CONNECTEDNESS AS MEASURE OF SYSTEMIC RISK IN THE EUROPEAN BANKING SYSTEM

Jyväskylä University
School of Business and Economics

Master's Thesis

2022

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Subject: Financial Economics
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ABSTRACT

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Title Connectedness as measures of systemic risk in the European banking system	
Subject Economics, IMDP in Banking and International Finance	Type of work Master's thesis
Date 11.02.2022	Number of pages 59

Abstract

The recent financial crisis and sovereign debt crisis in Europe have highlighted the need for systemic risk measures for macroprudential policy purposes. This thesis implemented three frameworks proposed by Billio et al. (2012) and Diebold & Yilmaz (2009, 2012, 2014) to investigate the interconnectedness of the European banking system as measures of systemic risk. The frameworks are applied using market data of a sample of 28 largest banks in Europe from 2001 to 2018. The empirical results show that systemic risk measures based on market data can identify periods of financial distress in the market. Besides, I also find that the European banking system in overall has become more connected, especially during the sovereign debt crisis. Different frameworks seem to depict quite different characteristics of the system connectedness. Moreover, the ranking of banks according to their contribution to the aggregate connectedness is not precisely consistent within itself over different periods. Nor is the banks' ranking consistent among different frameworks. The forecast error variance decomposition framework in Diebold & Yilmaz (2009, 2012, 2014) has the best out of sample performance in terms of identifying banks with the biggest losses during the crisis period. In consistent with previous literature, I do not find a strong relationship between the connectedness measures and other measures such as MES and Delta-CoVaR. Therefore, the results call for a more systematic view of systemic risk at multiple aspects.

Key words
Systemic risk, banking system, interconnectedness.

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1 INTRODUCTION

The financial crisis 2008 and the sovereign debt crisis in Europe have put forward a crucial need for understanding systemic risk and regulatory reform to monitor it within the financial system. The crises have shown us the shortcomings of the microprudential regulation when it comes to systemic events. Microprudential policies such as bank closure policy and capital adequacy requirements (under Basel I and Basel II) are not sufficient to deal with systemic risk. In fact, Acharya (2009) has shown that such policies can even intensify systemic events because they fail to account for the interactions among individual institutions. Since banks do not internalize the cost of failure of other banks in their own risk monitoring, they can actually be incentivized to take strategies that lead to failure when other banks fail. In other words, microprudential regulation is seriously inadequate by not accounting for the correlation risk, the consequence could be a default cascade scenario as described in Battistion et al. (2012b). Moreover, when there is a negative shock to the asset side of the balance sheet, microprudential capital requirements force banks to reserve more capital, which can lead to a funding crisis in the banking system or a credit crunch in other words. Consequently, the asset price shock is amplified and may result in a liquidity crisis in the system (Brunnermeier & Pedersen, 2009).

Given these limits of microprudential policies, the macroprudential regulation takes the viewpoint of the financial system as a whole. This macro view is of crucial importance when monitoring systemic risk since there are particular properties of the system that can only be seen from a system viewpoint. For example, Danielsson, Shin & Zigrand (2013) showed that a large part of the volatility during times of financial crisis was due to the amplification within the system. In general, the philosophical background for studying systemic risk is referred to as the fallacy of composition. It means that the aggregate system is different from the sum of each individual constituting the system. Therefore, for macroprudential purposes, systemic events must be examined at the system level.

The literature on the mechanism of systemic events is extensive. According to the 4 "L"s classification of Billio, Getmansky, Lo, & Pelizzon (2012), there are typically four main elements in a financial crisis: leverage (Adrian & Shin, 2010; Acharya & Thakor, 2016), liquidity (Cifuentes et al., 2005; Diamond & Rajan, 2005; Brunnermeier & Pedersen, 2009), loss (Adrian & Brunnermeier, 2016; Acharya et al., 2017) and linkages (Battiston et al., 2012a; Cai et al., 2018). Principally, the common feature among these papers is that they demonstrate the financial system as including financial stakeholders being connected with one another by their operating activities and/or the common exposure (the systematic risk). A systemic event occurs when there is a negative shock to the first 3 "L"s which is then amplified throughout the system through the linkages between firms. The results could be defaults of a large number of financial institutions (Nier et al.,2007; Upper, 2011; Battiston et al., 2012b), a significant increase in the tail event of the aggregate system (Segoviano & Goodhart, 2009), or a spillover effect on the real economy (He & Krishnamurthy, 2019). It is worth noting that the contagion risk would not exist if not due to the linkages among the financial institutions. In other words, financial interconnectedness has a crucial role in systemic events. However, it does not mean that connectedness has only an adverse effect on the system.

In fact, it has been well documented that financial interconnectedness has its benefit and detrimental impact on the system's stability (Elliott et al., 2014; Gai & Kapadia, 2010; Glasserman & Young, 2016). On the one hand, bilateral exposures in the interbank market and integration in the financial asset market at certain levels enhance the risk-sharing effect and are necessary for the liquidity creation of banks. On the other hand, in times of crisis, it is usually the same linkages that amplify initial shocks and increase the contagion risk (Allen et al., 2012; Ladley, 2013; Elliott et al., 2014; Gai & Kapadia, 2010; Glasserman & Young, 2016). In other words, even though interconnectedness has an irrefutable role in the transmission of shocks between financial institutions, there has not been much empirical evidence showing whether it increases the magnitude and likelihood of losses compared to less interconnected ones (Glasserman & Young, 2015).

Crucially important as it is, empirically measuring systemic risk has still been a challenging topic. As Betz et al. (2016) have pointed out, the high dimensionality of the connectedness in the underlying system makes it very difficult to identify the propagation channels of financial shocks, as well as the quantification of their relevance. The problem is even more difficult to solve due to the lack of propriety data on the direct linkages between firms. Moreover, an applicable framework for systemic risk analysis should incorporate both the time-series aspect and cross-sectional aspect. The time-series aspect of systemic risk is to serve as an early warning indicator of the system's vulnerability to prevent the build-up of systemic risk especially during the expansionary phases of the credit cycles. The cross-sectional aspect is needed to decompose the overall risk to each institution's marginal contribution so that the regulator can target the more systemically important ones (Black et al., 2016). Several papers have attempted to solve these issues by proposing measures of systemic risk using market data; see, for example, Billio et al. (2012), Diebold and Yilmaz (2014), Brownlees and Engle (2017), Adrian & Brunnermeier (2016), Acharya et al. (2017). However, these market-based measures have their disadvantages. First, they rely on the efficient market hypothesis to be true. Obviously, the measures can only be effective if the input market data; for example, stock prices, CDS spreads, equity option price, which contains information about the firms' riskiness. In other words, no matter how intricate a measure is, it can only be as good as the input data is. Fortunately, previous empirical studies have shown that market-based systemic measures could be relatively effective at giving early warning signals of distress in the system. Second, these market-based risk measures face a bigger problem in identifying systemically important firms. Benoit et al. (2013) showed that different measures suggested different rankings of systemically important firms. Löffler &

Raupach (2018) demonstrated that these measures could produce counterintuitive assessments of individual firms' contribution to the system's riskiness under certain assumptions about the distribution of the input data. More specifically, in cases of return model with multivariate normal risk factors or when returns are drawn from heavy-tailed distributions, Delta-CoVaR (Adrian & Brunnermeier, 2016) and marginal expected shortfall (Acharya et al., 2017) may suggest a decrease in a firm's systemic risk contribution to the system even though the firm's systematic risk, idiosyncratic risk, size or contagiousness increases.

The main objective of this thesis is to provide an extensive analysis of market-based connected measures of systemic risk in the European banking sector. To this purpose, the principal component analysis (PCA), the Granger causality analysis frameworks proposed by Billio et al. (2012), and the generalized variance decomposition developed by Diebold and Yilmaz (2009, 2012, 2014) are implemented during the sample period from January 2001 to December 2018. PCA framework is meant to capture the extent to which the financial institutions are unified concerning a certain number of common factors. Intuitively, the contagion risk is higher when the institutions become more unified in a smaller number of common factors (Allen et al., 2009; Ibragimov et al., 2011). The rationale for Granger causality analysis in financial interconnectedness is that short-term returns on financial assets should not be Granger caused by the returns on other assets when the market is efficient. However, in times of market turmoil, there would be some market frictions such as restriction on the short sale, borrowing constraints, and regulatory constraints such as value at risk constraint, marked-to-market balance sheet. Under these constraints and frictions, a negative shock to the return on certain assets can be propagated throughout the system (Zigrand, Danielsson & Shin, 2013; Diamond & Rajan, 2011; Elliott et al., 2014). Similar to the Granger causality analysis, the variance decomposition approach is also built up from a vector autoregression framework to investigate the spillover or the contagion effect. Moreover, while the Granger causality analysis can only measure the direction of the connectedness, the variance decomposition is supplementary to that by calibrating both the direction and the strength of such relationships.

Different from Billio et al. (2012) who analyse the relationships between different financial sectors, I focus only on the banking sector in this thesis. The motivation is that the European financial system is traditionally more bank-based, unlike the United States financial system who is more market-based (Allen & Gale, 1995). Moreover, the integrated banking system is the main contagion channel in the recent European sovereign debt crisis (Bolton & Jeanne, 2011). The data set includes the 28 largest European banks determined by the market capitalization in 2018. The 3 abovementioned frameworks are applied using the banks' weekly stock return from January 2001 to December 2018. In accordance with the "consistent" criterion for a systemic risk framework suggested by Borio & Drehmann (2009) and Black et al., (2016), the analysis is done on both the time-series dimension to examine the development of aggregate systemic of the system as a whole and on the cross-sectional dimension to identify the marginal contribution of individual banks.

The main findings of this thesis are as follows. First, the times series analyses performed with all three frameworks document that the aggregate connectedness of the European banking system increases dramatically during both the financial crisis and the sovereign debt crisis. Second, the connectedness of the European banking system seems to involve multiple aspects. Accordingly, the three frameworks are in disagreement with each other in terms of identifying systemically important banks. Third, contrary to Billio et al. (2012), I did not find a strong out of sample performance of the connectedness measures in predicting banks' losses during the crisis. The results in overall call for cautious use of a single measure of systemic risk. Instead, macroprudential regulation should monitor the systemic risk at multiple aspects in order to make informed decisions.

The remainder of the thesis proceeds as follows. Section 2 discusses the theoretical background on systemic risk in general and on the contagion risk in particular. Section 3 outlines some previous empirical research. Section 4 explains the three frameworks employed. Section 5 presents the empirical results, and the last section concludes.

2 THEORETICAL FRAMEWORK

2.1 Definition of financial systemic risk

There has been no universal definition of financial systemic risk. Different authors intentionally allow for different aspects in their definition of systemic they set out to deal with in their work from the start.

In general, there are three different approaches how systemic risk is defined in academic literature (Hansen, 2012). Freixas, Parigi & Rochet (2000), Diamond & Rajan (2005) define systemic risk as a bank run like instability of the financial system triggered by liquidity concerns about one or several banks in the system. In this first approach, the main focus is on how the contagion effect manifest itself throughout the system. The analysis of systemic risk in this first approach is of particular importance in the discussion about the role of the central bank as the lender of last resort. When the contagion risk is high, there is a strong incentive for central bank to act as the lender of last resort (Huang & Goodhart, 1999). In another strand of literature, Allen & Gale (2000), Shin (2008), Gai & Kapadia (2010), and Drehmann & Tarashev (2013) refer to systemic risk as the vulnerability of a financial net-work due to the interlinkages among the financial institutions in the network. Here the challenge is to identify when a financial network is potentially vulnerable and the nature of the disruptions that can trigger a problem. Alternatively, some other authors use the term in the context of "macroprudential regulation" to investigate certain proposed policies in their papers. Even though some economists have highlighted the importance of macroprudential regulation much already earlier (for example Borio, 2003), this strand of literature has become more and more popular after the Subprime crisis. Archrya (2009) argues that policies such as bank closure policy and capital adequacy requirements which usually operate at the individual level fails to mitigate systemic risk and may actually accentuate it. Similarly, Zhou (2013) argues that an unregulated system would has lower systemic risk than a system regulated at the micro level.

The definition of de Bandt , Hartmann, & Peydró (2012) is one of the most cited one since it can synthesize the above three notions. The authors de-fine systemic risk as the risk of experiencing a systemic event which impairs the efficiency and effectiveness of the financial system's main function as the channel to transmit savings into investment. A systemic event is defined in the narrow sense as an adverse event which affects several banks in a sequential manner, and through this contagious process impairs severely functioning of the financial system). In the broad sense, a systemic event means that a large number of banks in the system are in jeopardy as the consequence of severe and widespread ('systematic') shocks or the unravelling of significant imbalances that have built up over time. In this regard, de Bant et al. (2012) agree with Billio et al., (2012) that the bottom line in the definition of systemic risk is the contagion risk that impairs the stability of or the public confidence in the financial system. This thesis follows this definition of systemic risk. Especially, the focus is on the interconnectedness among the banks since it plays the crucial role in the occurrence of a systemic event (Bluhm & Krahnen, 2014).

2.2 The fragile nature of the financial system

de Bant et al. (2012) lay out three typical feature of the financial industry which makes it more vulnerable to systemic risk than other industries. First, the typical maturity transformation activity of banks exposes them to liquidity risk, which could be further amplified by the network effect to the whole system. Traditionally, banks take deposits, which can be withdrawn any time after very short notice, and then invest in projects with longer maturity date. Although this maturity mismatch of banks provides liquidity to the economy, it makes banks exposed to bank runs by depositors (Diamond & Rajan, 2001). More specifically, the stability of banks depends not only on the depositors' valuation of banks' investment profitability but also on the confidence that other depositors will not run the banks (Goldstein & Pauzner, 2004). However, this type of depositor-by-bank run can be fairly restrained by a depositor insurance scheme. The recent financial crisis shows how sever the liquidity problem caused by too strong reliance on short term wholesale funding can be.

Brunnermeier (2009) identifies two trends in the banking industry in the period leading up to the crisis that expose banks to a funding liquidity risk. The first trend is the strategy of structured investment vehicles (SIVs) or conduits which funds long term investment project by selling short term commercial paper (backed by a pool of mortgages, loans, or CDOs). The idea of this strategy is to transfer the maturity mismatch from the banks to these off balance sheet vehicles. However, the sponsor banks still need to provide it affiliated SIVs with a liquidity backstop to ensure funding liquidity for the vehicles. Therefore, banks still bear the liquidity risk from the conceived maturity mismatch even though it does not appear on the banks' balance sheet. On top of that, under the Basel I, banks do not have to hold any capital requirement for this liquidity backstop, which is basically has the same nature as a loan, this allows them to take even more risk. The liquidity risk of this strategy is due to their heavy reliance on the possibility of roll over short term debts by issuing new asset backed commercial papers. The second trend is the increasing constituent of repo funding in the banks' balance sheet. A repo contract allows banks to raise short term funding by selling collaterals with the promise to buy back in the future at a discount. The fact that overnight repo constitutes most of the increase in the banks' balance sheet puts a heavy bur-den on them to roll over their funding on a daily basis.

The second feature explaining the fragility of the financial industry identified by de Bant et al. (2012) is the highly connected interlinkages among the financial institutions which can arise from different sources such as interbank market, credit market, or asset market. Even though higher connections among banks can improve liquidity allocation and improve risk sharing in normal times, in times of crisis it is the same connections that aggravate the problem by amplifying an external shock (Georg, 2013). Since this feature is the main focus of this thesis, it will be investigated in more detail in the next section.

The third feature is the fact that progressively growing financial innovations may increase market uncertainty and put credibility of financial con-tracts in question in times of a market turmoil, and lead to a disruption of the financial system. For example, in the summer of 2007, when there was a significant doubt about the viability of structured finance products, investors simultaneously stopped buying commercial paper. This prevented the in-vestment vehicle from rolling over their short term funding. Or, after the bankruptcy of Lehman Brothers, the TED spread reached an all-time high, which reflects a loss of confidence in the interbank market. Banks actually re-fused to lend to each other, and instead started to hoard funding. This disabled even healthy banks from finding secured funding and as a consequence prompted a contagious system event. Petersen et al. (2011) argue that the securitization of mortgage loans is the main cause subprime mortgage crisis. Due to the increasingly intricately designed structured products such as mort-gage backed securities , collateralized debt obligations and to the complicated securitization process, serious issues related to information and valuation emerge d, which eventually resulted in ineffective risk mitigation. Moreover, Dang, Gorton, & Holmström (2010) point out that information sensitive debt can amplify an aggregate shock into a systemic crisis in the credit market since lenders seek to avoid adverse selection due to the increased asymmetric information problem. Furthermore, in a study of subprime mortgage market in the United States, Keys, Mukherjee, Seru, & Vig (2010) offer empirical evidence that increased securitization led to a decline in credit quality. One possible explanation is that securitization may reduce lenders' incentives to carefully screen and monitor borrowers by creating distance between a loan's originator and the bearer of the loan's default risk. Caccioli, Marsili, & Vivo (2009) study the impact of the proliferation of financial instruments on the market stability in a dynamic model of interacting agents . They find out that even though the proliferation of financial instruments enhanced the efficiency and completeness of the market, it accelerates market susceptibility, increasing return fluctuations and correlations among the risks in the banking system. The results therefore propose an adaptation of the interaction among trading activities in studies on financial market as a whole.

2.3 Contagion

As mentioned in the previous part, at the essence of analysis in systemic risk is the notion of contagion. This refers to the possibility that the distress of one financial institution propagates to others in the financial system, thus leading ultimately to a systemic crisis. Moreover, the contagion risk is often the justification for central bank intervention. Various theoretical studies have been done on systemic risk, taking into account different aspects of the topic. The theoretical literature on contagion effect can be roughly divided into two approaches including direct linkages (or financial contagion) and indirect balance sheet linkages (Allen & Carletti, 2013). It is worth mentioning that the channels described below do not occur separately but more often than not intertwine with one another in crises.

2.3.1 Financial contagion

2.3.1.1 Bank run

Early theoretical literature on banking crisis approach es the problem as a coordination game in which depositors either withdraw their funds from their accounts or keep funds on the accounts. A bank run may lead to realization of the contagion risk if failure of one bank triggers runs on other banks and in this way causes liquidity shortage in the interbank market. According to Allen, Babus, & Carletti (2009) the research on bank run can be divided into two dis-tinct groups according to whether or not the withdrawal panics by depositor are caused by fundamental changes in the real economy.

The first line of bank run literature describes it as purely panic based crisis. Bryant (1980) and Diamond & Dybvig (1983) model bank runs as self-fulfilling prophecies caused by random deposit withdrawals unrelated to changes in the real economy. In these models, while banks provide liquidity to the market by transforming illiquid assets to liquid liabilities, agents privately allocate their wealth unequally across different states and are at the same time constantly concerned about the cost of early asset liquidation of banks. The optimal equilibrium exists where agents withdraw their funds according to their private information. In this case, their demand can be met without costly liquidation of assets. However there also exists an undesirable equilibrium where bank run occurs because of the observation by all depositors that a large enough number of other depositors will withdraw.

The uncertainty about the fundamental knowledge can generate an undesirable equilibrium in these types of coordination games. Carlsson & van Damme (1993) study an incomplete information game, which they call a global game, in which the actual payoff structure of the game is randomly drawn from a given class of games and the players act according to their private noisy observations of the game to be played. They show that the lack of common knowledge about the underlying payoff structure creates a unique risk-dominant equilibrium for the game. Morris & Shin (1998) find similar results in the context of currency crises, when there is uncertainty about economic fundamentals. In the same way, Rochet & Vives (2004) adapt the global game in their analysis of the banking system and show that when there is uncertainty about the fundamental value of the banks' assets, there exists a unique Bayesian equilibrium where even a solvent bank may fail because it cannot find liquidity support from the market.

Thus, the authors justify the rationale for the public intervention as lender of last resort.

The second group of literature on bank run characterize it as an integral part of the business cycle. Apparently, the value of bank assets decreases in time of economic contraction. This raises concern among the depositors about the banks' ability to meet the demand to withdraw funds. If the depositors anticipate a big enough downturn in the real economy, they will withdraw their funds from banks (Allen et al., 2009). Accordingly, this strand of literature refers to bank run as an information based event, in contrast to the view of bank panics as random events described previously. Gorton (1988) provides empirical evidence supporting the view that banking panics are systematic events linked to the business cycle. He finds the information measure based on the liabilities of failed businesses is a strong predicting variable for banking panics during the national banking area. Allen & Gale (1998) develop a theoretical model in which the depositors make the decision to withdraw based on their observations of the return on the risky investments of the bank. It was concluded that the possibility of a bank run can sometimes be desirable by allowing for the optimal risk sharing and consumption allocation. However, when a bank run forces a too large early liquidation of the safe asset, the amount of consumption available to depositors is reduced and central bank intervention is needed. In a more recent theoretical paper, Goldstein & Pauzner (2004) adapt the global game approach to study banking crises under the assumption that the fundamentals of the economy are stochastic and the agents can only obtain privately noisy information about the economic fundamentals. The result is that there is a unique Bayesian equilibrium, in which a bank run occurs if and only if the fundamentals are below some critical value. Furthermore, they also compute the ex-ante probability of a bank run and find that it in-creases as banks offer higher short-term payment. Chari & Jagannathan (1988) demonstrate how asymmetric information can trigger a banking crisis. They show that bank runs can occur even if there is no depositor having any adverse information about the fundamentals. It is simply because the depositors cannot distinguish the long lines waiting to withdraw at banks are because of individual consumption need or due to the fact that informed depositor are getting out.

In sum, early literature on banking crisis mostly attempts to model it as a bank run phenomenon. This literature can be divided into two different strands base on whether bank runs are modelled as random self-fulfilling events, or as fundamental information based events related to the business cycle. However, the major weakness in this strand of literature is that since the contagion effect is simply captured so that the failure of one bank induces depositors of other banks to withdraw their funds, the network effect among banks is not examined thoroughly. More recent literature on the interbank markets deals with this issue.

2.3.1.2 Interbank market

The interbank market has an important role in maintaining the financial stability of the system since its main function is to deliver liquidity from the banks that have excess of liquidity to the ones that are in shortage of liquidity.

Haldane & May (2011) characterized the interbank network as having a robust yet fragile or "knife-edge" property. It means that the direct connections between banks have the benefit of increasing the risk sharing and improving liquidity allocation in normal times at the expense of increasing the risk of shock amplification in times of crisis. Acharya & Bisin (2014) attributed this property of interbank markets to a counterparty risk externality, which is an inherent feature of over-the-counter markets. Counterparty risk refers to the increased default risk of a counterparty on one contract when the counterparty has the same contract with another agent. This second contract of the counterparty has the risk of weakening its ability to perform on the first contract (Acharya & Engle, 2009). Moreover, the opacity of this externality increases as banks' interbank lending network grows since banks are unaware of the connections of its affiliated banks. Consequently, this can lead to default cascades in the interbank credit market (Battiston et al., 2012a).

An extensive strand of literature endeavours to examine the network structure that is less prone to this type of systemic risk in the interbank market and the extent to which diversification can mitigate systemic risk. In this strand of literature, Allen & Gale (2000) provide one the most influential analysis of the financial contagion through credit interlinkages among banks. Using a model in which the banks are connected to each other by exchanging interbank deposits, they show that the adverse effect of liquidity shocks on systemic risk can be mitigated by increasing the interconnectedness among banks in the complete networks, the network structure in which the amount of interbank deposit held by each bank is evenly spread over all banks. However, when the network structure is incomplete, the case in which each bank is connected to only a few number of other banks, higher connectivity is no longer desirable, and the system becomes more susceptible to contagion risk. The reason is that in the complete network, the liquidity shortage shocks are shared by every bank in the system: each bank pays its share by liquidating a small amount of its assets and hence there is no significant loss in the value of asset, which is one of the shock propagation channels in the model. In contrast, in the incomplete network, only the banks in the troubled region liquidate their assets, which results in losses in asset value. In the same spirit, Freixas et al. (2000) arrive at the same conclusion , that increasing interbank connections can enhance the system's resilience to a shock caused by insolvency of one bank caused by deposit withdrawal. However, the enhancement comes with a cost of several inefficient outcomes such as the excessive liquidation of productive investment, the reduced incentive to liquidate insolvent banks and the inefficient liquidation of solvent banks. Nier, Yang, Yorulmazer, & Alen-torn (2007) show that increasing interbank connectivity increases the contagion effect at first; however, after a certain threshold value is reached, higher connectivity makes the system more robust to shocks.

In contrast, there is another stream of work suggesting that full integration is not optimal in reducing contagion risk. Battiston et al. (2012b) use a continuous time dynamic agent-based model where banks are connected to each other through credit network. They show that the connectivity is optimal for the network resilience when it is at a moderate level, once exceeding this level, higher connectivity will increase both the probability and the magnitude of system failure. The main external effect in their model is the variation of financial robustness resulting from idiosyncratic shock of agents in the network i.e. "financial acceleration" and its positive feedback, which persists over time. After the optimal level of connectivity is reached, the adverse effect of this financial acceleration will outweigh the benefit of risk sharing and amplify the financial distress. Similarly, Stiglitz (2010) argue that full integration is also not optimal in the context of global financial markets. In a model where the connections between banks are created as a result of banks exchanging their projects, Allen, Babus, & Carletti (2012) find that systemic risk in the unclustered network structure is lower than that in the clustered asset network structure. In the clustered network, banks form several independent banking groups, while in the unclustered network, each bank connects to only two other banks in a circle. The rationale is that in the clustered structure, when there is a negative information regarding the solvency of one agent, the investor would deduce that the conditional probability of system failure is higher as defaults are more concentrated. Thus, the investors are more reluctant to roll over their short term funding and banks are forced to liquidate their assets. In other words, the main source of systemic risk in this model is the failure of banks to roll over short term debt, which put them into a liquidity crisis. This is in line with the depiction of Brunnermeier (2009) of the financial crisis. Furthermore, several earlier works have also shown that financial integration can facilitate the risk of financial contagion (Goldstein & Pauzner, 2004; Allen & Carletti, 2006).

At the same time, there are also several works expressing a more moderate view of the impact of financial integration on systemic risk. These works acknowledge the benefit of interbank connection to a certain degree while at the same time referring to conditions under which it can have adverse impact on the system stability. Applying techniques from the literature on complex networks into a financial system setting, Gai & Kapadia (2010) finds that while high connectivity help absorbing shocks by the dispersing the losses from the failure of one institution and hence reducing the probability of a default cascade event, it also magnifies the magnitude of the crisis once it does occur. In addition, they also highlight the fact that the system reacts differently to shocks of similar size depending on where the shocks hit the network. A smaller sized shock can have a more damaging impact on the system stability if it hit at critically pressure points. This provides justification for the classification of systemic events by Bilio et al. (2012). For example, Billio et al. (2012) classify the failure of the $5 billion hedge fund Long Term Capital Management as a systemic event but not the 2006 collapse of the $9 billion hedge fund Amaranth Advisors because the former puts more threat on a wider range of financial institutions. Moreover, Ladley (2011) in a static network setting finds that interbank connectivity is useful in sustaining system's stability by risk sharing only for small shocks; while for larger systemic shock, in the broad sense as in de Bant et al. (2012), it has the reverse effect. This result is in line with the observations made by Acemoglu, Ozdaglar, & Salehi (2015) who also reason that weak interconnection, in the case of a large shock, protects the system from a cascading default by limiting most of the losses to the more senior creditors of a distressed bank.

2.3.2 Contagion via indirect linkages

The second approach to contagion effect focuses on the systemic risk arising from the common asset exposure. The contagion mechanism of this channel is as follows. Institutions hold the same asset in their portfolios. Due to some exogenous shocks, one institution in the system has to liquidate the asset, which drives down the price of the asset. This has a negative impact on the portfolio value of other institutions in the system. In some cases, the affected institutions may have to liquidate other assets to meet certain constraints. If the impact would be large enough, there would be a systemic event in which contagion occurs across seemingly unrelated assets and across seemingly unrelated institutions (Braverman & Minca, 2014).

Previous literature has investigated different sources of initial shocks and types of constraint. Adrian & Shin (2010) point out empirically that procyclical leverage, a result of banks' active adjustment of balance sheet, can exert a significant impact on the aggregate market volatility and risk pricing which in turn leads to a dry up of market liquidity and a spiral of losses as depicted by Brunermeier & Pederson (2009). For example, there is a negative shock to the market value of some securities in a bank's portfolio, a shock large enough that the bank faces funding issues such as a run by its creditors or a failure to roll over its short term debt. As a consequence, the bank is forced to liquidate at least part of its portfolio to reimburse debt. If the securities are sold below the market price, the asset side of the balance sheet decreases more than the liability side and the bank's leverage goes up unintentionally (Battiston et al., 2012a).

Similarly, Greenwood, Landier, & Thesmar (2015) show that the contagion risk is worse when the illiquid assets in the market are held by the most levered banks. More specifically, a negative shock has a bigger impact on the system when the assets are held by more levered banks as due to the leverage constraint the more levered banks have to sell more in a fire sale. Gorton & Metrick (2012) examine the role of so called "securitized banking", which refers to securitization activities and repo funding, in the financial crisis. They argue that what caused the systemic crisis in 2008 is similar to a run in the repo market. Pointedly, increasing uncertainty about the counterparty risk lowers the value of assets in repo contracts. This in conjunction with the increasing repo haircuts caused by growing concerns about the liquidity of markets for the underlying products effectively put the banking system into a solvency crisis.

Besides, over-the-counter (OTC) contracts used by banks to hedge their asset risk can create a contagion channel. Zawadowski (2013) shows that entering into OTC contracts reduce the default risk of individual banks significantly. However, this asset risk reduction benefit has the side effect that makes banks more connected to each other in a network of OTC contracts. In other words, counterparty risk emerges as a by-product of asset risk hedging. The counterparty risk can be hedged by holding more equity. Nevertheless, Zawadowski (2013) shows that since banks do not internalize the benefit other banks get from their counterparty risk hedging activities, they do not have a strong incentive to hedge the counterparty risk arising from the OTC con-tracts. More specifically, when the probability of counterparty default is low even though it is optimal for the system as a whole that banks pay for holding excess equity for example by buying counterparty insurance, at the individual level, it is more costly to do so and hence not optimal for banks.

In this regard, liquidity crisis arising from fire sales of assets is one important contagion channel. Cifuentes, Shin, & Ferrucci (2005) presented a model where the banks' balance sheets are connected both directly through interbank market and indirectly through common assets holding. They find that the contagion effect from the failure of one bank in the system is mainly driven by asset price linkages. At certain values of the model parameters, a price shock can be amplified by the regulatory solvency constraints under the form of capital requirement to induce a downward spiral asset price effect. They also show that contagion is worst when the number of interconnections is at a moderate level and liquidity requirement can help prevent a systemic contagion through asset prices from occurring. Similarly, Kapadia, Drehmann, Elliott, & Sterne (2013) depict how asset price contagion can cause a liquidity crisis in the system due to cash flow constraints. Furthermore, Diamond & Rajan (2011) show how a liquidity crisis can build up ex ante due to contagion via required rates of return. They argue that in the face of a probable insolvency issue, illiquid banks can have a private incentive to hold and even load up more illiquid assets rather than selling them for the reason that the marginal cost is low.

In addition, there exists a strand of literature examining the effects of portfolio diversification at financial institutions on the stability of the system. In a two bank model where each bank invests in different activities, Wagner (2010) shows that while diversifying into the other bank's activities reduces the failure likelihood of each individual bank, it also increases the likelihood a joint failure. More specifically, as diversification increases, the marginal rate at which the variance of a bank's portfolio declines (the benefit of diversification) while the cost of diversification represented by early liquidation of assets in the economy increases. The reason is that diversification reduces the idiosyncratic risk of each bank portfolio while at the same time exposing them to similar sources of market risk. Hence, for a sufficiently large degree of diversification, the cost of diversification exceeds its benefits. Therefore, full diversification is not optimal. In the same way, Ibragimov, Jaffee, & Walden (2011) show that diversification is not desirable for the system even though it may be optimal for individual institutions when the probability distribution of the risk factors is moderately fat-tailed. Especially in the case of extremely heavy tailed risks, asset diversification is not optimal from both the system and individual perspective. This result is in consonance with De Vries (2005)'s model where banks are directly connected via interbank deposit and syndicated loans.

Another possible channel through which diversification can lead to systemic events is by reducing the welfare of the economy. For example, Goldstein & Pauzner (2004) applies a global game model, where two countries have independent fundamentals but share the same group of investors, to demonstrate that portfolio diversification can induce a self-fulfilling crisis by reducing the real wealth of the investors and making them more risk averse. Consequently, investors decide to withdraw their funding from other countries and crisis occurs. In addition, Acharya & Yorulmazer (2005) point out that banks are privately incentivized to invest in correlated assets to prevent costs arising from potential information spill over effect because they do not internalize the costs of a joint failure due to limited liability.

In sum, there are different forms under which a systemic event manifests itself. The common thread among different forms of systemic event is the notion of contagion. A systemic bank run occurs when where the failure of one bank induces the depositors of other banks to withdraw their funds. Direct connection via interbank lending and indirect connection via common asset exposure are two important contagion channels. Research has found that both the direct and indirect financial networks exhibit a robust-yet-fragile nature. Connections helps reducing the probability of a systemic event thanks to risk sharing. However, when a systemic event does occur, the consequences would be more calamitous due to the very same connectivity that helps prevent some events.

3 PREVIOUS EMPIRICAL STUDIES

There are several different approaches in the empirical studies of systemic risk measures. One strand of research attempts to estimate the direct bilateral linkages between financial institutions with the limited available data to build an intricate financial network. This strand of literature mostly investigates the relationship between the network topology and the financial stability of the system. Soramäki, Bech, Arnold, Glass, & Beyeler (2007) and Cont, Moussa, & Santos (2010) have documented power-law distributions for the connectedness degree in the US system and Brazilian interbank network, respectively. As a result, the financial network is scale-free, which means that a few institutions are accounting for most of the connections in the network. This result supports the "robust yet fragile" feature of the financial network argued by Gai & Kapadia (2010) and Caccioli, Catanach, & Farmer (2011). By contrast, using data on overnight interbank lending in Italia during the period 1999–2010, Fricke & Lux (2014) find that distributions with an exponential tail are a better description of the network connections and hence, refute the scale-free network structure.

Another strand of literature measures systemic risk by focusing on tail dependence over a given horizon. Betz, Hautsch, Peltonen, & Schienle (2016) apply a penalized two-stage fixed-effects quantile approach using the equity and CDS prices of 51 large European banks and 17 sovereigns to examine their interconnectedness based on their tail risk dependencies. They confirm that interconnectedness is an important factor in assessing the firm's systemic risk contribution. Segoviano & Goodhart (2009) treat the banking system as a portfolio of banks. They first construct the probability of distress for each bank using market data such as CDS and/or out-of-the-money option prices. Then, they construct the banking system multivariate density (BSMD) which is supposed to capture the distress linear and nonlinear dependence among the banks in the system. From the BSMD, they produce various measures of system stability. The main advantage of this method is that it can feature the dynamic changes in the distress dependence. Their empirical results suggest that the risk of joint distress of the European banks was lower than that of the US investment banks during the 2008 financial crisis. During the same period, UBS was the European bank under the highest stress. The distress of UBS exerted the highest stress on Barclays. Besides, the stability of the European banks was most reliant on the distress of Credit Suisse in September 2008. In addition, the probability of one US bank under distress conditional on one European bank becoming distressed is lower than the conditional probability of one European bank under distress given a US bank under distress, which suggests that the failure of the European financial system is more problematic for the global system. In a similar vein, Adrian & Brunnermeier (2016) suggest the use of Delta-CoVaR (ΔCoVaR) as a measure of the marginal contribution of individual banks to the riskiness of the system. A bank's ΔCoVaR is defined as the difference between the system's value at risk conditional on that bank at distress and the system's value at risk conditional on the bank's median state. They show that ΔCoVaR is dependent on leverage, size, and the business cycle. Acharya et al. (2017) measure systemic risk as firms' expected capital losses conditional on a negative tail event of the system, denoted as marginal expected shortfall (MES). They show that MES, together with leverage, can explain the cross-sectional returns of banks during the crisis better than traditional risk measures such as beta, volatility, and expected shortfall, which do not involve the tail dependence between the institution and the system. However, Idier, Lamé, & Mésonnier (2014) empirically show that standard balance sheet ratios are better predictors of firms' equity losses during the financial crisis than the MES. Kleinow, Moreira, Strobl, & Vähämaa (2017) perform empirical comparisons of MES and ΔCoVaR using the US data from 2005-2014. They find that the two measures provide different rankings of systemically important institutions.

In the spirit of this literature strand, Engle, Jondeau, & Rockinger (2015) investigate the systemic risk of European financial institutions over the 2000-2012 period. They measure systemic risk as the expected capital shortfall conditional on a significant stock market decline, estimated by the biggest 6-month market decline over the sample period, approximately 40%. This measure has a nice prudential meaning which is the equity buffer measured ex-ante that would be sufficient for the firm to face a systemic event. From the policy maker's point of view, this measure also corresponds to the minimum cost, in addition to the firm's endorsed debt, should the government decide to bail out the troubled firm. In this sense, the measure easily allows for the ranking of systemically important financial institutions. Their study sample includes 196 European financial firms from different sectors such as banks, insurance firms, financial services, and real estate firms. However, the results show that almost most of the systemic risk in Europe is composed of banks and insurance firms, approximately 83% and 15% respectively at the end of the sample period 2012. The reason is that financial services and real estate companies used comparatively much lower financial leverage, which is an important factor in the estimation of capital shortfall. This result seems counterintuitive considering the fact that the recent financial crisis originated from the real estate sector. However, these results actually pointed out that the fragility of the system is caused by the highly leveraged financial structure of the stakeholders, rather than that of the real estate companies themselves. At the individual institution level, the five most systemically important institutions are Deutsche Bank, Credit Agricole, Barclays, Royal Bank of Scotland, and BNP Paribas, accounting for 37% of the system's total expected shortfall in the case of a systemic event. It is worth noticing that while BNP has a relatively large market capitalization rate and low leverage, Credit Agricole has relatively small market capitalization and high leverage. This implies that there are different determinants of the systemic risk measure. At the country level, France and the UK together contributed to approximately 52% of the European financial sector's total exposure. Furthermore, industrial production and business confidence index are shown to be Granger caused by the aggregate measure in most countries. Therefore, this measure could be a promising early warning signal of distress in the real economy. In addition, 3-month interbank rate is found to be the main determinant of systemic measures in most countries. This is understandable because 3-month interbank rate is an important factor affecting the banks' balance sheet and the banking sector is the biggest contributor to systemic measures in most countries as mentioned earlier. The authors also have found that Europe has a more fragile financial system than the US does. In case of a new world crisis, the expected capital shortfall of the European financial system is larger than that of the US system. Besides, the relative ratio between the expected shortfall of the four riskiest banks to the GDP is slightly higher in Europe (3.7%) than in the US (2.7%). More importantly, the expected shortfall of the four riskiest banks in Europe is 4.45 times their total market capitalization rate while the same figure for the US is only 1.16. This implies that the European bank is much more undercapitalized than the banks in the US. Therefore, should a world crisis occur, it is much more difficult and costly to rescue the European banks.

Another strand evaluates the interconnectedness among the financial institutions to measure systemic risk. This strand extracts the information from the market data which is in theory supposed to capture both the direct linkages (via for example interbank market) and indirect linkages (via common exposures). Abbassi, Brownlees, Hans, & Podlich (2017) investigate the credit interconnectedness of German banks using a unique proprietary dataset from January 2006 to December 2013 and relate the results to the interconnectedness measure estimated from CDS data. They found that the interconnectedness retrieved from market data can capture banks' linkages via wholesale market and common assets holding.

Billio et al. (2012) propose the use of the principal component analysis and vector autoregression methods to quantify the interconnectedness as a measure of systemic risk. Applying the methods to the month equity return from January 1994 to December 2008, they empirically examine the interdependence of the 25 largest (determined by market capitalization) financial firms in each of the 4 sectors in the US including banks, insurance, brokerage, and hedge funds, each of which supposedly has a different role in the financial crisis. They were able to show that their measures can capture periods of financial distress in the system. Specifically, the proportion in the sample's return variation explained by the first principal component peaked in August 1998 and October 2008, the two most turbulent periods in the sample. The Granger causality relationships significant at 5% level increased dramatically in the 2006-2008 crisis period. The number of significant connections in 2006-2008 constituted 13% of all possible connections, which was more than twice of that during the tranquil 2002-2004 period. It is documented that in overall there is a positive correlation between the aggregate connectedness indicators and the empirical variance of the system. The correlations were strongest during the crisis period LTCM 1998 and the financial crisis 2008. However, during the 2001-2006 period, it seems that while the empirical system variance was decreasing, the connectedness aggregate indicators were increasing slowly. It is also worth mentioning that the banking sector was the most systemically important in the sense that it had the greatest number of Granger causality to and from the other sectors. To examine the predictive power of the connectedness measures, Billio et al. (2012) run regressions of Max%loss rankings on the rankings of the connectedness measures. Max%loss is defined as the maximum percentage loss in market capitalization during the crisis period from July 2007 to December 2008. The connectedness measures are estimated for two separate 3-year pre-crisis periods, October 2002–September 2005 and July 2004–June 2007, which respectively represent high and low levels of aggregate system connectedness. Their results showed that there was a significant positive relationship between the firms' PCAs measure and the losses firms suffered during the 2008 crisis. This result indicates that firms more exposed to the overall system are more likely to suffer large losses during the crisis. However, this result only stands for the PCAs measures of the October 2002–September 2005 period. A similar out-of-sample test using the Granger causality measures shed a clearer light on the direction of the relationship among the firms and their losses in the crisis. It is interesting to see that firms which Granger cause others during both of the pre-crisis periods suffered the most significant losses during the crisis, but not the firms which are Granger caused by others. Furthermore, the authors also found that firms with more Granger causality connections to the worst performed firms suffered larger losses than firms having fewer connections to them. These results suggest that Granger causality analysis can capture the spillover effects from firms with significant losses to firms with larger exposure to them.

Diebold & Yilmaz (2014) suggest using variance decomposition as a unified framework for measuring connectedness as a systemic risk measure. In essence, they measure connectedness as the proportion of forecast error variance of a variable accounted by each of the other variables in the system. This approach has the advantage that it allows for measuring both the strength and direction of connectedness. Similar to the Granger causality framework in Billio et al. (2012), the variance decomposition method can identify the direction of the connectedness at a pairwise and a system-wide level. In addition, it can also quantify the strength of each connectedness, which is not possible in the Granger causality framework. Parallel to the notion of Granger cause, the directional connectedness "to" others measures the impact of a shock to a variable on each of the other variables. The directional connectedness "from" others measures the impact a variable received coming from shocks to each of the other variables, this is comparable to the notion of being Granger caused in a VAR framework. Diebold & Yilmaz (2014) applied the framework to study the connectedness of a sample including thirteen major financial institutions in the US. Different from Billio et al. (2012), Diebold & Yilmaz used the stock return volatilities as input to their analysis. Their justification is that because volatility tends to be associated with investors' fear and uncertainty, studying volatility connectedness would help identify the crisis period more easily. An important finding in this paper is that there was a distinctive difference between the distributions of ”to” and “from” connectedness measures. Specifically, the estimated “to” connectedness measures vary more substantially across the variables than the estimated “from” connectedness measures do. The authors explained this difference as follows. Because the chosen institutions are the largest ones in the industry, they are expected to be interconnected. Therefore, a volatility shock to one institution would be distributed to most of the other institutions. As a result, the size of the volatility shock received by each stock will be relatively small. On the other hand, the directional “to” connectedness measures vary across stocks as the size of the volatility shocks and the centrality of the stocks from which the volatility shocks originate vary. From this result, it can be suspected that the “to” connectedness rather than the “from” connectedness measure would be the decisive factor in identifying the systemically important institutions. Besides, the authors have noticed that there could be some institutions that received little shocks from the others while simultaneously transmitting vastly to the others. Detecting these firms is a crucial task from the macro-prudential point of view because they are the potential threats to the system stability.

4 METHODOLOGY

In this thesis, I apply three frameworks proposed by Billio et al., (2012) and Diebold & Yilmaz (2009, 2012, 2014) to investigate the interconnectedness among the 28 largest banks in Europe as of the end of the study period December 2018. The principal component analysis is to assess the increase in the correlation among the assets return of the banks. Granger causality analysis provides a directional connection analysis among the banks' returns. The forecast error variance decomposition in Diebold & Yilmaz (2009, 2012, 2014) is analogous to the Granger causality framework in Billio et al., (2012) in the way that it also identifies the direction of the connections among the banks. In addition, it complements the Granger causality framework by allowing for the quantification of the strength of the directional connections. These three frameworks are useful as each of them provides both an aggregate indicator to assess the overall connectedness of the system in the time-series dimension and measures for individual banks' contribution in the cross-sectional dimension.

4.1 Principal component analysis (PCA).

Let $\boldsymbol{r}_i$ be the stock return of bank i; i=1,…,n. Define $\boldsymbol{z}_i \equiv (\boldsymbol{r}_i - \mu_i)/\sigma_i$, where $\mu_i = E(\boldsymbol{r}_i)$, and $\sigma_i^2 = Var(\boldsymbol{r}_i)$. Then the variance of the system σ_S^2can be written as:

$$\sigma_S^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} \sigma_i\sigma_j E(\boldsymbol{z}_i\boldsymbol{z}_j) \quad (1)$$

Let $\boldsymbol{w}_i = (w_{i1} \dots w_{in})$ transposed be a n-dimensional real-valued vector. Then the principal components can be defined as follow:

- The first principal component of r is the linear combination $\boldsymbol{y}_1 = w_1^T.r$ that maximizes Var($\boldsymbol{y}_1$) subject to the constraint $w_1^T w_1$ = 1.
- The second principal component of r is the linear combination $\boldsymbol{y}_2 = w_2^T.r$ that maximizes Var($\boldsymbol{y}_2$) subject to the constraint $w_2^T w_2$ = 1 and Cov ($\boldsymbol{y}_1, \boldsymbol{y}_2$) = 0.
- And so on to component *n-th*.

As a consequence, we have:

$$E(\boldsymbol{y}_i\boldsymbol{y}_j) = \boldsymbol{\lambda}_i \; if \; i = j; \; and \; E(\boldsymbol{y}_i\boldsymbol{y}_j) = 0, if \; i \neq j,$$

where $\boldsymbol{\lambda}_i$ is the i-th eigenvalue. (2)

The purpose of PCA is to yield an eigendecomposition of the variance covariance matrix of returns of the n banks into the orthonormal matrix of loadings $\boldsymbol{W}$, consisting of the eigenvectors of the correlation matrix of returns, and the diagonal matrix of eigenvalues Λ:

$$\boldsymbol{z}_i = \sum_{k=1}^{n} W_{ij}\, \mathbf{y}_j, \text{ since } \boldsymbol{W} \text{ orthonormal.} \quad (3)$$

From (2) and (3): $$E(\boldsymbol{z}_i\boldsymbol{z}_j) = \sum_{k=1}^{n}\sum_{l=1}^{n} W_{ik}W_{jl}E(\boldsymbol{y}_k\boldsymbol{y}_l) = \sum_{k=1}^{n} W_{ik}W_{jl}\boldsymbol{\lambda}_k \quad (4)$$

From (1) and (4): $$\sigma_S^2 = \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} \sigma_i\sigma_j W_{ik}W_{jl}\boldsymbol{\lambda}_k \quad (5)$$

W_{ij} is a factor loading of the *j-th* principal component on the returns of bank i.

Since the variance covariance matrix is positive definite, all of its eigenvalues are positive. In some cases, the eigenvector may give meaningful interpretation about the underlying factors. For example, the values of a certain eigenvector may show strong exposure to a certain country and weak exposure to the other country, then we can interpret this eigenvector is a proxy the economic condition of that particular country. On the other hand, an eigenvector can also be a reflection of several intertwined underlying factors unique to the studied sample. In this case, it is not easy to identify the underlying factors other than as a statistical artifact. Moreover, the compositions of the eigenvector may not be persistent over time since the interactions among the underlying factors are likely to change periodically (Kritzman et al., 2010).

Now, let (λ_1, W_1),...,(λ_n, W_n) be the eigenvalue–eigenvector pairs of the correlation matrix. We have:

$$\sum_{i=1}^{k} Var\ (\boldsymbol{r}_i) = \sum_{i=1}^{k} \lambda_i = \sum_{i=1}^{k} Var\ (\boldsymbol{y}_i);\ \text{for all } k \text{ from 1 to } n \quad (6)$$

To evaluate the aggregate connectedness of the system Billio et al. (2012) suggest the use of the following measure:

$$\frac{\sum_{i=1}^{k} Var\ (y_i)}{\sum_{i=1}^{n} Var\ (\boldsymbol{r}_i)} = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{n} \lambda_i} \quad (7)$$

The idea is that when the system is highly interconnected, a small number of principal components can explain most of the volatility in the system since the underlying sources of risk become more unified. However, this is simply an indication of market fragility in the sense that a negative shock is likely to propagate more quickly and broadly throughout the system because of higher connectivity. In other words, a high absorption ratio does not necessarily lead to market turbulence or financial distress.

Concerning the measure attributed to each individual bank, Billio et al. (2012) adopt the following measure of connectedness for each bank *i*. Conditional on the first *k* strong common components across the returns of all banks:

$$PCA_{i,k} = \frac{\sigma_i^2}{\sigma_s^2} \sum_{j=1}^{k} W_{ij}^2 \lambda_j \quad (8)$$

According to Billio et al. (2012), $PCA_{i,k}$ measures both the contribution and the exposure of the *i-th* bank to the aggregate risk of the system given a strong common exposure on the first *k* components among all banks' equity returns. In addition, when the fourth co-moments are finite, this also captures the contribution of the *i*-th institution to the multivariate tail dynamics of the system.

4.2 Granger-causality

First, to separate contagion and common factor exposure and filter out heteroskedasticity, I use the following model GARCH (1,1) for each bank i:

$$R_t^i = \mu_i + c_i R_t^m + a_{it};\quad a_{it} = \sigma_{it}.\epsilon_{it}$$
$$\sigma_{it}^2 = \omega_i + \alpha_i a_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 \quad (9)$$

;R_t^m is the return on the STOXX Europe 600 index used as proxy for the market.

I perform granger causality test on the standardized series: $\widehat{r_{it}} = \hat{a}_{it}/\hat{\sigma}_{it}$ where $\hat{a}_{it}$ is the residual from the mean equation and $\hat{\sigma}_{it}$ is fitted standard deviation from the above model. In essence, a time series *j* "Granger cause" another time series *i* if the predictions of the values of time series *i* based on both the past values of time series *i* and of time series *j* are better than based on only the past values of times series *i*. Specifically, consider a VAR(1) model of two standardized return series:

$$\begin{aligned} R_t^i &= b^i R_t^i + c^{ij} R_{t-1}^j + e_t^i, \\ R_t^j &= b^j R_t^j + c^{ji} R_{t-1}^i + e_t^j, \end{aligned} \tag{10}$$

; e_t^i and e_t^j are two white noise processes and $Cov(e_t^i, e_t^j) = 0$. Then, we say j Granger causes i if c^{ij} is statistically different from zero. Similarly, i Granger causes j if c^{ji} is statistically different from zero.

In an efficient financial market, we should not detect Granger causality. However, due to the contagion channels described in the literature review, we may detect some Granger causality depending on the degree of the connections and integration among banks.

To evaluate the aggregate connectedness of the system, Billio et al. (2012) define degree of Granger causality (DGC) as follows.

$$DGC \equiv \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j \neq i} (j \to i) \tag{11}$$

; where $(j \to i) = \begin{cases} 1 \; if \; j \; Granger \; cause \; i \\ 0, otherwise \end{cases}$

For each bank *i*, the following variables assessing its systemic importance is computed:

- Number of out Granger cause (#out): the number of other banks that bank *i* Granger causes divided by 27:

$$\#out = \frac{1}{(n-1)} \sum_{j \neq i} (i \to j) \tag{12}$$

- Number of in Granger caused (#in): the number of other banks that Granger cause bank *i* divided by 27.

$$\#in = \frac{1}{(n-1)} \sum_{j \neq i} (j \to i) \tag{13}$$

4.3 Forecast error variance decomposition.

Diebold & Yılmaz (2009, 2012, 2014) propose a framework for empirically estimating connectedness using variance decompositions from an approximated VAR model. The framework is briefly presented here, more detailed explanation of the framework can be found in the above referent papers.

Consider a first order VAR(1) model:

$$\boldsymbol{x}_t = \boldsymbol{\Phi} \boldsymbol{x}_{t-1} + \mathbf{e}_t \tag{14}$$

where $\boldsymbol{x}_t = (x_{1t}, x_{2t} \dots, x_{nt})$, $\boldsymbol{\Phi}$ is a n-by-n parameter matrix, and $\{\mathbf{e}_t\}$ is a sequence of serially uncorrelated random vectors with mean zero and covariance matrix $\boldsymbol{\Sigma}$. Assuming that the model is weakly stationary, apply the Cholesky decomposition to express the moving average presentation in terms of orthogonal innovations $\boldsymbol{\varepsilon}_t$ as:

$$\boldsymbol{x}_t = \sum_{i=0}^{\infty} \mathbf{A}_i \, \boldsymbol{\varepsilon}_{t-i}, \tag{15}$$

where:

$\boldsymbol{\varepsilon}_t = L^{-1}\mathbf{e}_t$; L is the lower triangular Cholesky factor of $\boldsymbol{\Sigma}$, $\mathrm{E}(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t') = \mathrm{I}$

$\mathbf{A}_0 = L$; $\mathbf{A}_i = \boldsymbol{\Phi}^i L$ for i =1,…,∞.

Now consider forecasting of $\boldsymbol{x}_{t+h}$ and the associated forecast error conditional on the observed value of $\boldsymbol{x}_t$.

The 1-step-ahead forecast is $\boldsymbol{x}_{t+1} = \boldsymbol{\Phi}\boldsymbol{x}_t$ with forecast error $\mathbf{A}_0\boldsymbol{\varepsilon}_{t+1}$

The 2-step-ahead forecast is $\boldsymbol{x}_{t+2} = \boldsymbol{\Phi}^2\boldsymbol{x}_t$ with forecast error $\mathbf{A}_0\boldsymbol{\varepsilon}_{t+2} + \mathbf{A}_1\boldsymbol{\varepsilon}_{t+1}$

In general, the h-step-ahead forecast is $\boldsymbol{x}_{t+h} = \boldsymbol{\Phi}^h\boldsymbol{x}_t$ and the associated forecast error is:

$$\sum_{i=0}^{\mathrm{h}-1} \mathbf{A}_i \, \boldsymbol{\varepsilon}_{t+h-i}. \tag{16}$$

The idea of Diebold & Yılmaz's framework is to use variance decomposition to separate the forecast error variance of each variable into parts attributable to its "own" shocks versus shocks to the other variables. For example, focusing on the $\{x_{1t}\}$ we can see that the h-step-forecast error is:

$$\sum_{j=1}^{n} \sum_{i=0}^{\mathrm{h}-1} \mathbf{a}_{1j}(i)\varepsilon_{jt+h-i} \tag{17}$$

; $\mathbf{a}_{1j}(i)$ is the j-th value in the first row of $\mathbf{A}_i$.

Since the sequence $\{\boldsymbol{\varepsilon}_t\}$ is serially uncorrelated its components are also uncorrelated, the h-step-ahead forecast error variance of x_{1t+h} denoted by:

$$\sigma_{x1}(h)^2 = \sum_{j=1}^{n} \sum_{i=0}^{h-1} \mathbf{a}_{1j}(i)^2. \tag{18}$$

Now we can decompose $\sigma_{x1}(h)^2$ into proportions due to each type of shock. The proportion of $\sigma_{x1}(h)^2$ due to shocks to ε_{jt} is:

$$\frac{\sum_{i=0}^{h-1} \mathrm{a}_{1j}(\mathrm{i})^2}{\sigma_{x1}(h)^2} \text{ for } j = 1,2,\ldots,n \tag{19}$$

When j=1 the above ratio is the proportion of $\sigma_{x1}(h)^2$ due to its own shocks ε_{1t}. The summation of (19) for j from 2 to n tells us the proportion of the movements in the sequence $\{x_{1t}\}$ caused by shocks to the other variables.

In general, Diebold & Yılmaz (2009) measure the total spillover effect *received by* x_{it} *from all the others* as:

$$\frac{\sum_{j=1,j\neq i}^{n} \sum_{k=0}^{h-1} \mathrm{a}_{ij}(k)^2}{\sigma_{xi}(h)^2} \tag{20}$$

Diebold & Yılmaz (2009) suggest that this measure can be used to rank the systemic importance of banks because it expresses how each bank is sensitive to shocks from the other institutions. This measure is comparable to the #*in* Granger causality measure in Billio et al. (2012) in that sense that the #*in* measure counts the number of banks that Granger cause bank i using the presentation of VAR model while this measures the fraction of movement in bank i's returns explained by shocks to the returns of all the other banks using the VMA presentation. In this thesis, I denote the measure in (20) by *from_others*.

Similarly, the analog of the #*out* measure in Billio et al. (2012), the number of other banks in the system that are Granger caused by bank i, is the total spillover effect *from bank i to all other banks*. This measure is denoted as *to_others* in this thesis and is constructed as follows:

$$\frac{\sum_{j=1,j\neq i}^{n}\sum_{k=0}^{h-1}\mathrm{a}_{ji}(k)^2}{\sum_{j=1}^{n}\sum_{k=0}^{h-1}\mathrm{a}_{ji}(k)^2} \tag{21}$$

This captures the total fraction of forecast error variances in all other banks that are contributed by shocks to bank i.

Besides, Diebold & Yılmaz (2009), Diebold & Yılmaz (2012) suggest using the total connectedness measure as an indicator of systemic risk.

$$\frac{\sum_{i,j=1,i\neq j}^{n}\sum_{k=0}^{h-1}\mathrm{a}_{ij}(k)^2}{\sum_{i=1}^{n}\sigma_{xi}(h)^2} \tag{22}$$

Simply put, (22) is the sum of off diagonal elements in the variance decomposition matrix divided by n (the number of banks). It represents the proportion of forecast variance of the system constituted by the interaction of the banks within the systems.

It is important to note that the above illustration relies on Cholesky decomposition which crucially depends on the ordering of the variables and hence, so is the resulting variance decompositions. Diebold & Yılmaz (2012) circumvent this problem by using the generalized variance decomposition (GVD) framework Koop, Pesaran, & Potter (1996) and Pesaran & Shin (1998). In contrast to Cholesky decomposition, the GVD framework no longer orthogonalizes shocks, but allows for correlated shocks by accounting for the empirical correlation. The GVD has the desirable advantage that it is robust to the ordering of the variables. However, the Cholesky decomposition is implemented in this paper for the sake of calculation simplicity. Moreover, Diebold & Yılmaz (2012) pointed out that the total connectedness is often robust to the ordering empirically.

4.4 The data

In this thesis, I analyze the connectedness at the individual bank level. It is also possible to apply the same frameworks to data at a larger level; for example, Black et al. (2016), Gibson et al. (2018) studied the systemic risks of European banks at the country level. I decided to follow Billio et al. (2012) and Betz et al. (2016) to study at the individual bank level for the reason that different banks have different idiosyncratic shocks which are likely to get average out when aggregating.

I decided to use only the largest banks in Europe with a minimum market capitalization of five billion euros at the end of study period, December 2018. The reason for choosing only the largest banks is to control for bank size as in Billio et al., (2012) and focus only on the banks' degree of connectedness. Further, banks with missing data were dropped. This selection process results in a study sample of 28 European banks. Names of the banks can be seen in the Appendix. For the main analysis, weekly stock prices of these banks were retrieved from Datastream. STOXX Europe 600 Banks (SX7P) index is used as proxy for the market. The studied period starts from January 2001 to December 2018. Following Billio et al. (2012), the sample data was partitioned into subsamples reflecting periods with different characteristics.

- Period 1: From January 2001 to December 2003.
- Period 2: From January 2004 to August 2007 when BNP Paribas announced the redemption suspension on three of its investment funds.
- Period 3: From September 2007 to December 2011, the peak of the European debt crisis, the first longer-term refinancing operations was announced by the ECB.
- Period 4: From January 2012 to June 2014 when the ECB for the first time lower its deposit facility rate (DFR) into negative territory.
- Period 5: From July 2014 to December 2018, the end of the sample period.

5 RESULTS AND DISCUSSION

5.1 Summary statistics

Table 1 reports some basic descriptive statistics about the financial market (STOXX Europe 600 Banks) index for each different time periods and the full sample period.

TABLE 1. Summary statistics for weekly returns of market value weighted bank index

	Mean (%)	SD (%)	Min (%)	Max (%)	Median (%)	Skew.	Kurt.
Full Sample	-0.12	3.95	-24.21	24.31	0.12	-0.54	5.92
Period 1	-0.14	3.87	-13.74	11.21	-0.29	-0.3	1.57
Period 2	0.22	1.79	-6.63	3.93	0.42	-0.96	1.68
Period 3	-0.62	5.88	-24.21	24.31	-0.57	-0.22	3.05
Period 4	0.33	3.35	-8.63	10	0.44	0.17	0.38
Period 5	-0.18	3.31	-18.94	7.25	0.02	-1.14	4.95

Overall, the financial market during the full study period is characterized by low negative average return, high standard deviation, wide range between min and max return, and high kurtosis. The first subperiod from January 2001 to December 2003 has high volatility and wide range between the max and the min return observations. The second period represents the most tranquil subperiod as it is characterized by positive mean return, the lowest standard deviation, and the smallest return min-max range. Not surprisingly, the crisis period from August 2007 to December 2011 is the one with the lowest average return and the highest standard deviation. The rescue programs executed by the ECB during period 4 seem to be effective at elevating the overall performance of the banking market since this period has the highest weekly mean return in the study sample even though the market uncertainty remains to be relatively high. The negative interest rate scheme has an adverse effect on the banking performance as we can see that the observed mean return is negative during period 5. More notably, period 5 has the highest kurtosis and lowest negative skewness. This means that during this period the return distribution has fat tail and some significant negative outliers.

Figure 1 depicts the time series of the market variance estimated from the GARCH (1,1) model. The market was quite volatile at the beginning until the middle of 2003, the volatility dropped dramatically, and the market stayed impressively tranquil. August 2007 marked the beginning of an extremely turbulent period. The market volatility peaked in around April 2009 and then fell to the level of just before the financial crisis for a short time until it rose significantly again in 2010 due to the unfolding sovereign debt crisis. The Brexit news in July 2016 was a big shock to the financial market as it drove up the market volatility to the second highest level during the whole study period.

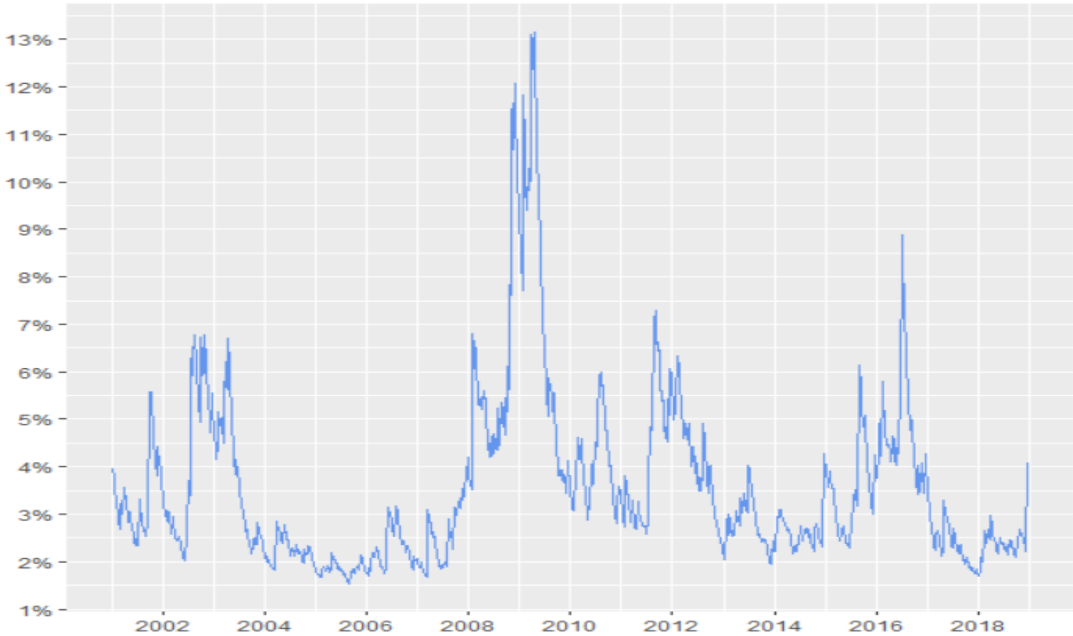

FIGURE 1. Banking index (SX7P) variance estimated from the GARCH(1,1) model

5.2 Principal component analysis

Figure 2 describes the estimates of cumulative risk fraction corresponding to the proportion of total variance explained by the principal components (the absorption ratio explained in (7)). The time series for the aggregate connectedness were constructed by applying (7) to 795 144-week rolling windows of the banks' weekly standardized returns. The return series are standardized by dividing each bank's returns by the fitted standard deviations from GARCH (1,1) model. The standardization step is to filter out the volatility clustering effect in the return series.

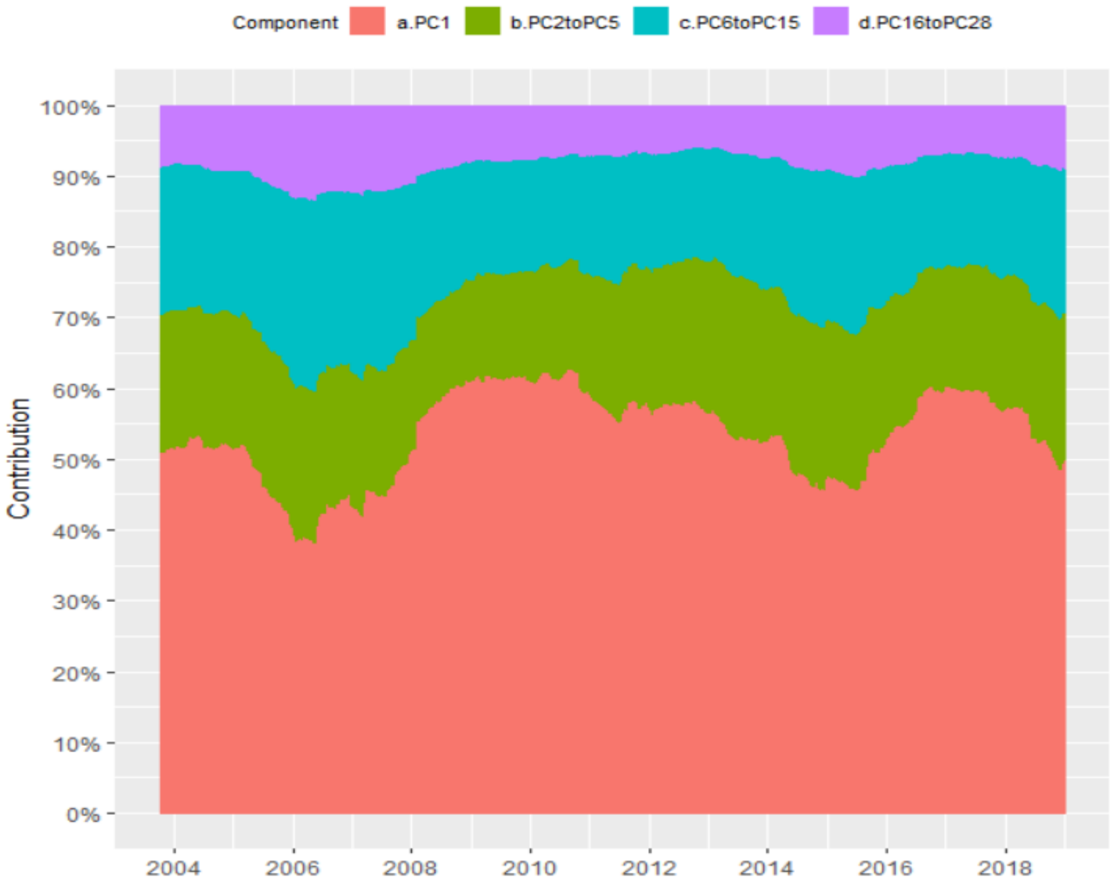

FIGURE 2. Principal components analysis of the standardized weekly returns of the 28 banks

Figure 2 shows the dynamic of the first principal component. It captures from 37% to 62% of the system return variation. For most of the study period, the first principal component captured more than 50% of return variation. The lowest level of the PC1 contribution was observed in January 2006. From that time, the PC1 eigenvalue started to increase rapidly along with the unfolding of the financial crisis, reaching its highest level in August 2010 due to sovereign debt crisis, dropping gradually from its peak, increasing quickly again in 2015 as a result of the negative interest rate regime and the fear caused by the Brexit news in 2016, and rising to near its previous crisis peak in January 2017. This result is in line with the empirical findings of Longin & Solnik (2001) who found that the co-movement among the equity markets is stronger during the financial distress period than in booming and normal periods. In distress times, the increased correlation among equity assets intensifies the connectedness through the common exposure channel.

The first five PCs have contributed to more than 70% of system variation for most of our study period except for the tranquil period 2. It is noteworthy that while the PC1's contribution started to fall from its peak in August 2010, the contribution of the PC1-PC5 kept staying at their relatively high level throughout the sovereign debt crisis and only started to decrease from January 2013. As a consequence, the contribution of the PC2-PC5 increased during the crisis period. This suggests that since the crisis occurred, the European banks became connected to each other at more layers than just the systematic or market impact. This observation advocates Aldasoro & Alves (2016) who highlighted the importance of the connections at multiple layers in studying financial interconnectedness. Under this scope, the popular systemic measures such as MES, ΔCoVaR could be inadequate to capture the multi facets of the connectedness as Benoit et al. (2013) have empirically shown that a one-factor model could explain from 83% to 100% of the variation in these estimates.

Table 2 presents cross-sectional mean, standard deviation, minimum, and maximum values of PCAS 1, PCAS 1–5 measures. The PCAS 1, PCAS 1–5 measures are calculated as presented in (8) for each subperiod with k=1, 5 respectively. These measures are based on the banks' weekly returns being divided by fitted standard deviation from GARCH(1,1) model to control for heteroskedasticity. In addition, cumulative risk fraction (or the absorption ratio) is calculated for PC 1, PC 1–5, and PC 1–15 for each subperiod.

TABLE 2. Summary statistics for PCAS measures

		PCAS 1×10^3	**PCAS 1–5×10^3**
Period 1	Mean	1.49	1.88
	Min	0.1915	0.22
	Max	4.49	4.98
	Sd	1.16	1.08
Period 2	Mean	1.32	1.85
	Min	0.42	0.70
	Max	2.52	4.03
	Sd	0.49	0.73
Period 3	Mean	1.38	1.89
	Min	0.40	0.65
	Max	4.26	6.72
	Sd	0.95	1.64
Period 4	Mean	1.31	2.88
	Min	0.27	0.38
	Max	2.82	22.65
	Sd	0.78	4.50
Period 5	Mean	1.30	2.47
	Min	0.34	0.56
	Max	3.39	15.64
	Sd	0.65	3.41

Cumulative Risk Fraction (%)

	Component 1	Components 1-5	Components 1-15

Period 1	52.6	72.1	92
Period 2	46.8	64.1	87.6
Period 3	60.9	77.6	93.4
Period 4	51.8	73.2	92.4
Period 5	56.7	74.2	92.1

Comparing the standard deviation over mean ratio of the PCAS 1 and PCAS 1-5, we can see that for all subperiods except for period 1, there were larger variations in the estimated PCAS 1-5 measures than in the PCAS 1 measures. This should not be surprising because the differences in the contribution and exposures among banks are more substantial when taking into account more common components. The implication is that there are more contagion channels of systemic risk than just the common market channel.

Different from Billio et al. (2012) who found that the mean, min and max of the PCAS measures for the US institutions are relatively persistent over time, we observe that except for the mean, there were significant variations in these measures of the European banks. Most notably, PCAS 1-5 had two extreme max values 22.65 and 15.64 observed in period 4 and period 5. Eurobank Holdings was the one associated with these max values. The interesting thing is that the large difference in the range between the min and max value of PCAS measures did not exist for PCAS 1, only for the PCAS 1-5 in period 4 and period 5. It means that the contribution and exposure of European banks to component 2 to component 5 increased during period 4 and period 5.

We can arrive at the same interpretation by looking at the cumulative risk fraction. The first principal component explains 52.6%, 46.8%, 60.9%, 51.8%, 56.7% of the banks' return variation in the five subperiods, respectively. The first five principal components captured 72.1%, 64.1%, 77.6%, 73.2%, 74.2% of the variability in bank's stock return during these five subperiods, respectively. There was a sharp decrease in the contribution of the first component from 60.9% at period 3 to 51.8% and 56.7% at period 4 and period 5, respectively. However, the contribution of the first five components altogether did not decline as much. It only fell by 4.4% from the level of 77.6% at period 3. It means that the return variation explained by the second to the fifth components together increased during period 4 and period 5.

All in all, the analysis of interconnectedness among European banks based on principal component analysis suggests that the contribution and exposure of the European banks to the other components increased relative to those to the first component representing the common market factor. These principal components could represent different risk factors. One prominent candidate is the domestic risk which arises from the residing country of the banks or the geographical area where the banks have their business. For example, Black et al. (2016) documented that there were notable differences in terms of the systemic risk contribution of European countries during the financial crisis and sovereignty debt crisis. This might be due to the traditional business model and portfolio holdings of different banking systems. This result is in line with Paltalidis, Gounopoulos, Kizys, & Koutelidakis (2015) who found that the northern euro area banking system was relatively robust to systemic risk while the southern euro area banking system was more vulnerable to a systemic event. The implication is that the interconnectedness within the European banking system has involved more facets since the financial crisis.

5.3 Granger causality analysis

Figure 3 depicts the time series of degree of Granger causality (DGC) measure as described in (11). For each of the 795 144-week rolling window, a VAR(1) is estimated for the standardized residual series $\widehat{r_{it}}$ as presented in 4.2. The DGC measure is calculated as the number of significant linear Granger causality relationships at 5% level as a percentage of all possible connections, which is equal to 756 (28 multiplied by 27).

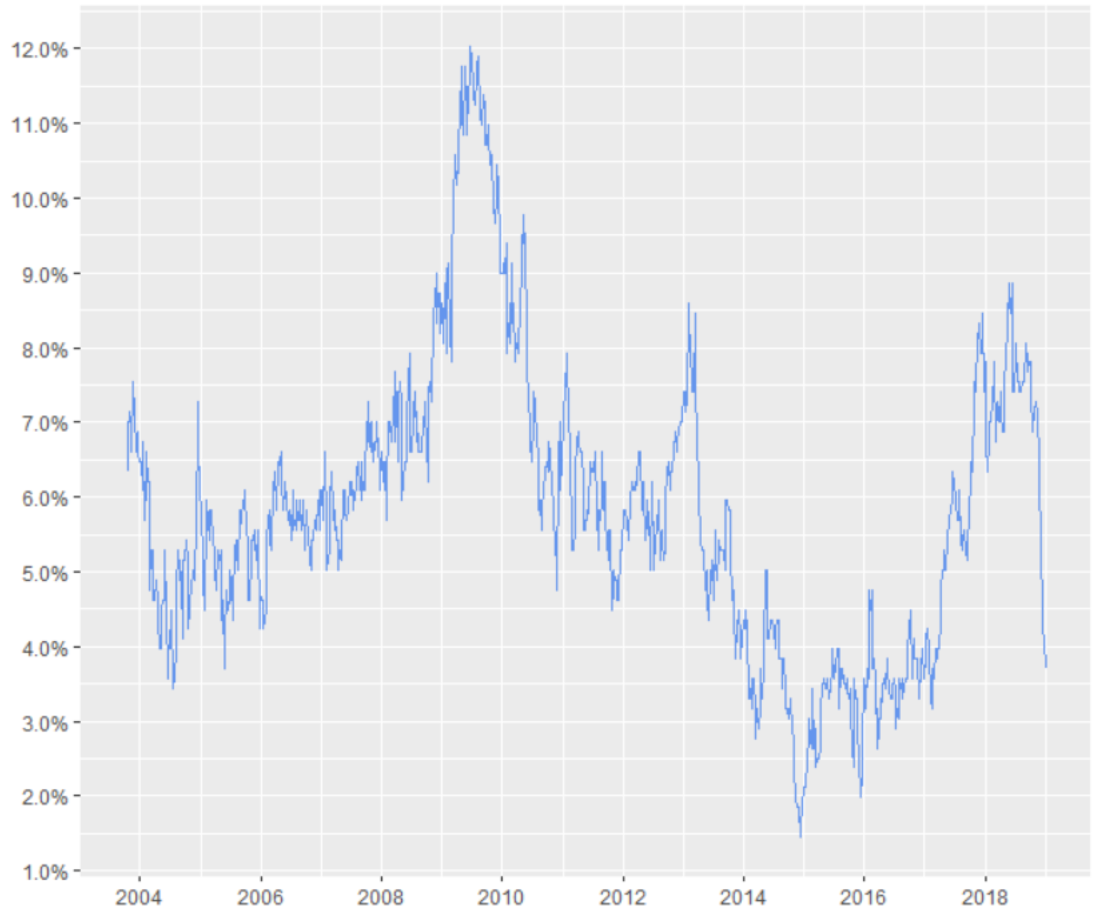

FIGURE 3. Number of connections as a percentage of all possible connections (Degree of Granger causality measure)

According to figure 3, the number of connections was small during the 2004-2006 period. The connections within the European banking system started to increase quickly from the beginning of 2006. In 2006, the total number of connections as a percentage of all possible connections was around 5%. It escalated dramatically since July of 2008 to reach its peak of the whole study period in May 2009 at 12%. Different from the result from the PCA part where the interconnectedness, for the most part, stayed at a high level for a longer period after the peak period, the number of statistically significant Granger causality relationships as a percentage of all possible connections fell off quickly to the same level at the precrisis in 2012 at around the 5.5% level, increased sharply again in 2013 to around 8.5%. The period from 2013 to 2015 witnessed a markedly decrease in the number of connections, despite some temporarily sudden increase in the middle of 2013 and the beginning of 2014. The DGC fluctuated around the 2% to 4.5% range during the 2015-2017 period, more than doubled from 2017 to nearly 9% of total connections in April 2018. This increase might be a reflection of market concerns about the negative interest rate regime and the Brexit news, which might have an adverse impact on the profitability of the banking business.

Table 3 contains the counting measures of Granger causality relationship for each bank in each sub-period as presented in (12) and (13).

TABLE 3. Summary statistics of the number of Granger causality relationships

	Period 1			**Period 2**			**Period 3**			**Period 4**			**Period 5**		
	#In	**#Out**	**#In+Out**	**#In**	**#Out**	**#In+Out**	**#In**	**#Out**	**#In+Out**	**#In**	**#Out**	**#In+Out**	**#In**	**#Out**	**#In+Out**
HSBC HOLDINGS	5	2	7	2	0	2	7	1	8	1	1	2	2	1	3
BNP PARIBAS	3	6	9	2	2	4	6	2	8	3	0	3	3	1	4
BANCO SANTANDER	3	0	3	1	0	1	4	1	5	1	0	1	1	2	3
UBS GROUP	2	1	3	1	4	5	2	2	4	0	0	0	3	2	5
NATWEST GROUP	4	10	14	2	2	4	5	13	18	1	0	1	4	6	10
ING GROEP	4	0	4	3	0	3	4	12	16	0	0	0	1	12	13
UNICREDIT	1	2	3	0	0	0	2	0	2	1	0	1	3	0	3
BARCLAYS	2	12	14	2	0	2	5	0	5	1	5	6	2	0	2
CREDIT SUISSE GROUP	3	4	7	4	14	18	5	1	6	0	1	1	4	0	4
BBV.ARGENTARIA	4	1	5	2	0	2	2	2	4	2	1	3	3	3	6
SOCIETE GENERALE	2	0	2	2	0	2	3	3	6	1	1	2	3	0	3
DEUTSCHE BANK	5	0	5	2	0	2	2	8	10	1	0	1	2	0	2
LLOYDS BANKING GROUP	4	0	4	4	0	4	7	6	13	1	1	2	3	1	4
KBC GROUP	1	2	3	0	13	13	5	0	5	2	0	2	2	0	2
INTESA SANPAOLO	1	0	1	3	0	3	1	1	2	2	0	2	2	0	2
STANDARD CHARTERED	7	1	8	4	0	4	6	1	7	2	0	2	1	1	2
NORDEA BANK	2	0	2	5	0	5	5	1	6	2	0	2	2	8	10
DANSKE BANK	2	1	3	2	0	2	3	1	4	2	2	4	0	0	0
COMMERZBANK	7	1	8	1	0	1	1	11	12	1	2	3	2	8	10
AIB GROUP	2	0	2	0	0	0	4	0	4	3	4	7	4	0	4
SVENSKA HANDELSBANKEN A	2	2	4	1	8	9	7	0	7	1	0	1	2	21	23
BANK OF IRELAND GROUP	2	0	2	0	0	0	4	7	11	0	12	12	2	0	2
SWEDBANK A	1	1	2	2	4	6	5	0	5	0	3	3	5	0	5
ERSTE GROUP BANK	2	1	3	2	0	2	2	6	8	1	2	3	5	1	6
NATIXIS	1	2	3	0	0	0	3	9	12	2	0	2	1	0	1
ALPHA BANK	2	6	8	0	1	1	3	15	18	1	1	2	3	2	5
BANCO COMR.PORTUGUES	2	18	20	1	2	3	5	0	5	4	2	6	0	0	0
EUROBANK HOLDINGS	0	3	3	2	0	2	1	6	7	2	0	2	5	1	6
Total Connection	**76**			**50**			**109**			**38**			**70**		

Similar to the results of Billio et al. (2012), we can see that the Granger causality relationships were truly dynamic. There were only 50 connections between European banks in the pre-crisis period. This figure more than doubled in the crisis period to 109 connections, encompassing 14.41% of all possible connections. In period 4, the total number of connections was only 38 (5% of total possible connections). Period 4 was also the one with the smallest number of connections among the 5 subperiods. This is at odds with the results from the PCA part, where the pre-crisis period was the least connected and the interconnectedness remained to be high after its peak in the crisis. The total connections increased by 84% to 70 connections (9.26% of all possible connections) during the negative interest rate and Brexit period.

The counting measures of Granger causality connections among individual European banks show that the number of connections of individual banks changed substantially in different periods. In the 2001-2003 period, Banco Comercial Portugues alone accounted for 26% of the number of total connections. Out of 20 significant Granger causality connections, Banco Comercial Portugues Granger caused 18 banks and being Granger caused by only 2 banks. However, in the subsequent periods, the number of its connections with the other banks decreased significantly to 3, 5, 6, 0 total connections with the other banks in period 2, period 3, period 4, period 5 respectively. The pattern is the same with Barclays. It was the bank with the second highest number of connections in the first period with 14 Granger causality connections. In the subsequent periods, it connected with only 2, 5, 6, 2 banks. On the other hand, the story was opposite with NatWest Group. In the 2001-2003 period, NatWest Group also had 14 Granger causality connections. This figure shrank to 4 connections in the second subperiod. However, in the crisis period 2007-2011, NatWest Group became the bank with the highest number of total connections, 18. In the following period, the number of total Granger connections of NatWest receded to 1, and then rose dramatically again to 10 in the 2014-2018 period.

A quite surprising finding is that the ranking of banks according to their total number of connections is not consistent over different periods. For example, in the precrisis period 2004-2007, the number of connections of Credit Suisse Group is 18. However, in the crisis period, this figure decreased by three times to 6 connections, which is opposed to the prevailing surge in the number of connections. The second most connected bank in the precrisis period also became less connected during the crisis with a fall from 13 to 5 Granger relationships. Conversely, Alpha bank had only 1 connection in the precrisis period; but during the crisis, it Granger caused 15 banks and was Granger caused by 3 banks. Alpha bank, together with NatWest Group were the most connected banks during the crisis with 18 Granger connections. The second most connected bank during the crisis was ING Groep, Granger causing 12 banks and being Granger caused by 4 banks. However, it did not have any Granger connections in the next period and swiftly became connected to 13 banks in the last period of the sample. Hypothesis testing performed on the correlations of the measures between each subsequent period showed that the strongest correlation was found between the total number of connections of period 5 and period 4. Yet, the Kendall's rank correlation was -0.24 but with the corresponding p-value of 0.11, meaning it was not statistically significant.

Besides, it is noteworthy that for most of the cases of banks with the greatest number of total connections, the Granger causing relationships, #out, constituted a disproportionate part of their connections. As a result, we can see that the number of "in" connections is spread out more evenly while the number of "out" connections is distributed in a way that a small number of banks accounted for most of the connections. The top 3 banks with the greatest number of Granger causing connections together comprised 53%, 70%, 37%, 55%, 59% of the total number of Granger causality relationships during the first, the second, the third, the fourth, and the fifth period respectively. This result is in agreement with the findings of previous empirical studies on the topology of interbank networks; for example, Boss et al., (2003) on the Austrian interbank market; Degryse, & Nguyen (2007) on the Belgium banking system. These studies show that interbank networks are often characterized by a so-called "money centre network" meaning that a few banks form many interconnections and there are many banks with a few connections in the network. According to Georg (2013), this type of network topology is more favourable for the system stability than a purely random network because it can contain the contagion effect better.

5.4 Connectedness measures based on forecast error variance decomposition.

Figure 4 describes the dynamic estimates of total connectedness described in (22) based on 795 144-week rolling windows, the forecast horizon for variance decomposition is 4 weeks. The estimates are calculated using the residual returns being filtered out heteroskedasticity with GARCH (1,1) model similar to the Granger causality analysis part.

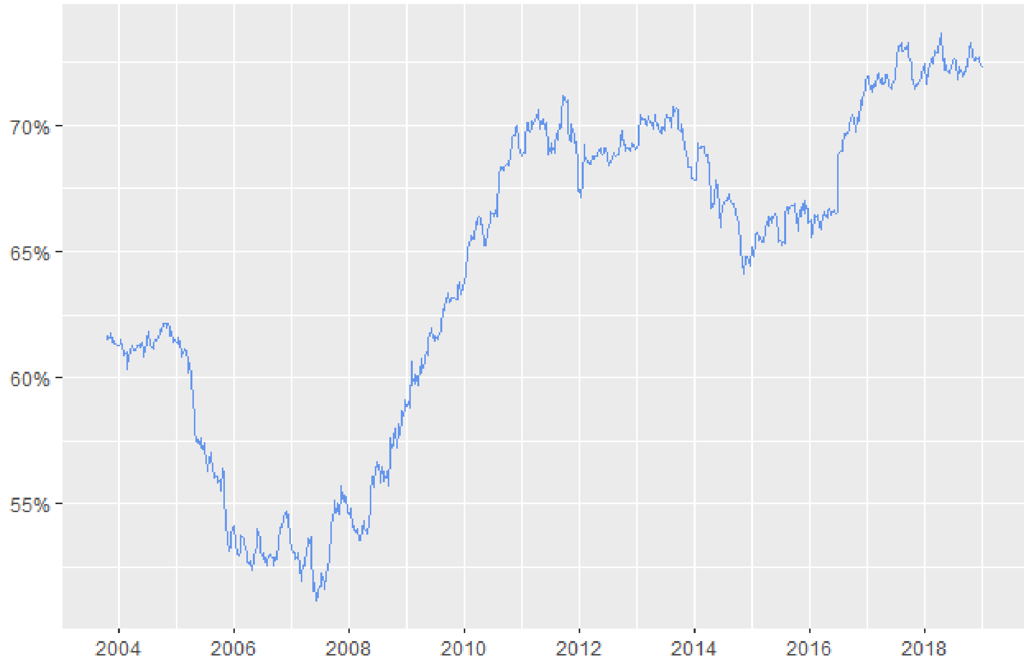

FIGURE 4. 144-week rolling window estimates of total connectedness measure defined in (6).

The total connectedness has some vivid patterns. It started at around 62% in 2004 and fell off quickly until 2006 to the level of 50% during the market booming period. Starting from early 2007, coinciding with the first signs of the financial crisis, the total volatility connectedness index increased continuously to 71% at the peak of the sovereign debt crisis at the end of 2011. The first three-year LTRO conducted by the ECB in December of 2011 in an effort to inject liquidity into the European banking system seemed to have a short term effect in reducing the connectedness since the total connectedness index was reduced to approximately 67% in the beginning of 2012 but then it started to rise again in 2012 and 2013 along with the market's concern about the potential default of Spain and Italy to reach close to the level of its peak in 2011 at 71%. A series of rescuing packages and plans to restructure the banking system helped recover the market from the end of 2013 to 2015. The total connectedness declined to 64% by 2015. Following the Brexit referendum in June 2016, the total connectedness increased dramatically, surpassing the highest level of the sovereign debt crisis to reach close to 74% in 2018.

Comparing figure 1, 2, 3, and 4, we can see that all of these aggregate risk indicators, the system variance, the contribution of the first principal component, the number of Granger relationships as a percentage of all possible connections, and the total connectedness index correlate have very high positive correlations during the financial crisis from 2007 to 2009. However, these indicators exhibit different patterns during the sovereign debt crisis from 2009 onwards. The system variance and the number of Granger connections reached their highest points in the whole sample period in mid-2009 and declined close to the level of the precrisis period quickly in early 2011. They rose again at the end of 2011 but were still far from their peaks in 2009. On the other hand, the system connectedness measured by the first principal component stayed at relatively the same level after the peak of the financial crisis in 2009 and slowly decreased from its peak in mid-2010 but never returned to the precrisis level. The total connectedness by variance decomposition kept increasing at the same speed after mid-2009 and only reached its sample climax at the end of 2011. It only started subsiding from the end of 2013 but still being higher than the 2009 level throughout the study period. A similar observation was made in Billio et al. (2012). It may suggest the fact these measures are capturing different facets of system connectedness.

Table 4 summarizes the forecast variance decomposition results for the 28 sample banks at each subperiod. The decomposition is based on the VAR (1) as suggested by AIC. The Cholesky factorisation was used with the variable ordering as in the column heading in Appendix A. *From_others* captures the fraction of the 4-week ahead forecast error variance contributed by the innovations to returns of all the other 27 banks. By definition, it is equal to 100% minus the forecast variance proportion constituted by the bank's idiosyncratic shocks. *To_others* gauges the total contribution of a bank's innovations to the forecast error variances of all the other banks' returns. This measure is not constrained to be lower than 100%. The total connectedness estimated as the mean of all banks' *from_others* (or equivalently, *to_others*) measures the overall fraction of all banks' return movement due to the spill-over effect. In addition to Table 4, Appendix A presents the estimation results for each bank at each period.

TABLE 4. Summary statistics of return connectedness analysis for each subperiod.

	Period 1		Period 2		Period 3		Period 4		Period 5	
	From_others	To_others	From_others	To_others	From_others	To_others	From_others	To_others	From_others	To_others
Min	39.99	30.45	15.77	16.42	38.31	25.62	36.42	23.49	38.68	12.81
1st Quantile	51.97	44.61	44.62	38.15	62.84	55.79	59.53	49.41	61.67	44.57
Median	61.39	55.97	52.91	47.57	67.89	64.19	69.07	67.77	75.14	75.61
3rd Quantile	68.93	70.07	59.54	61.59	72.4	81.12	76.41	82.79	79.13	88.54
Max	78.55	127.95	66.55	89.98	77.24	101.21	82.37	127.87	84.12	122
Total Connectedness	**60.04**		**50.27**		**65.80**		**66.55**		**69.13**	

Some notable features of connectedness can be seen from table 2 and appendix A. First, different from the previous frameworks, the aggregate connectedness of the system according to variance decomposition did not decrease during the period right after the crisis period. It remained at relatively the same level and even increased during the last subperiod - period 5 with the negative interest rate regime and Brexit event. Second, different from the Granger relationship counting measures above where we observed that the "#out" measure was disproportionately greater than the "#in" measure, these measures based on variance decomposition produced relatively more proportional results for "*from_others*" and "*to_others*". In addition, we can notice the two measures exhibit a strong correlation. The lowest correlation between them was 0.86, detected in Period 1. The crisis period had the strongest correlation between the two connectedness measures, 0.94. Furthermore, the ranking of banks according to the two measures over subsequent periods was also more consistent over time. Although the correlations between the first three periods were found to be not significant, Kendall's rank correlations between period 4 and period 3 were 0.59 and 0.50 for the "*from_others*" and the "*to_others*" respectively. Period 5 and period 4 had even stronger rank correlations, 0.66 and 0.64 for the "*from_others*" and the "*to_others*" respectively. Nevertheless, the fact that the forecast variance decomposition method produced a more consistent ranking of banks over subperiods than the Granger causality relationship counting measures did does not necessarily mean that one is a better framework than the other. It may be because each method reflects different aspects of the connectedness between banks. And while the underlying connectedness of the Granger relationship is more unstable over time, the variance decomposition reflects the connectedness features that have become more persistent.

Third, the spread of the "*to_others*" directional connectedness measure is clearly wider than that of the "*from_others*" measure. For example, during the crisis period, the difference between the bank with the highest "*from_others*" measure (KBC group) and the bank with the lowest one (Standard Chartered) is 38.93%, while the difference between the max and min values of "*to_others*" measure is 75.59%, nearly twice as much the range of "*from_others*" measure. In period 4 and period 5, the same figure for "*from_others*" measure is 45.95% and 45.44%, for "*to_others*" measure is 104.38% and 109.39%. The discrepancy in ranges of the two measures deepened as the total aggregate connectedness increased. Diebold & Yilmaz (2014) found a qualitatively similar result regarding the volatility connectedness within the US financial system. Their analysis produced an even greater difference between the variation in the "*to_others*" measure and in the "*from_others*" measure. In their volatility connectedness analysis, even the difference between the median and the first quantile of the "*to_others*" measure is larger than the min-max range of the "*from_others*" measure. According to Diebold & Yilmaz (2014), the large variation in the "*to_others*" measure can be explained as follow. When an idiosyncratic shock hits a particular stock, the spillover effect it creates within the system varies greatly depending on its centrality in the network. A bank's centrality can be determined by the on and off balance sheet connections it has with the other banks in the system. In addition to the varying size of the shock hitting a specific bank, since the banks are vastly different in their balance sheet structures, the directional connectedness "*to_others*" also varies across banks to large extent. Besides, it's worth remembering that a similar observation was made earlier with the analogue of these measures using the Granger causality framework. We have noticed that the "#out" measure had a larger variation than the "#in" did. These results imply that the difference in the systemic importance ranking of a bank depends on the strength of the impact it had on the other banks more than the effect it receives.

5.5 Out of sample results

A useful systemic risk measure should be applicable to provide early warning signals to the regulators. In this part, I examined the out-of-sample performance of the three studied frameworks in two ways. First, following the common approach as in Billio et al. (2012) and Idier et al. (2014), I investigate the ability of the individual banks' connectedness measures to identify ex-ante the banks that suffer the most during the crisis. Second, following the approach of Engle et al. (2015), I explored the ex-ante predictive power of the aggregate connectedness indicators on several financial economic variables including annual industrial production growth rates, annual changes in the unemployment rate, and the financial market returns.

5.5.1 Do the connectedness measures predict bank losses during the recent crisis?

In this part, I investigate the relationship between the individual banks' connectedness measures estimated before the crisis and several loss measures including the empirical banks' maximum losses, MES, and ΔCoVaR estimated historically during the crisis. According to Benoit et al., (2017), there are two approaches in the literature of quantitatively measuring systemic risk. While the first approach aims to provide indicators discerning the specific sources of systemic risks such as contagion, bank runs, or liquidity crises, the second approach is not built upon a particular source of risk. But rather, the second approach aims to support macroprudential tools that act as "Pigovian systemic risk taxes" whose purpose is to govern banks' risk-taking so that they act in a way that would be optimal for the system as a whole. In this way, the connectedness measures can be sorted into the first approach since they measure the potential for contagion between banks. Marginal Expected Shortfall (MES) in Acharya et al. (2017) and ΔCoVaR in Adrian & Brunnermeier (2016) are two prominent measures in the second category. From another perspective in Billio et al. (2012), the connectedness measures are concerned with the linkages between banks in the system while MES and ΔCoVaR can be regarded as loss-based measures because they quantify the expected losses of the individual institutions (or the system) conditional on a distress event of the system (or the individual institutions).

The three measures for historical losses during the crisis period are computed as follow:

- Max%loss (as used in Billio et al., 2012): This is the maximum percentage loss suffered by each bank. It is computed as the difference between the market capitalization of each bank at the end of August 2007 and the minimum market capitalization during Period 3 divided by the market capitalization at the end of August 2007.
- Marginal expected shortfall (MES) of bank i is estimated empirically as in Acharya et al. (2010) according to the following equation:

$$MES^i = -\frac{1}{\#days}\sum_d R_d^i;$$

d is the 5% worst days of the market index in period 3. $\#days$ is the number of days where the market had the biggest 5% losses in period 3. The minus sign is to interpret MES as losses. Simply put, this represents the average return of each bank in the worst 5% days of the market.

- Delta-CoVaR is estimated by quantile regression as in Adrian & Brunnermeier (2016) according to the following steps:
    - Run a q% quantile regression of the system returns on each bank's returns R_i and estimate $\widehat{\beta}_q^i$; the coefficient on the bank return R_i.
    - Estimate the q% sample quantile $\widehat{VaR}_q^i$ and the median $\widehat{VaR}_{0.5}^i$ using each bank's returns.
    - Estimate $\Delta\text{CoVaR}_q^i = -\widehat{\beta}_q^i(\widehat{VaR}_q^i - \widehat{VaR}_{0.5}^i)$. q is chosen to be 5 in the calculation. This can be understood as the contribution of bank i to the system's Value at Risk.

Following Billio et al. (2012), each bank is assigned a ranking according to each connectedness measure and loss measures separately. I run univariate regressions of each loss measure rankings computed during the crisis period (period 3) on the connectedness rankings estimated during the two precrisis periods (period 2 and period 1). As illustrated in the previous parts, the two precrisis periods (period 1, period 2) reflect different connected properties of the system. While period 1 witnesses high market volatility and connections between banks, period 2 is characterized by tranquil market movement and low connectivity. For each regression, the coefficients on the connectedness measure ranking, the corresponding p-value and Kendal rank coefficient are investigated to see which measures perform well in terms of identifying ex-ante the most severely hit banks during the crisis.

Table 5, Table 6, and Table 7 present the regression results with Max%loss rankings, MES rankings, and ΔCoVaR rankings respectively as the dependent variable. There are several notable points. First, most of the statistically significant coefficients are on the PCAS measures and the measures based on variance decomposition framework. Specifically, from table 5 we can see that the coefficient of from_others and to_others rankings are 0.559 and 0.504 respectively, both of these estimates are significant at 1% level, indicating that there is a strong positive relationship between the from_others and to_others measures of banks and their losses during the crisis. The exposure of banks to the overall risk of the system entailed by the first principal component during period 1 also had a positive coefficient significant at the 10% level.

Second, table 7 reported counterintuitive results on the relationship between connectedness based on variance decomposition and ΔCoVaR. The coefficient on the from-others ranking for period 1 is -0.524 and is statistically significant at the 1% level. The negative sign of the coefficient suggests that the banks that received the most impact from the other banks during the precrisis tend to have less negative effect on the system if they fail. The negative sign of the coefficient on to-others is even more counterintuitive because it indicates that the system is less harmed conditional on a tail event of the banks whose shocks exert the more adverse impact on the other banks. However, the coefficient on to-others is only significant at the 10% level. These results, in conjunction with some previous papers such as Jaeger-Ambrozewicz (2013), Löffler & Raupach (2017), and Benoit et al. (2013), demonstrated that a critical issue with the use of some market-based systemic measures is that sometimes they can produce very different rankings on the systemically important institutions. A possible explanation for the contradicting results of ΔCoVaR is provided by Jaeger-Ambrozewicz (2013). He showed that Delta-CoVaR can be problematic when the return distribution is not Gaussian. And it is common knowledge that the return distribution is far from being Gaussian during crisis time. Another reason could be that as demonstrated in Benoit et al. (2013), the rankings of Delta-CoVaR measured empirically by quantile regression is equivalent to the rankings of individual institutions' value at risk in isolation and hence, not fully reflecting the dependence structure between the system and individual bank. Moreover, Kleinow et al. (2017) did empirical research comparing different systemic measures with a study sample of 122 US financial institutions from 2004-2015. They also found that ΔCoVaR produced very different rankings than the other systemic measures including MES, codependence risk, and the lower tail risk.

Third, we can see that the connectedness measures estimated during the booming period just before the crisis occurred did not perform well in terms of identifying banks' losses during the crisis. PCAS 1-5 was the best measure in terms of detecting banks that suffered the most during the crisis with the associated p-value at 0.051. Granger causality measure #Out of period 2 also seemed to be weakly associated with Max%loss in crisis with the corresponding p-value of the ranking coefficient at 0.096 and Kendall τ correlation at 0.258. Billio et al. (2012) found a similar result indicating that the financial institutions that greatly affected other institutions are more likely to suffer large losses during the crisis. All the other measures estimated during period 2 did not have any forecasting performance on any of the loss measures. Billio et al. (2012) 's result also showed that the explanatory power of the individual institutions' PCAS and Granger causality measures decreased notably in comparison with the same measures computed during the previous period. This result highlights the main weakness of systemic measures estimated during tranquil periods. The reason could be that during booming periods, the volatility is low. Therefore, the beneficial risk-sharing effect of connectedness is more dominant. The detrimental contagion effect due to the same connections only become more powerful as the magnitude of shocks increases during volatile periods as described in Gai & Kapadia (2010) and Ladley (2013).

TABLE 5. Predictive power of the connectedness measures on Max%loss

	Max%loss		
	Coeff	p-value	Kendall τ
Period 1			
PCA 1	0.320*	0.097	0.201
PCA 1-5	0.123	0.532	0.074
#In	0.324	0.105	0.237
#Out	-0.080	0.696	-0.064
#In+Out	0.106	0.598	0.082
From_others	0.559***	0.002	0.407***
To_others	0.504***	0.006	0.365***
Period 2			
PCA 1	0.011	0.954	0.021
PCA 1-5	0.372*	0.051	0.217
#In	0.023	0.923	0.018
#Out	0.334*	0.096	0.258*
#In+Out	0.259	0.190	0.189
From_others	0.201	0.304	0.164
To_others	0.228	0.244	0.164

TABLE 6. Predictive power of connectedness measures on MES.

	MES		
	Coeff	p-value	Kendall τ
Period 1			
PCA 1	0.202	0.303	0.148
PCA 1-5	0.214	0.274	0.148
#In	0.068	0.740	0.053
#Out	-0.158	0.434	-0.111
#In+Out	-0.029	0.885	-0.025
From_others	0.222	0.257	0.132
To_others	0.190	0.332	0.122
Period 2			
PCA 1	0.253	0.193	0.190
PCA 1-5	0.021	0.914	-0.005
#In	0.094	0.649	0.060
#Out	-0.119	0.617	-0.083
#In+Out	0.011	0.956	0.014

From_others	0.273	0.160	0.185
To_others	0.264	0.175	0.175

TABLE 7. Predictive power of connectedness measures on Delta_CoVaR

	Delta_CoVaR		
	Coeff	p-value	Kendall τ
Period 1			
PCA 1	0.250	0.200	0.159
PCA 1-5	0.210	0.284	0.148
#In	-0.062	0.763	-0.059
#Out	0.033	0.870	0.035
#In+Out	-0.059	0.768	-0.037
From_others	-0.524***	0.004	-0.333**
To_others	-0.342*	0.075	-0.206
Period 2			
PCA 1	0.200	0.308	0.106
PCA 1-5	-0.037	0.851	-0.048
#In	0.124	0.545	0.090
#Out	0.121	0.611	0.083
#In+Out	0.097	0.630	0.071
From_others	0.007	0.971	0.026
To_others	-0.022	0.912	0.016

5.5.2 The aggregate connectedness indicators and the macroeconomy

So far, we have studied interconnectedness as a measure of systemic risk within the banking system. However, it is also important to examine the measures in relation to the macroeconomy because from the regulator's perspective the adverse impact of a financial crisis on the economic stability and public welfare is why containing systemic risk is so crucial. Indeed, The European Central Bank (ECB) (2015) defines systemic risk as a risk of financial instability "*so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially*". Or according to The Global Financial Stability Report of the IMF (2009), systemic risk is: "*the risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and that has the potential to cause serious negative consequences for the real economy.*"

Therefore, this part aims to explore the interactions between the aggregate connectedness indicators defined in (7), (11), (22) and a set of economic variables including industrial production index for the Euro area, Euro area unemployment, and the STOXX Europe 600 Banks Index return. All these variables are conducted in annual changes. More specifically, the following VAR (1) is implemented:

$$\boldsymbol{Y}_t = \boldsymbol{\mu} + \sum_{i=1}^{p} \mathbf{A}_i \boldsymbol{Y}_{t-i} + \boldsymbol{\varepsilon}_t$$

Where: $\boldsymbol{Y}_t$ are the endogenous variables including the annual industrial production growth rate, annual changes in the unemployment rate, the market index return, and the aggregate connectedness indicators defined in (7), (11), (22). p = 1.

Table 8 reports the t-statistics for the Granger causality tests between the variables. There are 182 monthly observations for each variable from October 2003 to December 2018. The observations for monthly connectedness indicators are taken as the average of the weekly estimations for that month. PCA1 and PCA5 are computed according to (7) with k=1 and 5 respectively. DGC is computed according to (11). Total_con is estimated by applying (22) to the banks' standardized returns.

From table 8, we can see that the only aggregate connectedness measures that Granger cause annual changes in industrial production index and annual unemployment rate come from the principal component analysis framework. The signs of the coefficients indicate that common exposure to the first principal component is favorable for the macroeconomy. However, increasing exposure to the components at more layers can be harmful to the real economy.

TABLE 8. Test statistics on the coefficients of the VAR(1) model**.**

Variables	Equation						
	IPI	Urate	Ma_re	PC1	PC5	DGC	Total_con
IPI	-1.95	-3.89	-0.34	0.57	0.18	-0.32	1.23
Urate	-5.25	5.13	-0.21	0.00	-0.09	1.61	-0.19
Ma_re	1.23	-2.22	-6.41	-2.83	-3.22	-1.06	-0.94
PC1	**3.65**	**-2.59**	-1.15	0.05	-1.08	-0.13	-1.19
PC5	**-3.83**	**2.86**	1.23	2.36	3.36	-0.15	1.30
DGC	0.27	1.08	-0.10	-0.64	-0.19	0.03	2.00
Total_con	0.46	-0.78	-0.21	0.98	1.48	0.83	3.50

6 CONCLUSION

This thesis provides a dynamic analysis of the connectedness within the European banking system as measures of systemic risk with a focus on the recent financial crisis and the sovereign debt crisis period. The principal component analysis, Granger causality relationship, and forecast error variance decomposition are implemented to assess different aspects of connectedness.

The results from principal component analysis imply that the nature of the connectedness itself can be very dynamic. Specifically, the contribution of more components other than the exposure to the common market has increased after the financial crisis and seems to become more relevant factors during the sovereign debt crisis. Accordingly, these results suggest a more cautious use of the popular systemic risk measures such as MES, and Delta-CoVaR. As Benoit et al. (2017) demonstrated that under certain assumptions about the covariance matrix and dependence structure between the individual banks and market returns, these measures can become one dimensional in the sense they rank systemically important banks in the order equivalent to the rankings based on individual exposure to systematic risk or value at risk in isolation. Consequently, the regulatory implication is that the regulators should incorporate different layers of the connectedness structure when monitoring systemic risk similar to the spirit put forward by Aldasoro & Alves (2018).

The directional connectedness frameworks including Granger causality relationship and forecast error variance decomposition are both built upon a vector autoregressive framework. For this reason, they are comparative and complementary to each other. While the Granger causality approach expresses the connectedness only in a binary sense, whether or not there is a connection between two banks in which way, the forecast error variance decomposition keeps track of not only the direction but also the magnitude of the connectedness. On the other hand, the forecast error variance decomposition is more restrictive because certain identification assumptions are necessary while the Granger causality framework does not require such assumptions. The analysis based on these frameworks showed that while banks were relatively heterogeneous in the influence they have on all the other banks in the system, there was less variation in the potential impact they receive from the system. This result contributes to the literature strand regarding the financial network literature in two ways. First, the previous empirical literature studying the effect of financial structure on system stability finds that the financial network often exhibits scale-free topology, meaning that a few institutions are having a large number of connections and a large number of institutions have a few connections. In this case, the system is more robust to a failure of a random institution. Or in other words, there is less likelihood of a financial contagion (Caccioli et al., 2011; Georg, 2013). The results of Granger causality and forecast error variance decomposition suggest that more thorough studies in the same fashion need to be done with a clear distinction between the distributions of in-degree and out-degree because it is plausible that the relationship between the connection distribution and system stability is dependent on the type of connection (in or out) examined. Indeed, Avella et al. (2016) showed that the case where the network is more concentrated in the distribution of #*in* links is a better scenario for the system stability than one where #*out* link distribution is more concentrated. In this regard, the empirical results in this thesis documented that the European banking network is more concentrated in the #*out* link distribution, which is not an ideal situation for the system stability.

Second, as indicated in Diebold & Yilmaz (2014), a natural consequence of the heterogeneity in #*out* connections and the homogeneity in #*in* connections at the same time is that there could be banks that exert high impact on the other banks while simultaneously receiving little impact from the others. Regulators should identify these banks because they could be the systemically important ones in the sense that they pose potential contagion risk to the system while having little shock dampening beneficial effect of the connections. However, the difficulty is that the banks with such properties identified according to the two network methods are different. For example, during the crisis period, according to the Granger causality network, they were Natwest Group and Alpha bank, while the variance decomposition framework identified BNP Paribas and KBC group as such banks. Therefore, in agreement with previous literature comparing different systemic measures (Kleinow et al., 2017; Benoit et al., 2017), this thesis advocates that systemic risk assessment should be approached with multiple measures in order to provide a comprehensive diagnosis of the system stability.

The out-of-sample analysis showed that the forecast error variance decomposition framework was the most capable one in terms of identifying firms that declined the most during the crisis. However, the connectedness measures based on this framework only performed well when measured during the period of high market volatility but not in the tranquil period. This may be because high connectedness indicates the potential for contagion and only manifests itself when there is a strong shock to the system, while the same connectedness may have the shock stabilizing benefit by risk-sharing in the case of small system shocks, as indicated by Ladley (2013) and Acemoglu et al., (2015). Besides, there was no significant positive relationship between the connectedness measures and other measures including MES and Delta-CoVaR. This again confirms the mismatch between different market-based systemic measures in terms of identifying systemically important institutions as have been demonstrated in previous empirical studies such as Benoit et al., (2017) and Kleinow et al., 2017.

To sum up, this thesis has investigated the interconnectedness between European banks as measures of systemic risk. The results showed that connectedness measures based on market data can capture fairly well the periods of financial distress and have moderate out-of-sample performance. In the meantime, from a regulatory perspective, this thesis resonates with previous literature in calling for cautious use of a single systemic measure since different methods may pick up different connectedness features and hence provide very different rankings of systemically important banks.

Lastly, further research is recommended in two ways. First, an empirical study implementing the same framework but with the inclusion of the insurance sector should be considered as Billio et al., (2012) documented that it was also a significant source of connectedness in the US financial system. Second, studies investigating the relationship between the connectedness measures and banks' characteristics are recommended, as Löffler & Raupach (2017) has shown that market-based measures such as MES and Delta-CoVaR can run into bizarre cases in which these measures are positively associated with individual banks' idiosyncratic risk and systematic risk. Such cases, if exists for the connectedness measures, should be inspected carefully because if the measures are applied in regulation, they can actually incentivize banks to take more risk in order to have a lower systemic risk contribution ranking in the eyes of the regulators.

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APPENDIX

From_other and To_other measures based on return forecast error variance decomposition.

	Period 1		Period 2		Period 3		Period 4		Period 5	
	From_others (%)	To_others (%)	From_others (%)	To_others (%)	From_others (%)	To_others (%)	From_others (%)	To_others (%)	From_others (%)	To_others (%)
HSBC HOLDINGS	50.82	42.76	53.89	49.06	49.97	37.84	36.42	24.77	43.89	24.25
BNP PARIBAS	52.35	45.43	57.66	60.49	76.89	96.44	76.30	80.97	84.12	122.00
BANCO SANTANDER	48.31	62.48	55.96	49.91	74.36	76.79	76.72	79.46	80.07	100.20
UBS GROUP	39.99	32.58	59.43	58.35	65.52	64.46	71.05	65.45	73.37	66.47
NATWEST GROUP	71.38	86.94	65.19	89.98	68.28	63.92	67.39	69.17	75.59	79.36
ING GROEP	40.97	30.45	61.35	68.72	72.13	81.37	77.20	85.69	82.15	109.19
UNICREDIT	67.07	64.72	59.87	69.51	76.84	94.01	77.26	87.19	80.41	100.99
BARCLAYS	63.06	67.62	54.85	50.48	71.62	81.66	65.13	64.08	74.70	80.52
CREDIT SUISSE GROUP	46.38	30.96	51.94	45.55	62.96	54.46	74.70	81.82	76.39	78.62
BBV.ARGENTARIA	47.76	49.16	54.67	50.59	75.96	87.09	79.09	96.04	77.61	79.60
SOCIETE GENERALE	52.88	51.67	65.26	81.88	76.14	95.41	82.37	127.87	83.32	115.93
DEUTSCHE BANK	53.45	45.14	49.04	40.41	73.21	81.03	75.82	89.48	76.69	75.33
LLOYDS BANKING GROUP	56.23	43.18	62.70	71.57	62.86	66.98	65.53	59.29	72.25	63.86
KBC GROUP	70.74	69.43	44.75	38.26	77.24	101.21	75.03	78.42	80.18	95.91
INTESA SANPAOLO	40.22	30.88	56.57	46.07	71.87	69.01	79.64	100.50	78.81	87.73
STANDARD CHARTERED	64.70	64.36	34.17	30.88	38.31	25.62	49.24	23.49	52.61	32.81
NORDEA BANK	60.24	44.49	51.38	42.90	62.76	58.48	54.48	54.97	66.08	58.07
DANSKE BANK	68.34	58.76	45.74	37.80	47.09	31.44	44.81	24.89	58.54	37.07
COMMERZBANK	57.80	48.52	30.66	18.39	65.81	56.24	78.88	103.12	80.38	90.97
AIB GROUP	74.37	87.03	59.91	64.87	62.56	52.20	61.12	37.01	38.68	12.81
SVENSKA HANDELSBANKEN A	65.89	54.54	44.22	44.96	49.50	34.00	54.29	52.39	62.71	55.43
BANK OF IRELAND GROUP	75.89	106.92	66.55	84.56	64.44	61.54	62.06	49.31	76.87	82.20
SWEDBANK A	74.80	84.96	49.91	56.01	59.04	54.04	52.61	49.44	63.13	52.65
ERSTE GROUP BANK	70.70	76.13	21.62	16.42	68.55	69.93	70.75	61.14	65.83	44.63
NATIXIS	78.55	127.95	42.47	36.49	64.50	61.71	74.79	79.63	76.46	75.89
ALPHA BANK	62.55	57.40	42.37	37.37	67.59	60.40	61.91	56.04	49.03	44.41
BANCO COMR.PORTUGUES	57.36	44.64	15.77	23.39	68.19	59.85	59.23	35.81	55.51	28.76
EUROBANK HOLDINGS	68.30	71.99	49.74	42.75	68.33	65.42	59.64	46.01	50.29	40.03
Total Connectedness	**60.04**		**50.27**		**65.80**		**66.55**		**69.13**	