets/Equity						0.0875		
						(0.1198)		
TA* Global Liquidity							0.0106	
							(0.0073)	
TA * Global Economic Activity								0.7780*
								(0.4417)
# of observations	243	243	243	243	243	243	243	243
# of groups	27	27	27	27	27	27	27	27
# of instruments	26	27	27	27	27	27	27	27
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen p-value	0.23	0.18	0.22	0.24	0.21	0.20	0.23	0.21
Sargan p-value	0.18	0.13	0.17	0.15	0.17	0.13	0.16	0.11
AR(2) p-value	0.46	0.31	0.38	0.33	0.43	0.56	0.37	0.87

Windmeijer (2005) corrected robust standard errors in parentheses. The dependent variable is excess TO Spillovers at the 90^{th} Percentile. The table also includes time dummies, number of groups, number of instruments, Hansen and Sargan over-identification tests, and AR(2) test of the error terms. *, **, and *** denote statistically significant coefficient at the 10%, 5% and 1% levels, respectively. As a result of the CIPS unit root test of Pesaran (2007), Total Assets and Global Economic Activity variables are used after first-differencing. Due to endogeneity concerns, the following variables are instrumented with their own lags up to four quarters: Tier 1 Ratio, NPL Coverage Ratio, Assets/Equity.

Table 12. Determinants of Systemic Risk Contagion During the Covid-19 Pandemic

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged Excess TO Spillovers	0.4553***	0.5030***	0.4425***	0.4373***	0.3922***	0.4131***	0.4396***	0.4401***
	(0.1255)	(0.1263)	(0.1232)	(0.1233)	(0.1263)	(0.1209)	(0.1232)	(0.1231)
Return on Assets	0.0779***	-1.5721**	0.0695***	0.0651**	0.0777***	0.0630**	0.0671***	0.0670***
	(0.0191)	(0.7256)	(0.0254)	(0.0255)	(0.0195)	(0.0247)	(0.0255)	(0.0256)
Tier 1 Ratio	0.0476	0.1037**	0.0427	0.0579	0.1134**	0.0592	0.0589	0.0585
	(0.0353)	(0.0456)	(0.0346)	(0.0365)	(0.0525)	(0.0369)	(0.0366)	(0.0364)
Deposit/Assets	0.0047	0.0098**	0.0063	0.0027	0.0135**	0.0068	0.0063	0.0063
	(0.0041)	(0.0049)	(0.0042)	(0.0049)	(0.0068)	(0.0046)	(0.0042)	(0.0042)
Total Assets (TA)	-0.6218***	-0.9777***	-0.5937***	-0.5821***	-0.6093***	-0.5062***	-0.5900***	-0.5926***
	(0.1472)	(0.2261)	(0.1473)	(0.1475)	(0.1384)	(0.1296)	(0.1477)	(0.1485)
NPL Coverage Ratio	0.0238	0.0205	0.0405*	0.0415**	0.0434**	0.0478**	0.0425**	0.0409**
	(0.0213)	(0.0231)	(0.0208)	(0.0209)	(0.0221)	(0.0209)	(0.0208)	(0.0208)
Total Assets/Equity	0.1428***	0.2560***	0.1176***	0.1143***	0.1638***	0.1019***	0.1164***	0.1163***
	(0.0429)	(0.0682)	(0.0404)	(0.0407)	(0.0430)	(0.0355)	(0.0407)	(0.0406)
Global Liquidity	0.0019	0.0153	0.0219	0.0220	0.0173	0.0087	0.0086	0.0220
	(0.0098)	(0.0160)	(0.0166)	(0.0169)	(0.0129)	(0.0113)	(0.0115)	(0.0168)
Global Economic Activity	0.2984	-0.0048	0.2494	0.2588	0.0542	0.2730	0.2135	0.2026
	(0.2008)	(0.2453)	(0.2064)	(0.2053)	(0.2618)	(0.2175)	(0.2316)	(0.2326)
TA * Return on Assets		0.1269**						
		(0.0561)						

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TA * Tier 1 Ratio			0.0012 (0.0012)					
TA * Deposit/Assets				0.0003 (0.0003)				
TA * NPL Coverage Ratio					-0.0007 (0.0005)			
TA * Total Assets/Equity						0.0002 (0.0003)		
TA* Global Liquidity							0.0004 (0.0004)	
TA * Global Economic Activity								0.0037 (0.0040)
# of observations	189	189	189	189	189	189	189	189
# of groups	27	27	27	27	27	27	27	27
# of instruments	24	25	25	25	25	25	25	25
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen p-value	0.22	0.38	0.22	0.21	0.30	0.21	0.21	0.21
Sargan p-value	0.11	0.12	0.16	0.17	0.16	0.17	0.15	0.14
AR(2) p-value	0.31	0.36	0.35	0.36	0.35	0.37	0.36	0.35

Windmeijer (2005) corrected robust standard errors in parentheses. The dependent variable is excess TO Spillovers at the 90^{th} Percentile. The table also includes time dummies, number of groups, number of instruments, Hansen and Sargan over-identification tests, and AR(2) test of the error terms. *, **, and *** denote statistically significant coefficient at the 10%, 5% and 1% levels, respectively. As a result of the CIPS unit root test of Pesaran (2007), Total Assets and Global Economic Activity variables are used after first-differencing. Due to endogeneity concerns, the following variables are instrumented with their own lags up to four quarters: Tier 1 Ratio, NPL Coverage Ratio, Assets/Equity.

2.4.1.2. Capital Adequacy

According to Tables 9-12, the coefficient of Tier 1 Ratio is negative and significant during the GFC and ESDC sub-periods. Several banks worldwide with inadequate capital levels and insufficient liquidity were unprepared for the GFC, and some of them, such as Lehman Brothers, Northern Rock, and AIG failed. Undercapitalization problems and bank bailouts continued during the ESDC, and capital adequacy remained at the core of systemic risk discussions. Therefore, it should not be surprising to find capital's mitigating effect on systemic risk during the GFC and ESDC. As for the remaining sub-periods, the Tier 1 ratio is insignificant during the 2014-2017 turmoil and Covid-19 crisis. This changeover could be explained by globally elevated regulatory capital after the Lehman collapse. Basel III framework introduced several capital buffers to address the shortcomings in the pre-GFC regulatory framework, and FIs boosted their resilience by building up their capital buffers[25]. These buffers appear to serve their purpose since the contagious effect of capital inadequacy on systemic risk is eliminated. As a result, the Tier 1 ratio has no significant effect on the contagion of systemic risk during the 2014-2017 turmoil and Covid pandemic sub-periods.

2.4.1.3. Profitability

Profitability, represented by the return on assets in my regressions, provided interesting findings. Given that interest rates have remained mostly low throughout my sample period, one could expect to see the "search for yield" phenomenon's aggravating effect on risk transmission. However, according to Tables 9-12, the ROA has an aggravating effect on contagion only during the Covid-19 sub-period and no significant effect during the other sub-periods. This finding shows that, despite operating under very low interest rates during 2008-2015, banks did not contribute to systemic risk transmission through profitability. The results are in line with several studies such as Weiß et al. (2014), Anginer et al. (2014), Black et al. (2016) in which the authors also find no relation between profitability and systemic risk. During the Covid-19 period, however, I find profitability as a strong contributor to systemic risk transmission, similar to several studies that identify

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[25] This tendency is evident in our sample since the average of Tier 1 ratio prior to the GFC is 8.5% whereas the full sample average is 13.2%.

return on assets as a driver of systemic risk[26] (Di Maggio and Kacperczyk, 2017; Kurtzman et al., 2022; Qin and Zhou, 2019; Miller and Wanengkirtyo, 2020, Rahman et al., 2022). Finally, the interaction term[27] of bank size and ROA has positive and significant coefficients during the ESDC, 2014-2017 turmoil, and Covid-19 sub-periods, indicating the search for yield for larger banks. So, it could be argued that larger banks are involved in riskier activities compared to their smaller counterparts, but "search for yield" did not become widespread until the Covid-19 pandemic. This contradicts Buch et al. (2014), in which the authors find no additional risk taking by large banks when interest rates remain low for a long time.

2.4.1.4. Funding Structure

In my sample, the share of deposits in total assets is 50%, 51.6%, 55.5%, and 58.7% during the GFC, ESDC, 2014-2017 turmoil, and Covid-19 periods, respectively. The upward trend in deposit/assets ratio shows banks' increased preference of deposits over wholesale funding[28] . Despite this tendency, Tables 9-12 show that the coefficient of deposits/assets ratio is only found significant during the 2014-2017 turmoil sub-period with a negative coefficient and found insignificant during the other sub-periods. This result is surprising since a strand of the literature identify the reduction in deposits' share in total funding among the main determinants of liquidity risk during the GFC[29] (López-Espinosa et al., 2013; Altunbas et al., 2022) while another strand highlights the moral hazard problem caused by high reliance on deposit funding under generous deposit insurance systems (Gropp et al., 2014; Calomiris and Jaremski, 2016; Calomiris and Chen, 2018). Despite funding preferences of banks in the sample have shifted towards deposits over the years, my findings indicate that banks decreased systemic risk

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[26] First, banks faced profitability challenges due to low-rate environment that lasted for a decade, despite confronting the Covid-19 pandemic with robust capital and liquidity ratios. This tendency was enhanced by surged loan loss provisions and tightened lending standards (International Monetary Fund, 2020).

[27] Following Laeven et al (2016), we include size-related interaction terms obtained by multiplying total assets by the other five regressors.

[28] Funding structure of banks changes substantially during the last fifteen years. Prior to the GFC, wholesale borrowing peaked, and retail deposits' share in liabilities fell (Agur, 2013). Large banks enjoyed acquiring low-cost short-term funding by wholesale, using it to provide mortgages or investment loans. As the GFC emerges wholesale funding plummeted. Banks, SIFIs in particular, were forced to adjust themselves in line with Basel III criteria by deleveraging, drifting apart from off-balance sheet activities, and decreasing the maturity mismatch in their balance sheets. The share of wholesale borrowing has not reached its pre-GFC levels since then. Providing funds from the wholesale market, however, underwent a transformation, and FIs started to prefer collateralized short-term borrowing since the GFC.

[29] According to the BIS, banks that rely on deposits rather than wholesale funding witnessed milder increases in CDS spreads during the Covid-19 pandemic (Basel Committee on Banking Supervision, 2021).

contributions through deposit funding only during the 2014-2017 turmoil sub-period. I also find no evidence of moral hazard arising from increased share of deposit funding, even though all banks in my sample are subject to deposit insurance systems.

2.4.1.5. Credit Quality

According to Tables 9-12, credit risk, represented by the NPL coverage ratio, affects systemic risk contagion negatively during the GFC, ESDC, and 2014-2017 turmoil sub-periods. This finding indicates that the uncovered portion of the NPLs constituted an important contributor to systemic risk transmission until the Covid-19 pandemic[30]. Policymakers introduced several forbearance measures to support bank capital, lending, and profitability during the Covid-19 pandemic. Since these actions included reducing risk-asset weights and delaying NPL classifications, they directly affected the NPL coverage ratios. As underlined by Hulster et al. (2014), NPL ratios often have a downward bias due to forbearance measures and under-reporting practices. Indeed, most banks in my sample witnessed sharp increases in NPL coverage ratios during the Covid-19 period. Thus, forbearance measures make it difficult to compare the Covid-19 period with other crisis periods in terms of credit risk and question the reliability of indicators related to credit risk within this period. Finally, banks were financially and operationally in better condition, and their asset quality was higher during the Covid-19 period than in the GFC and ESDC periods (World Bank, 2020). Meeting the Covid-19 crisis with healthier financial ratios may have limited the mitigating effect of NPL coverage ratios on systemic risk contagion.

2.4.1.6. Leverage

In line with the literature considering leverage as one of the main drivers of systemic risk, I find that the coefficient of leverage is positive and significant during the GFC, 2014-2017 turmoil, and the Covid-19 periods. Since the coefficient of leverage is much larger during the Covid-19 period, it could be inferred that the effect of leverage on systemic risk contagion has been more substantial in the Covid-19 sub-period. This finding is congruent with Duan et al. (2021) which determine leverage as one of the main drivers

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[30] It should be noted that when size-related interaction terms are added to the regressions (2), (5), (7) and (8) in Table 10, the NPL coverage ratio becomes statistically insignificant during the ESDC.

of systemic risk in the Covid-19 pandemic. Contrary to studies finding higher aggravating effect of excessive leverage on systemic risk for large banks (Gandhi and Lustig, 2015; Dávila and Walther, 2020), I do not find the interaction term of bank size and leverage statistically significant in any of four sub-period regressions. So, I conclude that bank size does not amplify the effect of leverage on systemic risk contagion.

2.4.2. Common Correlated Effects Mean Group (CCEMG) Estimator

My dataset includes 27 banks from 9 countries with various asset sizes, capital structures, and leverage ratios. In addition to cross-section dependence and significant heterogeneity in the dataset, there is also endogeneity between some variables. Hence I employ a methodology that deals with these issues in a panel setting. The CCEMG estimator (Pesaran 2006; Chudik and Pesaran, 2015; Neal, 2015) serves my purpose. By replacing the use of OLS in the unit-specific regressions to GMM and employing lags of estimators to form the instrument set, the advanced version of CCEMG estimator is not only robust to cross-section dependence, but also to endogeneity (Neal, 2015)[31].

Table 13 in Appendix denotes the estimation results of the CCEMG. The Tier 1 and NPL coverage ratios have negative and significant coefficients across the panel, indicating that systemic risk contagion decreases as capital adequacy and credit quality increases. Financial leverage also drives contagion as the coefficient of assets/equity is found to be significant. However, the return on assets and deposit/assets ratios have no effect on systemic risk contagion in CCEMG estimations. The results are mostly congruent with Tables 9-12. The CCEMG estimator captures the determinants affecting systemic risk contagion in at least two crisis periods between 2004-2021. Surprisingly, the coefficient of the total assets is insignificant, conflicting with my earlier findings and several studies in the literature. Discrepancies in my results could be caused by the differences in sample size since the CCEMG estimator considers the full sample rather than sub-periods.

In addition to providing results for the entire panel, the CCEMG estimator also provides bank-specific results. Bank-specific results indicate that 12 out of 27 banks have negative and significant coefficients for the Tier 1 and NPL coverage ratios, while bank

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[31] The CCEMG methodology is elaborated in Appendix 5.

size and leverage seem to drive contagion for 10 banks. Consonant to the mixed findings in the literature, the CCEMG estimator yields several positive and negative statistically significant coefficients for deposits/assets and return on assets variables in bank-specific results. In contrast, these variables have no significant coefficients in panel regressions. These mixed findings might indicate an individual tendency for moral hazard rather than a generalized trend. Finally, the results of the CCEMG estimator do not show significant national and regional clustering at the bank level, although it presents similar findings for some banks.

2.4.3. Time-varying Vector Autoregressions with Stochastic Volatility

Notwithstanding the valuable information it provides on the bank level, the CCEMG estimator fails to capture the nonlinearity and time variation in the data set. Moreover, some of its findings conflict with results from the sub-period analysis in section 4.1. Since the CCEMG estimator is designed for medium to large panels, I cannot run a sub-period analysis due to insufficient observations. The inability to make a healthy comparison for sub-periods leads us to perform another robustness check to evaluate both time variation and parameter heterogeneity. The time-varying vector autoregression model is suited to my needs since it examines impulse responses after shocks to the observables in different crisis periods while addressing the problem of endogeneity. In this respect, I employ the time-varying parameter VAR (TVP-VAR) model (Primiceri, 2005; Nakajima, 2011) with $kx1$ vector of observables including 7 variables (excess systemic risk spillovers, ROA, Tier 1 ratio, deposit/assets, total assets, NPL coverage ratio, assets/equity)[32].

The TVP-VAR model presents two outputs. First, it plots the time-varying impulse responses of systemic risk contagion for selected horizons (1, 4, and 8 quarters ahead) at all points in time, reflecting the dynamic relationship between balance sheet strength and systemic risk transmission during 2004-2021. Second, it exhibits the impulse responses sampled in 2008Q3,2011Q4,2020Q1, representing the GFC, ESDC, and

[32] See Appendix 6 for detailed information

Covid-19 crisis, respectively. These findings show how systemic risk contagion reacts to shocks during different turmoil periods[33].

2.4.3.1. Time-varying Impulse Responses at All Points in Time

Figure 17 denotes time-varying impulse responses at all points in time obtained from the TVP-VAR model. To reflect the general trend, I make an aggregation by taking the arithmetic mean of the impulse responses of 27 banks. The impulse responses of the contagion to a return on assets shock are positive throughout the sample period. While the 1 quarter-ahead response peaks during the second quarter of 2012 and gradually declines thereafter, the 1-year and 2-year responses have upward trends, steepening after the end of 2014 and peaking during the Covid-19 pandemic. The elevated effect of ROA on contagion in the Covid-19 period supports my findings in section 4.1.

The impulse responses of the Tier 1 ratio remain at negative territory during the sample period while the magnitude of negative impulses weakens gradually. This result supports my earlier findings, showing that the power of capital adequacy in mitigating risk propagation reduced over the years. The findings point out the magnitude of negative impulse responses strengthens during 2014-2017, contradicting the findings in my sub-period analysis. Unlike 1-quarter ahead and 1-year ahead responses, 2-year ahead responses hover around zero throughout the period and indicate a significant negative effect only during 2015-2018. So, it could be argued that capital adequacy's mitigating effect on contagion is stronger in the short term.

Systemic risk contagion's response to NPL coverage ratio shocks follows a similar trend to its responses to the Tier 1 ratio shocks. Impulse responses obtained from NPL coverage ratio shocks are negative during 2004-2021 and exhibit a V-shape pattern. Figure 17 denotes NPL coverage has a strong extenuating effect on contagion until 2014, its effectiveness declines gradually, and longer-term responses get closer to zero during the Covid-19 pandemic. This result corroborates my findings in section 4.1,

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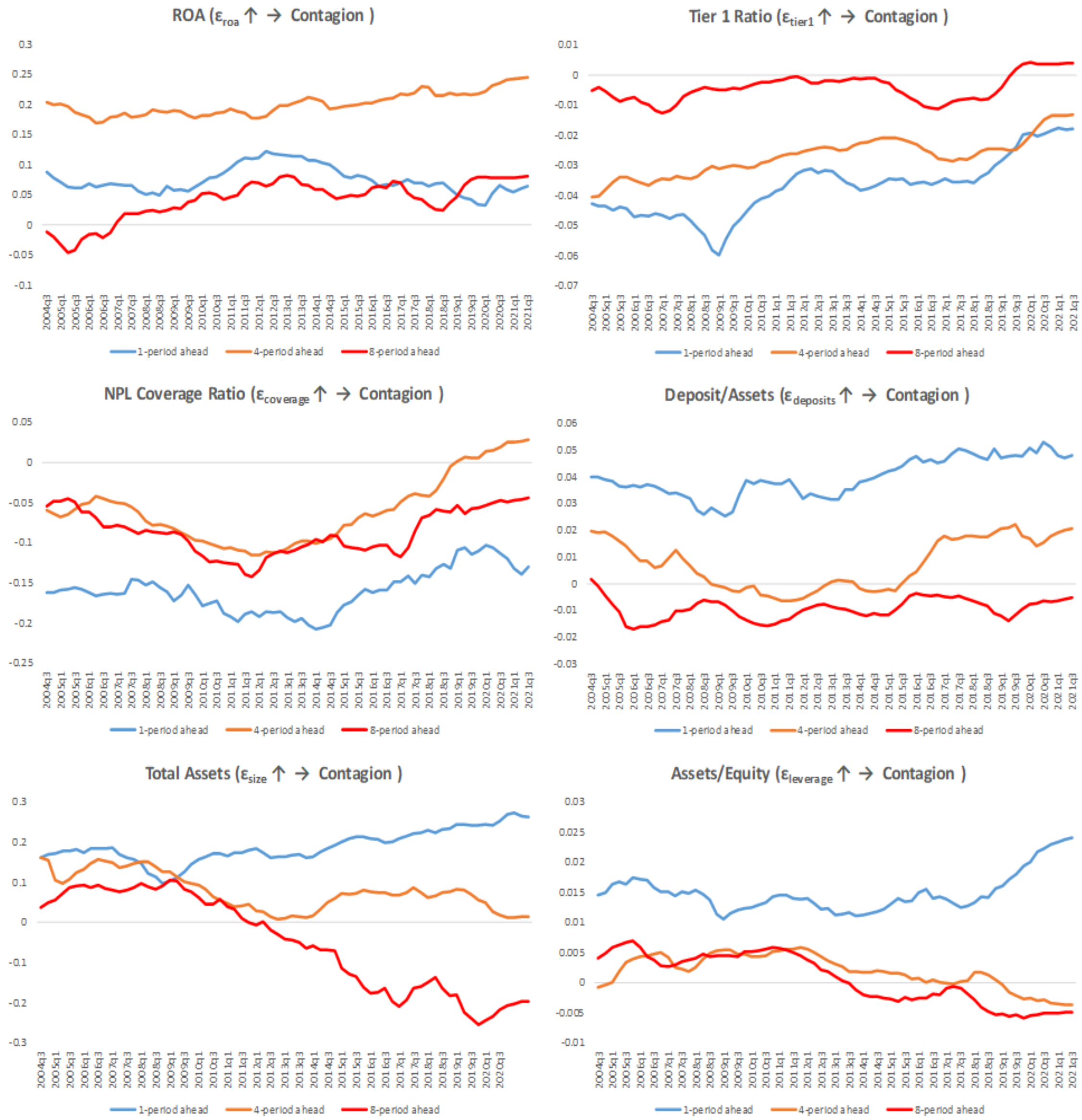
[33] I only report impulse responses of systemic risk spillovers to shocks to other variables. I also omit the impulse responses of 27 banks at all points of time to save space. These results are available upon request from the author.

indicating that the NPL ratio loses its effectiveness in reducing contagion during the pandemic.

The impulse responses of deposits/assets shocks emphasize the importance of the time structure of responses. While the 1-quarter ahead responses are positive throughout the sample period, 2-year ahead responses remain in negative territory. This behavior might indicate that the moral hazard effect caused by deposit insurance systems becomes more pronounced in the longer term. In contrast, deposit funding still stabilizes in the short term. However, moral hazard seems to prevail, especially during the Covid-19 pandemic, given the stronger magnitude and the steepening trend in 1-year ahead and 2-year ahead responses after 2014. This conclusion is in line with my earlier findings to a certain extent since the negative and significant coefficients obtained during the ESDC, and 2014-2017 sub-periods (Table 9-12) match the periods in which 1-year ahead and 2-year ahead impulse responses remain at the negative territory. Banks' increased preference for collateralized short-term borrowing from the wholesale market since the GFC (Agur, 2013) might have offset the aggravating effects of providing wholesale funding on systemic risk contagion. Furthermore, expanded coverage of deposit insurance systems and increased coverage limits after the GFC (Demirguc-Kunt et al., 2015) could have made banks' increased reliance on deposit funding relatively riskier.

Shocks to total assets present the most dramatic divergence in impulse responses across different horizons. Impulse responses remain positive and follow a similar trajectory until the second quarter of 2009, branching off to separate channels afterward. Accordingly, the 1-quarter ahead and 1-year ahead impulse responses are positive throughout the sample, while the magnitude and trend of the 1-quarter ahead response are stronger and steeper, respectively. 2-year ahead impulse response, on the other hand, follows a contrasting path, indicating an adverse relation between size and contagion after 2013, in line with my findings in section 4.1. In light of my results from panel GMM, CCEMG, and TVP-VAR models, the effect of size on contagion seems dependent on the period analyzed and the term structure. I infer that while bank size fuels contagion in the short run, it mitigates it in the long run. As mentioned in section 2.1.1.1, this could be explained by the lagged effects of government subsidies or advanced hedging mechanisms of larger banks.



The figure denotes the impulse responses at all points in time during the 2004q3-2021q3 period. The blue, orange, and red lines represent time-varying impulse responses for one-quarter, one year, and 2 year horizons for the TVP-VAR model, respectively.

Figure 17. Time-varying Impulse Response Functions at All Points in Time

Figure 17 indicates that shocks given to leverage produce positive and consistent impulse responses across all horizons until 2013. However, a divergence is noticed between impulse responses: 1-year ahead and 2-year ahead responses move into negative territory after 2013, and 1-quarter ahead responses gain an upward trend after 2018. Hence, 1-quarter ahead responses identify leverage among the main determinants of contagion and denote magnitude is stronger after 2018, whereas 1-year ahead and 2-year ahead responses indicate a weaker and unsustained contribution to systemic risk contagion. The 1-quarter ahead impulse response's significant gain of momentum supports my findings in sub-period analysis, highlighting leverage's pronounced effect on contagion during the Covid-19 pandemic. The maturity structure of debt might cause divergence in shorter-term, and longer-term impulse responses since both short-term and long-term debt is included in liabilities.

2.4.3.2. Time-varying Impulse Responses for Selected Horizons

After examining impulse responses to shocks at all points in time, I now focus on impulse responses sampled in 2008Q3,2011Q4,2020Q1, representing the GFC, ESDC, and Covid-19 periods, respectively[34]. Figure 18 in Appendix 7 exhibits impulse responses to shocks obtained in three tumultuous periods for 27 banks. The results emphasize the heterogeneity across banks. For some banks explicit search for yield is seen during all crisis periods (Bank of America, Deutsche Bank, Royal Bank of Canada, Credit Suisse) while others manage to reduce systemic risk contagion through increased ROA ratios (J.P. Morgan, Nordea, Bank of Montreal). This distinction confirms my earlier findings on profitability. A similar distinction is evident in the impulse responses obtained from deposit funding shocks, as some banks show signs of moral hazard (BNY Mellon, Royal Bank of Canada, Banco Santander) while others enjoy stabilizing role of deposit funding (Danske Bank, Truist Financial, UBS). In line with my inference in sections 2.4.1 and 2.4.2, shocks to capital adequacy generate negative and significant impulse responses in general, but I also observe surprisingly positive impulse responses for some banks. NPL coverage ratio, another important attenuator of systemic risk contagion according to my earlier findings, has an indisputable negative effect on contagion for banks such as Scotiabank, Intesa Sanpaolo, and Mizuho, while it has insignificant or limited effects for some banks. Finally, size and leverage are found to drive systemic risk contagion for most banks, although there are negative impulse responses calculated after size and leverage shocks.

In addition to heterogeneity among banks, impulse responses also highlight the variability of responses to balance sheet shocks in different periods. For instance, ROA shocks for Wells Fargo produced positive impulse responses during the GFC and ESDC, but negative impulse responses during the Covid-19 pandemic. This also applies to

[34] The figure denotes impulse responses only at 3 different selected time points: 2008Q3,2011Q4,2020Q1. I give shocks to the variables during each crisis period when the MES reaches its peak and starts to alleviate. Contrary to section 2.4.1, I do not include 2014-2017 period since the MES during the 2014-2017 period have three peaks.

shocks to deposit/assets and total assets for J.P. Morgan, as the impulse responses of contagion are negative during the Covid-19 period but positive during the GFC and ESDC. The Covid-19 period demonstrates its uniqueness by altering the impulse responses of NPL coverage ratio shocks for Royal Bank of Canada and Banco Santander, assets/equity shocks for UBS and Truist Financial, and Tier 1 ratio shocks for Danske Bank and BNY Mellon. During the Covid-19 crisis, the most remarkable shift in impulse responses is observed in shocks to deposit/assets as impulse responses of four banks (J.P. Morgan, Bank of America, Sumitomo Mitsui, and Banco Santander) altered compared to previous crisis periods. Similar differentiation in impulse responses is also observed for Mizuho (ROA, Tier 1 ratio, assets/equity), UBS (Tier1 ratio and deposit/assets), Commerzbank (Tier 1 ratio), and BNY Mellon (Tier 1 ratio) during the GFC period. Finally, Bank of Montreal stands out in relief during the ESDC period by having significantly different impulse responses for shocks given to deposit/assets, total assets, and NPL coverage ratio compared to the GFC and Covid-19 periods.

2.5. CONCLUSION

This chapter explores the determinants of systemic risk contagion. Instead of investigating why systemic events occur, I wonder how systemic shocks transmit and crises spread. Following several studies in the literature, I use explanatory variables derived from balance sheets of banks representing size, profitability, capital adequacy, credit quality, leverage, and funding structure. As systemic shocks are known to be less frequent and usually more significant, I use excess adverse systemic risk spillovers at the 90^{th} percentile as my dependent variable.

I find that determinants of systemic risk contagion vary over time. I highlight that the determinants differ in each crisis episode as I find no factor that persistently drives contagion. Instead, I find that some determinants gradually lose their influence on the propagation of shocks, while others are effective only during a single period of turmoil. In this respect, my findings echo the findings of Weiß et al. (2014) to a certain extent. The results also show significant heterogeneity across banks, and I do not detect clustering at the national or regional levels. In this context, my results are also coherent with Afonso et al. (2015), who detect significant time-variation and heterogeneity across countries in determinants of EMU sovereign spreads.

All banks in my sample are subject to the criteria set by the Basel Committee but must also comply with national regulations. Yet, despite operating in the same country and meeting the same legal requirements, some banks prefer to be levered up with higher NPL coverage ratios, while others adhere to short-term wholesale funding with larger Tier 1 capital. The strengths and weaknesses of financial ratios give banks a unique stance reflecting their riskiness. Even if a bank’s systemic risk contribution moves closely with its peers, at some point, the idiosyncratic features kick in, and they stand out from other banks. I show that each bank’s calculated systemic risk scores and excess systemic risk propagation have different peaks and troughs, although they share some commonalities with other banks. The prominence of each determinant in different crisis periods explains why contribution to contagion among banks differs over time.

Time-varying impulse responses denote that, in addition to heterogeneity among banks, balance sheet shocks’ impact on systemic risk contagion also varies significantly over time for each bank. For example, shocks to J.P. Morgan’s total assets and deposit/assets produce negative impulse responses during the Covid-19 period but positive impulse responses during the GFC and ESDC periods. These results imply that, unlike previous crises, J.P. Morgan's size and propensity to provide funding through deposits do not create contagion during the Covid-19 pandemic but rather mitigate it. One might argue that this turnaround is caused by alleviated moral hazard concerns or better diversification of risks. The total assets and deposit/assets ratio of J.P. Morgan surged before the Covid-19 pandemic and exceeded their long-term trends. Another reason for this turnaround could be the threshold effect for each variable. However, more data are needed to scrutinize this issue further.

My findings reveal that determinants of systemic risk change over time, and static surveillance methods may fail to capture factors that propagate systemic risk. Since the main drivers of risk transmission vary in each period of turmoil, a combination of risk factors could establish a more holistic regulatory approach rather than focusing on a single factor. The importance of dynamic systemic risk monitoring is emphasized in many studies (Lund-Jensen, 2012; Moore and Zhou, 2012) while others underline the inadequacy of current systemic risk regulations and offer new perspectives involving a combination of several factors (Varotto and Zhao, 2018; Hott, 2022; Bostandzic et al., 2022). In light of my findings and the relevant literature, a holistic systemic risk surveillance model, which uses high-frequency data and incorporates several risk factors simultaneously, could be used to detect systemic risk contagion. The model's dynamic nature could allow policymakers to monitor financial markets more frequently while integrated risk factors help them intervene with a broader set of information. As documented in the literature, rapid deleveraging during crises may further fuel the spread of systemic risk. Rather than urging banks to reduce leverage at such times hastily, the surveillance system could be designed to tolerate banks to a certain degree, allowing policymakers to address leverage and liquidity mismatches. In this respect, the surveillance system could act like a smart early-warning system, thanks to the advanced and holistic view provided by high-frequency data. The Basel III approach combining liquidity, capital, and leverage is a solid step in monitoring systemic vulnerabilities, but it could be further advanced by our suggestions above. Consequently, the conditions for banks to be considered SIFIs could also be updated more frequently with a broader set of indicators. The SIFI list and the accompanying additional regulations could be updated more frequently than once a year, contributing to financial stability.

Future studies could focus on bilateral interactions between financial institutions. Rather than using a bank's aggregated spillovers to other banks, examining contagion by employing bilateral spillovers between banks could produce more comprehensive findings, subject to the availability of bilateral exposures. Another suggestion is expanding the scope of this study by covering non-bank financial institutions such as hedge funds and insurance companies. It might also be interesting to perform a similar analysis at the national level by employing aggregated country level data. Finally, considering maturity composition of deposits and debt could enrich the findings.

CONCLUDING REMARKS

This dissertation examines systemic risk contagion through two linked chapters, each contributing to different strands of the literature. In the first chapter, I construct a new contagion test, based on time varying Granger causality and dynamic conditional correlation approaches. I apply the test to the systemic risk contributions of 36 of the world's 50 largest banks from 13 countries during the period 2004-2021. By matching periods with extreme jumps in correlations with time periods where the causality test statistic is statistically significant, the test provides a systemic risk contagion metric. The contagion metric takes the value "1" if there is a match, and "0" otherwise. Thus, this approach, combining correlation with causality, not only provides a robust contagion test, but also a time-varying, directional contagion indicator. Employing the new contagion metric, I identify contagion episodes and the direction of contagion across countries over the sample period. I find that there are several episodes of contagion, particularly concentrated during four crisis periods (The GFC, the ESDC, 2014-2017 turmoil period, and Covid-19 Pandemic), and that both uni-directional and bi-directional contagion are evident. The contagion episodes have different durations and the net transmitters and receivers of systemic risk differ significantly in each. I find that the US is the epicenter of transmission during the GFC, and contagion from the US to other regions occurs about a year before Lehman's collapse, just as the US yield curve is inverted. During the ESDC, Europe and the UK are at the forefront, transmitting risks to United States and Canada at different times for different durations. Interconnectedness during the 2014-2017 period is higher compared to the other crisis periods due to abundance of notable systemic events. As a result, the contagion mechanism during this period is more complex compared to other crisis periods. Finally, despite fundamental differences between Covid-19 crisis period with other crisis periods, contagion dynamics are similar to those observed during the 2014-2017 turbulence period and bi-directional contagion appears to be quite widespread.

In the first chapter, I also scrutinize systemic risk spillovers across 36 banks, identify the main risk transmitters, and analyze changes in network topology during the four major contagion episodes. Since the MES series are leptokurtic and fat tailed, I focus on tail events and aim to find the main transmitters of systemic risk after extreme shocks. In line with this objective, I employ the Quantile Connectedness methodology, which enables gauging connectedness measures after system-wide extreme adverse and beneficial shocks. In this respect, I compute systemic risk connectedness measures at the 1st, 10th, 50th, 90th, and 99th percentiles to represent the effects of extremely beneficial, beneficial, average, adverse, and extremely adverse shocks, respectively. I then identify the main transmitters of systemic risk and examine the network topology of systemic risk propagation for the four crisis episodes. Accordingly, the main systemic risk transmitters differ not only across percentiles, but also across crisis periods. Over the full sample period 2004-2021, European banks are estimated to be the main overall transmitters of systemic risk after extremely adverse shocks, with the exception of the GFC period. The findings of the first chapter emphasize the inadequacy of focusing on the effects of average shocks in systemic risk analysis, as systemic shocks tend to be larger. The findings also show that each contagion episode and turmoil period have different characteristics.

The second chapter of the dissertation investigates the determinants of systemic risk contagion. The literature highlights idiosyncratic features in explaining risk transmission and emphasizes the importance of time variation and non-linearity in systemic risk analysis. Following the literature and considering my findings in the first chapter, I follow a time-varying approach that takes into account endogeneity and uses bank-level balance sheet data representing size, profitability, capital adequacy, credit quality, leverage, and funding structure. Similar to the first chapter, I measure systemic risk by MES. However, since the contagion metric I derive in the first chapter yields a bilateral binary variable, I cannot use it as a dependent variable while using unilateral balance sheet data. Thus, I construct a new contagion metric by defining systemic risk contagion as "*extreme amplification of spillover effects at the 90th percentile that cannot be explained by usual linkages and fundamentals*". In the next step, I investigate how idiosyncratic characteristics of banks affect systemic risk contagion. In this respect, I use the Arellano-Bover/Blundell-Bond dynamic panel GMM estimator, the Common Correlated Effects Mean Group estimator and the Time-varying Vector Autoregressions. These methodologies not only have properties to deal with endogeneity but also have unique features complementing each other. I find that the determinants of systemic risk contagion differ in each crisis episode and that no factor persistently drives contagion. Instead, I find that some determinants gradually lose their influence on the propagation of shocks, while others are effective only during a single period of turmoil. The results also show significant heterogeneity across banks, and I do not detect clustering at the national or regional level. The findings of the second chapter reveal that the drivers of systemic risk change over time, and static surveillance methods may fail to capture the factors that propagate systemic risk.

All banks in the sample are subject to the criteria set by the Basel Committee but must also comply with national regulations. Yet, banks operate under different combinations of financial ratios, reflecting their preferences in risk management. Thus, despite a bank's systemic risk contribution moving closely with its peers, at some point, the idiosyncratic features kick in, and they differ from other banks. I show that each bank's calculated systemic risk scores and excess systemic risk propagation have different peaks and troughs, although they share some commonalities with other banks. I assert that since the main drivers of risk transmission differ in each period of turmoil, a combination of risk factors, rather than focusing on a single factor, may establish a more holistic and time varying regulatory approach. The importance of implementing dynamic systemic risk monitoring (Lund-Jensen, 2012; Moore and Zhou, 2012) and the inadequacy of current systemic risk regulations as well as the need for new perspectives involving a combination of several factors (Varotto and Zhao, 2018; Hott, 2022; Bostandzic et al., 2022) are already emphasized in the literature. In light of my findings and the relevant literature, a holistic systemic risk surveillance model, which uses high-frequency data and incorporates several risk factors simultaneously, could be used to detect systemic risk contagion. The model's dynamic nature could allow policymakers to monitor financial markets more frequently while integrated risk factors help them intervene with a broader set of information. In this respect, the surveillance system could act like a smart early-warning system, thanks to the advanced and holistic view provided by high-frequency data. The Basel III approach combining liquidity, capital, and leverage is a solid step in monitoring systemic vulnerabilities, but it could be further advanced by my suggestions above. Consequently, the conditions for banks to be considered SIFIs could also be updated more frequently with a broader set of indicators. The SIFI list and the accompanying additional regulations could be updated more frequently than once a year, contributing to financial stability.

The scope of the study could be widened by expanding the regional coverage by including banks from more countries such as Australia, Mexico, China, India, Russia, South Africa, and Brazil. It might also be interesting to perform a similar analysis either by employing country-level data or data of non-bank FIs such as hedge funds and insurance companies. Considering maturity composition of deposits and debt, charter values of banks and deposit insurance systems could enrich the findings. Finally, the network topology could be examined in more detail, employing more sophisticated community detection measures and spatial tools. Future studies could focus on bilateral interactions between financial institutions. Rather than using a bank's aggregated spillovers to other banks, examining contagion by employing bilateral spillovers between banks could produce more comprehensive findings, subject to the availability of bilateral exposures.

BIBLIOGRAPHY

Acemoglu, D., Ozdaglar, A. & Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *The American Economic Review*, 105(2), 564–608. http://www.jstor.org/stable/43495393

Acharya, V. V. (2009). A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability*, 5(3), 224-255. https://doi.org/10.1016/j.jfs.2009.02.001

Acharya, V.V. & Kulkarni, N. (2012), What saved the Indian banking system: State ownership or state guarantees?. *The World Economy*, 35: 19-31. https://doi.org/10.1111/j.1467-9701.2011.01382.x

Acharya, V.V., Pedersen, L. H., Philippon, T. & Richardson, M., (2013). How to calculate systemic risk surcharges. In: Haubrich, Joseph G., Lo, Andrew W. (Eds.), *Quantifying Systemic Risk*. University of Chicago Press.

Acharya, V.V., Pedersen, L. H., Philippon, T. & Richardson, M., (2017). Measuring systemic risk. *The Review of Financial Studies*, Volume 30, Issue 1, January 2017, Pages 2–47, https://doi.org/10.1093/rfs/hhw088

Acharya V.V., Thakor, A.V., (2016). The dark side of liquidity creation: Leverage and systemic risk. *Journal of Financial Intermediation*, Volume 28, 4-21, ISSN 1042-9573, https://doi.org/10.1016/j.jfi.2016.08.004

Acharya, V.V. & Viswanathan, S. (2011), Leverage, moral Hazard, and liquidity. *The Journal of Finance*, 66: 99-138. https://doi.org/10.1111/j.1540-6261.2010.01627.x

Acharya, V. V. & Yorulmazer, T. (2008). Information contagion and bank herding. *Journal of Money, Credit and Banking*, 40(1), 215-231, https://www.jstor.org/stable/25096246

Acosta-Smith, J., Grill, M. & Lang, J. H. (2020). The leverage ratio, risk-taking and bank stability. *Journal of Financial Stability*, 100833, ISSN 1572-3089, https://doi.org/10.1016/j.jfs.2020.100833

Admati A. & Hellwig, M., (2014). *The bankers' new clothes: What's wrong with banking and what to do about it: with a new preface by the authors*. Economics Books, Princeton University Press, edition 1, number 10230.

Adrian, T. & Brunnermeier, M. K. (2016). CoVaR. *American Economic Review*, 106(7), 1705-41, https://www.aeaweb.org/articles/pdf/doi/10.1257/aer.20120555

Adrian, T & Shin, H. S. (2010). Liquidity and leverage, *Journal of Financial Intermediation*. 19(3), 418-437, https://doi.org/10.1016/j.jfi.2008.12.002

Afonso, A., Arghyrou, M. G., Bagdatoglou, G. & Kontonikas, A., (2015). On the time-varying relationship between EMU sovereign spreads and their determinants. *Economic Modelling,* Volume 44, Pages 363-371, ISSN 0264-9993, https://doi.org/10.1016/j.econmod.2014.07.025

Agur, I, (2013), Wholesale bank funding, capital requirements and credit rationing. *Journal of Financial Stability*, 9(1), 38-45, https://doi.org/10.1016/j.jfs.2013.01.003

Ahrend, R. & A. Goujard (2012), International capital mobility and financial fragility - part 1. Drivers of systemic banking crises: The role of bank-balance-sheet contagion and financial account structure. *OECD Economics Department Working Papers,* No. 902, OECD Publishing, Paris, https://doi.org/10.1787/5kg3k8ksgglw-en

Aït-Sahalia, Y, Cacho-Diaz, J & Laeven R.J.A. (2015). Modeling financial contagion using mutually exciting jump processes. *Journal of Financial Economics*, 117(3), 585-606, ISSN 0304-405X, https://doi.org/10.1016/j.jfineco.2015.03.002

Alali, F. & Jaggi, B. (2011). Earnings versus capital ratios management: role of bank types and SFAS 114. *Rev Quant Finan Acc* 36, 105–132, https://doi.org/10.1007/s11156-010-0173-4

Alessi, L., Bruno, B., Carletti, E. & Neugebauer, K. (2019). What drives bank coverage ratios: Evidence from the euro area. *JRC Working Papers in Economics and Finance*, No. 2019/14, ISBN 978-92-76-08889-9, Publications Office of the European Union, Luxembourg.

Alessi, L., Bruno, B., Carletti, E., Neugebauer, K. & Wolfskeil I. (2021). Cover your assets: non-performing loans and coverage ratios in Europe. *Economic Policy*, Volume 36(108), 685–733, https://doi.org/10.1093/epolic/eiab013

Allegret, J., Raymond, H. & Rharrabti, H. (2017). The impact of the European sovereign debt crisis on banks stocks. Some evidence of shift contagion in Europe. *Journal of Banking & Finance*, 74, 24-37, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2016.10.004

Allen, L, Bali, T. G. & Tang, Yi. (2012). Does systemic risk in the financial sector predict future economic downturns? *Review of Financial Studies* 25(10), 3000-3036, https://doi.org/10.1093/rfs/hhs094

Allen, F., and Gale, D. (2000). Financial contagion. *Journal of Political Economy*, 108(1) 1–33. https://doi.org/10.1086/262109

Aloui, C. & Hkiri, B. (2014). Co-movements of GCC emerging stock markets: New evidence from wavelet coherence analysis. *Economic Modelling*, 36, 421-431, ISSN 0264-9993, https://doi.org/10.1016/j.econmod.2013.09.043

Aloui, C., Nguyen, D. K. & Njeh, H., (2012). Assessing the impacts of oil price fluctuations on stock returns in emerging markets. *Economic Modelling*, 29(6), 2686-2695, https://doi.org/10.1016/j.econmod.2012.08.010

Alper, C.E. & Yilmaz, K. (2004). Volatility and contagion: evidence from the Istanbul stock exchange. *Economic Systems*, 28(4), 353-367, ISSN 0939-3625, https://doi.org/10.1016/j.ecosys.2004.08.003

Alter, A. & Beyer, A., (2014). The dynamics of spillover effects during the European sovereign debt turmoil, *Journal of Banking & Finance*. 42, 134-153, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2014.01.030

Altunbas, Y., Marques-Ibanez, D., van Leuvensteijn, M. & Zhao, T. (2022). Market power and bank systemic risk: Role of securitization and bank capital. *Journal of Banking and Finance*, https://doi.org/10.1016/j.jbankfin.2022.106451

Anandarajan, A., Hasan, I., & McCarthy, C. (2007). Use of loan loss provisions for capital, earnings management and signalling by Australian banks. *Accounting & Finance*, 47(3), 357-379, https://doi.org/10.1111/j.1467-629X.2007.00220.x

Anderson, R. I., Chen, Y. & Wang, L., (2015). A range-based volatility approach to measuring volatility contagion in securitized real estate markets. *Economic Modelling*, 45, 223-235, ISSN 0264-9993, https://doi.org/10.1016/j.econmod.2014.10.058

Ando, T., Greenwood-Nimmo, M. & Shin, Y. (2022) Quantile connectedness: Modeling tail behavior in the topology of financial networks. *Management Science,* 0(0). https://doi.org/10.1287/mnsc.2021.3984

Ang, A. & Bekaert, G. (2002), International asset allocation with regime shifts. *Review of Financial Studies*, 15(4), 1137-1187, https://doi.org/10.1093/rfs/15.4.1137

Ang, A. & Longstaff, F. A., (2013). Systemic sovereign credit risk: Lessons from the U.S. and Europe. *Journal of Monetary Economics*, 60(5), 493-510, https://doi.org/10.1016/j.jmoneco.2013.04.009

Anginer, D., Demirguc-Kunt, A., & Zhu, M. (2014). How does competition affect bank systemic risk?. *Journal of Financial Intermediation*, 23(1), 1-26, https://doi.org/10.1016/j.jfi.2013.11.001

Anginer, D. & Demirguc-Kunt, A., 2018. Bank runs and moral hazard: A review of deposit insurance. *Policy Research Working Paper Series*, 8589, The World Bank.

Angkinand, A. P. (2009). Banking regulation and the output cost of banking crises. *Journal of International Financial Markets, Institutions and Money*, 19(2), 240-257, https://doi.org/10.1016/j.intfin.2007.12.001

Angkinand, A., & Wihlborg, C. (2010). Deposit insurance coverage, ownership, and banks' risk taking in emerging markets. *Journal of International Money and Finance*, 29(2), 252- 274, https://doi.org/10.1016/j.jimonfin.2009.08.001

Angelini, P., Maresca G. & Russo, D. (1996). Systemic risk in the netting system. *Journal of Banking & Finance*, 20(5), 853-868, ISSN 0378-4266, https://doi.org/10.1016/0378-4266(95)00029-1

Antzoulatos, A. A. & Tsoumas, C. (2014). Institutions, moral hazard and expected government support of banks. *Journal of Financial Stability*, 15, 161-171, ISSN 1572-3089, https://doi.org/10.1016/j.jfs.2014.09.006

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58, 277–297, https://doi.org/10.2307/2297968

Arellano, M., & Bover, O., (1995). Another look at the instrumental variable estimation of error-component models. *Journal of Econometrics*, 68, 29-51, https://doi.org/10.1016/0304-4076(94)01642-D

Arghyrou, M. G. & Kontonikas, A. (2012). The EMU sovereign-debt crisis: Fundamentals, expectations and contagion. *Journal of International Financial Markets, Institutions and Money*, 22(4), 658-677, ISSN 1042-4431, https://doi.org/10.1016/j.intfin.2012.03.003

Arner, D., Avgouleas, E. & Gibson, E. (2021). *Lessons from three decades of banking crisis resolution: Overstating moral hazard?*. in Nonperforming loans in asia and europe— causes, impacts, and resolution strategies. Edited by John Fell, Maciej Grodzicki, Junkyu Lee, Reiner Martin, Cyn-Young Park, and Peter Rosenkranz.

Aye, G.C., Christou, C. & Gupta, R. (2022). High-Frequency contagion between aggregate and regional housing markets of the United States with financial assets: Evidence from multichannel tests. *J Real Estate Finan Econ* . https://doi.org/10.1007/s11146-022-09919-8

Aymanns, C., Caccioli, F., J. Farmer, D. & Tan, V.W.C. (2016). Taming the Basel leverage cycle. *Journal of Financial Stability*, (27), 263-277, ISSN 1572-3089, https://doi.org/10.1016/j.jfs.2016.02.004

Aymanns, C, & Farmer, J. D. (2015). The dynamics of the leverage cycle. *Journal of Economic Dynamics and Control,* (50), 155-179, ISSN 0165-1889, https://doi.org/10.1016/j.jedc.2014.09.015

Aymanns, C. & Georg, C. (2015). Contagious synchronization and endogenous network formation in financial networks. *Journal of Banking & Finance*, 50, 2015, 273-285, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2014.06.030

Bae, K., Karolyi, A. & Stulz, R.M. (2003). A new approach to measuring financial contagion. *Review of Financial Studies*, 16(3), 717-763, https://www.jstor.org/stable/1262714

Baglioni, A., Beccalli, E. & Boitani, A. (2013). Is the leverage of European banks procyclical?. *Empirical Economics*, 45, 1251–1266. https://doi.org/10.1007/s00181-012-0655-4

Baig, T. & Goldfajn, I. (1999). Financial Market Contagion in the Asian Crisis. *IMF Staff Papers*, 46, 167-195.

Balboa, M., López-Espinosa, G. & Rubia, A. (2015). Granger causality and systemic risk. *Finance Research Letters*, 15, Pages 49-58, ISSN 1544-6123, https://doi.org/10.1016/j.frl.2015.08.003

Ballester, L., Casu, B. & González-Urteaga, A. (2016). Bank fragility and contagion: Evidence from the bank CDS market. *Journal of Empirical Finance*, 38(A), pp. 394-416, https://doi.org/10.1016/j.jempfin.2016.01.011

Bank for International Settlements (BIS). (1994). *64th Annual Report*. Basel, Switzerland: BIS.

Banulescu, G. & Dumitrescu, E., (2015). Which are the SIFIs? A Component Expected Shortfall approach to systemic risk. *Journal of Banking & Finance*, Elsevier, vol. 50(C), 575-588, https://doi.org/10.1016/j.jbankfin.2014.01.037

Baruník, J. & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk, *Journal of Financial Econometrics*, Volume 16, (2), 271–296, https://doi.org/10.1093/jjfinec/nby001

Basel Committee on Banking Supervision (2013). *Consultative document, fundamental review of the trading book: A revised market risk framework*, BIS, Basel, Switzerland.

Basel Committee on Banking Supervision. (2021). *Early lessons from the Covid-19 pandemic on the Basel reforms.* Bank for International Settlements. ISBN - 978-92-9259-491-6 (online).

Battiston, S., Puliga, M. & Kaushik, R. (2012). DebtRank: Too central to fail? Financial networks, the FED and systemic risk. *Sci Rep,* 2, 541, https://doi.org/10.1038/srep00541

Baumöhl, E. & Lyócsa, Š. (2014). Volatility and dynamic conditional correlations of worldwide emerging and frontier markets. *Economic Modelling*, (38), 175-183, ISSN 0264-9993, https://doi.org/10.1016/j.econmod.2013.12.022

Beatty, A. & Liao, S. (2014). Financial accounting in the banking industry: A review of the empirical literature, *Journal of Accounting and Economics*, 58(2–3), 339-383, ISSN 0165-4101, https://doi.org/10.1016/j.jacceco.2014.08.009

Beccalli, E., Boitani, A. & Di Giuliantonio, S. (2015). Leverage pro-cyclicality and securitization in US banking, *Journal of Financial Intermediation*, 24(2), 200-230, ISSN 1042-9573, https://doi.org/10.1016/j.jfi.2014.04.005

Beirne, J. & Fratzscher, M. (2013). The pricing of sovereign risk and contagion during the European sovereign debt crisis. *Journal of International Money and Finance*, Elsevier, 34(C), 60-82, https://doi.org/10.1016/j.jimonfin.2012.11.004

Bekaert, G., Harvey, C. R. & Ng, A. (2005). Market integration and contagion. *The Journal of Business*. 78 (1), 39–70, https://doi.org/10.1086/426519

Benoit, S., Colletaz, G., Hurlin, C. & Perignon, C., A (2013). Theoretical and empirical comparison of systemic risk measures. *HEC Paris Research Paper*, No. FIN-2014-1030.

BenSaïda, A., Litimi, H. & Abdallah, O., (2018), Volatility spillover shifts in global financial markets, *Economic Modelling*, 73(C), 343-353, https://doi.org/10.1016/j.econmod.2018.04.011

Béreau, S., Debarsy, N., Dossougoin, C. & Gnabo, J., (2022). Contagion in the banking industry: a Robust-to-endogeneity analysis, *HAL Working Papers*, halshs-03513049.

Berger, A. N., Roman, R. A. & Sedunov, J. (2020). Did TARP reduce or increase systemic risk? The effects of government aid on financial system stability, *Journal of Financial Intermediation*, (43), 100810, ISSN 1042-9573, https://doi.org/10.1016/j.jfi.2019.01.002

Billio, M., Casarin, R., Costola, M. & Iacopini, M. (2021). COVID-19 spreading in financial networks: A semiparametric matrix regression model. *Econometrics and Statistics*, ISSN 2452-3062, https://doi.org/10.1016/j.ecosta.2021.10.003

Billio, M., Getmansky, M., Lo, A.W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics,* 104(3), 535-559, https://doi.org/10.1016/j.jfineco.2011.12.010

Billio, M., Frattarolo, L., Gatfaoui, H. & de Peretti, P. (2016). Clustering in dynamic causal networks as a measure of systemic risk on the Euro Zone. *CES Working Paper*, 2016.46, http://dx.doi.org/10.2139/ssrn.2861266

Billio, M. & Pelizzon, L. (2003), Contagion and interdependence in stock markets: Have they been misdiagnosed? *Journal of Economics and Business*, (55), 405-426, https://doi.org/10.1016/S0148-6195(03)00048-1

Black, L., Correa, R., Huang, X. & Zhou, H. (2016). The systemic risk of European banks during the financial and sovereign debt crises. *Journal of Banking & Finance*, 63, 107-125, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2015.09.007.

Black, L. & Hazelwood, L. N. (2013). The effect of TARP on bank risk-taking, *Journal of Financial Stability*, 9(4), 790-803, ISSN 1572-3089, https://doi.org/10.1016/j.jfs.2012.04.001

Blasques, F., Bräuning, F. & van Lelyveld, I. (2018). A dynamic network model of the unsecured interbank lending market, *Journal of Economic Dynamics and Control*, (90), 310-342, ISSN 0165-1889, https://doi.org/10.1016/j.jedc.2018.03.015

Blasques, F., Koopman, S. J., Lucas, A. & Schaumburg, J. (2016). Spillover dynamics for systemic risk measurement using spatial financial time series models. *Journal of Econometrics*, 195(2), 211-223, ISSN 0304-4076, https://doi.org/10.1016/j.jeconom.2016.09.001

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87, 115-43, https://doi.org/10.1016/S0304-4076(98)00009-8

Bodart, V. & Candelon, B. (2009). Evidence of interdependence and contagion using a frequency domain framework, *Emerging Markets Review*, 10(2), 140-150, ISSN 1566-0141, https://doi.org/10.1016/j.ememar.2008.11.003

Bonaccolto, G., Caporin, M. & Panzica, R. (2019). Estimation and model-based combination of causality networks among large US banks and insurance companies, *Journal of Empirical Finance*, (54), 1-21, ISSN 0927-5398, https://doi.org/10.1016/j.jempfin.2019.08.008

Bond, S. R. (2002). Dynamic panel data models: a guide to micro data methods and practice. *Portuguese Economic Journal*, 1, 141–162, https://doi.org/10.1007/s10258-002-0009-9

Bonga-Bonga, L. (2018). Uncovering equity market contagion among BRICS countries: An application of the multivariate GARCH model, *The Quarterly Review of Economics and Finance*, (67), 36-44, ISSN 1062-9769, https://doi.org/10.1016/j.qref.2017.04.009.

Borio, C., Furfine, C. & Lowe, P., (2001). *Procyclicality of the financial system and financial stability: issues and policy options*. BIS Papers chapters, in: Bank for International Settlements (ed.), Marrying the macro- and micro-prudential dimensions of financial stability, (1), 1-57, Bank for International Settlements.

Borio, C. & Zhu, H. (2012). Capital regulation, risk-taking and monetary policy: A missing link in the transmission mechanism?. *Journal of Financial Stability*, 8(4), 236-251, ISSN 1572-3089, https://doi.org/10.1016/j.jfs.2011.12.003

Bostandzic, D. & Weiß, G.N.F. (2018). Why do some banks contribute more to global systemic risk?, *Journal of Financial Intermediation*, 35(A), 17-40, ISSN 1042-9573, https://doi.org/10.1016/j.jfi.2018.03.003

Bostandzic, D., Irresberger, F., Juelsrud, R., & Weiß, G. (2022). Do capital requirements make banks safer? Evidence from a quasinatural experiment. *Journal of Financial and Quantitative Analysis*, 57(5), 1805-1833. https://doi.org/10.1017/S0022109021000612

Boubaker, S., Jouini, J. & Lahiani, A. (2016). Financial contagion between the US and selected developed and emerging countries: The case of the subprime crisis, *The Quarterly Review of Economics and Finance*, (61), 14-28, ISSN 1062-9769, https://doi.org/10.1016/j.qref.2015.11.001

Boubakri, N., El Ghoul, S., Guedhami, O. & Hossain, M. (2020). Post-privatization state ownership and bank risk-taking: Cross-country evidence. *Journal of Corporate Finance*, 64, 101625, ISSN 0929-1199, https://doi.org/10.1016/j.jcorpfin.2020.101625

Bouri, E., Saeed, T., Vo, X.V & Roubaud, D. (2021). Quantile connectedness in the cryptocurrency market, *Journal of International Financial Markets, Institutions and Money,* 71, 101302, ISSN 1042-4431, https://doi.org/10.1016/j.intfin.2021.101302

Boyd, J. H., De Nicolo, G., & Smith, B. D. (2004). Crises in competitive versus monopolistic banking systems. *Journal of Money, Credit and Banking*, 36, 487-506, https://www.jstor.org/stable/3838948

Boyer, B., Gibson, M. & Loretan, M., (1999). Pitfalls in tests for changes in correlations. *Federal Reserve Board Working Paper*, vol. 597R.

Brownlees, C. & Engle, R.F. (2017). SRISK: a conditional capital shortfall measure of systemic risk. *ESRB Working Paper Series*, 37, European Systemic Risk Board.

Brownlees, C, Hans, C. &, Nualart, E. (2021). Bank credit risk networks: Evidence from the Eurozone, *Journal of Monetary Economics*, 117, 585-599, ISSN 0304-3932, https://doi.org/10.1016/j.jmoneco.2020.03.014

Brunetti, C., Harris, J. H., Mankad, S. & Michailidis, G. (2019). Interconnectedness in the interbank market. Journal of *Financial Economics*, 133(2), 520-538, ISSN 0304-405X, https://doi.org/10.1016/j.jfineco.2019.02.006

Brunnermeier, M., (2001). *Asset pricing under asymmetric information - bubbles, crashes, Technical Analysis and Herding*. Oxford University Press, Oxford.

Brunnermeier, M.K., Dong, G. N. & Palia, D. (2020). Banks' non-interest income and systemic risk. *Review of Corporate Finance Studies*, 9(2), 229-255, http://dx.doi.org/10.2139/ssrn.3328890

Brunnermeier, M., & Oehmke, M., (2013). The maturity rat race. *Journal of Finance*, 68(2), 483–521, https://doi.org/10.1111/jofi.12005

Brunnermeier, M. & Pedersen, L.H. (2009). Market liquidity and funding liquidity, *The Review of Financial Studies*, 22(6), 2201-2238, https://doi.org/10.1093/rfs/hhn098

Buch, C. M., Eickmeier, S. & Prieto, E. (2014). In search for yield? Survey-based evidence on bank risk taking, *Journal of Economic Dynamics and Control*, (43), 12-30, ISSN 0165-1889, https://doi.org/10.1016/j.jedc.2014.01.017

Bussière, M., Meunier, B. & Pedrono, J. (2020). Heterogeneity in bank leverage: The funding channels of complexity. *Banque de France Working Paper*, No. 771, http://dx.doi.org/10.2139/ssrn.3638922

Caccioli, F., Shrestha, M., Moore, C. & Farmer, J.D. (2014). Stability analysis of financial contagion due to overlapping portfolios, *Journal of Banking & Finance*, 46, 233-245, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2014.05.021.

Calabrese, R., Elkink, J.A. & Giudici, P. S. (2017). Measuring bank contagion in Europe using binary spatial regression models, *Journal of the Operational Research Society,* 68(12), 1503-1511, DOI: 10.1057/s41274-017-0189-4

Calmès, C. & Théoret, R. (2013). Market-oriented banking, financial stability and macro-prudential indicators of leverage, *Journal of International Financial Markets,* *Institutions and Money,* (27), 13-34, ISSN 1042-4431, https://doi.org/10.1016/j.intfin.2013.07.004

Calomiris, C. W. & Chen, S. (2018). The spread of deposit insurance and the global rise in bank asset risk since the 1970s. *NBER Working Papers*, 24936, National Bureau of Economic Research, Inc., DOI 10.3386/w24936.

Calomiris, C. W. & Jaremski, M. (2016), Deposit insurance: Theories and facts. *Annual Review of Financial Economics,* 8(1), 97-120, https://doi.org/10.1146/annurev-financial-111914-041923

Calvo, S. & Reinhart, C., (1996). Capital flows to Latin America: Is there evidence of contagion effects?. *Policy Research Working Paper Series*, 1619, The World Bank.

Caporale, G. M., Cipollini, A. & Spagnolo, N. (2005). Testing for contagion: a conditional correlation analysis, *Journal of Empirical Finance*, 12(3), 476-489, ISSN 0927-5398, https://doi.org/10.1016/j.jempfin.2004.02.005

Caporale, G. M., Kang, W., Spagnolo, F. & Spagnolo, N. (2021). Cyber-attacks, spillovers and contagion in the cryptocurrency markets, *Journal of International Financial Markets, Institutions and Money*, (74), 101298, ISSN 1042-4431, https://doi.org/10.1016/j.intfin.2021.101298

Caporin, M., Pelizzon, L., Ravazzolo, F. & Rigobon, R. (2018) Measuring sovereign contagion in Europe, *Journal of Financial Stability*, 34, 150-181.

Caporin, M. & Costola, M., (2022), Time-varying Granger causality tests in the energy markets: A study on the DCC-MGARCH Hong test, *Energy Economics*, (111), 106088, ISSN 0140-9883, https://doi.org/10.1016/j.eneco.2022.106088

Celik, S. (2012). The more contagion effect on emerging markets: The evidence of DCC-GARCH model, *Economic Modelling*, 29(5), 1946-1959, ISSN 0264-9993, https://doi.org/10.1016/j.econmod.2012.06.011

Chaudron, R.F.D.D. (2018). Bank's interest rate risk and profitability in a prolonged environment of low interest rates, *Journal of Banking & Finance*, 89, 94-104, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2018.01.007

Chelley-Steeley, P.L. (2005). Modeling equity market integration using smooth transition analysis: A study of Eastern European stock markets. *Journal of International Money and Finance*, 24(5), 818-831, https://doi.org/10.1016/j.jimonfin.2005.04.007

Chen, H., Cummins, J. D., Viswanathan, K. S. & Weiss M. A. (2014). Systemic risk and the interconnectedness between banks and insurers: An econometric analysis. *The Journal of Risk and Insurance,* 81(3), 623–52. http://www.jstor.org/stable/24548084

Chen, C. Y., Härdle, W. K. & Okhrin, Y. (2019). Tail event driven networks of SIFIs, *Journal of Econometrics*, 208(1), 282-298, ISSN 0304-4076, https://doi.org/10.1016/j.jeconom.2018.09.016.

Chiang, T.C., Jeon, B.N. & Li, H., (2007), Dynamic correlation analysis of financial contagion: Evidence from Asian markets, *Journal of International Money and Finance* 26(7), 1206-1228, https://doi.org/10.1016/j.jimonfin.2007.06.005

Chiarella, C., ter Ellen, S., He, X. & Wu, E. (2015). Fear or fundamentals? Heterogeneous beliefs in the European sovereign CDS market, *Journal of*

Empirical Finance, (32), 19-34, ISSN 0927-5398, https://doi.org/10.1016/j.jempfin.2014.11.003

Chinazzi, M., Fagiolo, G., Reyes, J. A. & Schiavo, S. (2013), Post-mortem examination of the international financial network, *Journal of Economic Dynamics and Control*, 37(8), 1692-1713, ISSN 0165-1889, https://doi.org/10.1016/j.jedc.2013.01.010

Chudik, A. & Pesaran, M.H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors, *Journal of Econometrics*, 188(2), 393-420, ISSN 0304-4076, https://doi.org/10.1016/j.jeconom.2015.03.007

Cincinelli, P., Pellini, E. & Urga, G. (2021). Leverage and systemic risk pro-cyclicality in the Chinese financial system, *International Review of Financial Analysis*, (78), 101895, ISSN 1057-5219, https://doi.org/10.1016/j.irfa.2021.101895

Claessens, S., Dornbusch, R. & Park, Y.C. (2001). *Contagion: Why crises spread and how this can be stopped* . In: Claessens, S., Forbes, K.J. (eds) International Financial Contagion. Springer, Boston, MA. https://doi.org/10.1007/978-1-4757-3314-3_2

Claeys, P. & Vasicek, B. (2014). Measuring bilateral spillover and testing contagion on sovereign bond markets in Europe. *Journal of Banking and Finance*, 46, 151–165, https://doi.org/10.1016/j.jbankfin.2014.05.011

Colletaz, G., Levieuge, G. & Popescu, A. (2018). Monetary policy and long-run systemic risk-taking. *Journal of Economic Dynamics and Control*, (86), 165-184, ISSN 0165-1889, https://doi.org/10.1016/j.jedc.2017.11.001

Constantin, A., Peltonen, T. A. & Sarlin, P. (2018). Network linkages to predict bank distress, *Journal of Financial Stability*, 35, 226-241, ISSN 1572-3089, https://doi.org/10.1016/j.jfs.2016.10.011

Cordella, T. & Yeyati, E.L., (2003). Bank bailouts: moral hazard versus value effect. *J. Financ. Intermediation,* (12), 300-330, https://doi.org/10.1016/S1042-9573(03)00046-9

Cornett, M. M., McNutt, J.J., Strahan, P., & Tehranian, H. (2011). Liquidity risk management and credit supply in the financial crisis. *Journal of Financial Economics*, 101(2), 297-312, https://doi.org/10.1016/j.jfineco.2011.03.001

Corsi, F., Lillo F., Pirino, D. & Trapin, L. (2018). Measuring the propagation of financial distress with Granger-causality tail risk networks, *Journal of Financial Stability*, (38), 18-36, ISSN 1572-3089, https://doi.org/10.1016/j.jfs.2018.06.003

Cronin, D., Flavin, T. J. & Sheenan, L. (2016). Contagion in Eurozone sovereign bond markets? The good, the bad and the ugly, *Economics Letters*, 143, 5-8, ISSN 0165-1765, https://doi.org/10.1016/j.econlet.2016.02.031

Cull, R. & Senbet, L. & Sorge, M., (2004). Deposit Insurance and Bank Intermediation in the Long Run. *BIS Working Papers*, 156, Bank for International Settlements.

Curcio, D., & Hasan, I. (2015). Earnings and capital management and signaling: The use of loan-loss provisions by European banks. *The European Journal of Finance*, 21(1), 26-50.

Dagher, J., Dell'Ariccia, G., Laeven, L., Ratnovski, L. & Tong, H. (2016). Benefits and costs of bank capital. *IMF Staff Discussion Notes*. 2016/004, ISBN: 9781498387712, ISSN: 2617-6750, https://doi.org/10.5089/9781498387712.006

Damar, H. E., Meh, C.A. & Terajima, Y. (2013). Leverage, balance-sheet size and wholesale funding. *Journal of Financial Intermediation*, 22(4), 639-662, ISSN 1042-9573, https://doi.org/10.1016/j.jfi.2013.07.002

Danielson, J.T. (2003). On the Feasibility of Risk Based Regulation. *CESifo Economic Studies*, 49, 157-179.

Darby, M. R. (1997). Over-The-Counter derivatives and systematic risk to the global financial system, *Advances in International Banking and Finance*, v3(1), 215-235, DOI 10.3386/w4801

Davis, E. P. (1995), *Debt, Financial Fragility, and Systemic Risk* (Oxford, 1995; online edn, Oxford Academic, 1 Nov. 2003), https://doi.org/10.1093/0198233310.001.0001

Dávila, E. & Walther, A. (2020). Does size matter? Bailouts with large and small banks. *Journal of Financial Economics*, 136(1), 1-22, https://doi.org/10.1016/j.jfineco.2019.09.005

De Bandt, O. & Hartmann, P., (2000). Systemic risk: A survey, *European Central Bank Working Paper Series*, (35).

De Grauwe, P. & Ji, Y. (2013). Self-fulfilling crises in the Eurozone: An empirical test, *Journal of International Money and Finance*, (34), 15-36, ISSN 0261-5606, https://doi.org/10.1016/j.jimonfin.2012.11.003

De Jonghe, O. (2010). Back to the basics in banking? A micro-analysis of banking system stability, *Journal of Financial Intermediation*, 19(3), 387-417, ISSN 1042-9573, https://doi.org/10.1016/j.jfi.2009.04.001

De Nicolo, G. & Kwast, M. L. (2002). Systemic risk and financial consolidation: Are they related?, *Journal of Banking & Finance*, 26(5), 861-880, ISSN 0378-4266, https://doi.org/10.1016/S0378-4266(02)00211-X

Degryse, H. & Nguyen, G. (2007). Interbank exposures: an empirical examination of contagion risk in the Belgian banking system. *International Journal of Central Banking*, (3), 132–171, https://www.ijcb.org/journal/ijcb07q2a5.pdf

Dell'Ariccia, G., Laeven, L. & Marquez, R., (2011). Monetary Policy, Leverage, and Bank Risk-taking. *CEPR Discussion Papers*, 8199, C.E.P.R. Discussion Papers.

Dell'Ariccia, G. & Marquez, R. (2013). Interest rates and bank risk-taking channel. *Annual Review of Financial Economics*. (5), 123–141, https://doi.org/10.1146/annurev-financial-110112-121021

DeLong, G. & Saunders, A. (2011). Did the introduction of fixed-rate federal deposit insurance increase long-term bank risk-taking?, *Journal of Financial Stability*, 7(1), 19-25, ISSN 1572-3089, https://doi.org/10.1016/j.jfs.2008.09.013

Demirguc-Kunt, A. & Detragiache, E. (1997). The determinants of banking crises in developing and developed countries, *IMF Working Paper*, WP/97/106.

Demirgüç-Kunt, A. & Detragiache, E. (2002). Does deposit insurance increase banking system stability? An empirical investigation, *Journal of Monetary Economics*, 49(7), 1373-1406, ISSN 0304-3932, https://doi.org/10.1016/S0304-3932(02)00171-X

Demirguc-Kunt, A. & Huizinga, H. (2010). Bank activity and funding strategies: The impact on risk and returns, *Journal of Financial Economics*, 98(3), 626-650, ISSN 0304-405X, https://doi.org/10.1016/j.jfineco.2010.06.004

Demirguc-Kunt, A., Kane, E. & Laeven, L. (2015). Deposit insurance around the world: A comprehensive analysis and database, *Journal of Financial Stability*, 20, 155-183, ISSN 1572-3089, https://doi.org/10.1016/j.jfs.2015.08.005

Dewandaru, G., Masih, R. & Masih, A.M.M. (2016). What can wavelets unveil about the vulnerabilities of monetary integration? A tale of Eurozone stock markets, Economic Modelling, (52), Part B, 981-996, ISSN 0264-9993, https://doi.org/10.1016/j.econmod.2015.10.037

di Iasio, G., Battiston, S., Infante, L. & Pierobon, F. (2013). Capital and contagion in financial networks. *MPRA Paper*, 52141, University Library of Munich, Germany.

Di Maggio, M. & Kacperczyk, M. (2017). The unintended consequences of the zero lower bound policy, *Journal of Financial Economics,* 123(1), 59-80, ISSN 0304-405X, https://doi.org/10.1016/j.jfineco.2016.09.006

Diamond, D. W. & Rajan, R. G. (2009). The credit crisis: Conjectures about causes and remedies. *The American Economic Review,* 99(2), 606–610. http://www.jstor.org/stable/25592466

Diebold, F.X. & Yilmaz, K. (2009), Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. *The Economic Journal*, 119, 158-171. https://doi.org/10.1111/j.1468-0297.2008.02208.x

Diebold, F.X. & Yilmaz, K. (2012), Better to Give than to Receive: Forecast-Based Measurement of Volatility Spillovers, International Journal of Forecasting, 28(1), 57-66, https://doi.org/10.1016/j.ijforecast.2011.02.006

Diebold, F.X. & Yilmaz, K. (2014), On the network topology of variance decompositions: Measuring the connectedness of Financial Firms. *Journal of Econometrics,* 182(1), 119-134, https://doi.org/10.1016/j.jeconom.2014.04.012

Dimitrios, D., & Kenourgios, D., (2013). Financial crises and dynamic linkages among international currencies. *Journal of International Financial Markets, Institutions and Money*, Elsevier, vol. 26(C), 319-332, https://doi.org/10.1016/j.intfin.2013.07.008

Ding, D., Han, L. & Yin, L. (2017) Systemic risk and dynamics of contagion: a duplex inter-bank network, *Quantitative Finance*, 17(9), 1435-1445, https://doi.org/10.1080/14697688.2016.1274046

Dolado, J.J. & Lütkepohl, H. (1996). Making Wald tests work for cointegrated VAR systems, *Econometric Reviews*, 15(4), 369-386, DOI: 10.1080/07474939608800362

Drehmann, M. & Tarashev, N., (2011). Systemic importance: some simple indicators. *BIS Quarterly Review*, Bank for International Settlements, March.

Duan, Y., El Ghoul, S., Guedhami, O., Li, H. & Li, X. (2021). Bank systemic risk around COVID-19: A cross-country analysis, *Journal of Banking & Finance*, (133), 106299, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2021.106299

Duchin, R & Sosyura, D. (2014). Safer ratios, riskier portfolios: Banks′ response to government aid, *Journal of Financial Economics*, 113(1), 1-28, ISSN 0304-405X, https://doi.org/10.1016/j.jfineco.2014.03.005

Dungey, M., Fry, R., González-Hermosillo, B. & Martin, V.L. (2005), *A comparison of alternative tests of contagion with applications*, in Dungey, M. and Tambakis, D. (Eds), Identifying International Financial Contagion: Progress and Challenges, Oxford University Press, New York, NY, pp. 60-85.

Dungey, M. & Gajurel, D. (2014). Equity market contagion during the global financial crisis: Evidence from the world's eight largest economies, *Economic Systems*, 38(2), 161-177, ISSN 0939-3625, https://doi.org/10.1016/j.ecosys.2013.10.003

Dungey, M. & Gajurel, D. (2015). Contagion and banking crisis - International evidence for 2007–2009, *Journal of Banking & Finance*, 60(C), 271-283, https://doi.org/10.1016/j.jbankfin.2015.08.007

Dungey, M. & Zhumabekova, D. (2001), Testing for contagion using correlations: some words of caution, *Federal Reserve Bank of San Francisco Working Paper*, No. 9.

Edwards, S., (1998), Interest rate volatility, capital controls, and contagion, *NBER Working Paper*, 6756, DOI 10.3386/w6756.

Edwards, S. (2000), Contagion. *World Economy*, (23), 873-900, https://doi.org/10.1111/1467-9701.00307

Elliott, M., Golub, B. & Jackson, M.O. (2014). Financial networks and contagion. *American Economic Review*, 104(10), 3115-53, https://www.aeaweb.org/articles/pdf/doi/10.1257/aer.104.10.3115

Elsinger, H., Lehar, A. & Summer, M. (2006). Risk Assessment for Banking Systems. *Management Science*, 52(9), 1301-14. http://www.jstor.org/stable/20110606.

Elyasiani, E., Mester, L. & Pagano, M.S., (2014), Large capital infusions, investor reactions, and the return and risk-performance of financial institutions over the business cycle, *Journal of Financial Stability*, 11(C), 62-81, https://doi.org/10.1016/j.jfs.2013.11.002

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics,* 20(3), 339-350. http://www.jstor.org/stable/1392121

European Banking Authority. (2021). *Differences in provisioning practices in the United States and the European Union*. Thematic Note EBA/REP/2021/13.

European Central Bank. (2009). *Financial stability review*, December. Tech. rep. European Central Bank.

Faccio, M., Masulis, R.W. & McConnell, J.J. (2006). Political connections and corporate bailouts. *The Journal of Finance*, (61), 2597-2635. https://doi.org/10.1111/j.1540-6261.2006.01000.x

Faia, E., Ottaviano, G.I.P. & Sanchez Arjona, I., (2017). International Expansion and Riskiness of Banks, *CEPR Discussion Papers*, 11951, C.E.P.R. Discussion Papers.

Faia, E., Laffitte, S. & Ottaviano, G.I.P. (2019) Foreign expansion, competition and bank risk, *Journal of International Economics*, 118, 179-199, ISSN 0022-1996, https://doi.org/10.1016/j.jinteco.2019.01.013.

Farhi, E., & Tirole, J. (2012). Collective Moral Hazard, Maturity Mismatch, and Systemic Bailouts. *The American Economic Review*, 102(1), 60–93. JSTOR, http://www.jstor.org/stable/41408769

Favero, C.A. & Giavazzi, F., (2002). Is the international propagation of financial shocks non-linear?: Evidence from the ERM, *Journal of International Economics*, 57(1), Pages 231-246, ISSN 0022-1996, https://doi.org/10.1016/S0022-1996(01)00139-8

Fernández-Rodríguez, F., Gómez-Puig, M. & Sosvilla-Rivero, S. (2016). Using connectedness analysis to assess financial stress transmission in EMU sovereign bond market volatility, *Journal of International Financial Markets, Institutions and Money*, 43, 126-145, ISSN 1042-4431, https://doi.org/10.1016/j.intfin.2016.04.005

Fiala, T. & Havranek, T. (2017). The sources of contagion risk in a banking sector with foreign ownership, *Economic Modelling*, (60), 108-121, ISSN 0264-9993, https://doi.org/10.1016/j.econmod.2016.08.025

Financial Stability Board (2010): *Reducing the moral hazard posed by systemically important financial institutions*, October.

Flavin, T.J. & Panopoulou, E., (2010). Detecting shift and pure contagion in east Asian equity markets: a unified approach. *Pacific Economic Review*, 15(3), 401-421, https://doi.org/10.1111/j.1468-0106.2010.00510.x

Folkerts-Landau, D. (1990). Systemic financial risk in payment systems. *IMF Working Paper,* No. 90/65, Available at SSRN: https://ssrn.com/abstract=884911

Forbes, K. J. & Chinn, M. D., (2004). A Decomposition of global linkages in financial markets over time. *The Review of Economics and Statistics*, MIT Press, 86(3), 705-722, https://www.jstor.org/stable/3211792

Forbes, K. & Rigobon, R. (2002), No contagion, only interdependence: Measuring stock market co-movements. *Journal of Finance*, 57, 2223-2262, https://doi.org/10.1111/0022-1082.00494

Fostel, A., & Geanakoplos, J. (2008). Leverage Cycles and the Anxious Economy. *American Economic Review*, 98(4): 1211-44, https://www.jstor.org/stable/29730120

Franch, F., Nocciola, L. & Vouldis, A., (2022). Temporal networks in the analysis of financial contagion, *European Central Bank Working Paper*, 2667.

Fry, R., Martin, V. L. & Tang, C. (2010). A new class of tests of contagion with applications, *Journal of Business & Economic Statistics*, 28(3), 423-437, https://www.jstor.org/stable/20750850

Fry-McKibbin, R. & Hsiao, C. Y. (2018). Extremal dependence tests for contagion, *Econometric Reviews*, 37(6), 626-649, https://doi.org/10.1080/07474938.2015.1122270

Fry-McKibbin, R. & Hsiao, C. Y. & Martin, V. L. (2019) Joint tests of contagion with applications. *Quantitative Finance*, 19(3), 473-490, https://doi.org/10.1080/14697688.2018.1475747

Gai, P. & Kapadia, S., (2010). Contagion in financial networks, *Bank of England working papers,* 383, Bank of England.

Gambacorta, L. & Mistrulli, P. E., (2004). Does bank capital affect lending behavior?, *Journal of Financial Intermediation*, 13(4), 436-457, ISSN 1042-9573, https://doi.org/10.1016/j.jfi.2004.06.001

Gandhi, P. & Lustig, H. (2015). Size Anomalies in U.S. Bank Stock Returns. *The Journal of Finance*, (70), 733-768. https://doi.org/10.1111/jofi.12235

Geanakoplos, J., (2010). *The leverage cycle*. In: Acemoglu, D., Rogoff, K., Woodford, M. (Eds.), NBER Macro-economics Annual 2009, vol. 24, University of Chicago Press, pp. 165.

Georg, C. (2013). The effect of the interbank network structure on contagion and common shocks, *Journal of Banking & Finance*, 37(7), 2216-2228, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2013.02.032

Ghosh, A., Saidi, R. & Johnson, K. (1999). Who moves the Asia-Pacific stock markets — US or Japan? Empirical evidence based on the theory of co-integration. *The Financial Review,* 34 (1), 139-170, https://doi.org/10.1111/j.1540-6288.1999.tb00450.x

Girardi, G. & Ergün, T. A., (2013), Systemic risk measurement: Multivariate GARCH estimation of CoVaR, *Journal of Banking & Finance*, 37(8), 3169-3180, https://doi.org/10.1016/j.jbankfin.2013.02.027

Gómez-Puig, M. & Sosvilla-Rivero, S. (2013). Granger-causality in peripheral EMU public debt markets: A dynamic approach, *Journal of Banking & Finance*, 37(11), 4627-4649, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2013.05.002

Gómez-Puig, M. & Sosvilla-Rivero, S. (2014). Causality and contagion in EMU sovereign debt markets, *International Review of Economics & Finance*, (33), 12-27, ISSN 1059-0560, https://doi.org/10.1016/j.iref.2014.03.003

Gómez-Puig, M. & Sosvilla-Rivero, S. (2016), Causes and hazards of the euro area sovereign debt crisis: Pure and fundamentals-based contagion, *Economic Modelling*, 56, issue C, p. 133-147, https://doi.org/10.1016/j.econmod.2016.03.017

Gorton, G., & Metrick, A. (2012). Securitized banking and the run on repo. *Journal of Financial Economics,* 104(3), 425–51, https://doi.org/10.1016/j.jfineco.2011.03.016

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. *Econometrica*, 37(3), 424–38. JSTOR, https://doi.org/10.2307/1912791

Gravelle, T., Kichian, M. & Morley, J., (2006). Detecting shift-contagion in currency and bond markets, *Journal of International Economics*, 68(2), 409-423, https://doi.org/10.1016/j.jinteco.2005.07.005

Griliches, Z. & Hausman, J. A. (1986). Errors in variables in panel data, *Journal of Econometrics*, 31(1), 93-118, ISSN 0304-4076, https://doi.org/10.1016/0304-4076(86)90058-8

Grinis, I., (2015). Credit risk spillovers, systemic importance and vulnerability in financial networks, *LSE Research Online Documents on Economics,* 60954, London School of Economics and Political Science, LSE Library.

Gropp, R, Gruendl, C. & Guettler, A. (2014). The Impact of Public Guarantees on Bank Risk-Taking: Evidence from a Natural Experiment, *Review of Finance*, 18(2), 457–488, https://doi.org/10.1093/rof/rft014

Gropp, R., & Vesala, J. (2004). Deposit insurance, moral hazard and market monitoring. *Review of Finance*, 8(4), 571–602, https://doi.org/10.1093/rof/8.4.571

Guo, F., Chen, C.R. & Huang, Y. S. (2011), Markets contagion during financial crisis: A regime-switching approach. *International Review of Economics & Finance*, 20(1), 95-109, https://doi.org/10.1016/j.iref.2010.07.009

Hałaj, G. (2018). System-wide implications of funding risk, *Physica A: Statistical Mechanics and its Applications*, 503, 1151-1181, ISSN 0378-4371, https://doi.org/10.1016/j.physa.2018.08.060

Hamao, Y., Masulis, R. W., & Ng, V. K., (1990). Correlations in price changes and volatility across international stock markets, *The Review of Financial Studies,* 3, 281-307, https://www.jstor.org/stable/2962024

Härdle, W. K., Wang, W. & Yu, L. (2016). TENET: Tail-Event driven NETwork risk, *Journal of Econometrics*, 192(2), 499-513, ISSN 0304-4076, https://doi.org/10.1016/j.jeconom.2016.02.013.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 50(4), 1029–1054. https://doi.org/10.2307/1912775

Hautsch, N., Schaumburg, J., & Schienle, M. (2015). Financial network systemic risk contributions. *Review of Finance*, (19), 685–738, https://doi.org/10.1093/rof/rfu010

He, F. & Chen, X. (2016), Credit networks and systemic risk of Chinese local financing platforms: Too central or too big to fail?: –based on different credit correlations using hierarchical methods, *Physica A: Statistical Mechanics and its Applications*, 461, 158-170, https://doi.org/10.1016/j.physa.2016.05.032

Hemche O., Jawadi, F., Maliki, S.B. & Cheffou A. (2016). On the study of contagion in the context of the subprime crisis: A dynamic conditional correlation-multivariate GARCH approach. *Economic Modelling* 52, 292-299, https://doi.org/10.1016/j.econmod.2014.09.004

Hilscher, J. & Nosbusch, Y., (2010). Determinants of sovereign risk: Macroeconomic fundamentals and the pricing of sovereign debt. *Review of Finance*, European Finance Association, 14(2), 235-262, https://doi.org/10.1093/rof/rfq005

Hodula, M., Janku, J. & Pfeifer, L., (2021). Interaction of cyclical and structural systemic risks: Insights from around and after the global financial crisis. Czech National Bank Research *and Policy Notes,* 2021/03.

Hong, Y. (2001). A test for volatility spillover with application to exchange rates, *Journal of Econometrics*, 103(1–2), 183-224, ISSN 0304-4076, https://doi.org/10.1016/S0304-4076(01)00043-4

Hong, Y., Liu, Y. & Wang, S. (2009), Granger causality in risk and detection of extreme risk spillover between financial markets, *Journal of Econometrics*, 150(2), 271-287, ISSN 0304-4076, https://doi.org/10.1016/j.jeconom.2008.12.013

Hoque, H., Andriosopoulos, D., Andriosopoulos, K. & Douady, R. (2015). Bank regulation, risk and return: Evidence from the credit and sovereign debt crises, *Journal of Banking & Finance*, 50, 455-474, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2014.06.003

Hott, C. (2022). Leverage and risk taking under moral hazard. *J Financ Serv Res,* 61, 167–185, https://doi.org/10.1007/s10693-021-00359-8

Hovakimian, A., Kane, E. & Laeven, L., (2012). Variation in systemic risk at US banks during 1974-2010. *NBER Working Paper,* No. 18043.

Huang, R. & Ratnovski, L (2011). The dark side of bank wholesale funding, *Journal of Financial Intermediation*, 20(2), 248-263, ISSN 1042-9573, https://doi.org/10.1016/j.jfi.2010.06.003

Huang, X., Zhou, H. & Zhu, H. (2009). A framework for assessing the systemic risk of major financial institutions. *J. Bank.Finance*, 33(11), 2036-2049, https://doi.org/10.1016/j.jbankfin.2009.05.017

Huang, X., Zhou, H. & Zhu, H. (2012). Systemic risk contributions. *J. Financ. Serv. Res.*, 42, 1-29, https://doi.org/10.1007/s10693-011-0117-8

Huizinga, H. & Laeven, L. (2019). The procyclicality of banking: evidence from the Euro Area. *IMF Economic Review*, Palgrave Macmillan;International Monetary Fund, vol. 67(3), pages 496-527, September.

Hulster, K., Salomao-Garcia, V. & Letelier, R. (2014). Loan classification and provisioning: Current practices in 26 ECA countries. *Financial Sector Advisory Center (FinSAC) working paper series*. World Bank Group.

Hwang, J., & Sun, Y. (2018). Should we go one step further? An accurate comparison of one-step and two-step procedures in a generalized method of moments framework. *Journal of Econometrics*, 207(2), 381–405, https://doi.org/10.1016/j.jeconom.2018.07.006

Iannotta, G., Nocera, G. & Sironi, A. (2013). The impact of government ownership on bank risk, *Journal of Financial Intermediation*, 22(2), 152-176, ISSN 1042-9573, https://doi.org/10.1016/j.jfi.2012.11.002

International Monetary Fund. (2020). *Global Financial Stability Report: Bridge to Recovery.* October 2020.

Ioannidou, V. P., & Penas, M. F. (2010). Deposit insurance and bank risk-taking: Evidence from internal loan ratings. *Journal of Financial Intermediation*, 19(1), 95-115, https://doi.org/10.1016/j.jfi.2009.01.002

Ivashina, V. & Scharfstein, D. (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics*, 97(3), 319–338, https://doi.org/10.1016/j.jfineco.2009.12.001

Jammazi, R., Ferrer, R., Jareño, F. & Hammoudeh, S. M. (2017). Main driving factors of the interest rate-stock market Granger causality, *International Review of Financial Analysis*, 52, 260-280, ISSN 1057-5219, https://doi.org/10.1016/j.irfa.2017.07.008

Jawadi, F., Louhichi, W. & Cheffou, A. I,. (2015). Testing and modeling jump contagion across international stock markets: A nonparametric intraday approach, *Journal of Financial Markets*, 26, 64-84, ISSN 1386-4181, https://doi.org/10.1016/j.finmar.2015.09.004

Jorion, P. & Zhang, G. (2007). Good and bad credit contagion: Evidence from credit default swaps, *Journal of Financial Economics*, 84(3), 860-883, https://doi.org/10.1016/j.jfineco.2006.06.001

Jutasompakorn, P., Lim, C. Y., Ranasinghe, T. & Yong, K. O. (2021). Impact of Basel III on the discretion and timeliness of Banks' loan loss provisions, *Journal of Contemporary Accounting & Economics*, 17(2), 100255, ISSN 1815-5669, https://doi.org/10.1016/j.jcae.2021.100255

Kalemli-Ozcan, S., Sorensen, B. & Yesiltas, S. (2012). Leverage across firms, banks, and countries, *Journal of International Economics*, 88(2), 284-298, ISSN 0022-1996, https://doi.org/10.1016/j.jinteco.2012.03.002

Kanda, P., Burke, M. & Gupta, R. (2018). Time-varying causality between equity and currency returns in the United Kingdom: Evidence from over two centuries of data, *Physica A: Statistical Mechanics and its Applications*, 506, 1060-1080, ISSN 0378-4371, https://doi.org/10.1016/j.physa.2018.05.037

Karim, D., Liadze, I., Barrell, R. & Davis, E. P. (2013). Off-balance sheet exposures and banking crises in OECD countries, *Journal of Financial Stability*, 9(4), 673-681, ISSN 1572-3089, https://doi.org/10.1016/j.jfs.2012.07.001.

Kenourgios, D. (2014), On financial contagion and implied market volatility, *International Review of Financial Analysis*, 34, 21-30, https://doi.org/10.1016/j.irfa.2014.05.001

Kenourgios, D. & Dimitriou, D. (2014), Contagion effects of the global financial crisis in US and European real economy sectors. *Panoeconomicus*, 61(3), 275-288, https://doi.org/10.2298/PAN1403275K

Kenourgios, D., Samitas, A. & Paltalidis, N. (2011). Financial crises and stock market contagion in a multivariate time-varying asymmetric framework, *Journal of International Financial Markets, Institutions and Money*, 21(1), 92-106, ISSN 1042-4431, https://doi.org/10.1016/j.intfin.2010.08.005

Khaled, A., Creti, A. & Chevallier, J. (2018). Oil price risk and financial contagion. *The Energy Journal*. 39, Special Issue 2. https://doi.org/10.5547/01956574.39.SI2.kgue

Khan, S. & Park, K. W. K., (2009). Contagion in the stock markets: The Asian financial crisis revisited", Journal of Asian Economics 20(5), 561-569, https://doi.org/10.1016/j.asieco.2009.07.001

Kilic, E., Lobo, G. J., Ranasinghe, T. & Sivaramakrishnan, K. (2013). The impact of SFAS 133 on income smoothing by banks through loan loss provisions. *The Accounting Review*. 88(1): 233–260. doi: https://doi.org/10.2308/accr-50264

King, M. A. & Wadhwani, S. (1990). Transmission of volatility between stock markets, *The Review of Financial Studies*, 3(1), 5–33, https://doi.org/10.1093/rfs/3.1.5

Kleinow, J., & Moreira, F. (2016). Systemic risk among European banks: A copula approach. *Journal of International Financial Markets Institutions and Money*, 42, 27–42 , https://doi.org/10.1016/j.intfin.2016.01.002

Knaup, M., Wagner, W. Forward-Looking Tail Risk Exposures at U.S. Bank Holding Companies. *Journal of Financial Services Research,* 42, 35–54 (2012). https://doi.org/10.1007/s10693-012-0131-5

Koop, G., Pesaran, M.H. & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models, *Journal of Econometrics*, 74(1), 119-147, ISSN 0304-4076, https://doi.org/10.1016/0304-4076(95)01753-4

Koutmos, G. & Booth, G. G., (1995), Asymmetric volatility transmission in international stock markets, *Journal of International Money and Finance*, 14(6), 747-762, https://doi.org/10.1016/0261-5606(95)00031-3

Koutmos, D. (2018). Return and volatility spillovers among cryptocurrencies, *Economics Letters*, 173, 122-127, ISSN 0165-1765, https://doi.org/10.1016/j.econlet.2018.10.004

Kurtzman, R., Luck, S. & Zimmermann, T. (2022). Did QE lead banks to relax their lending standards? Evidence from the Federal Reserve's LSAPs, *Journal of Banking & Finance*, 138, 105403, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2018.08.009

Kuzubas, T. U., Saltoğlu, B. & Sever, C. (2016). Systemic risk and heterogeneous leverage in banking networks, *Physica A: Statistical Mechanics and its Applications*, 462, 358-375, ISSN 0378-4371, https://doi.org/10.1016/j.physa.2016.06.085

Laeven, L. & Majnoni, G. (2003). Loan loss provisioning and economic slowdowns: Too much, too late?. *Journal of Financial Intermediation*, 12, 178-197, https://doi.org/10.1016/S1042-9573(03)00016-0

Lahrech, A. & Sylwester, K. (2011). U.S. and Latin American stock market linkages, *Journal of International Money and Finance*, 30(7), 1341-1357, ISSN 0261-5606, https://doi.org/10.1016/j.jimonfin.2011.07.004

Langfield, S, Liu, Z. & Ota, T. (2014). Mapping the UK interbank system, *Journal of Banking & Finance*, 45, 288-303, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2014.03.031

Laeven, L., Ratnovski, L, & Tong, H. (2016). Bank size, capital, and systemic risk: Some international evidence, *Journal of Banking & Finance*, 69, Supplement 1, S25-S34, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2015.06.022

Leavens, D. H. (1945). Diversification of investments, *Trusts and Estates*, 80(5), 469-473.

Lee, S. B. & Kim, K.J., (1993), Does the October 1987 crash strengthen the co-movements among national stock markets?. *Review of Financial Economics*. 3, 89-102, https://doi.org/10.1002/j.1873-5924.1993.tb00574.x

Lee, S. H. (2013). Systemic liquidity shortages and interbank network structures, *Journal of Financial Stability*, 9(1), 1-12, ISSN 1572-3089, https://doi.org/10.1016/j.jfs.2012.12.001.

Lee, T. & Yang, W. (2014). Granger-causality in quantiles between financial markets: Using copula approach, *International Review of Financial Analysis*, 33, 70-78, ISSN 1057-5219, https://doi.org/10.1016/j.irfa.2013.08.008

Lehar, A. (2005). Measuring systemic risk: A risk management approach. *Journal of Banking and Finance*, 29, 2577–2603, https://doi.org/10.1016/j.jbankfin.2004.09.007

Lin, L., Kuang, Y., Jiang, Y. & Su, X. (2019). Assessing risk contagion among the Brent crude oil market, London gold market and stock markets: Evidence based on a new wavelet decomposition approach, *The North American Journal of Economics and Finance*, 50, 101035, ISSN 1062-9408, https://doi.org/10.1016/j.najef.2019.101035

Loaiza Maya, R.A., Gomez-Gonzalez, J.E. and Melo Velandia, L.F. (2015), Latin American exchange rate dependencies: A regular vine copula approach. *Contemp Econ Policy*, 33: 535-549. https://doi.org/10.1111/coep.12091

Lobo, G. J., & Yang, D. H. (2001). Bank managers' heterogeneous decisions on discretionary loan loss provisions. *Review of Quantitative Finance and Accounting*, 16(3), 223-250, https://doi.org/10.1023/A:1011284303517

Londono, J M. (2019). Bad bad contagion, *Journal of Banking & Finance*, 108, 105652, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2019.105652

Longin, F. & Solnik, B. (2001), Extreme Correlation of International Equity Markets. *The Journal of Finance*, 56, 649-676. https://doi.org/10.1111/0022-1082.00340

Longstaff, F. A. (2010). The subprime credit crisis and contagion in financial markets, *Journal of Financial Economics*, 97(3), 436-450, ISSN 0304-405X, https://doi.org/10.1016/j.jfineco.2010.01.002

Loretan, M. (1996). Economic models of systemic risk in financial systems, *The North American Journal of Economics and Finance*, 7(2), 147-152, ISSN 1062-9408, https://doi.org/10.1016/S1062-9408(96)90005-4

López-Espinosa, G., Moreno, A., Rubia, A. & Valderrama, L. (2012). Short-term wholesale funding and systemic risk: A global CoVaR approach, *Journal of Banking & Finance*, 36(12), 3150-3162, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2012.04.020

López-Espinosa, G., Rubia, A., Valderrama, L. & Antón, M. (2013). Good for one, bad for all: Determinants of individual versus systemic risk, *Journal of Financial Stability*, 9(3), 287-299, ISSN 1572-3089, https://doi.org/10.1016/j.jfs.2013.05.002

Lu, F., Hong, Y., Wang, S., Lai, K. & Liu, J. (2014). Time-varying Granger causality tests for applications in global crude oil markets, *Energy Economics*, 42, 289-298, ISSN 0140-9883, https://doi.org/10.1016/j.eneco.2014.01.002

Luchtenberg, K. F. & Vu, Q. V. (2015). The 2008 financial crisis: Stock market contagion and its determinants, *Research in International Business and Finance*, 33, 178-203, ISSN 0275-5319, https://doi.org/10.1016/j.ribaf.2014.09.007

Lund-Jensen, K. (2012). Monitoring systemic risk based on dynamic thresholds. *IMF Working Paper*. WP/12/159.

Markose, S., Giansante, S. & Shaghaghi, A. R. (2012). 'Too interconnected to fail' financial network of US CDS market: Topological fragility and systemic risk, *Journal of Economic Behavior & Organization*, 83(3), 627-646, ISSN 0167-2681, https://doi.org/10.1016/j.jebo.2012.05.016.

Markowitz, H. M. (1952). Portfolio Selection, *Journal of Finance*, 7(1), 77-91, https://doi.org/10.2307/2975974

Masih, A. M. & Masih, R., (1997), Dynamic linkages and the propagation mechanism driving major international stock markets: An analysis of the pre-and post-crash eras, *The Quarterly Review of Economics and Finance*, 37(4), 859-885, https://doi.org/10.1016/S1062-9769(97)90008-9

Masson, P. (1999), Contagion: macroeconomic models with multiple equilibria, *Journal of International Money and Finance*, 18(4), 587-602, https://doi.org/10.1016/S0261-5606(99)00016-9

Memmel, C. & Sachs, A., (2013). Contagion in the interbank market and its determinants, *Journal of Financial Stability*, 9(1), 46-54, ISSN 1572-3089, https://doi.org/10.1016/j.jfs.2013.01.001.

Miele, M. G. & Sales, E. (2011). The financial crisis and regulation reform. *Journal of Banking Regulation,* 12(4), 277–307, https://doi.org/10.1057/jbr.2011.7

Miller, S. & Wanengkirtyo, B., (2020). Liquidity and monetary transmission: a quasi-experimental approach, *Bank of England Working Papers*, 891, Bank of England.

Mollah, S., Quoreshi, A.M.M.S. & Zafirov, G. (2016). Equity market contagion during global financial and Eurozone crises: Evidence from a dynamic correlation analysis, *Journal of International Financial Markets, Institutions and Money*, 41, 151-167, ISSN 1042-4431, https://doi.org/10.1016/j.intfin.2015.12.010

Moore, T. & Wang, P. (2014). Dynamic linkage between real exchange rates and stock prices: Evidence from developed and emerging Asian markets, *International Review of Economics & Finance*, 29, 1-11, ISSN 1059-0560, https://doi.org/10.1016/j.iref.2013.02.004

Moore, K. & Zhou, C. (2012). Identifying systemically important financial institutions: Size and other determinants, *De Nederlandsche Bank Working Paper*, No. 347, http://dx.doi.org/10.2139/ssrn.2104145

Morris, R. D., Kang, H. & Jie, J. (2016). The determinants and value relevance of banks' discretionary loan loss provisions during the financial crisis, *Journal of Contemporary Accounting & Economics,* 12(2), 176-190, ISSN 1815-5669, https://doi.org/10.1016/j.jcae.2016.07.001

Nakajima, J. (2011). Time-varying parameter VAR model with stochastic volatility: An overview of methodology and empirical applications. *Monetary and Economic Studies*, 29, 107-142.

Neal, T. (2015). *Estimating Heterogeneous Coefficients in Panel Data Models with Endogenous Regressors and Common Factors*. University of New South Wales, Australia.

Ng, A., 2000, Volatility spillover effects from Japan and the US to the Pacific–Basin, *Journal of International Money and Finance*, 19(2), 207-233, https://doi.org/10.1016/S0261-5606(00)00006-1

Ng, J., Saffar, W. & Zhang, J.J. (2020). Policy uncertainty and loan loss provisions in the banking industry. *Rev Account Stud*, 25, 726–777, https://doi.org/10.1007/s11142-019-09530-y

Nier, E., Yang, J., Yorulmazer, T. & Alentorn, A. (2007). Network models and financial stability, *Journal of Economic Dynamics and Control*, 31(6), 2033-2060, ISSN 0165-1889, https://doi.org/10.1016/j.jedc.2007.01.014.

Nistor, S. & Ongena, S. R. G. (2020). The Impact of Policy Interventions on Systemic Risk across Banks. *Swiss Finance Institute Research Paper*, No. 20-101, http://dx.doi.org/10.2139/ssrn.2580791

Pais, A. & Stork, P.A. (2013), Bank size and systemic risk. *Eur Financial Management*, 19, 429-451. https://doi.org/10.1111/j.1468-036X.2010.00603.x

Paltalidis, N., Gounopoulos, D., Kizys, R. & Koutelidakis, Y. (2015). Transmission channels of systemic risk and contagion in the European financial network, *Journal of Banking & Finance*, 61, Supplement 1, S36-S52, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2015.03.021.

Papana, A., Kyrtsou, C., Kugiumtzis, D., Diks, C. (2017). Financial networks based on Granger causality: A case study, *Physica A: Statistical Mechanics and its Applications*, 482, 65-73, ISSN 0378-4371, https://doi.org/10.1016/j.physa.2017.04.046

Papanikolaou, N. I. & Wolff, C. C. (2014). The role of on- and off-balance-sheet leverage of banks in the late 2000s crisis. *Journal of Financial Stability*, 14, 3–22, https://doi.org/10.1016/j.jfs.2013.12.003

Papanikolaou, N. I. & Wolff, C. C. (2015). Leverage and Risk in US Commercial Banking in the Light of the Current Financial Crisis, *CEPR Discussion Paper*, No. DP10890, Available at SSRN: https://ssrn.com/abstract=2676596

Patro, D., Qi, M. & Sun, X. (2013). A simple indicator of systemic risk. *J. Financ. Stabil*. 9(1), 105–116, https://doi.org/10.1016/j.jfs.2012.03.002

Pesaran M.H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. Econometrica, 74(4), 967–1012. http://dx.doi.org/10.1111/j.1468-0262.2006.00692.x

Pesaran, M.H. (2007), A simple panel unit root test in the presence of cross-section dependence. *J. Appl. Econ*. 22, 265-312. https://doi.org/10.1002/jae.951

Pesaran, M.H. & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models, Eco*nomics Letters*, 58(1), 17-29, ISSN 0165-1765, https://doi.org/10.1016/S0165-1765(97)00214-0

Phelan, G. (2016). Financial Intermediation, Leverage, and Macroeconomic Instability. *American Economic Journal: Macroeconomics*, 8(4): 199-224, https://www.aeaweb.org/articles/pdf/doi/10.1257/mac.20140233

Philippas, D. & Siriopoulos, C. (2013). Putting the “C” into crisis: Contagion, correlations and copulas on EMU bond markets, *Journal of International Financial Markets, Institutions and Money*, 27, 161-176, ISSN 1042-4431, https://doi.org/10.1016/j.intfin.2013.09.008

Phillips, P. C. B., Shi, S., & Yu, J. (2015a). Testing for Multiple Bubbles: Historical Episodes of Exuberance and Collapse in the S&P 500. *International Economic Review*, 56, 1043–1078, https://doi.org/10.1111/iere.12132

Phillips, P. C. B., Shi, S., & Yu, J. (2015b). Testing for Multiple Bubbles: Limit Theory of Real Time Detectors. *International Economic Review*, 56, 1079–1134, https://doi.org/10.1111/iere.12131

Piccotti, L. R. (2017). Financial contagion risk and the stochastic discount factor, *Journal of Banking & Finance*, 77, 230-248, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2017.01.012

Pindyck, R.S., & Rotemberg, J.J. (1990). The Excess Co-Movement of commodity prices, *The Economic Journal*, 100(403), 1173–89. https://doi.org/10.2307/2233966

Poledna, S., Thurner, S., Farmer, J. D. & Geanakoplos, J. (2014). Leverage-induced systemic risk under Basle II and other credit risk policies, *Journal of Banking & Finance*, 42, 199-212, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2014.01.038

Poon, S., Rockinger, M. & Tawn, J. (2004). Extreme Value Dependence in Financial Markets: Diagnostics, Models, and Financial Implications, *The Review of Financial Studies*, 17(2), 581–610, https://doi.org/10.1093/rfs/hhg058

Primiceri, G.E. (2005). Time varying structural vector autoregressions and monetary policy, *The Review of Economic Studies*, 72(3), 821–852, https://doi.org/10.1111/j.1467-937X.2005.00353.x

Qin, X. & Zhou, C. (2019). Financial structure and determinants of systemic risk contribution, *Pacific-Basin Finance Journal*, 57, 101083, ISSN 0927-538X, https://doi.org/10.1016/j.pacfin.2018.10.012

Raddatz, Claudio E. (2010). When the Rivers Run Dry: Liquidity and the Use of Wholesale Funds in the Transmission of the U.S. Subprime Crisis. *World Bank Policy Research Working Paper*, No. 5203, Available at SSRN: https://ssrn.com/abstract=1559720.

Rahman, M.L., Troster, V., Uddin, G. S. & Yahya, M. (2022). Systemic risk contribution of banks and non-bank financial institutions across frequencies: The Australian experience, *International Review of Financial Analysis*, 79, 101992, ISSN 1057-5219, https://doi.org/10.1016/j.irfa.2021.101992

Rajan, R.G. (2006), Has Finance Made the World Riskier?. *European Financial Management*, 12: 499-533. https://doi.org/10.1111/j.1468-036X.2006.00330.x

Rigobon, R. (2019). Contagion, Spillover, and Interdependence. *Economía*, 19, 69-99. https://doi.org/10.1353/eco.2019.0002

Rochet, J. & Tirole, J. (1996). Interbank lending and systemic risk. *Journal of Money, Credit and Banking*, 28(4), 733-62. https://doi.org/10.2307/2077918

Roy, A. D. (1952). Safety first and the holding of assets. *Econometrica,* 20(3), 431–450, https://doi.org/10.2307/1907413

Rua, A & Nunes, L. C. (2009). International comovement of stock market returns: A wavelet analysis, *Journal of Empirical Finance*, 16(4), 632-639, ISSN 0927-5398, https://doi.org/10.1016/j.jempfin.2009.02.002

Sachs, A. (2014) Completeness, interconnectedness and distribution of interbank exposures—a parameterized analysis of the stability of financial networks, *Quantitative Finance*, 14(9), 1677-1692, https://doi.org/10.1080/14697688.2012.749421

Sachs, J., Tornell, A. & Velasco, A. (1996). Financial crises in emerging markets: The lessons from 1995, *Brookings Papers on Economic Activity*, 1, 147-215, https://doi.org/10.2307/2534648

Samarakoon, L. P. (2011). Stock market interdependence, contagion and the U.S. financial crisis: The case of emerging and frontier markets. *Journal of International Financial Markets, Institutions and Money,* 21(5), 724-742, https://doi.org/10.1016/j.intfin.2011.05.001

Samitas, A. & Tsakalos, I. (2013). How can a small country affect the European economy? The Greek contagion phenomenon, *Journal of International Financial Markets, Institutions and Money*, 25, issue C, 18-32, https://doi.org/10.1016/j.intfin.2013.01.005

Sander, H. & Kleimeier, S. (2003). Contagion and causality: an empirical investigation of four Asian crisis episodes. *Journal of International Financial Markets Institutions and Money*, 13(2), 171–186, https://doi.org/10.1016/S1042-4431(02)00043-4

Sargan, J. D. (1958). The Estimation of Economic Relationships using Instrumental Variables. *Econometrica*, 26(3), 393–415. https://doi.org/10.2307/1907619

Schularick, M. & Taylor, A.M. (2012). Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008. *American Economic Review*, 102(2): 1029-61 , https://www.aeaweb.org/articles/pdf/doi/10.1257/aer.102.2.1029

Scott, H. S. (2014). *Interconnectedness and Contagion - Financial Panics and the Crisis of 2008* (June 26, 2014). Available at SSRN: https://ssrn.com/abstract=2178475

Sedunov, J. (2016). What is the systemic risk exposure of financial institutions?, *Journal of Financial Stability,* 24, 71-87, ISSN 1572-3089, https://doi.org/10.1016/j.jfs.2016.04.005

Shen, P., Li, W., Wang, X. & Su, C. (2015), Contagion effect of the European financial crisis on China's stock markets: Interdependence and pure contagion, *Economic Modelling*, 50, 193–199, https://doi.org/10.1016/j.econmod.2015.06.017

Shi, S., Phillips, P.C.B. & Hurn, S. (2018), Change detection and the causal impact of the yield curve. *J. Time Ser. Anal*., 39, 966-987. https://doi.org/10.1111/jtsa.12427

Shi, S., Hurn, S. & Phillips, P.C B. (2020). Causal change detection in possibly integrated systems: Revisiting the money–income relationship, *Journal of Financial Econometrics*, 18(1), 158–180, https://doi.org/10.1093/jjfinec/nbz004.

Shleifer, A. & Vishny, R. W. (2010). Unstable banking, *Journal of Financial Economics*, 97(3), 306-318, ISSN 0304-405X, https://doi.org/10.1016/j.jfineco.2009.10.007

Sibande, X., Gupta, R. & Wohar, M. E. (2019). Time-varying causal relationship between stock market and unemployment in the United Kingdom: Historical evidence from 1855 to 2017, *Journal of Multinational Financial Management*, 49, 81-88, ISSN 1042-444X, https://doi.org/10.1016/j.mulfin.2019.02.003

Siebenbrunner, C., Sigmund, M. & Kerbl, S. (2017). Can bank-specific variables predict contagion effects?. *Quantitative Finance*, 17(12), 1805-1832, https://doi.org/10.1080/14697688.2017.1357974

Siebenbrunner, C. & Sigmund, M. (2019). *Quantile Panel Estimation of Financial Contagion Effects*, Editor(s): Mike Tsionas, Panel Data Econometrics, Academic Press, 2019, 639-664, https://doi.org/10.1016/B978-0-12-815859-3.00020-2

Silva, T. G., Souza, S. R. S. & Tabak, B. M. (2017). Monitoring vulnerability and impact diffusion in financial networks, *Journal of Economic Dynamics and Control*, 76, 109-135, ISSN 0165-1889, https://doi.org/10.1016/j.jedc.2017.01.001

Souza, S. R. S., Tabak, B. M, Silva, T. G. & Guerra, S. M. (2015). Insolvency and contagion in the Brazilian interbank market, *Physica A: Statistical Mechanics and its Applications*, (431), 140-151, ISSN 0378-4371, https://doi.org/10.1016/j.physa.2015.03.005.

Sui, L. & Sun, L. (2016). Spillover effects between exchange rates and stock prices: Evidence from BRICS around the recent global financial crisis, *Research in International Business and Finance*, 36, 459-471, ISSN 0275-5319, https://doi.org/10.1016/j.ribaf.2015.10.011

Shahzad, S. J. H., Bouri, E., Ahmad, T., Naeem, M. A., Vo, X. V. (2021). The pricing of bad contagion in cryptocurrencies: A four-factor pricing model, *Finance Research Letters*, 41, 101797, ISSN 1544-6123, https://doi.org/10.1016/j.frl.2020.101797.

Straetmans, S. & Chaudhry, S.M. (2015). Tail risk and systemic risk of US and Eurozone financial institutions in the wake of the global financial crisis, *Journal of International Money and Finance*, 58, 191-223, ISSN 0261-5606, https://doi.org/10.1016/j.jimonfin.2015.07.003

Susmel, R. & Engle, R. F. (1994), Hourly volatility spillovers between international equity markets, *Journal of International Money and Finance*, 13(1), 3-25, https://doi.org/10.1016/0261-5606(94)90021-3

Tasca, P., Mavrodiev, P., & Schweitzer, F. (2014). Quantifying the impact of leveraging and diversification on systemic risk. *Journal of Financial Stability*, 15, 43–52, https://doi.org/10.1016/j.jfs.2014.08.006

Tedeschi, G., Mazloumian, A., Gallegati, M. & Helbing, D. (2012). Bankruptcy cascades in interbank markets. *PLoS ONE*, 7(12), e52749. https://doi.org/10.1371/journal.pone.0052749

Teng, H. J., Chang, C. O. & Chen, M.C. (2017). Housing bubble contagion from city centre to suburbs. *Urban Studies*, 54(6), 1463–1481. https://www.jstor.org/stable/26151425

Xu, T.T., Hu, K. & Das, U.S. (2019). Bank Profitability and Financial Stability. *IMF Working Paper*. WP/19/5.

Thakor, A.V. (2014). *Leverage, system risk and financial system health: How do we develop a healthy financial system?.* In: Lindblom, T., Sjögren, S., Willesson, M. (eds) Governance, Regulation and Bank Stability. Palgrave Macmillan Studies in Banking and Financial Institutions. Palgrave Macmillan, London. https://doi.org/10.1057/9781137413543_2

Theodossiou, P. & Lee, U. (1993), Mean and volatility spillovers across major national stock markets: Further empirical evidence, *Journal of Financial Research*, 16, 337–50, https://doi.org/10.1111/j.1475-6803.1993.tb00152.x

Thurner, S. (2011). Systemic financial risk: Agent based models to understand the leverage cycle on national scales and its consequences. *OECD Working Paper*, IFP/WK/FGS(2011)1, Organisation for Economic Co-operation and Development International Futures Programme.

Thurner, S., Farmer, J. D. & Geanakoplos, J. (2012). Leverage causes fat tails and clustered volatility, *Quantitative Finance*, 12(5), 695-707, https://doi.org/10.1080/14697688.2012.674301

Toda, H. Y. & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes, *Journal of Econometrics*, 66(1–2), 225-250, ISSN 0304-4076, https://doi.org/10.1016/0304-4076(94)01616-8

Valencia, F. (2014). Monetary policy, bank leverage, and financial stability, *Journal of Economic Dynamics and Control*, 47, 20-38, ISSN 0165-1889, https://doi.org/10.1016/j.jedc.2014.07.010

Vallascas, F. & Keasey, K. (2012). Bank resilience to systemic shocks and the stability of banking systems: Small is beautiful, *Journal of International Money and Finance*, 31(6), 1745-1776, ISSN 0261-5606, https://doi.org/10.1016/j.jimonfin.2012.03.011

Varotto, S. & Zhao, L. (2018). Systemic risk and bank size, *Journal of International Money and Finance*, 82, 45-70, ISSN 0261-5606, https://doi.org/10.1016/j.jimonfin.2017.12.002

Verma, R., Ahmad, W., Uddin, G. S. & Bekiros, S. (2019). Analysing the systemic risk of Indian banks, *Economics Letters*, 176, 103-108, ISSN 0165-1765, https://doi.org/10.1016/j.econlet.2019.01.003

Wahlen, J. (1994). The nature of information in commercial bank loan loss disclosures. *The Accounting Review*, 69(3), 455-478, http://www.jstor.org/stable/248234

Walter, J. R. (1991). Loan loss reserves. *FRB Richmond Economic Review*, 77(4), 20-30, Available at SSRN: https://ssrn.com/abstract=2126215

Wang, G., Xie, C., Lin, M. & Stanley, H. E. (2017). Stock market contagion during the global financial crisis: A multiscale approach, *Finance Research Letters*, 22, 163-168, ISSN 1544-6123, https://doi.org/10.1016/j.frl.2016.12.025

Wang, G. Xie, C., He, K. & Stanley, H.E. (2017). Extreme risk spillover network: application to financial institutions, *Quantitative Finance*, 17:9, 1417-1433, https://doi.org/10.1080/14697688.2016.1272762

Wang, G., Jiang, Z., Lin, M., Xie, C. & Stanley, H. E. (2018). Interconnectedness and systemic risk of China's financial institutions, *Emerging Markets Review*, 35, 1-18, ISSN 1566-0141, https://doi.org/10.1016/j.ememar.2017.12.001.

Wang, X., Liu, H., Huang, S. & Lucey, B. (2019). Identifying the multiscale financial contagion in precious metal markets, *International Review of Financial Analysis*, 63, 209-219, ISSN 1057-5219, https://doi.org/10.1016/j.irfa.2019.04.003

Weiß, G. N.F., Bostandzic, D. & Neumann, S. (2014). What factors drive systemic risk during international financial crises?, *Journal of Banking & Finance*, 41, 78-96, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2014.01.001

Weiß, G. N.F & Mühlnickel, J. (2014). Why do some insurers become systemically relevant?, *Journal of Financial Stability*, 13, 95-117, ISSN 1572-3089, https://doi.org/10.1016/j.jfs.2014.05.001.

Westerlund, J. (2008). Panel cointegration tests of the Fisher effect. *J Appl Econ,* 23(2), 193-233. http://dx.doi.org/10.1002/jae.967

Williams, B. (2016). The impact of non-interest income on bank risk in Australia, *Journal of Banking & Finance*, 73, 16-37, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2016.07.019

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators, *Journal of Econometrics*, 126(1), 25-51, ISSN 0304-4076, https://doi.org/10.1016/j.jeconom.2004.02.005.

Wong, E., Fong, T., & Choi, H. (2011). Procyclicality of loan-loss provisioning and systemic risk in the Hong Kong banking system. *Hong Kong Monetary Authority Quarterly Bulletin*. Occasional Paper No. 1.

World Bank. (2020). *COVID-19 and Non-Performing Loan Resolution in the Europe and Central Asia region*. Policy Note.

Zedda, S. & Cannas, G. (2020). Analysis of banks' systemic risk contribution and contagion determinants through the leave-one-out approach, *Journal of Banking & Finance*, 112, 105160, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2017.06.008.

Zhang, X., Lu, F. & Tao, R. (2021). The time-varying causal relationship between the Bitcoin market and internet attention. *Financial Innovation*, 7(66). https://doi.org/10.1186/s40854-021-00275-9

Zhang, Y., Zhou, L., Chen, Y., & Liu, F. (2022). The contagion effect of jump risk across Asian stock markets during the Covid-19 pandemic. *The North American Journal of Economics and Finance*, 61, 101688. https://doi.org/10.1016/j.najef.2022.101688

Zhang, W., Zhuang, X., Wang, J. & Lu, Y. (2020). Connectedness and systemic risk spillovers analysis of Chinese sectors based on tail risk network, *The North American Journal of Economics and Finance*, 54, 101248, ISSN 1062-9408, https://doi.org/10.1016/j.najef.2020.101248.

Zhu, Y., Yang, F. & Ye, W. (2018). Financial contagion behavior analysis based on complex network approach. Annals of Operations Research, 268, 93-111, https://doi.org/10.1007/s10479-016-2362-6

APPENDICES

APPENDIX 1: Marginal Expected Shortfall (MES)

Let N and r_{it} denote the number of firms and the i^{th} firm's return at time t, respectively. Then, the market return (r_{mt}) is calculated by taking the value-weighted average of all firms' returns:

$$r_{mt} = \sum_{i=1}^{N} w_{it}\, r_{it} \tag{1}$$

where w_{it} denotes the i^{th} firm's relative market capitalization. The ES at the a% level is the expected return in the worst a% of the cases. However, it is possible to extend the ES to the general case, in which the returns exceed a given threshold C. The conditional ES of the system is shown as:

$$ES_{mt}(C) = E_{t-1}(r_{mt}|r_{mt} < C) = \sum_{i=1}^{N} w_{it}\, E_{t-1}(r_{it}|r_{mt} < C) \tag{2}$$

Then, the MES is calculated by taking the partial derivative of the equation above with respect to w_{it}.

$$MES_{it}(C) = \frac{\partial ES_{mt}(C)}{\partial w_{it}} = E_{t-1}(r_{it}|r_{mt} < C) \tag{3}$$

$MES_{it}(C)$ gauges the marginal contribution of the i^{th} firm to the systemic risk. As the value of MES rises, the i^{th} firm's contribution to the overall risk of the financial system increases.

APPENDIX 2: Quantile Connectedness Approach

The n-variable quantile VAR model of p^{th}order is stated below:

$$y_t = c(\tau) + \sum_{i=1}^{p} \varphi_i(\tau)\, y_{t-i} + e_t(\tau) \qquad t = 1, 2, \dots \dots .., T \tag{1}$$

where y_t is the n-vector of dependent variables, $\varphi_i(\tau)$ is the matrix of lagged coefficients of the dependent variable at quantile τ. $c(\tau)$ and $e_t(\tau)$ shows n-vector of intercepts and residuals at quantile τ, respectively. $\hat{\varphi}_i(\tau)$ and $\hat{c}(\tau)$ is estimated by postulating that the residuals are accordant with the population quantile restriction stated as follows:

$$Q_\tau\big(e_t(\tau)|y_{t-1}, \dots \dots, y_{t-p}\big) = 0 \tag{2}$$

The τ^{th} conditional quantile response of y is denoted in equation below in which $e_t(\tau)$ could be estimated at every quantile τ:

$$Q_t\big(y_t|y_{t-1}, \dots .., y_{t-p}\big) = c(\tau) + \sum_{i=1}^{p} \hat{\varphi}_i(\tau) y_{t-i} \tag{3}$$

Following Diebold and Yilmaz (2014), it is possible to calculate the spillover index for each quantile by rewriting equation (1) as an infinite order moving average process:

$$y_t = \mu_t + \sum_{0}^{\infty} \omega_s(\tau)\, e_{t-s}(\tau), \qquad t = 1,2, \dots ., T \tag{4}$$

with

$$\mu_t = \big(I_n - \varphi_1(\tau) - \varphi_2(\tau) - \cdots - \varphi_p(\tau)\big)^{-1} c(\tau) \tag{5}$$

and

$$\omega_s(\tau) = \left\{ \begin{matrix} 0, s < 0 \\ I_n, s = 0 \\ \varphi_1(\tau)\omega_{s-1}(\tau) + \cdots + \varphi_p(\tau)\omega_{s-p}(\tau), s > 0 \end{matrix} \right\} \tag{6}$$

where y_t consists of sum of e_t at each quantile τ.

As Diebold and Yilmaz (2014) stress, results based on traditional Cholesky-factor identification may be sensitive to variable ordering. To overcome this problem, we follow generalized variance decomposition (GVD) approach of Koop et al. (1996) and Pesaran and Shin (1998) involving invariant ordering of the variables. Then, the generalized forecast error variance decomposition (GFEVD) resulting from the impact of different variables with forecast horizon H is calculated as follows[35]:

$$d_{ij}(H) = \frac{\rho_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' h_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' h_h \sum e_j\right)} \qquad (7)$$

where $d_{ij}(H)$ denotes the contribution of the j^{th} variable to the prediction error of the variable when the forecast horizon is H, Σ denotes the covariance matrix for the error vector, ρ_{jj} is j^{th} diagonal element of Σ, and e_j is a selection vector with j^{th} element unity and zeros elsewhere. Since shocks for each variable are not orthogonal in the GVD framework, sums of forecast error variance contributions might be different than 1. Therefore, connectedness indexes are based on $\widetilde{D}^g = \left[\tilde{d}_{ij}^g\right]$, where $\tilde{d}_{ij}^g = \frac{d_{ij}^g}{\sum_{j=1}^N d_{ij}^g}$.

To calculate the spillover index by using the information in the variance decomposition matrix, the effect attributable to each variable is standardized as:

$$\widetilde{d}_{ij}(H) = \frac{d_{ij}(H)}{\sum_{j=1}^{n} d_{ij}(H)} \qquad (8)$$

where $\sum_{j=1}^{n} d_{ij}(H) = 1$ and $\sum_{i,j=1}^{n} d_{ij}\,(H) = N$. In addition to calculating connectedness measures introduced by Diebold and Yilmaz (2014), it is also possible to produce connectedness measures at the τ^{th} conditional quantile by employing the framework stated above. The total connectedness index (TCI) at the τ^{th} quantile could be gauged as:

$$TCI(\tau) = \frac{\sum_{i=1}^{N} \sum_{j=1, i\neq j}^{N} {d_{ij}}^h(\tau)}{\sum_{i=1}^{N} \sum_{j=1}^{N} {d_{ij}}^h(\tau)} x100 \qquad (9)$$

The directional spillover effects at quantile τ from all indicators to index i (FROM Spillovers) and from index i to all indicators (TO Spillovers) are calculated by equations 10 and 11, respectively:

$$S_{i\leftarrow}(\tau) = \frac{\sum_{j=1, i\neq j}^{N} {d_{ij}}^h(\tau)}{\sum_{j=1}^{N} {d_{ij}}^h(\tau)} x100 \qquad (10)$$

$$S_{\to i}(\tau) = \frac{\sum_{j=1, i\neq j}^{N} {d_{ji}}^h(\tau)}{\sum_{j=1}^{N} {d_{ji}}^h(\tau)} x100 \qquad (11)$$

[35] d_{ij}^{gH} denotes entries of the H-step generalized variance decomposition matrix D^{gH}.

Then, the net spillover index is calculated as follows:

$$NS_i(\tau) = S_{\to i}(\tau) - S_{i\leftarrow}(\tau) \tag{12}$$

Finally, the spillover index denoting pairwise interactions at quantile τ is gauged as:

$$S_{ij} = {d_{ji}}^h(\tau) - {d_{ij}}^h(\tau) \tag{13}$$

APPENDIX 3: Crisis Periods in Empirical Analysis

a. **The Global Financial Crisis (GFC):** The GFC emerged from the subprime mortgage market in the U.S. and quickly spread to the financial system. It was effective in the 2008-2009 period, but the financial markets started to give signals of turbulence as of the third quarter of 2007. The GFC is often regarded as the worst crisis since the Great Depression.
b. **The European Sovereign Debt Crisis (ESDC):** The ESDC occurred at the end of 2009, before the wounds caused by GFC had yet to be healed. It was a balance of payments crisis and fueled by structural and fiscal weakness of Eurozone members. Although the crisis was effective until 2013, it was mostly contained in 2012.
c. **2014-2017 Turmoil:** This period included many notable events such as the oil shock, the Russian annexation of Crimea, the Chinese stock market turmoil, the Brazilian economic crisis, and the Brexit process. Depending on the economic, political, and military events experienced in many countries, this period does not have a specific concept. In this context, this period differs from the other crisis periods that we examine.
d. **Covid-19 Pandemic:** Covid-19 emerged in December 2019 and most of the countries faced recession in the first quarter of 2020 due to disruption of supply chains, lockdowns, and other measures. Despite being uneven across sectors, the economic recovery has been relatively quick thanks to supportive fiscal and monetary policies implemented around the world.

APPENDIX 4: Arellano-Bover/Blundell-Bond Estimator

The dynamic GMM estimator is first proposed by Arellano and Bond (1991) and improved by Arellano and Bover (1995) and Blundell and Bond (1998). Let equation (1) denote a dynamic panel estimation:

$$y_{it} = \alpha_i + \sum_{j=1}^{p} \rho_j y_{it-j} + \beta X_{it} + u_{it} \tag{1}$$

where y_{it}, y_{it-j}, X, α_i, u_{it} are the response variable, lagged response variable, vector of explanatory variables, time-invariant unobserved individual effects, and error term, respectively. To wipe out the fixed effects and the bias caused by time-invariant unobserved heterogeneity, both sides of the equation are first-differenced. The first-differenced equation below yields the difference GMM estimator (Arellano and Bond, 1991).

$$\Delta y_{it} = \alpha_i + \rho_j \sum_{j=1}^{p} \Delta y_{it-j} + \beta \Delta X_{it} + \Delta u_{it} \tag{2}$$

The difference-GMM estimator estimates the equation above by using lagged explanatory variables as instruments, which are shown in equation (3). The instruments should not be correlated with Δu_{it}.

$$Z = \{\mathrm{y}_{it-1}, \mathrm{y}_{it-2}, \dots \dots, \mathrm{y}_{it-n}, \mathrm{X}_{it-1}, \mathrm{X}_{it-2}, \dots \dots, \mathrm{X}_{it-m}\} \tag{3}$$

To limit the increase in measurement errors on the explanatory variables due to first-differencing (Griliches and Hausman, 1986) and ensure the robustness of the instruments for the first-differenced equations (Arellano and Bover, 1995), Arellano and Bover (1995) and Blundell and Bond (1998) introduced a new methodology that uses the first-differenced variables as instruments for the equations in levels in a system of equations exhibited below.

$$\begin{bmatrix} y_{it} \\ \Delta \mathrm{y}_{it} \end{bmatrix} = \delta \begin{bmatrix} y_{it-j} \\ \Delta y_{it-j} \end{bmatrix} + \beta \begin{bmatrix} X_{it} \\ \Delta X_{it} \end{bmatrix} + u_{it} \tag{4}$$

Although the new estimations are more efficient compared to the estimations obtained by the difference-GMM estimator (Blundell and Bond, 1998), unobserved heterogeneity persists. To eliminate the unobserved heterogeneity, the model is assumed to possess the orthogonality conditions denoted in equation (5) which involves instrumenting the differenced equations with lagged levels and level equations with lagged differences.

$$E\left[\Delta X_{it-j}(\alpha_i u_{it})\right] = E\left[\Delta y_{it-j}(\alpha_i u_{it})\right] = 0 \tag{5}$$

APPENDIX 5: Common Correlated Effects Mean Group Estimator

The CCEMG model is estimated as follows:

$$y_{it} = \alpha_i + \beta_i x_{it} + \varphi_i f_t + \varepsilon_{it} \tag{1}$$

where x_{it} and y_{it} denote observables, β_i shows the unit-specific slope on the observable estimator, α_i is the group fixed effects capturing time-invariant heterogeneity across groups, f_t[36] is the unobserved common factor with heterogeneous factor loadings φ_i, and ε_{it} is the idiosyncratic error term. Equation (1) is augmented with the cross-sectional averages of the dependent and explanatory variables as in equation (2) and estimated for each cross section.

$$y_{it} = \alpha_i + \beta_i x_{it} + \delta_i \bar{y}_{it} + \theta_i \bar{x}_{it} + \varphi_i f_t + \varepsilon_{it} \tag{2}$$

In case of endogeneity, exogenous variables, cross-section averages and lags of the endogenous regressors and/or dependent variable could be assigned to the set of instruments (Z) (Neal, 2015). To gain efficiency under heteroskedasticity and autocorrelation (or both), equation (2) is estimated by 2SLS and residuals $(\tilde{u}_{it})$ are calculated. After that, the covariance of the second moments $\left(Var(Z_i'\tilde{u}_{it})\right)$ are estimated. In order to acquire a consistent GMM estimator with an efficient HAC weight matrix, the inverse of the $Var(Z_i'\tilde{u}_{it})$ is used as the weight matrix. The mean group estimator for the CCEMG model is obtained by calculating the mean of each coefficient over each individual regression as stated below:

$$CCEMG = N^{-1} \sum_{i=1}^{N} \hat{\beta}_i \tag{3}$$

where $\hat{\beta}_i$ is the estimates of coefficients in equation (2).

[36] f_t can be nonstationary and nonlinear.

APPENDIX 6: Time-varying Parameter Vector Autoregressions with Stochastic Volatility

The Time-varying Parameter VAR Model with Stochastic Volatility is represented by

$$y_t = c_t + B_{1t}y_{t-1} + \cdots + B_{st}y_{t-s} + e_t\ , \quad e_t \sim N(0, \Omega_t), \tag{1}$$

for $t = s+1, \dots, n$, where y_t is a vector of observables, $B_{1t}, B_{2t}, \dots, B_{st}$ are matrices of time-varying coefficients, Ω_t is a time-varying covariance matrix, and e_t is a structural shock. The identification is done recursively through the decomposition of $\Omega_t = A_t^{-1}\Sigma_t\Sigma_t {A'}_t^{-1}$, where $\Sigma_t = diag(\sigma_{1t}, \sigma_{2t}, \dots, \sigma_{kt})$, and A_t is a lower-triangular matrix with the diagonal elements equal to 1. β_t is defined as the stacked row vector of $B_{1t}, B_{2t}, \dots, B_{st}$, while $a_t = (a_{1t}, a_{2t}, \dots, a_{qt})'$ is the stacked row vector of the lower-triangular elements of A_t, and $h_t = (h_{1t}, h_{2t}, \dots, h_{kt})$ where $h_t = \log(\sigma_{it}^2)$. Then, the time-varying parameters follows the random walk process stated below:

$$\begin{array}{l} \beta_{t+1} = \beta_t + u_{\beta t}\ , \\ a_{t+1} = a_t + u_{at}\ , \\ h_{t+1} = h_t + u_{ht}\ , \end{array} \qquad \begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix}\right), \tag{2}$$

For $t = s+1, \dots, n$, with $e_t = A_t^{-1}\Sigma_t\varepsilon_t$, where Σ_a and Σ_h are diagonal, $\beta_{s+1} \sim N(\mu_{\beta_0}, \Sigma_{\beta_0})$, $a_{s+1} \sim N(\mu_{a_0}, \Sigma_{a_0})$ and $h_{s+1} \sim N(\mu_{h_0}, \Sigma_{h_0})$[37].

[37] See Primiceri (2005) and Nakajima (2011) for details.

APPENDIX 7: Tables and Figures

Table 13. Bank-specific Results of the CCEMG Estimator

	Return on Assets	Tier 1 Ratio	Deposits/ Assets	Total Assets	NPL Coverage Ratio	Assets/ Equity	Global Liquidity	Global Economic Activity	Constant
All Banks	-0.0056	-0.0495***	0.0037	0.0982	-0.3337**	0.0489**	-0.0006	0.2676	-1.3442
	(0.1651)	(0.0176)	(0.0065)	(0.7926)	(0.1578)	(0.0203)	(0.0039)	(0.501)	(3.2835)
JP Morgan	-0.1287	0.0393	0.0235	-0.2797	-0.0621	0.0841*	0.0277	-2.553	-18.3899*
	(0.2543)	(0.0764)	(0.0177)	(0.3176)	(0.1399)	(0.0467)	(0.0178)	(1.7012)	(9.9135)
Bank of America	0.3843***	-0.0456	0.0181	-0.5007	-0.029	-0.0021	0.0187	-1.2582	10.6434
	(0.1229)	(0.0691)	(0.0145)	(0.3457)	(0.0695)	(0.0622)	(0.0155)	(1.5671)	(9.6815)
Citi	0.0013	-0.1538**	0.0085	-0.2126	-0.2125	0.0849	-0.0078	-2.5488*	8.5238
	(0.097)	(0.0623)	(0.0257)	(0.4897)	(0.2111)	(0.0698)	(0.0197)	(1.3172)	(9.4452)
Wells Fargo	0.1462	-0.2394***	0.0013	0.9327***	-0.2135**	0.1872***	0.0085	-0.7179	13.691
	(0.1858)	(0.0876)	(0.016)	(0.3258)	(0.0854)	(0.0272)	(0.015)	(1.3341)	(11.2767)
Deutsche Bank	1.0558*	-0.1879*	0.0455**	0.5107*	0.7874	0.0814*	-0.0268	1.4062	-8.811***
	(0.5454)	(0.0988)	(0.0223)	(0.3052)	(0.7508)	(0.0484)	(0.0185)	(1.4521)	(9.2152)
Banco Santander	-0.0912	-0.0827**	0.0079	0.657	-0.2273	0.0117	0.0238	0.5558	5.2146
	(0.3348)	(0.0385)	(0.0204)	(0.4537)	(0.5135)	(0.0729)	(0.0151)	(1.3778)	(10.025)
Mizuho	0.5664**	0.0873	0.0214	-0.2548	0.793	0.0160	0.0094	-0.7925	5.9798
	(0.2893)	(0.0602)	(0.0217)	(0.4474)	(0.7254)	(0.0161)	(0.0179)	(1.5658)	(13.6586)
Mitsubishi	0.2168	0.0314	-0.0324	-0.9076	-1.1696**	0.0862	0.0031	-0.5883	3.0322
	(0.1963)	(0.0884)	(0.0258)	(1.084)	(0.5043)	(0.0743)	(0.0192)	(1.2921	(11.6834)
Sumitomo Mitsui	0.4178	-0.1289*	-0.0054	0.3981*	-1.9491***	0.0769	-0.0037	3.2887**	28.3269**
	(0.4669)	(0.0732)	(0.0176)	(0.2392)	(0.7085)	(0.0593)	(0.0262)	(1.6746)	(12.8891)
Royal Bank of Canada	-1.1042*	-0.0223	-0.0059	0.3056	-0.4972**	0.0695*	-0.0255	6.0369***	-8.5145
	(0.6028)	(0.1345)	(0.0226)	(0.8252)	(0.2151)	(0.0419)	(0.0175)	(1.7077)	(9.2452)

Table 13. Bank-specific Results of the CCEMG Estimator (Continued)

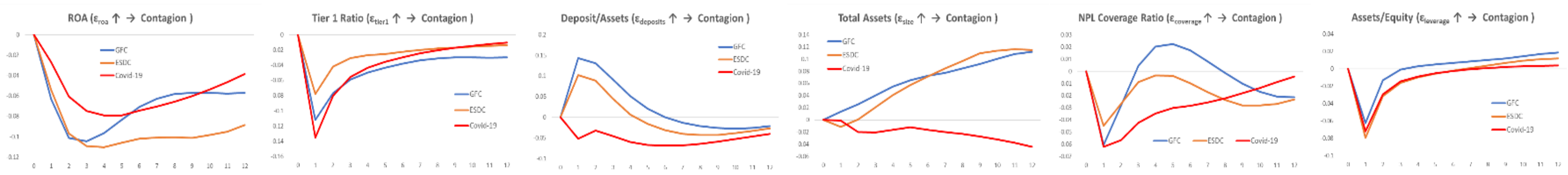
	Return on Assets	Tier 1 Ratio	Deposits/ Assets	Total Assets	NPL Coverage Ratio	Assets/ Equity	Global Liquidity	Global Economic Activity	Constant
Toronto	-1.0954*	-0.0173	0.002	1.719***	0.0043	0.0412	-0.0534***	3.4601**	-7.3975
	(0.5637)	(0.0278)	(0.0098)	(0.649)	(0.1087)	(0.0335)	(0.0173)	(1.484)	(8.9220)
Unicredit	-0.0973	-0.1159*	0.0151***	0.5306	-1.0698*	0.0442*	-0.0185	2.7618**	7.0011
	(0.0769)	(0.0685)	(0.0041)	(0.3674)	(0.6119)	(0.0246)	(0.0164)	(1.3026)	(9.563)
UBS	0.249	0.0217	-0.0265*	1.0415*	-0.2059	0.0304	0.0117	-0.6496	-2.8932
	(0.1715)	(0.0211)	(0.0144)	(0.5568)	(0.6658)	(0.0188)	(0.0184)	(1.2689)	(12.2463)
BBVA	0.1663	0.0366	-0.0376*	-1.0318	0.0473	0.026	0.0097	-3.1643*	-16.2394*
	(0.2278)	(0.0819)	(0.0194)	(2.4467)	(0.1406)	(0.029)	(0.0156)	(1.7771)	(9.433)
Credit Suisse	0.2806**	-0.152***	-0.055***	0.9301*	-2.7877***	-0.0222	-0.006	-0.6199	-23.669**
	(0.1306)	(0.0553)	(0.0204)	(0.4855)	(0.7448)	(0.0248)	(0.0188)	(1.3789)	(10.3517)
Scotiabank	0.7328	-0.2141*	0.0741	2.6282*	0.461	0.1639	-0.0186	-1.6486	-23.3571*
	(0.746)	(0.1102)	(0.0775)	(1.3764)	(0.3576)	(0.103)	(0.0184)	(2.4079)	(12.608)
Nordea	-0.0475	-0.096	0.0848**	-1.813	-2.8115***	0.0814*	-0.0287*	1.7612	13.1618
	(0.3399)	(0.0915	(0.0402)	(1.5112)	(0.9685)	(0.0472)	(0.0151)	(1.4725)	(11.7898
Intesa Sanpaolo	-0.1422*	0.0314	-0.0092**	-0.4043	-1.3898**	-0.026	0.002	0.7362	3.7621
	(0.077)	(0.0708)	(0.0042)	(0.6376)	(0.6523)	(0.028)	(0.0162)	(1.3079)	(8.7573)
Bank of Montreal	-3.705***	-0.1947*	0.0579***	4.8065***	-0.7115***	0.23***	0.0223	1.5826	19.5999**
	(0.6512)	(0.1182)	(0.0181)	(1.2822)	(0.2483)	(0.0732)	(0.0157)	(1.3548)	(8.9263)
Danske Bank	-0.5089**	-0.0092	-0.0125	-0.4257	0.6331	0.0216	-0.0078	4.5287**	-13.2538
	(0.2224)	(0.0532)	(0.0305)	(0.424)	(0.4517)	(0.0281)	(0.0172)	(2.101)	(9.9433)
Bancorp	-0.1455	-0.1077**	-0.0046	16.1202***	-0.2013***	0.068	0.0057	-1.7768	-44.28***
	(0.1838)	(0.0516)	(0.0174)	(4.4443)	(0.0762)	(0.0898)	(0.0168)	(1.638)	(11.7896)

Table 13. Bank-specific Results of the CCEMG Estimator (Continued)

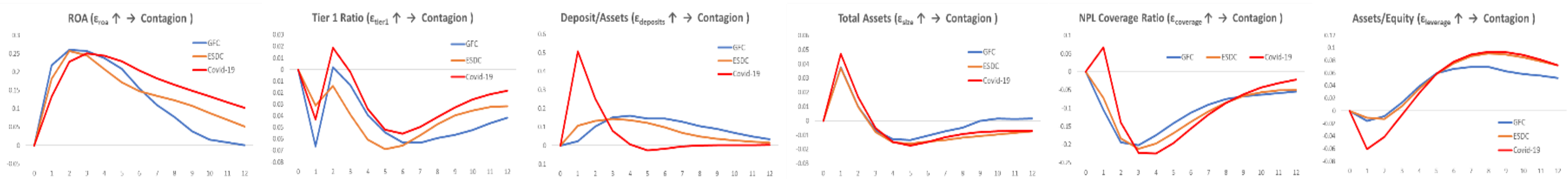
	Return on Assets	Tier 1 Ratio	Deposits/ Assets	Total Assets	NPL Coverage Ratio	Assets/ Equity	Global Liquidity	Global Economic Activity	Constant
Canadian Imperial	-0.2272*	0.0392	-0.0147	9.3264	-0.4162	0.0317	0.0014	3.8562***	11.0544
	(0.1303)	(0.0709)	(0.0125)	(5.9808)	(0.2687)	(0.0491)	(0.0154)	(1.4906)	(11.5014)
Commerzbank	0.2613	-0.1318**	-0.0231	-1.2721	-0.8702	0.0862***	0.024*	-4.1107**	6.3179
	(0.2441)	(0.0614)	(0.0166)	(0.8927)	(0.8456)	(0.0233)	(0.0145)	(1.6958)	(11.8121)
Truist Financial	0.1063	0.0003	-0.0218	-0.3846	-0.2588**	0.3371***	0.013	-2.5521*	-11.4821
	(0.1114)	(0.0757)	(0.0231)	(1.1677)	(0.1194)	(0.0967)	(0.016)	(1.3965)	(9.8208)
PNC	-0.0479	-0.1402**	-0.0279**	-0.1824	0.0857	0.1704**	0.028	2.7535	24.6278**
	(0.1922)	(0.0684)	(0.0117)	(2.2715)	(0.3444)	(0.0689)	(0.02)	(1.728)	(11.0324)
Capital One	0.0691	-0.0571	0.0373***	7.0474**	-0.0135	-0.087	-0.0096	-0.7457	4.871
	(0.0786)	(0.0361)	(0.0144)	(3.3434)	(0.0261)	(0.0926)	(0.0169)	(1.3811)	(10.1437)
BNY Mellon	0.1234	-0.0586	-0.0298**	-0.0434	-0.0397*	0.1489***	-0.0196	-1.777	-3.8118
	(0.116)	(0.0546)	(0.0132)	(1.1418)	(0.023)	(0.0431)	(0.0178)	(1.385)	(11.9876)

The dependent variable is excess TO Spillovers at the 90th Percentile. *, **, and *** denote statistically significant coefficient at the 10%, 5% and 1% levels, respectively. According to the Cross-section Dependence Test of Westerlund (2008) the error terms are cross-sectionally dependent. As a result of the CIPS unit root test of Pesaran (2007), Total Assets and Global Economic Activity variables are used after first-differencing. Due to endogeneity concerns, the following variables are instrumented with their own lags up to four quarters: Tier 1 Ratio, NPL Coverage Ratio, Assets/Equity.

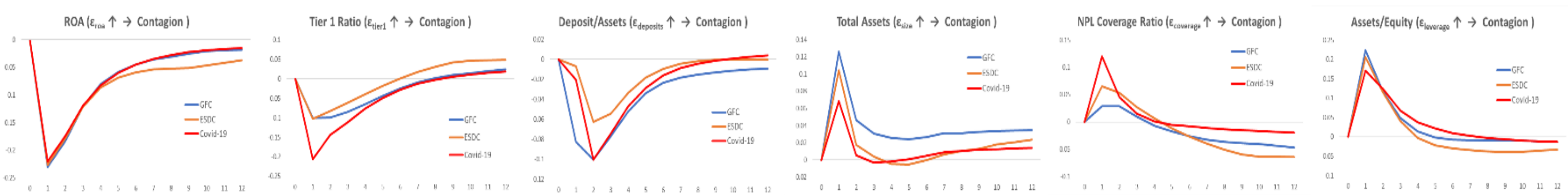
JP Morgan



Bank of America



Citi



Wells Fargo

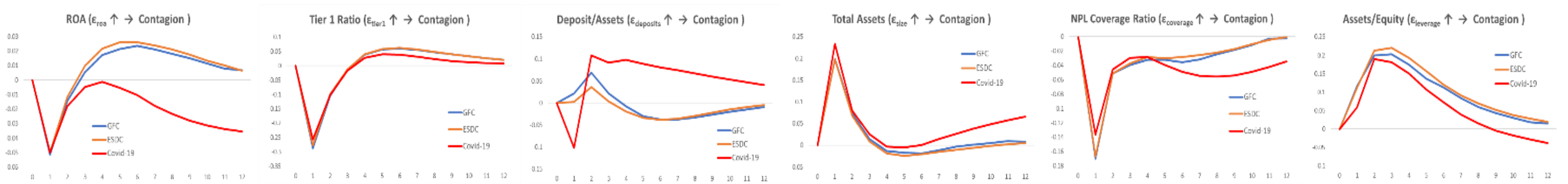
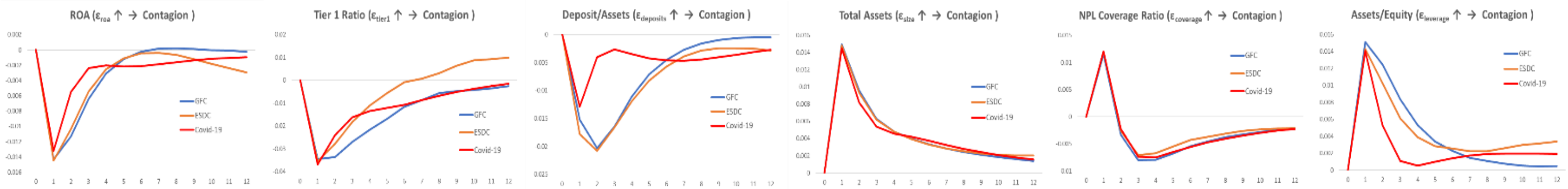
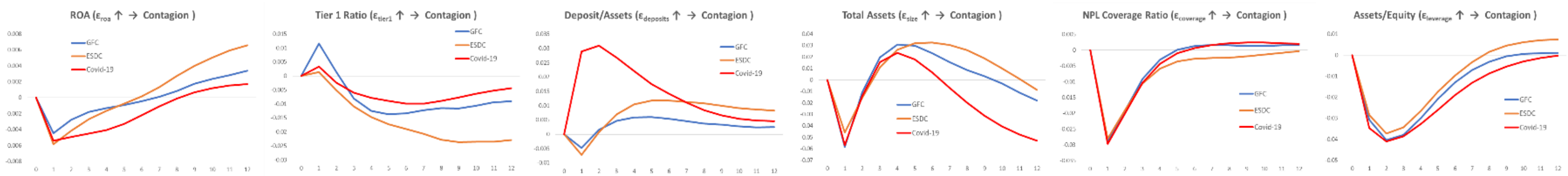


Figure 18. Time-varying Impulse Responses at the GFC, ESDC, and Covid-19 Crisis

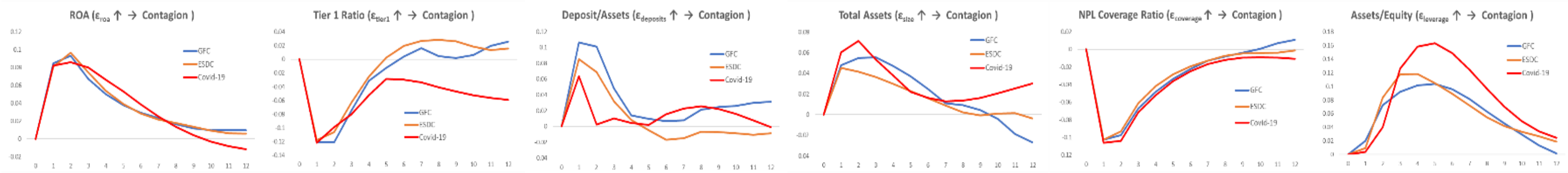
Mitsubishi



Sumitomo Mitsui



Deutsche Bank



Banco Santander

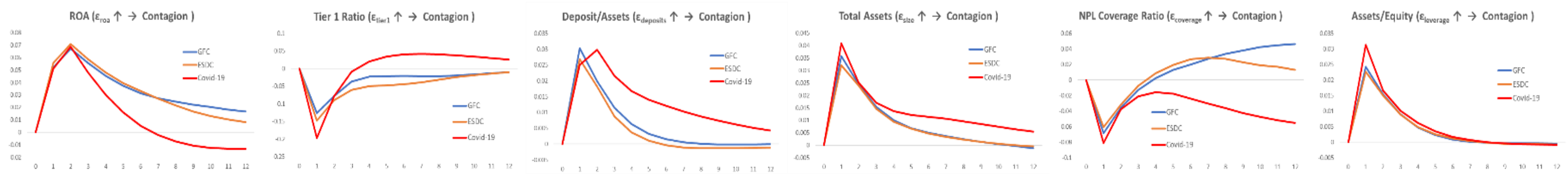
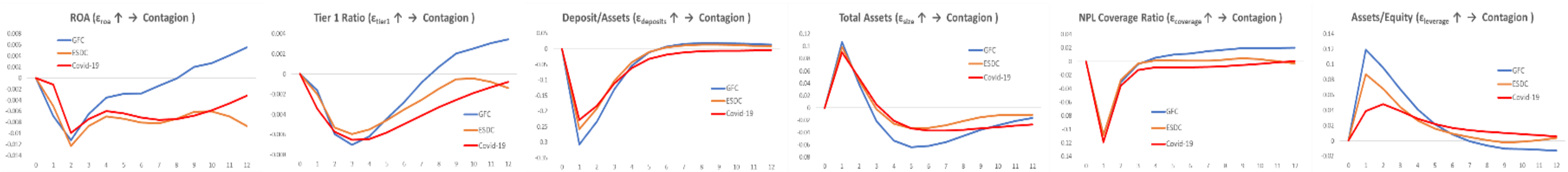
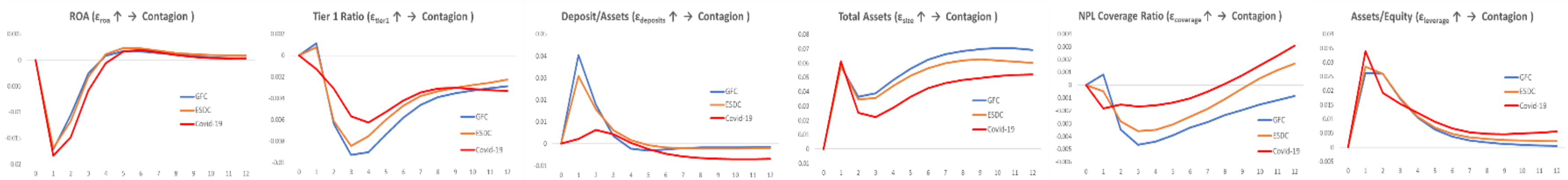


Figure 18. Time-varying Impulse Responses at the GFC, ESDC, and Covid-19 Crisis (Continued)

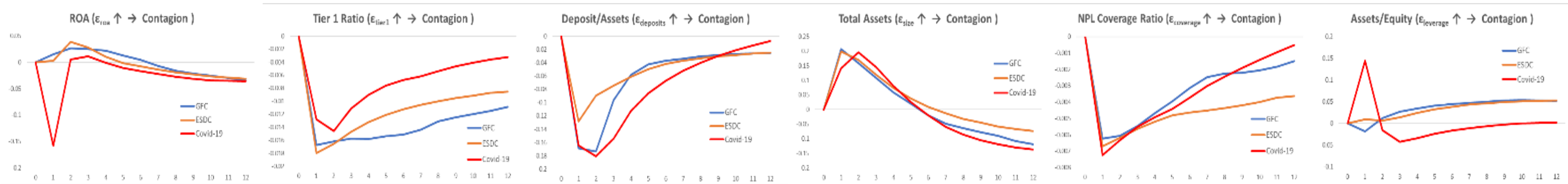
Mizuho



Toronto



BBVA



Royal Bank of Canada

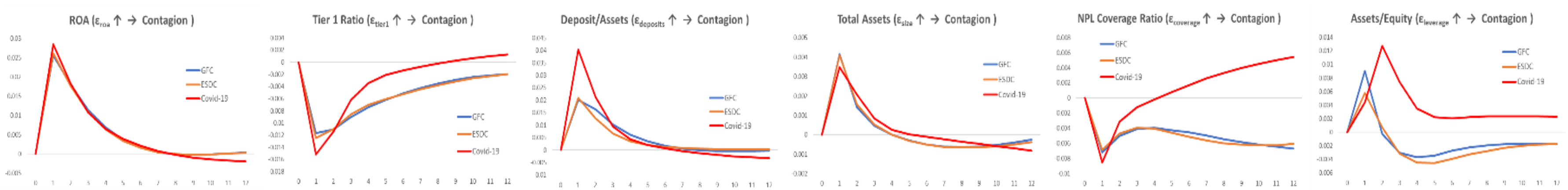
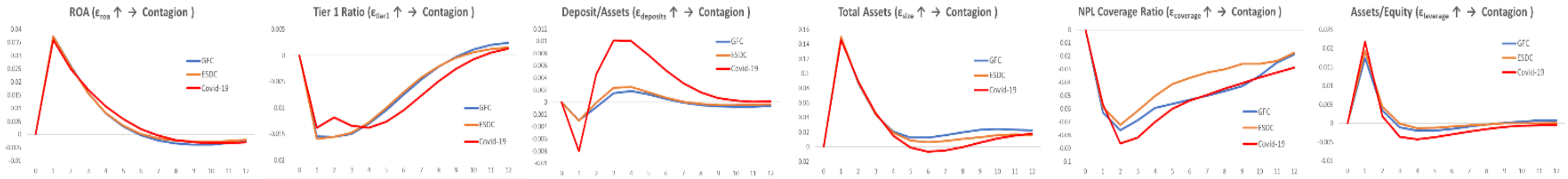
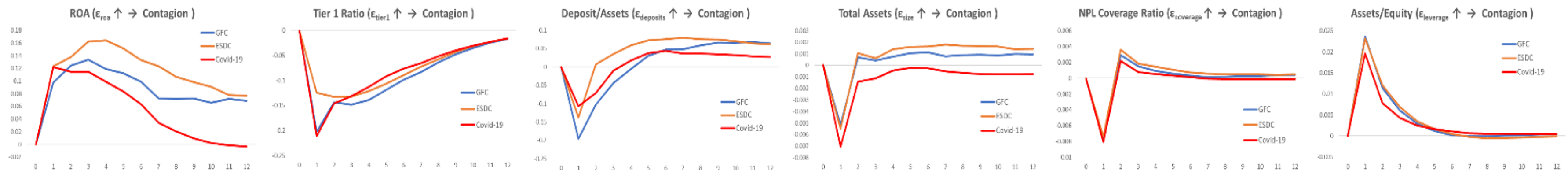


Figure 18. Time-varying Impulse Responses at the GFC, ESDC, and Covid-19 Crisis (Continued)

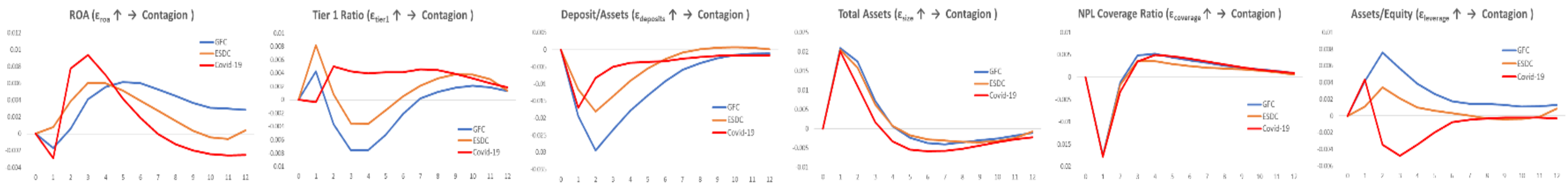
Scotiabank



Credit Suisse



UBS



UniCredit

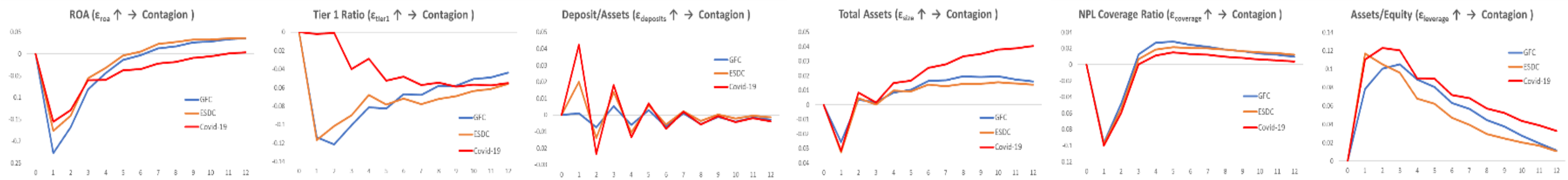
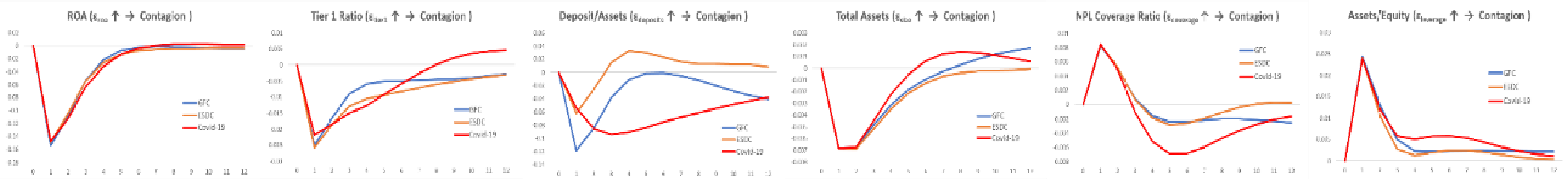
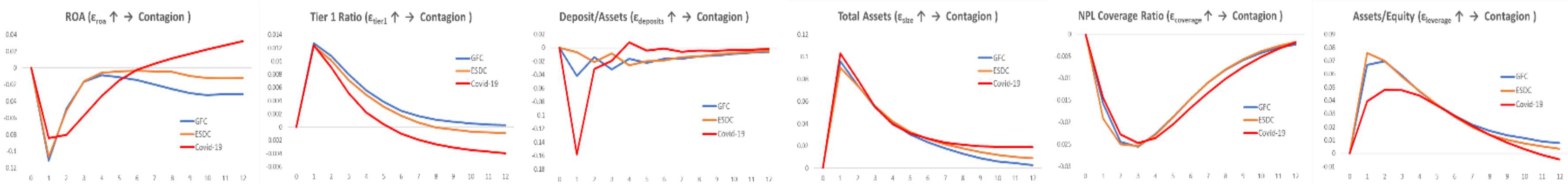


Figure 18. Time-varying Impulse Responses at the GFC, ESDC, and Covid-19 Crisis (Continued)

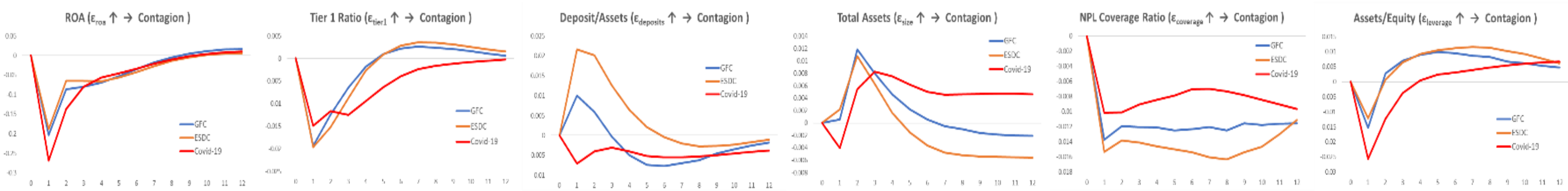
Nordea Bank



Intesa Sanpaolo



Bank of Montreal



Danske Bank

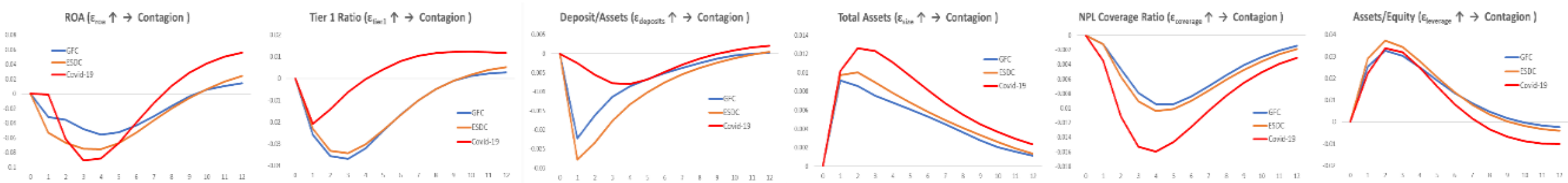
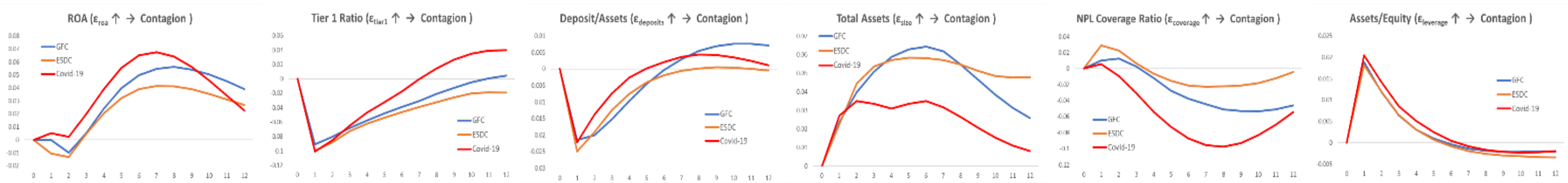
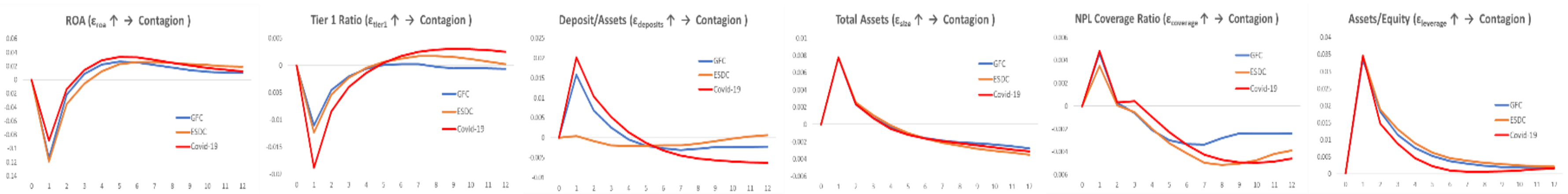


Figure 18. Time-varying Impulse Responses at the GFC, ESDC, and Covid-19 Crisis (Continued)

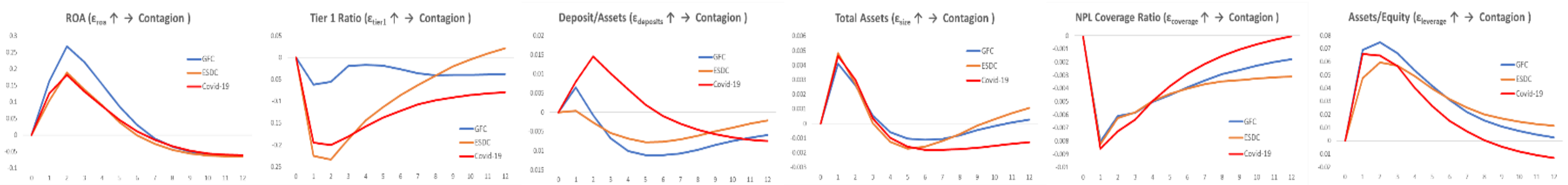
Bancorp



Canadian Imperial



Commerzbank



Truist Financial

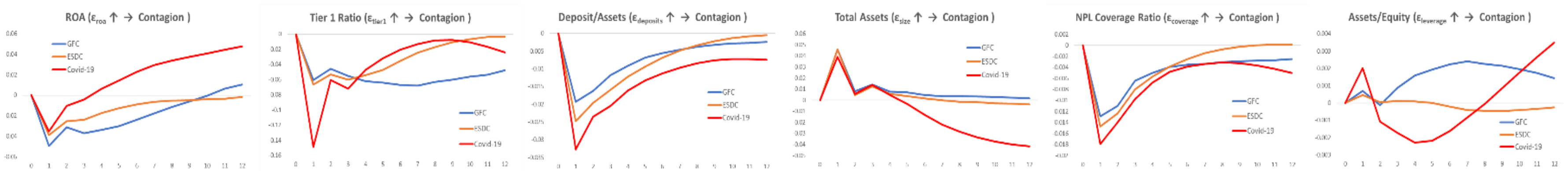
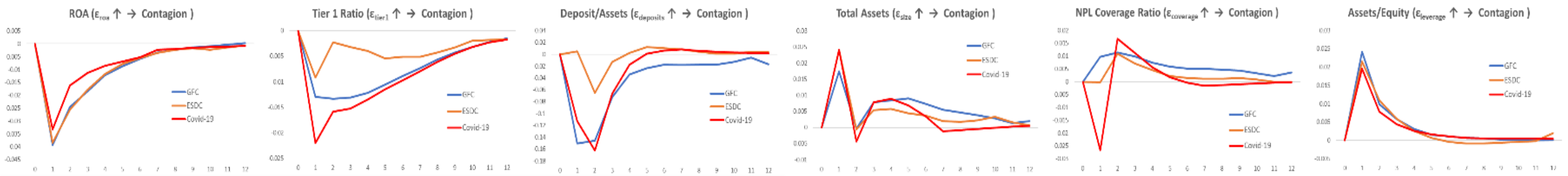
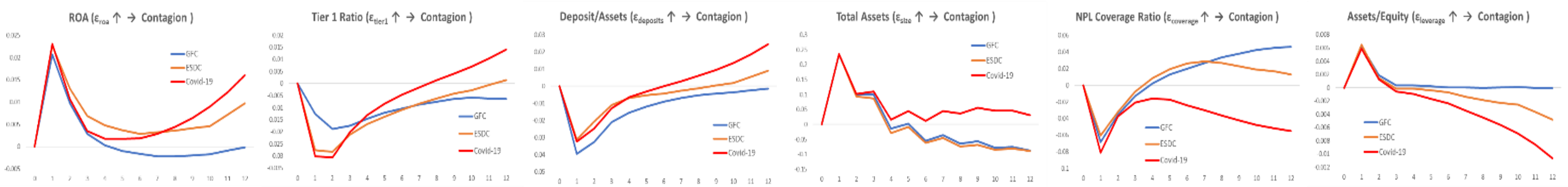


Figure 18. Time-varying Impulse Responses at the GFC, ESDC, and Covid-19 Crisis (Continued)

PNC Bank



Capital One



BNY Mellon

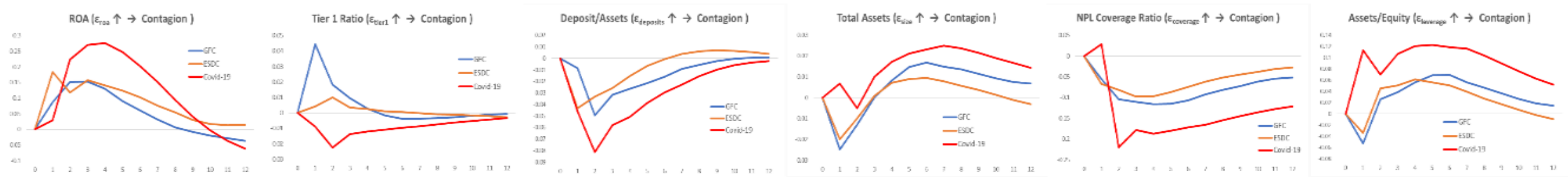


Figure 18. Time-varying Impulse Responses at the GFC, ESDC, and Covid-19 Crisis (Continued)

APPENDIX 8: ETHICS COMMISSION FORM

HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
ETHICS COMMISSION FORM FOR THESIS

HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS

Date: 12/30/2022

Thesis Title: On the Contagion of Financial Risk

My thesis work related to the title above:

1. Does not perform experimentation on animals or people.
2. Does not necessitate the use of biological material (blood, urine, biological fluids and samples, etc.).
3. Does not involve any interference of the body's integrity.
4. Is not based on observational and descriptive research (survey, interview, measures/scales, data scanning, system-model development).

I declare, I have carefully read Hacettepe University's Ethics Regulations and the Commission's Guidelines, and in order to proceed with my thesis according to these regulations I do not have to get permission from the Ethics Board/Commission for anything; in any infringement of the regulations I accept all legal responsibility and I declare that all the information I have provided is true.

I respectfully submit this for approval.

Name Surname:	Burak Sencer Atasoy
Student No:	N15246756
Department:	Economics
Program:	Doctor of Philosophy in Economics - Ph.D.
Status:	☐ MA ☒ Ph.D. ☐ Combined MA/ Ph.D.

ADVISER COMMENTS AND APPROVAL

Prof. Dr. İbrahim Özkan

APPENDIX 9: ORIGINALITY REPORT

HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
Ph.D. DISSERTATION ORIGINALITY REPORT

HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS

Date: 01/16/2023

Thesis Title : On the Contagion of Financial Risk

According to the originality report obtained by myself/my thesis advisor by using the Turnitin plagiarism detection software and by applying the filtering options checked below on 01/16/2023 for the total of 97 pages including the a) Title Page, b) Introduction, c) Main Chapters, and d) Conclusion sections of my thesis entitled as above, the similarity index of my thesis is 7 %.

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1. ☒ Approval and Decleration sections excluded
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3. ☒ Quotes excluded
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I declare that I have carefully read Hacettepe University Graduate School of Social Sciences Guidelines for Obtaining and Using Thesis Originality Reports; that according to the maximum similarity index values specified in the Guidelines, my thesis does not include any form of plagiarism; that in any future detection of possible infringement of the regulations I accept all legal responsibility; and that all the information I have provided is correct to the best of my knowledge.

I respectfully submit this for approval.

Name Surname:	Burak Sencer Atasoy
Student No:	N15246756
Department:	Economics
Program:	Doctor of Philosophy in Economics - Ph.D.
Status:	☒ Ph.D. ☐ Combined MA/ Ph.D.

ADVISOR APPROVAL

APPROVED.

Prof. Dr. İbrahim Özkan