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MODELING AND ANALYZING SYSTEMIC RISK IN EUROPEAN BANKING SECTOR

Par

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Title: Modeling and analyzing systemic risk in European banking sector

Key words: systemic risk, ownership structure, liquidity creation, artificial intelligence.

Résumé: This dissertation investigates the systemic risk subject in three different empirical frameworks. Besides listing the existing works related to the systemic risk in the first chapter, we examine the impact of two risk-taking factors in affecting the systemic risk level of European banks. The second chapter investigates the impact of the ownership structure on systemic risk contribution of 79 banks in 16 western European countries during the 2004-2016 period. The results show that higher ownership concentration is associated with greater banks' systemic risk contribution. Moreover, we found that banks' systemic risk contribution is even stronger for banks where institutional investors and States are the largest controlling owners. We go deeper and investigate the effect of regulatory variables on the relationship between systemic risk and ownership structure. We find that higher ownership concentration increased banks' systemic risk contribution in countries with high deposit insurance, lower capital stringency and higher asset diversification. The third chapter explores the effect of another risk-taking incentive, the liquidity creation, on banks systemic risk contribution end exposure. We use the same sample consisting of 79 European banks during the 2004-2016 period. The findings emphasize that during normal time, systemic risk exposure of banks are exacerbated by high liquidity creation. Moreover we show that, during distress times, high liquidity creation affects negatively not only banks exposure to systemic risk but also their contribution. Chapter four investigates a different facet of the systemic risk. Using a sample of 134 banks in 16 European countries ranging from 2002 to 2016, we construct three forecasting methods to predict systemic risk contribution and exposure values. We use artificial neural network, support vector machine and generalized autoregressive conditional heteroscedasticity specification. Our results show that two hidden layers artificial neural networks outperform other models in effectively predicting systemic risk.

Titre : Modélisation et analyse du risque systémique des établissements bancaires Européens

Mots clés : risque systémique, structure actionnariale, création de liquidité, intelligence artificielle

Résumé: Cette thèse examine le sujet du risque systémique dans trois cadres empiriques différents. A part de citer la liste des travaux existants liés au risque systémique dans le premier chapitre, nous examinons l'impact de deux facteurs de prise de risque sur le niveau de risque systémique des banques européennes. Le deuxième chapitre étudie l'impact de la structure de propriété sur la contribution du risque systémique de 79 banques de 16 pays Européens sur la période 2004-2016. Les résultats montrent qu'une concentration plus élevée de la propriété est associée à une plus hausse contribution du risque systémique des banques. De plus, nous avons constaté que la contribution des banques au risque systémique était encore plus forte pour les banques où les investisseurs institutionnels et les États étaient les principaux actionnaires majoritaires. Nous allons plus loin et étudions l'effet des variables réglementaires sur la relation entre le risque systémique et la structure de propriété. Nous constatons que la concentration de la propriété accroît la contribution du risque systémique des banques dans les pays où la garantie des dépôts est élevée, où les fonds propres sont moins exigeants et où la diversification des actifs est plus grande. Le troisième chapitre explore l'effet d'une autre incitation à la prise de risque, la création de liquidités, sur l'exposition et la contribution des banques au risque systémique. Nous utilisons le même échantillon composé de 79 banques européennes au cours de la période 2004-2016. Les conclusions soulignent que, en temps normal, l'exposition au risque systémique des banques est aggravée par une forte création de liquidités. De plus, nous montrons que, en période de crise, une forte création de liquidité affecte négativement non seulement l'exposition des banques au risque systémique, mais également leur contribution. Le chapitre quatre examine une autre facette du risque systémique. En utilisant un échantillon de 134 banques dans 16 pays européens pendant la période 2002-2016, nous avons construit trois méthodes de prévision pour prédire la contribution et l'exposition des banques au risque systémique. Nous utilisons un réseau neurone artificiel, support vecteur machine et la spécification generalized autoregressive conditional heteroscedasticity. Nos résultats montrent que les réseaux de neurones artificiels à deux couches cachées surpassent les autres modèles en ce qui concerne la prévision du risque systémique.

The opinions expressed in

this dissertation are those of the PhD

candidate and do not necessarily reflect the views

of the University of Rennes1 and the Lebanese University.

To my beloved husband, Tarek BADRAN

For his love, support, encouragement and patience.

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“*We cannot solve*

problems by using the same kind

of thinking we used when we created them”

Albert Einstein

SUMMARY

GENERAL INTRODUCTION

During the last decades, significant concerns about the stability of national and international financial systems have been raised. Several reports, official summits, advanced studies and academic papers were made to reflect these concerns. Systemic risk has been one of the major focuses for financial studies and regulatory supervisors long before the global financial crisis of 2008-2009. Yet, this crisis has demonstrated that this topic, the systemic risk, may be one of an insufficiently investigated areas and that previous studies failed to detect and estimate such a risk. Despite the variety of studies on this topic, this thesis attempts to investigate different aspects of systemic risk that haven't been studied recently.

Systemic risk definitions began to appear in the mid-'90s of the XX century, but their impacts have intensified after the global financial crisis of 2008. While we do not have an unanimous definition of the systemic risk, it is commonly known that any systemic risk definition agrees on three points that are summarized in the following G-10 (2010) definition: "*Systemic financial risk is the risk that an event will trigger a loss of economic value or confidence in, and attendant increases in uncertainly about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy*." In other words, a systemic event corresponds to a trigger point which causes significant disruption in the financial system and finally spreads out the real economy (Benoit, 2014). Another definition of systemic risk is: "*Any set of circumstances that threatens the stability of or public confidence in the financial system*" (Billio et al., 2012). The European Central Bank (2010) defines the 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*". Other definitions of systemic risk may be related to specific mechanisms like correlated exposures (Acharya et al., 2017), spillover to the economy (Group of Ten, 2001), negative externalities (Brownlees and Engle, 2012) and contagion (Paltalidis et al., 2015). Before the crisis, definitions put more emphasis on the contagion. However, after the outbreak of the crisis, more attention has been paid to disturbances in financial system functions.

Systemic risk concerns most of agents of the financial system and may disrupt the performance of several financial sectors' functions. In this line, Smaga (2014) argue that the most important element of systemic risk is the transmission of disturbances (shocks) between interconnected elements of the system that can lead to a systemic event in the economy. Long before the 2008 crisis, Oort (1990) argued that the systemic failure may be caused due to a dense network of connections among banks, new banks products and due to external events such as debt crises or any changes in market rates. In this line, regulators paid more attention to this topic in the Basel Committee on Banking Supervision (BCBS, 2013) who argued that banks may be classified as global systemically important banks (G-SIBs) according to a set of five indicators that may also considered as key drivers of systemic risk. These five indicators are institution’s size, interconnectedness (intra-financial system assets and liabilities and securities outstanding), substitutability or financial institution infrastructure (assets under custody, payments activity and underwritten transactions in debt and equity markets), complexity (amount of OTC derivatives, trading securities and level 3 assets), and cross-border activities (cross-jurisdictional claims and liabilities).

This thesis contribute to the systemic risk debate in two important ways, the academic perspective by offering theoretical and empirical frameworks contributing thus to the existing strand of research that investigate systemic risk, and the regulatory or managerial perspective by addressing the concerns of regulators considering the systemic fragility.

To understand the systemic risk, it is important to find a way to quantify it as well as identify its sources as determinants. First, to measure systemic risk, regulators and market participants measure and monitor systemic risk using various methods and techniques. A broad collection of measurements and techniques have been proposed and implemented to estimate the systemic risk and capture its diverse facets. Several researches were made to estimate the systemic risk, and different methods were used to quantify its magnitude and its effects on the financial system. In this line, Bisias et al. (2012) surveyed a list of 31 different systemic risk measures, conceptual frameworks and potential channels of financial distress that have been developed over the past several years. These measures are classified, according their types and the data they required, into macroeconomics measures, network measures, forward-looking risk measures, and cross-sectional measures. In this thesis we list some of these measures as well as other new researches. These measures, as well as others, are detailed thereafter in Chapter 1. Second, considering systemic risk sources, systemic risk can be issued from three main origins: (i) from *instruments* such as loans, bonds, equities and derivatives instruments, because the idea behind using such instruments is to transfer the risk to a third party, also these instruments carry additional counterparty risk- creating the default dependent contracts; (ii) from *markets* such as bilateral over-the-counter (OTC) trading in the markets, because OTC derivatives, along with many others features of the financial system, increased the interconnectedness between financial institutions and hence may have made the system less robust; and (iii) from *institutions* such as banks, securities dealers, insurance companies and so on. Chen et al. (2016) show that the risk can propagate by the fact that financial institutions are interconnected directly by holding debt claims against each other. Another way of propagation of the risk is the fact that institutions are bound by the market liquidity in selling assets when facing distress. Authors studied how these two ways of risk can interact to transmit the risk from individual to system-wide disclosure. In our study we focus on the third source of systemic risk – institutions, and the contagion risk caused by institutions linkages. Financial institutions are interconnected to each other by several types of links. They knit a network based on relations between them. These relations can lead to a systemic risk that differs according to the links types. Banks are one of these financial institutions that transmit the systemic risk to other banks or even other companies such as insurance companies or industrial companies. More specifically, we focus on the banking sector in European countries.

While the scholarly researches present a useful tool and a helpful framework to estimate systemic risk, they should be regarded as a starting point, not a conclusion. From this viewpoint, we hope this thesis will fill a gap in this debate by investigating systemic risk determinants which are ignored by recent investigations. Beyond constructing another method to measure systemic risk, the aim of this thesis is to study its determinants and find how it can be exacerbated or mitigated according to some factors. We also go further by forecasting systemic risk to be able to construct a provisory tool to predict future systemic crises magnitude. More precisely, in **Chapter 1**, we provide a brief literature review about systemic risk that covers its different perspectives: definitions, measures, determinants, regulations and applications. **Chapter 2** is devoted to study the impact of the corporate governance on the systemic risk. **Chapter 3** investigates the relationship between systemic risk and liquidity creation. These two chapters aim to examine two risk taking proxies, ignored by recent studies, which may affect the systemic risk. And finally, in **Chapter 4**, we present a distinctive angle of the subject by addressing a forecasting tool to predict systemic risk. Doing so gives us a better view about systemic risk and banking systems performance. Additionally we show how regulators and authorities can use these perspectives to pay more attention on systemic risk in order to mitigate its negative consequences. This thesis also allows us to shed light on the conditions that make it possible to ensure efficient behavior in the banking industry.

While many attempts have been made to reform banks' operations, less attention has been paid to the role of the corporate governance and its impact on systemic risk. The recent financial crisis of 2008 showed that corporate governance mechanisms constitute one of the most important factors that influence the systemic risk. However, this area is still in the early stage of development. Therefore more discussion and analysis of the role of the governance within controlling systemic risk would be an essential part of regulations and policies. Despite the explosion of researches that have been done on corporate governance at individual firm level, few researches address its impact on systemic risk. As recently noted, the contribution of an individual firm to the overall risk may be more relevant than the individual firm risk itself during crisis period (Anginer et al., 2014). From this perspective, corporate governance practices of financial institutions – institution specific attributes– may influence the systemic risk level– overall risk-taking phenomenon. Some researchers (e.g., Diamond and Rajan, 2009; Kirkpatrick, 2009) claim that, to an important extent, the weak corporate governance contributed to the destabilization of the financial system in 2008. More specifically, the Basel Committee on Banking Regulation and Supervision (BIS, 2010b) drew attention to the ownership structure as it plays a key role within the corporate governance framework. In this line, Laeven and Levine (2009) found that bank risk is higher in banks having large owners with substantial cash flow rights where owners tend to advocate for more risk taking than managers. In the same vein, Saghi-Zedek and Tarazi (2015) investigate the impact of shareholders' excess control right on profitability and risk. Authors find that before the crisis higher default risk and lower profitability are related to the presence of excess control right, and an opposite results during the crisis of 2008. Beltratti and Stulz, (2012) document that, during the financial crisis, banks with more shareholder-friendly boards have a bad performance. Similarly, Ferreira et al. (2013) report that higher empowerment owners in banks led to higher risk explained by weaker performance during the crisis. These studies suggest that financial institutions with controlling owners and strong shareholders tend to be riskier than banks with weak owners (Shleifer and Vishny, 1986; Laeven and Levine, 2009).

Another ownership criterion that affects the risk-taking incentives is shareholders' categories. For instance, banking institutions and other institutional investors may be more willing to undertake risky strategies, in contrary to families and managers (Caprio et al., 2007; Esty, 1998; Saghi-Zedek and Tarazi, 2015). Those risk incentives could translate into a greater systemic risk caused by the herding behavior. Like any default phenomenon, banks' risks are contagious. In this context, Acharya (2009) shows that the individual danger could transform into higher systemic threat by the risk shifting phenomenon.

From this point of view, in **Chapter 2**, we investigate the relationship between systemic risk and ownership structure, an important internal mechanism of corporate governance. More precisely, in **Chapter 2**, we ask whether the effect of controlling shareholders on banks' systemic risk contribution is different than that of widely held banks. Moreover, we test the effect of owners' type on the relationship we found between systemic risk and ownership concentration. Using a sample of European banks over the 2004-2016 period, we show that higher ownership concentration is associated with greater banks' systemic risk contribution. We found that this result is even stronger for banks controlled by institutions. Additionally, we investigate the effect of regulatory and institutional variables on the relationship between systemic risk and ownership structure. While ownership structure belongs to the internal governance mechanisms, regulation could be considered as an external governance force. After the recent global crisis, country authorities and financial regulators examined several existing regulatory schemes in order to maintain the financial stability. Among other regulatory variables, we focus on deposit insurance schemes, capital stringency and asset diversification. Our motivation for this specification is that the ownership structure effect on systemic risk contribution could be driven by the differences in the owners' regulatory regimes and their institutional environment. On another hand, corporate governance theory suggests that ownership structure affects the ability of owners to influence risk (Jensen and Meckling, 1976). Also, Laeven and Levine (2009) argue that banks regulations affect the risk-taking incentives of owners differently from managers. Authors find that bank's risk is associated with greater deposit insurance, more stringent capital and higher activity restrictions for controlled banks. Consistent with recent researches, we find higher systemic risk contribution is associated with concentrated ownership in banks with higher deposit insurance schemes, higher capital stringency and higher asset diversification guidelines.

Second, the recent subprime crisis emphases how an individual bank liquidity shortage can be translated into a system-wide liquidity crisis. Particularly, the crisis demonstrated that some sources of funding can quickly evaporate. This phenomenon is treated as a sign that liquidity is crucial not only at individual level but also at aggregate level. In response to the stresses experienced by banks during the crisis, liquidity rules and ratios were imposed by the Basel III Accord (2010–2011) such as the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR) to ensure that banks have sufficient high-quality liquid assets to survive an acute stress scenario. The modern theory on financial intermediation dictates that banks, in order to be competitive, must perform correctly their two central roles in the economy: transforming risks and creating liquidity. Indeed, creating liquidity is considered an important role of banks as they provide liquidity to the rest of the economy. To create liquidity, banks finance relatively long-term illiquid assets with relatively short-term liquid liabilities or deposits, or through loan commitment and similar claims. Therefore, banks provide cash to the rest of the economy by holding illiquid assets. Thus risk appears if some of these liquid liabilities are claimed urgently. While liquidity creation represents an important macroeconomic factor, it may also lead to a financial crisis (Berger and Bouwman, 2017). Authors find that high liquidity creation helps predict financial crises. Allen and Gale (2004) argue that liquidity serves as a channel through which contagion is spread from bank to bank. Banks' liquidity is determined by their ability to obtain financing form issued claims against its terminal cash flows. This financing can be originated from debt as well as from equity. While debt-based financing threat exists by the fact that it may be some liquidation in urgent states, equity-based financing disciplines managers to efficiently choose their projects to enhance their ex-post cash flows compensations; which may reduce the ex-ante liquidity that leads to an inefficient liquidation (Acharya and Thakor, 2016). In its turn, this liquidation decision made by some creditors gives asymmetric information to other banks' creditors that may choose to liquidate their banks based on other bank liquidation decisions due to a systematic shock rather than common asset-value shock. **Chapter 3** is therefore devoted to test the effect of the excessive liquidity creation on systemic risk of banking sector in European countries.

Another bilateral link between institutions is information. The informational contagion appears when the depositors and investors believe that the failure of one bank or institution is a signal of the health of other banks, and then there is an informational link between these two banks, and potential for contagion. This way of contagion usually used in the network theory approach, discussed later on, considers the bridges presented between two or more banks.

Institutions and especially banks make payments to each other as a result of their clients' operations. Those interbank payments constitute a network in which banks are linked to each other. Despite its important role in the financial sector, the important expansion of the daily interbank payments values has raised considerable interest about the potential systemic risk that may be conducted by contagion. This contagion effect arises when the failure of a large financial institution to settle payment obligations generates sequence of responses that threatens the stability of the financial system. This effect is also referred to as a domino effect. For instance, Freixas and Parigi, (1998) argue that the when the net positions are settled at the end of the day only, banks will keep less reserves and expose them to contagion as it implies interbank credit, leading to a trade-off. Afonso and Shin (2011) discuss the possibility of freezes and show that a potential disruptions and disequilibrium can be produced even when banks mechanical rules are used for sending payments in normal times.

Two main views on the relationship between systemic risk and the structure of financial system have been suggested in the academic literature and the policy world after the financial crisis. The first focuses on the fact that the "incompleteness" of the financial network is a key source of instability; this is because individual banks are exposed to the liabilities of the financial institutions. In this case, to limit the exposure of the banks to other institutions, more complete financial network are required in order to minimize systemic failures. On the other hand, the second view hypothesizes that the high level of interconnectedness in the financial system leads to a fragile status and facilitate the spread of the distress from an institution to another. In other words, completeness is not always a guarantee for stability. And perhaps, sometimes financial networks in which banks are only weakly connected to one another would be less prone to systemic failures. This is a cause of the fact that the senior liabilities of banks, can act as shock absorbers. Weak interconnections guarantee that the more senior creditors of a distressed bank bear most of the losses and hence, protect the rest of the system against cascading defaults (Acemoglu et al., 2013). Briefly, we can propose that an excessive build-up of individual bank liquidity may lead to a crisis: when the macroeconomic risk is high, more deposits flow to the banking sector, which drive banks to lower their lending standards and higher their lending activities. This increases bank liquidity creation that may create an asset bubble and thus bank failures (Acharya and Naqvi, 2012). In **Chapter 3**, using a novel hand collected data for 16 banks in western European countries, we find that excessive liquidity creation in European banks increases their systemic risk exposure and contribution during the last financial crisis of 2008.

Finally, most of the previous models focus on the components of the systemic risk and its determinants. Yet there are few papers that forecast the systemic risk using historical values. Financial time series forecasting is considered one of the most challenging subjects in the modern forecasting area for many reasons. First, complete historical information are not always available which gives financial time series a noisy characteristic because the information that is not included in the model is considered as a noise. Second, financial time series are not always distributed in the same way; their distribution may change over time which makes them non-stationary. Finally, they are deterministically turbulent; while they can be considered random at the short term, they can be deterministic at the long-term. Therefore, forecasting systemic risk, which belongs to the financial time series, in a correct way, becomes a promising challenge. **Chapter 4** is devoted to this end. Recently, the “machine learning” technique becomes one of the most intelligent techniques used by researchers and practitioners. The “Machine learning” terminology is explained by the fact that the machine learns from the previous experience to improve its performance up on a similar experience in the future. Form this point of view, in **Chapter 4** we implement a systemic risk forecasting method using two of the most used learning techniques recently: artificial neural network (ANN) and support vector machine (SVM). We also forecast systemic risk using a famous volatility clustering tool, the autoregressive conditional heteroskedasticity (GARCH) specification. In this study, we aim to examine the effectiveness of the machine learning techniques compared with the GARCH fitting to a hand collected data on 16 European banks during the 2002-2016 period. We found that the artificial neural networks with two hidden layers forecast banks’ systemic risk contribution and exposure in an efficient way.

This thesis dissertation is organized as follows. In the first chapter, we review a literature about the systemic risk and its different facets. The second chapter discusses the relationship between systemic risk and the ownership structure. In chapter 3, we investigate the impact of liquidity creation and systemic risk. Chapter 4 presents the methods used to forecast the systemic risk. And finally, we conclude the thesis hypotheses and their corresponding findings and contributions.

CHAPTER 1

LITERATURE REVIEW

Systemic risk existed even before the outbreak of the financial crisis; however, their negative effects have driven regulators to increase the interest of their researches in exploring their nature and developing ways to mitigate them. Before getting into the empirical and theoretical studies of the thesis, we recall the literature about systemic risk from different aspects. This chapter is devoted for this end.

The objective of this chapter is to identify the notion of systemic risk in the banking industry and report analyzes that have been done in various contexts. Additionally, we show how each angle of this literature helped us to construct the frameworks of this thesis.

This chapter is organized as follows. In Section 1, we start by listing the existing measures of systemic risk. We present measures' methods, their implementations, their applications, and data they are applied to. We also report differences between measures and their characteristics. Doing so allows us to choose the convenient measures to use in this thesis and what measures are capable to capture the right angle of the risk we want to evaluate. This also helped us to find out which measures are adaptable to be applied to our data.

As illustrated in the introduction, we investigate the impact of the ownership structure as a risk-taking variable on systemic risk of European banks. Section 2 is thus devoted to list the recent researches about governance mechanisms and systemic risk in general, and ownership structure and systemic risk in particular. We report in short the governance mechanisms in banks and how each mechanism may be related somehow to the systemic risk. This review makes us able to detect what mechanisms are not investigated yet and if they constitute a workable field to be investigated.

We also study the impact of the liquidity creation on systemic risk. Therefore, in Section 3 we describe how recent researches linked the liquidity creation behavior to the systemic risk. first we recall the modern theory on financial intermediation of banks and how this intermediation, despite of its crucial role in the economy, may generate a systemic risk and financial instability. Second we report the existing theoretical and empirical literatures on liquidity creation and how it may generate systemic crises. By analyzing, combining and understanding these researches, besides others, we were able to detect the important role of the liquidity creation in determining the level of systemic risk of banks.

And because the systemic nature of a bank depends not only on its characteristics (i.e. governance, liquidity, and other) but also on its place in a network, in Section 4 we report a brief summary on the application of the network theory on the systemic risk. Banks knit a network based on relationships between them, and as we were interested, and we still are, in the beginning of the thesis in studying the systemic risk through the network theory, we begun our work by constructing networks and testing the relationships presented within these networks, we summarize the methodology used in this study, list the quantities we measure, and present the preliminary results we obtain. We also report the difficulties we faced during our work which led us to reorient the methodology because of the limited time to finish the thesis work. However, this approach gave us a general point of view on interactions between banks and their interbanking relations. It also provided us with a broad idea about the centrality of banks in the networks they are belonging to.

After the global crisis of 2008, financial regulators and supervisors shed light on the necessity of making the banking system less vulnerable to economic shocks. Regulators developed prudent microeconomic and macroeconomic policies and emphases prudential regulation to put in place safeguards for financial systems stability. The last section, Section 5, is devoted to present how regulatory policies treat the systemic risk debate and what are the firewalls they created to prevent damage from systemic risk. This literature gives us a hand to identify the impacts of our findings and their contributions to the regulatory requirements.

1.1. Measuring systemic risk

The existing possible definitions of the systemic risk suggest that more than one risk measure exist. And because one cannot control what is not measured, statistical measures and quantitative analyses are required to capture the systemic risk and its impact on the financial system. As mentioned in their prudential regulation of banks, the Basel Committee III defined the key element that stands behind the detection of systemic risk, the global systemically important financial institutions (G-SIFIs), institutions, due to their size and importance in the financial market and the risks they might pose to the financial system if they were to experience difficulties, are subject to additional constraints on risk exposures (Georg, 2011). Also, the Financial Stability Board (FSB) defined the G-SIFIs as: "*Financial institutions whose disorderly failure, because of their size complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity*" (Financial Stability Board, 2011a, 2011b). These institutions are identified using a number of attributes like size, lack of substitutability, interconnectedness and complexity that we will discuss later on. Additionally, the financial stability board (FSB) has identified also the domestic systemically important banks (D-SIBs) at individual countries level. These institutions are required to put aside more capital as part of their operations to increase the financial stability. Moreover, the International Monetary Fund (IMF), in its review of 2009 “Global Financial Stability Report”, focuses on the utility of adequate tools that can detect systemic risk in early stages. This detection allows regulators to control the crisis and prevent its consequences (International Monetary Fund, 2009).

Several researches were made to estimate the systemic risk, and different methods were used to quantify its magnitude and its effects on the financial system. In this line, Bisias et al. (2012) surveyed a list of 31 different systemic risk measures, conceptual frameworks and potential channels of financial distress that have been developed over the past several years. In their survey, measures are classified, according to their types and the data they required, into macroeconomics measures; network measures, forward-looking risk measures, and cross-sectional measures. In this section we list some of these measures as well as other new researches.

While a wholly new strand of literature emerged straight after the financial crisis of 2008 having a goal of measuring systemic risk, we do not have a singular measure that can capture systemic risk from its various angles and perspectives. However, these attempts to develop systemic risk measures still present some sophistication and shortfalls. These measures belong generally to two categories: macroprudential and microprudential measures. The first category, macroprudential measures, is used to capture the overall risk of the entire system, whereas the second category, microprudential measures, has the goal of account for individual contributions of companies to the overall systemic risk.

The most traditional used measures of bank-level risk are the value-at-risk (VaR) and the expected shortfall (ES). The theoretical foundations for VaR are based on the portfolio theory of Markowitz (1952). VaR calculates the maximum value of the loss on a given portfolio for an assumed probability of loss during a given period. In other words, VaR defines the amount that the institution should keep aside to face any problems and control any predicted distress situation. For example, with a confidence level of 95%, 5% VaR is the most that bank or institution loses with 95% confidence. The concept behind the computation of VaR is to prevent a liquidity losses triggered by a loss in the case of a low probability event. While this measure was widely used by banks, it only focuses on the risk taken by banks and other financial institutions individually which is not sufficient to prevent crises as it measures the risk of firms in isolation. Additionally, it only estimates the losses at a fixed level; returning to our example, if the negative payoff is below 5% VaR threshold, then the VaR does not capture it. In contrast, the expected shortfall (ES) does not suffer from this problem as it measures the expected loss conditional on the loss being greater than the VaR.

After the shortcoming of the famous Value at Risk (VaR) to detect the conditional fails, several researches have been done in order to estimate the correlated risk that can trigger the financial market. In this line, Acharya et al. (2017) proposed a systemic risk measure, the systemic expected shortfall (SES), which measures the financial institution's contribution to systemic risk. Authors introduced the marginal expected shortfall (MES), an extension of the ES, which measures the expected risk of a bank conditioning on the overall market risk. Back to our example, the 5% MES of a specific bank is the expected return of this bank when the market (or a specific system) is experiencing its 5% worst days of outcomes. Similarly, one of the most common systemic risk measure is the Conditional Value at Risk (CoVaR) proposed by Adrian and Brunnermeier (2016). After the weakness of the famous Value at Risk (VaR) to identify a systemic risk before and during the global crisis, the CoVaR came as an extension of the VaR to fill this gap. The concept behind the CoVaR is taking into consideration the distress of other institutions when measuring the risk. In their work, authors measure the systemic risk by the contribution of each institution to the overall risk of the system (ΔCoVaR). At 5% confidence level, for instance, ΔCoVaR measures the contribution of a specific bank when it experiences its 5%VaR to the overall risk of the market. In other words, the ΔCoVaR measures how much the system's 5%VaR change when an institution reaches a distress situation. Authors found that, according to ΔCoVaR, the contribution was pretty high during the crisis of 2008 and the VaR was insufficient in the cases of systemic events. Their contribution measure is constructed by projecting CoVaR on lagged firm characteristics such as size, leverage, maturity mismatch, and industry dummies. Later, López-Espinosa et al. (2012) applied the CoVaR measure on international banks, to identify the main factors behind systemic risk. Authors find that short-term wholesale funding is a key determinant in triggering systemic risk episodes. In contrast, they find weaker evidence that either size or leverage contribute to systemic risk within the class of large international banks, which is an exceptional finding. These measures are considered as cross-sectional measure as they estimate the relation among the risks of firms and test their dependencies.

It is important for risk measurement - systemic or otherwise - to have a forward looking view at different times in the future and under various circumstances. To achieve that, models were made to estimate the risk, its probability and magnitude. Risk modeling often postulates one or more probability distributions or stochastic processes to capture the behavior of the system given its historical data. One of the forward-looking risk analysis is the contingent claims analysis, the CCA approach, proposed by Jobst and Gray (2013), who suppose that the equity of a firm can be viewed as a call option on its assets and the debt of the firm can be modeled as being long risk-free debt and short a put option on the firm's assets. Authors use the standard Brownian drift-diffusion model used in the Black-Scholes-Merton model to determine the risk-adjusted balance sheet of firms. Authors found that the total expected losses are highest between the periods just after Lehman's collapse (September 2008) and end-July 2009. Also they found that more than 50% of these loses could have been transferred to government in the default event. Another forward forecasting method is the Mahalanobis distance used by Kritzman and Li (2010) who define a "financial turbulence" as a situation in which asset prices perform in an unconventional way, like extreme price moves, decoupling of correlated assets and convergence of uncorrelated assets. Authors use the Mahalanobis distance as in Merton (1973), which measures the unusual behavior of a set of return knowing their historical values. First, authors find that returns to risks are considerably lower during turbulent periods than during non-turbulent periods regardless the source of turbulence. Second, they find that financial turbulence is highly persistent, once it begins, it usually continues for a period of weeks until the market digests it. Additionally, the option implied probability of default (iPoD), proposed by Capuano (2008), computes the probability of default of the bank using the probability density of the value of assets and applying the cross-entropy minimization which is frequently used in optimization and rare-event probability estimation. Authors find a remarkable jump of iPoD during the 2008 crisis and that the changes option-iPoD appeared to be a leading indicator for changes in the level of CDS spread. In their approach, Goodhart and Segoviano (2009) define the banking system as a portfolio of banks and they develop a systemic risk measure based on the banking system multivariate density (BSMD). The BSMD characterizes both, the individual and the joint asset value movements of the portfolio. Authors compute their systemic risk measure for U.S., the

E.U. and the world banking system. They find that the U.S. banks are highly correlated and the distress dependence across banks rises during the crisis. Kritzman et al. (2010) have measured the systemic risk via the absorption ratio (AR). The AR captures the extent to which markets are unified or tightly coupled. The authors find that the AR of U.S. industries are highly negatively correlated with the stock prices.

As Benoit et al. (2013) mentioned in their works about in the systemic risk measures comparison, a good risk measure for risk should capture many different facets that describe the importance of a given financial institution in the financial system. Authors insist on the fact that the future systemic risks should combine various sources of information to be able to track all the angles of this risk. This information must be collected from balance-sheet data, proprietary data on positions and market data. Among all these systemic risk measures, which one is the best to quantify it? Researches were made to find the best systemic risk measure. For example, Rodríguez-Moreno and Peña (2013) discuss whether the simpler systemic risk can be the better one. Authors compare measures based on two levels, the micro-level and the macro-level. Because most banks have several traded claims (e.g., stocks, bonds, CDS) that contain information on the individual and joint probability of default, they found that measures based on CDSs outperform measures based on the stock market and on the interbank market whereas equity market do not provide a direct information about such risk.

After that, many applications of these measures were made on various aspects of the financial system. Additionally, statistical models were applied to the financial sectors to estimate the systemic risk. Surveying the literature, one can notice that the most used measures of systemic risk are captured by either the contribution of each institution to the overall risk, or by its exposure to this risk. These two metrics are able to give a sufficient, relatively saying, interpretation of the systemic risk of institutions. Following recent literature on systemic risk of banks, we adopt the ΔCoVaR of Adrian and Brunnermeier (2016) to estimate banks contribution to the systemic risk, and the MES of Acharya et al. (2017) to account for banks' exposure to the systemic risk. Since these two measures are directly related to the stocks prices that reflect a good amount of information about stocks and market behavior, we believe that they can correctly present an important image about the situation of banks.

1.2. Systemic risk and governance

Even though there is an amplified interest toward measuring systemic risk during the last years, surprisingly little is known so far about the effect of the governance specific attributes on the level of systemic risk. Although it is claimed that, to an important extent, the financial crisis of 2008 can be attributed to weak corporate governance arrangements (Kirkpatrick, 2009; Diamond and Rajan, 2009; BIS, 2010b).

Back to the basic academic theory done by Jensen and Meckling (1976), it is commonly agreed that there is a presence of a strong link between governance and risk-taking. This link may be especially strong for financial firms (Laeven and Levine, 2009; Beltratti and Stulz, 2012; Ferreira et al., 2013; Ellis et al., 2014). Ellis et al. (2014) argue that governance problems are more acute in banking institutions than in other sectors: basically, banks have limited liabilities that bring on an additional problem between shareholders and debt-holders after shifting risk up the capital structure to the detriment of debt-holders (Jensen and Meckling, 1976), and since the risk is deliberated through banks assets choice and since there is a higher payoff asymmetry due to the higher leverage, banks are thus more considered with these principal-agent problems that constitute a core governance mechanism.

To study the relationship between governance and systemic risk, Ellis et al. (2014) offer four solutions to strengthen the bank governance. First, banks' regulatory capital should increase, second, the compensation structure of managers could be reformed, third, in the event of stress, a credible prospect of bailing-in creditors must be implemented and fourth, there must be a reform in the company structure such as shareholding control rights.

Another ownership criterion that affects the risk-taking incentives is shareholders' categories. For instance, banking institutions and other institutional investors may be more willing to undertake risky strategies, in contrary to families and managers (Caprio et al., 2007; Esty, 1998; Saghi-Zedek and Tarazi, 2015). Those risk incentives could translate into a greater systemic risk caused by the herding behavior. Like any default phenomenon, banks' risks are contagious. In this context, Acharya (2009) shows that the individual danger could transform into higher systemic threat by the risk shifting phenomenon. Recently, Battaglia and Gallo (2017) test the effect of ownership concentration measured by the cash flow rights of the largest ultimate shareholder. A significant positive relationship is detected between systemic risk and ownership concentration. However, ownership concentration can affect bank performance in either positive or negative manner. While concentrated ownership leads owners to take risky strategies to increase the value of the firm, it can also drive large shareholders to take actions to pursue their own benefits at the expense of other minor shareholders.

Indeed, several studies addressed the risk within the firm, i.e., at the individual level. But recently, the literature on the effect of corporate governance on systemic risk tends to be more explored. Before listing the researches made in the corporate governance field, we report in short the governance mechanisms in banks. Among other possible definitions, corporate governance can be defined as a set of economic and institutional mechanisms to induce the self-interested controllers of a corporation to make decisions that maximize the value of its owners (Denis and McConnell, 2003). These mechanisms are generally categorized into internal mechanisms like board of directors, the ownership structure, executive compensation, and financial disclosure and external mechanisms like the takeover market, the legal infrastructure, and the product market competition. While external governance mechanisms are nearly absent in banks, internal mechanisms are crucial for maintaining the good performance of banks.

Levine (2004) considered that corporate governance of banks is not only important but also unique. This importance arises from the fact that banks play a central role in stabilizing the whole market as they are extremely vulnerable to shocks. Banks -that are themselves corporations- are considered as the major source of lending for other firms; however it is important that they face a sound governance to be able to exert effective governance to other firms. Basel Committee on Banking Supervision (BIS, 2010) highlighted the importance of sound corporate governance schemes in the financial institutions considering that effective corporate governance practices are crucial to build public trust and therefore establishing confidence in the banking system.

While the structure and the size of the board of directors gained a broad importance in studying banks performance, little is known about its impact on systemic risk. For instance, De Andres and Vallelado (2008) suggest that there is an inverted U-shaped relationship between bank performance and board size, and between the proportion of non-executive directors and performance. Adams and Mehran (2012) find that board size is positively related to banking performance. Pathan and Faff (2013) go deeper and studied how the structure of boards can influence banking performance. Authors report that banks performance is negatively related to both board size and independent directors and positively influenced by the gender diversity. In the same line, while Peni and Vähämaa (2012) find that US banks with small boards and more independent directors have a higher profitability and market valuation during the crisis of 2008, Minton et al. (2014) argued that financial expertise among independent directors is strongly related to lower banking performance during the crisis whereas it was weakly associated with better performance before the crisis. Furthermore, Fahlenbrach and Stulz (2011) argue that, during the financial crisis, banks with chief executive officers whose incentives were better aligned with the interests of shareholders had a bad performance. Beltratti and Stulz (2012) argue that banks with higher leverage ratios have negative stock returns during the crisis and banks with strong boards performed worse than other banks. While these researches are related to banks performance, one cannot separate the systemic risk from the individual risk and especially during crises. Thus we can say that these findings are related somehow to the systemic risk in an indirect way.

On the other hand, Jamshed et al. (2015) studied the impact of a strong corporate governance and board of directors on the systemic risk. Authors argued that financial institutions with strong corporate governance mechanisms and friendly shareholder boards, i.e. when they provide effective monitoring and stronger protection of shareholder's interests and more generally better alignment of managers' interests with those of the shareholders (Jamshed et al., 2015), are associated with higher level of systemic risk, a result consistent with the findings of Aebi et al. (2012), Beltratti and Stulz (2012), Erkens et al. (2012) and Peni and Vähämaa (2012). In this vein, the Basel Committee on Banking Supervision promoted an adequate number of independent directors in board of directors. Additionally, Ellul and Yerramilli (2013) proposed that stronger risk management functions decrease banks' tail risk. To find the effect of boards on systemic risk, Battaglia and Gallo (2017) recently argue that small boards of directors and high percentage of independent directors enhance banks performance and reduce systemic risk. In contrary to the results of the previous studies, Erkens et al. (2012) and Berger et al (2016) find no significance relation between the board size and bank performance, in terms of profitability and risk during the crisis. Particularly, Erkens et al. (2012) show that there is no support that the board size affects the measure of bank risk behavior. Likewise, Berger et al. (2016) argue that management structures of US commercial banks, including board size, are not decisive for banks' stability during the recent financial crisis.

Another important governance mechanism is the ownership structure. In this line, the Basel Committee on Banking Regulation and Supervision (BIS, 2010b) highlights that within this corporate governance framework, ownership structure plays a key role. Saghi-Zedek and Tarazi (2015) investigate the impact of shareholders' excess control rights, i.e., when there is a divergence between control rights (i.e., the right to vote and therefore to control) and cashflow rights (i.e., the right to receive dividends) on bank profitability and risk. Authors argue how the crisis of 2008 might have modified such an impact. Authors found that before the crisis excess control rights enhanced the banks' performance. Their results show also that the relationship between excess control rights and bank profitability is enhanced in family controlled banks as well as in countries with weak shareholder protection.

As said before, diversified owners like banks and institutional investors tend to be more willing to undertake risky incentives. This diversification phenomenon may allow for a high risk correlation at the aggregate level. Acharya (2009) and Wagner (2011) show that the risk is reallocated by the diversification and not eliminated; which reduces the individual risk of institutions but increases the fragility of the system; those results are agreeing with Winton (1997) who shows that pooling elevates the joint failure risk. Another result of diversification caused by diversified owners is the enhancement of interdependent financial networks. Recently, Battiston et al. (2012) argued that this interdependence among financial institutions, especially banks, led to a higher systemic fragility contribution. Weiß et al. (2014) find that systemic risk increases by banks with larger boards whereas it is negatively related to the board independence as outside directors should be more concerned about externalities than directors with direct relations with bank.

Briefly, previous studies demonstrate that corporate governance mechanisms constitute an essential key to control risk-taking incentives influencing the corporate risk in the financial firms, and consequently, the systemic risk. In this line, several studies show the importance of a sound risk management culture and the presence of the chief risk officer on board in enhancing banks value and decreasing their risks (Battaglia and Gallo, 2017; Ellul and Yerramilli, 2013).

1.3. Systemic risk and liquidity

The modern theory on financial intermediation claims that banks exist because they achieve two main roles in the economy: they create liquidity and they transform risk. The first who analyses the role of banks in creating liquidity and thus prompting the economic growth is Smith (1776). The modern theory argued that banks' liquidity is created on their balance sheet by financing relatively illiquid assets with relatively liquid liabilities (Bryant, 1980; Diamond and Dybvig, 1983). However, banks also create liquidity off the balance sheet through loan commitments and similar claims to liquid funds (Holmström and Tirole, 1998; Kashyap et al., 2002). The second fundamentally role, risk transformers, is done by issuing riskless deposits to finance risky loans. There is a coincidence between risk transformation and liquidity creation. Therefore deep studies are essential to distinguish between the two roles.

The recent financial crisis has showed how quickly liquidity shortages of one institution may be translated into a system-wide liquidity crisis. In other words, an excessive liquidity transformation can have negative externalities for the entire financial sector (Adrian and Boyarchenko, 2018). In this vein, Acharya and Naqvi (2012) argue that during stress scenario, deposits flow into banks which lead them to increase their lending activities thus increasing the liquidity creation and generate asset price bubbles therefore threaten the banking sector stability. Excessive risk taking and greater bank liquidity may also be generating from off-balance sheet using loan commitment (Thakor, 2005). While studies on early warning systems for financial crisis usually focus on macroeconomic variables, liquidity creation should be included in systemic risk models as it a good bank level variable that affect system's stability (Brunnermeier et al., 2011). Keys et al. (2010) and Dell'ariccia et al. (2012) provide empirical evidence that high liquidity creation may have contributed to the financial crisis.

Another liquidity related phenomenon that may affect systemic risk is leverage. In fact, high levered banks are principal contributor of the recent financial crisis. High financial leverage, especially short-term leverage, lead banks to employ illiquid loans and risky securities which contribute to their failure (Adrian and Shin, 2010; Mian and Sufi, 2011; Acharya et al., 2013; Goel et al., 2014). This leverage rising which is characterized by capital and liquidity deficit increases then the systemic risk of financial institutions. There appears then the strong link between bank-specific and systemic risk characteristics (Acharya and

Thakor, 2016). Authors argue that while high leverage may improve the liquidity of banks viewed in isolation, it may also make the system more fragile.

Contagion occurs when losses in one financial institution transfers to other institutions that are linked to the first one. The literature on systemic risk has explored different ways of bilateral interactions and their impact on the financial system stability. In his work, Benoit et al. (2015) explored that the contagion lies under several forms. Perhaps the simplest way of contagion between banks is created by the fact that banks owe liabilities against each other, this phenomenon is referred to as the balance-sheet contagion. Such links can spread banks defaults through domino effects. Thus, liquidity shortages of one bank, could easily transfer into banks connected to it via interbanking transactions and balance sheet duties. More precisely, if one bank could not repay its liabilities to other banks when they are due, perhaps those later banks find themselves unable to meet some or all cash payments to other banks.

1.4. Systemic risk and network theory

Since bank systemic risk is not only related to its internal mechanisms, but also to its position within the network it belongs to, network theory has gained an abundant importance in the financial field. It is commonly thought that financial institutions and especially banks form a connected network. This connection might be strong and it may cause a large systemic risk or it may be weak so the risk will stay in the small area of the bank. To test the strength of these networks, authors usually use centrality measures and topological indicators.

The financial networks literature includes two distinct approaches. The first approach describes network structure using topological indicators. The literature often relates these indicators to “model” graphs using network theory. This approach does not assume a mechanism by which shocks are transmitted within the network, and thus is referred to here as static network analysis (Ivan Alves et al., 2013). The literature on static networks suggests that national interbank networks tend to be tiered: that is, they comprise a few central nodes and many less significant nodes. Such networks exhibit low density and a distribution of exposures concentrated in a few nodes. Eisenberg and Noe (2001), Boss et al. (2004), Gai et al. (2011), Puhr et al. (2012), Tirado (2012) and Kanno (2015) describe examples of this approach. For example, based on the Austrian central credit register, Boss et al. (2004) and Puhr et al. (2012) find that the Austrian interbank market is tiered and that banks within subsectors tend to cluster together. In his work, Kanno (2015) contributes to the existing literature-systemic risk and network literature-by assessing the network structure of bilateral exposures in the Japanese interbank market. Author analyzed the systemic risk implied in the Japanese interbank network using various network measures and models such as directed graphs, centrality measures, degree distributions, and modified susceptible-infected-removable (SIR) models. Kanno finds that the betweenness centrality has the highest discriminative power among other centrality measures in selecting systemically important banks in the Japanese financial system. Moreover, author finds that the topology structure of the Japanese interbank network performs like a small-world or scale-free networks.

The second approach takes into consideration the response of the network structure to shocks to assess the strength of contagion channels and the resilience of the network. This type of analysis is known as dynamic network analysis. Dynamic network analysis is used to explore the resilience of a network in certain stress scenarios. This often involves simulation: the network is exposed to an external shock which propagates through the system via one or more contagion assumed channels, affecting the balance sheets of individual institutions (Ivan Alves et al., 2013). Shock propagation can take two types: mechanical or behavioral. The mechanical treatment of a shock is restricted to automatic balance sheet adjustments by financial institutions. Shocks to the balance sheets are entirely governed by accounting equalities, and there are no behavioral reactions by institutions. The inclusion of behavioral aspects, such as management decisions taken in response to a stress scenario, provides potentially greater realism. Behavioral assumptions usually relate to banks' liquidity management, and thus to liquidity contagion. Some papers contribute to the literature on systemic risk in interbank markets by focusing on the analyses of contagion effects (e.g., Elsinger et al., 2006; Cocco et al., 2009; Haldane and May, 2011). To investigate the dynamic propagation of systemic risk, Billio et al. (2012) measure the direction of the relationship between institutions using Granger causality and applied the theory to the monthly returns of hedge funds, banks, broker/dealers, and insurance companies. Authors find that all four sectors have become highly interrelated over the past decade, likely increasing the level of systemic risk in the finance and insurance industries through a complex and time-varying network of relationships. Their results show an asymmetry in the degree of connectedness among the four sectors, and banks play much more important role in transmitting shocks than other financial institutions.

In their works, Allen and Gale (2000) and Freixas and Parigi (1998) suggested that a more interconnected architecture improve the strength of the system face to the insolvency of any individual bank. They explain their suggestion by the fact that the losses of a distressed bank in a highly connected network can be divided among more creditors which reduces the impact of negative shocks to individual banks. However, Vivier-Lirimont (2006) argues that the tendency of a systemic failure increases when the number of a bank's counterparty increases. Allen and Gale (2000) and Freixas et al. (2000) argue that the possibility of contagion depends on the precise structure of the interbank market. Allen and Gale (2002) consider different lending structures in a banking system consisting of four banks that hold claims on each other. They show that for the same shocks some structures would result in contagion while others would not. In particular, a "complete" structure of claims, in which every bank has symmetric exposures to all other banks, is much more stable than an "incomplete structure, where banks are linked only to one neighbor. Disconnected structures are more prone to contagion than "complete" structures, but they prevent contagion from spreading to all banks (Drehmann and Tarashev, 2013). Finally, Freixas et al. (2000) show that the possibility of contagion in a system with money-centre banks, where the institutions on the periphery are linked to banks on the center but not to each other, crucially depends on the precise values of the model's parameters. Diebold and Yılmaz, (2014) measure the connectedness of financial firms using variance decomposition. They show that variance decompositions define weighted, directed network, so that they can measure the connectedness across firms using network literature measures. They track the daily time-varying connectedness of major U.S. financial institutions' stock volatilities in recent years focusing on the financial crisis of 2007-2008. They confronted the issues provided by Schweitzer et al. (2009) about the financial network modeling. Those latter authors find that "in a complex-network context, links are not binary but are weighted according the economic interaction under consideration".

Another strand of the literature analyses complex artificial networks in aim to detect patterns which could make them prone to contagion. For example, Nier et al. (2007) find negative and non-linear relationship between contagion and capital. The relationship between contagion and level of interbank lending to other assets is also non-linear. An increase in interbank lending from a low level has no effect on contagion, as losses are absorbed by capital. If interbank lending exceeds a threshold, then second round effects begin to appear and contagion increases quickly. Increasing the degree (which measures the number of connection between nodes) of the interbank network generates an M-shaped graph that reflects the interplay of two effects. On the one hand, adding more links increases the channels through which contagion may occur. On the other hand, any further increases raise the resiliency by sharing losses across a larger number of counterparts. The relative importance of the two effects depends on the level of connectivity and the amount of capital in the system (Drehmann and Tarashev, 2013).

Systemic risk is also related to inter-connection and correlation of different parts of a market. After measuring network centralities, researches were made to identify the type of the network and consequently the propagation of the systemic risk within the network. For this reason, authors use the topological indicators that give an idea about the behavior of network's nodes. In this paragraph we list several studies made in this aspect. Financial network studies can be categorized into three main groups. The first group of studies applies the contagion theory to financial systems to simulate the behavior of a financial system under different network setups. The second group focuses on the correlation-based networks and the structure of a financial market in different time periods. The third group analyses the structure of the inter-bank debt network among the countries. Most researches fall into the last group. In this line, Pecora and Spelta (2015) analyzed the topological properties of the network of the Euro area banking market. Their results argue that the network follows power law distributions in both binary and weighted degree. This result indicates that the network is fragile. Additionally a direct link between an increase of control diversification and a rise in the market power was presented and not all the financial institutions with high valued total assets are systemically important. Haldane and May (2011) used the dynamics of ecological food webs to explore the interplay between complexity and stability in deliberately simplified models of financial networks. Boginski et al. (2006) represented the stock market data as the market graph, and construct a network by calculating cross-correlations between pairs of stocks. Dastkhan and Shams Gharneh (2016) studied the cross-shareholding network in the Tehran Stock Exchange (TSE). Authors used the centrality measure to determine the type of their network. Their results show that the TSE follows a scale free network; in other word it is fertile for systemic events and the cross-shareholding network is a good representative of a systemic risk. Despite the large studies that use the network theory in the financial field, none has introduced the concept of the ownership structure.

Interested by this theory, the network theory, we tried in the first stages of the thesis work to apply its topology on our subject, the systemic risk. Unfortunately, due to a lack of information and incomplete databases about the ownership structure of banks, we didn't be able to investigate the hypotheses we build about presenting the banking sector as a network. Although, we obtain some interesting preliminary results that we will present in this paragraph.

The main idea was to build a network composed of nodes and links connecting the nodes. The nodes are representing the banks of our sample, and the links represent the ownership relationship between banks; i.e., what percentage each bank hold from the capital of other bank. We implement both a directed weighted network because of the two following reasons: first, the percentage held by bank A of the capital of bank B is not the same percentage held by bank B from bank A, thus the use of a directed network; second, not all owners hold the same percentage from the capital of one bank, thus the utility of a weighted network. This directed network is or directed graph, also called *digraph*, is a network in which each edge has a direction. Such edges are themselves called *directed edges* and are represented by vectors or arrows that describe the direction of the relation between vertices. And because in a network, not all relations have the same weight, size and strength, it is useful to describe edges as having weight, or value to them, this is the concept behind a weighted network. So finally we are working with a weighted directed network or graph.

After building the network, we estimate centrality measures that quantify how important vertices or edges are in a network. The centrality measures we calculate are the in-degree to estimate the number of edges incoming to a vertex, the out-degree estimate the number of edges ingoing to a vertex and the weighted degree to account for edges weights. Additionally, we study the topology of the network constructed to determine its nature and characteristics.

Finally to be able to establish a relationship between systemic risk and ownership interconnections, we run panel regression with the degree measures as variables of interest, systemic risk calculated using the conditional value at risk (CoVaR) as a dependent variables and a set of independent variables to control for banks characteristics that may affect the systemic risk.

Before presenting our results, we should mention that we faced some difficulties concerning the database. First, we haven't full information about the ownership structure of banks of our sample. For example, for a bank A, we won't be able collect the information about both its owners and its subsidiaries. The second complication was in constructing the network. To efficiently construct a network reflecting the banking sector in Europe, we should consider as much banks as we can, this criterion leave us with a huge amount of banks and institutions that are located in foreign countries for which we do not have access to their information. Therefore, for simplicity, we restrict our database to European banks in 16 countries for which normal databases provide detailed information about their ownership structure. However, we still haven't resolved the problem of incomplete information due to non available reports.

Despite the difficulties listed previously, we proceed in our empirical investigations that we report their results hereafter. Our results show that the European banking sector is bow-tie structured with the existence of a bunch of nodes with many in-degree and out-degree as well as some nodes with only inward arcs and outward arcs. Considering the relationship between systemic risk and ownership interconnections, our results suggest that the relationship between systemic risk and the ownership connectedness is an upward U-shaped relationship with a statistically significance level. This U-shaped relationship can be interpreted by the existing of a turning point that change the direction of the curve, in other words, there is a specific weighted degree, i.e. a specific ownership percentage or owners numbers, that can change the sign of the relationship between systemic risk and ownership connectedness. Moreover, the identification of systemically important companies identified by the centrality measures may be considered as an effective way to control systemic risk in the case of crisis events.

1.5. Systemic risk and regulation

Systemic risk regulation debate has gained serious attention after the latest financial crisis. Authorities shed light on the importance of dealing with systemic risk problem on national and international levels to be able to maintain the systemic stability. While considerable measures have been undertaken to mitigate systemic risk, the analysis of additional reforms continues. Financial regulators and agencies focus thus on risk measures to construct their frameworks. Basel accords (I, II and III) were the references for large number of risk models used by the regulation agencies. Back to the first Basel accord (1988), regulators focused on credit risk models and appropriate risk-weighting of assets. This accord drive banks to take in consideration both credit risk and market risk. After that, in 1996, the Market Risk Amendment introduces additional capital charges for banks' assets that are exposed to market risk. One famous model was VaR models. Then banks develop their own ratios and expose it to supervisory authorities to get the approval. While the standardized models used previously are concerned in small banks with limited exposure to market risk, they were used in the case of systemic failure. But the related risk charges do not adequately capture the market risk exposure of the assets. This shortcoming has led to further reforms and modifications in the Basel framework. The committee introduced an incremental default risk charge to VaR models. In 2004, Basel II developed the framework for risk models. The supervisory agencies are required to consider and control individual bank risk as well as the systemic risk. Additionally, the supervisors focused on the maintaining of liquidity risk, concentration risk, and legal risk.

As mentioned previously, one of the most pressing questions in the later of the financial crisis was how to identify and deal with the systemically important financial institutions (SIFIs). Several studies were done to indentify these SIFIs. For instance, Benoit (2014) determined the optimal size of the system when measuring systemic importance of a bank. He showed how to adjust market-based systemic risk measures to identify the important institutions. Another work to identify the SIFIs is Guerra et al. (2016) who measured the systemic risk based on contingent claims approach and banking sector multivariate density. The authors applied network measures to analyze bank common sector exposure. Their measures captured the moments of systemic risk increment in the Brazilian banking sector. Basel III frame work proposed regulations about the systemic risk and the SIFSs. It increases the quality and quantity of banking capital, introduces two liquidity ratios and one leverage ratio. These regulations were implemented in January 1st 2013 and must be fully established by January 1st 2019. Basel III comprises changes in all three pillars of Basel II standards. The first pillar consists of minimum capital requirements, the second describes the banking supervision and the third pillar enforces the market discipline by enhancing the transparency of bank's risk. Under Basel III, the banks are forced to hold 4.5% common equity instead of 2% to cover both on and off- balance sheet risks. Additionally, banks have to meet two liquidity ratios, the liquidity coverage ratio (LCR) that covers short term disruptions and the net stable funding ratio (NSFR) that addresses longer-term problems arising from illiquidity. In addition, Basel III implements a leverage ratio that the Committee suggested to begin with

3% as a transition period. These ratios were criticized by many economists. In this line, Blundell-Wignall and Atkinson (2010) find that this mechanism improves some aspects of the risk management process instead of addressing the main problems of the risk-weighting approach. Authors argue that Basel III does not solve the problem of portfolio invariance, as there are no additional capital requirements for concentrated portfolios. Basel III also proposed the estimation of the probability of default during a longer time horizon based.

Moreover, regulators achieve a broader macroprudential policy which is a complement to microprudential policy. The macro- and micro-prudential analyses differ in terms of their objectives and understanding on the nature of risk. Under the microprudential perspective, risk is considered as exogenous, and each potential shock triggering a financial crisis has its origin beyond the behavior of the financial system. The aim of the traditional microprudential regulations is to insure the safety and stability of individual financial institutions, whereas the macroprudential regulation focuses on stability of the financial system as a whole. It addresses the evolution of the risk over time or the "time dimension" of the risk and the distribution of risk in the financial system at a given point in time or the "cross-sectional dimension".

The main objective of macro-prudential regulation is to minimize the risk and the macroeconomic costs of financial disclosures. It is recognized as a necessary method to fill the gap between macroeconomic policy and the traditional micro-prudential regulation of financial institutions (Saporta, 2009). In the aftermath of the late-2000s financial crisis, there was a growing consensus among policymakers and economic researchers about the need to reorient the regulatory framework towards a macro-prudential perspective. The macroprudential view considers that risk factors may present as a systemic phenomenon. Thus the macroprudential policy recognizes the relationship between individual firms and the market.

During the last few years, the financial stability board (FSB) has been investigating some issues related to the macroprudential policies. The FSB identified a range of tools in various countries to address systemic risk (Financial Stability Board, 2011a). These tools belong into three categories: (i) tools to address financial stability risks arising from rapid credit expansions; (ii) tools to address amplification mechanisms of systemic risk such as leverage and maturity mismatches; and (iii) tools to limit spillover effects from the failure of SIFIs defined before.

Researches were not only limited on measuring systemic risk as a single factor of risk, but they also extend the limits to find the effect of the financial factors on the systemic risk. Girardi and Tolga Ergün (2013) estimated the systemic risk of 74 U.S. financial institutions by applying the multivariate generalized autoregressive conditional heterosedasticity (GARCH) model to calculate CoVaR. Authors changed the definition of financial distress from an institution being at its VaR to being at most at its VaR to be able to consider more severe distress events. Authors found that the VaR and CoVaR are weakly related in both time series and cross sectional studies. Authors also found that the size, leverage and equity of the firm are crucial for explaining institutions' contribution to systemic risk. Several studies also document that various institutions' factors affect systemic risk. For instance, Brunnermeier et al. (2012), Pais and Stork (2013), Anginer et al. (2014), Mayordomo et al. (2014), De Jonghe et al. (2015), Acharya and Thakor (2016) and recently Bostandzic and Weiß (2018) document that the size of the institution, the non-interest income, the capital ratio, the lending activities, the proportion of non-performing loans, and bank competition may explain the systemic risk of financial institutions. De Jonghe et al. (2015) studied the way that size and scope interact in their impact on systemic risk. Authors indicate that scope expansion and innovation is less detrimental for systemic risk the larger the bank is and becomes beneficial for medium sized and large banks. Another factor that affects the systemic risk is bank competition. De Jonghe et al. (2015) argue that non-interest income affects small and large banks' exposure to systemic risk in a different way; authors show that while non-interest income reduces large banks' systemic risk exposures, it increases that of small banks. Anginer et al. (2014) argue that lower systemic risk is associated with higher competition as banks tend to take diversified risks which lessen the fragility of the banking system. All these variables are firm level factors that affect the system level stability. Thus one can believe that a clear and strict separation of micro- and macro-prudential policies is not always achievable.

Current regulatory reforms shed light on the importance of measuring and controlling systemic risk. To determine the focus of these reforms it is essential to analyze which banking features and forms of regulations matter for bank performance on the systemic level. Hence, the objective of this thesis is to investigate the impact of banking factors on systemic risk. In this thesis, our findings contribute not only to the microprudential policies by investigating firm level variables, but also link them to the financial system as a whole determined by the systemic risk. Thus, our results address both, micro- and macro-prudential policies by suggesting how individual factors may affect systemic stability.

Briefly, the aim of this chapter is to recall the prior literature on systemic risk debate. We report the measures that have been done to capture systemic risk from various aspects and compare them to be able to detect which measure is convenient to our study, hypotheses and database. We also present the studies that have investigated the risk-taking factors such as governance mechanisms and liquidity creation in banks. Doing so allows us first to understand how banks level variables may affect systemic stability of the financial sector and second it helped us identify which variables are not investigated yet. More specifically, our work fills in the gap in the literature by tackling two important risk taking behaviors of banks, the ownership structure and the liquidity creation. We also contribute to the network theory literature in the financial field by measuring the importance of banks in networks they are belonging to. Although we faced some problems during this analysis, we shed light on the relevance of going deeper in this approach to draw some serious conclusions. Finally, by reviewing the literature on systemic risk within a regulatory framework, we find that despite the extensive work that have been made to deal with the consequences of this risk, studies and interpretations of further reforms and policies continue. Thus, our work contributes to this literature by adding new findings that may help in assessing systemic stability by paying attention on factors that have been ignored by recent studies.

CHAPTER 2

Systemic risk in European banks: does ownership structure matter?

This chapter draws from the contribution of Mohamad Jezzini, Nadia Saghi, Zainab Srour, and Jean-Laurent Viviani (2016). Systemic risk in European banks: does ownership structure matter?

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ABSTRACT

This paper conducts the first empirical assessment of theories concerning banks' systemic risk contribution and their ownership structures. We empirically test whether ownership concentration explains the cross-variation in systemic risk contribution for a sample of European banks over the 2004-2016 period and how this effect may vary depending on the category of the largest controlling shareholder. The results show that higher ownership concentration is associated with greater banks' systemic risk contribution. Moreover, we found that banks' systemic risk contribution is even stronger for banks where institutional investors and States are the largest controlling owners. Additionally, we investigate the effect of the regulatory variables on the relationship between systemic risk and ownership structure. Our results show that higher ownership concentration increased banks' systemic risk contribution in countries with high deposit insurance, lower capital stringency and higher asset diversification. Overall, our findings contribute to the literature examining the determinants of banks' systemic risk in particular and financial stability as a whole and have several policy implications.

JEL Classification: *G21, G28, G32*

Keywords: European banking, ownership structure, systemic risk contribution

2.1. Introduction

The global financial crisis of 2008 highlights the inherently unstable nature of banking institutions and their incentives toward excessive risk taking, with a renewed debate on systemic fragility and macro-prudential regulation. As such, beyond re-examining systemic risk1 assessment practices (e.g., Huang et al., 2012; Girardi and Tolga Ergün, 2013; Adrian and Brunnermeier, 2016; Brownlees and Engle, 2012, 2017; Acharya et al., 2017), a growing strand of literature has investigated the factors behind the cross-sectional variation in banks' systemic risk and some works (e.g., Anginer et al., 2014; Weiß et al., 2014; De Jonghe et al., 2015; Jamshed et al., 2015; Laeven et al., 2016) have specifically examined the role played by environmental factors (regulation, network, competition) and financial institutions characteristics (e.g., size, diversification, profitability). Importantly, these papers perceive systemic risk as the correlation of banks' risk-taking and highlight the relevance to not only focus on the risk of individual financial institutions, but also on the individual bank's contribution to the risk of the financial system as a whole. While the literature on the measurement of systemic risk is amplified, studies on the determinants of financial institutions systemic risk exposure are only burgeoning. Despite the ongoing interest toward the driving factors of systemic risk exposure, surprisingly so far there are few studies that test whether corporate governance mechanisms of banks may be responsible on the correlation among banks' risk-taking (Jamshed et al., 2015) but there are no studies that specifically test the effect of the ownership structure on the systemic risk. The objective of this paper is to fill this gap in the literature.

More precisely, in this paper we investigate the relationship between ownership structure and the systemic risk of banking institutions. Specifically, we look at the effect of ownership concentration on banks' systemic risk contribution and how this effect may vary depending on the category of controlling shareholders involved in banks' decision-making. Ownership structure is known to be the driving force behind the risk-taking incentives in nonfinancial firms in general and banks in particular (e.g., Jensen and Meckling, 1976; Galai and Masulis, 1976; Laeven and Levine, 2009). In this paper we presume that beyond affecting the individual risk of banks, ownership structure (i.e., ownership concentration and the category of shareholders) may be responsible for the correlation of banks' risk-taking behavior at the aggregate level, leading to more systemic fragility.

[1] A systemic event corresponds to a trigger point which causes significant disruption in the financial system and finally spreads out the real economy (Benoit, 2014).

We frame our empirical investigation around two theoretical keystones: *systemic risk-shifting* and *systemic diversification* phenomena. First, risk-taking incentives and culture depend on ownership concentration. Banks with controlling owners tend to be riskier than widely held banks (i.e., with no controlling shareholder), holding other factors constant (Shleifer and Vishny, 1986; Laeven and Levine, 2009). Risk-taking incentives may also vary across different shareholder categories. For instance, diversified owners like banking institutions and other institutional investors may have stronger incentives to undertake risky strategies (e.g., Galai and Masulis, 1976; Saunders et al., 1990; Esty, 1998). In contrast, atomistic shareholders like families or manager controlled banks may be less willing to undertake risky strategies to preserve their human capital skills and private benefits of control (Morck et al., 2000). Those risk incentives taken at the individual level may result in a herding behavior and could directly translate into greater systemic risk exposure of banking institutions. As in any limited liability firm, diversified owners have incentives for risk-shifting after collecting funds from bondholders and myopic depositors (e.g., Galai and Masulis, 1976; Esty, 1998). In this context, Acharya (2009) theoretically shows that such a risk shifting behavior could translate into higher systemic risk as a consequence of the high correlation that arises from the limited liabilities feature of banks that learn from each other and prefer thus to invest in similar fields. This kind of contagion is referred to as *systemic risk-shifting* phenomenon.

Second, unlike atomistic individual owners (such as families), diversified owners –especially institutional investors– are known to have prior experience in loans syndication (Lim et al., 2014), securities and insurance underwriting, brokerage and mutual fund activities and, as a consequence, banks may find it easier to invest in different areas and to choose very diversified portfolios. Such a behavior may allow for risk diversification at the individual level but for higher risk correlation at the aggregate level because activity diversification increases the likelihood of overlapping strategies across banks. In this context, Acharya (2009) and Wagner (2011) theoretically show that although diversification and risk sharing reduce the risk exposure of individual institutions, the financial system may become more fragile and vulnerable because the risk is reallocated (and not eliminated) across the system. In the same vein, Winton (1997) argues that pooling (diversification) elevates the joint failure risk. More recently, Battiston et al. (2012) recognize that the interdependence among banks that arises from financial network relationships, that were developed for the sake of risk diversification, led financial institutions to contribute more to the systemic risk of the financial system and at the same time, become more vulnerable to contagion risk. In short, while diversification reduces the risk of an individual bank, it increases the systemic risk. This systemic risk contagion is referred to as *systemic diversification phenomenon*.

Regardless of the contagion channel (*systemic risk-shifting* or *systemic diversification*), in this article, we assume that ownership structure can affect the systemic risk not only through the total risk taken by a financial institution at the individual level but also through specific contribution to systemic stability at the aggregate level. We refer to these two contagion channels as the *risk culture hypothesis*. If this conjecture is empirically supported, we expect ownership concentration to be associated with greater systemic risk contribution and that such an effect should be stronger in banks controlled by diversified owners like institutional investors.

Specifically, in this paper we use detailed ownership information on 79 publicly-listed banks based in 16 Western European countries[2] over the 2004-2016 period to test the effect of ownership structure on banks' systemic risk contribution and how this effect might differ depending on the largest controlling shareholder category. More precisely, the objective of this paper is to test whether the risk taking incentives of controlling owners at the individual level translate into higher systemic risk exposure at the aggregate level.

We account for various factors and, consistent with the *risk culture conjecture*, we find that higher ownership concentration leads to higher banks' systemic risk contribution as measured by the delta Conditional Value at Risk (ΔCoVaR) and this relationship may vary on the category of the bank's largest controlling shareholder. Specifically, we find that the effect of ownership concentration on systemic risk contribution is higher for banks controlled by other banking institutions, institutional investors or States. This result suggests that shareholders risk-taking incentives at the individual level lead to a herding behavior and greater correlated risk-taking at the aggregate level, making banks more vulnerable to systemic shocks.

Finally, we show that the effect of ownership structure on systemic risk contribution may be mitigated of exacerbated by the regulatory environment. Our results show that the relationship between systemic risk and ownership structure is stronger in countries with

[2] Since our objective is to test the effect of ownership concentration on systemic risk contribution we focus on European countries where ownership is known to be more concentrated compared to other countries, for instance, the U.S. (La Porta et al., 1998). Additionally, European banks contribute more to global systemic risk than banks in the United States because of the lower quality of their loan portfolios and their higher relative interconnectedness with the financial system (Bostandzic and Weiß, 2018).

higher deposit insurance schemes, less capital stringency and higher asset diversification strategies.

Our paper makes several contributions to the systemic risk and corporate governance literature. First, we build a bridge between the two strands of the literature by investigating the effect of ownership structure on banks' systemic risk exposure. Instead of focusing on systemic risk measurement (e.g., Brownlees and Engle, 2012, 2017; Adrian and Brunnermeier, 2016; Acharya et al., 2017), in this paper we rather examine differences in the systemic risk contribution. In doing so, we also contribute to the ongoing literature investigating the determinants of systemic risk (e.g., Brunnermeier et al., 2012; Anginer et al., 2014; De Jonghe et al., 2015; Acharya and Thakor, 2016) and introduce ownership structure as a new driving force behind systemic fragility. Our study further adds to the literature exploring the effect of ownership structure on banks systemic risk (e.g., Laeven and Levine, 2009). Instead of focusing on the risk of individual financial institutions, we explore the role of ownership structure in explaining the individual bank's contribution to the risk of the financial system as a whole. We hence contribute on the recent debate on systemic fragility.

Our study also contributes to the post-crisis debate on systemic fragility. Our findings support the regulatory perspective arguing that the contribution of an individual financial institution to the system's risk may be more relevant than the individual risk of that institution. Additionally, we examine the impact of the institutional and regulatory environment on the relationship between banks' systemic risk and their ownership structure, which is a particular link between bank-specific mechanism and system-specific environment. Finally, our results also address the concerns of the Basel Committee on Banking Supervision (BIS, 2010) highlighting the importance of sound corporate governance schemes in the banking industry and requiring the disclosure of banks' ownership for further monitoring.

The remainder of the paper is structured as follows. In Section 2, we describe the data and define the empirical model. Section 3 reports the sample characteristics and performs some univariate analyses. In Section 4, we present the econometric results and assess how the relation between systemic risk and ownership structure varies with regulatory environment. Section 5 provides the robustness checks and Section 6 concludes the paper.

2.2. Data, variables and model

Before presenting the empirical findings and results, we describe the sample, the variables and the model.

2.2.1. Sample selection

Our study spans the 2004-2016 period and focuses on publicly traded banks based in 16 Western European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Norway, Netherlands, Portugal, Sweden, Spain, Switzerland and the United Kingdom.[3]

Our ownership data come from Orbis database while accounting and market data used in this study come primarily from the Bloomberg database. Regulatory variables' data come from the Bank Regulation and Supervision Surveys conducted in World Bank. All banks in the sample report unconsolidated annual financial statements following an accounting period from January 1st to December 31st.

For the time period and countries covered by our study, we identify 163 banks for which Orbis database provides detailed information on banks' ownership structure. We then collect for these banks information on balance sheets and income statements from the Bloomberg database. We also obtain weekly market data necessary to compute systemic risk indicators from the Bloomberg database. We eliminate observations for which Bloomberg does not provide information on financial and market variables of interest as well as banks with discontinuously traded stocks. To minimize the effect of outliers, we winsorize the main financial variables at the 1% and 99% levels. We then end up with a final sample of 79 banks corresponding to 528 year observations (see Tables 1 and 2 for a breakdown of the sample by country and year).[4]

[Insert Tables 1 and 2 about here]

2.2.2. Variables definition

In this paper, we question whether ownership structure affects banks' systemic risk contribution. To achieve that, we first define the dependent variable reflecting banks' systemic risk. Then we define our independent variable of interest (ownership structure). Finally, we describe the set of control variables introduced in our regressions. Descriptive statistics and other details on all variables used in our regressions are reported in Table 3.

[3] We do not include Luxembourg within the set of Western European countries because no bank provides ownership data consistent with the criteria we use to define our cleaned sample.
[4] According to the Bloomberg classification, our sample includes mostly commercial banks (89%) but also diversified and investment banking institutions (11%).

2.2.2.1. Measuring banks' systemic risk

The dependent variable in our empirical analysis is systemic risk measured using the Delta Conditional Value at Risk (ΔCoVaR) – as initially proposed by Adrian and Brunnermeier (2017) – for each bank of our sample.

First, the system's CoVaR is the VaR of the financial system if a particular institution is under financial distress.[5] To estimate CoVaR, we collect from the Bloomberg database weekly data as used in Adrian and Brunnermeier (2016). We then run the following quantile[6] regressions including a vector of state variables (M_{t-1}):

$$\begin{cases} X_t^i = \alpha_q^i + \gamma_q^i * M_{t-1} + \varepsilon_{q,t}^i \\ X_t^{s|i} = \alpha_q^{s|i} + \beta_q^{s|i} * X_t^i + \gamma_q^{s|i} * M_{t-1} + \varepsilon_{q,t}^{s|i} \end{cases} \quad (1)$$

where X_t^i is the return[7] of the institution i at time t; M_{t-1} is a vector of lagged state variables including: volatility index (V2X) which captures the implied volatility in the stock market, liquidity spread which is the difference between the three-month repo rate and the three-month bill rate, the change in the three-month bill rate, the change in the slope of the yield curve which is the difference between German ten-year government bond yield and the German three-month Bubill rate, the change in credit spread measured by the spread between ten-year Moody's seasoned BAA-rated corporate bond, and finally the German ten-year government bond and the S&P 500 return index as a proxy for market equity returns (Anginer et al., 2014; Adrian and Brunnermeier, 2016); $X_t^{s|i}$ is the return of the system s conditional on the return of the bank i at time t; and ε_t^i and $\varepsilon_{q,t}^{s|i}$ are the error terms.

We then use the predicted values from regression in Eq.(1) to obtain:

$$\begin{cases} VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^{s|i} * M_{t-1} \\ CoVaR_{q,t}^{s|i} = \hat{\alpha}_q^{s|i} + \hat{\beta}_q^{s|i} * VaR_{q,t}^i + \hat{\gamma}_q^{s|i} * M_{t-1} \end{cases} \quad (2)$$

where $VaR_{q,t}^i$ is the VaR of the institution i at time t; and $CoVaR_{q,t}^{s|i}$ is the VaR of the system s conditional on the distress situation of the institution i (i.e., when it is at its $VaR_{q,t}^i$) at time t.

[5] In our empirical framework, we define the financial system as the set of all banks in the sample.
[6] See Appendix A for a detailed explanation of quantile regression.
[7] In our study, we define the return as ln $(\frac{P_t^i}{P_{t-1}^i})$, where P_t^i is the price of stock i at time t.

Finally, we measure the contribution of each bank to the system's risk using the ΔCoVaR defined as the difference between the VaR of the system when a particular institution i becomes financially stressed (i.e., at the qth percentile) and the VaR of the system when the institution is at its median (i.e., 50% percentile). Formally, the ΔCoVaR is expressed as follows:

$$\Delta \mathrm{CoVaR}_{q,t}^{s|i} = \mathrm{CoVaR}_{q,t}^{s|i} - \mathrm{CoVaR}_{0.5,t}^{s|i} \tag{3}$$

ΔCoVaR is computed at q=1% for each bank for the 2004-2016 period, and at q=5% for robustness considerations. ΔCoVaR measures each bank contribution to the system's risk; with lower values of ΔCoVaR indicating higher systemic risk contribution. The annual ΔCoVaR for each bank is calculated as the mean of the weekly ΔCoVaRs of each year.[8] For robustness considerations, we also compute the annual $\Delta\mathrm{CoVaR}_{med}$ as the median value of weekly ΔCoVaRs of each year.

2.2.2.2. Measuring ownership structure

In this paper, we aim to investigate the effect of ownership structure on banks' contribution to systemic risk.

To measure ownership concentration, we collect from Orbis information on all direct shareholders for each bank included in the sample for the year 2016.[9] We follow previous studies on both banking institutions (Caprio et al., 2007; Laeven and Levine, 2009) and nonfinancial firms (La Porta et al., 1999; Laeven and Levine, 2008) and set a control threshold of 10% assuming that it provides a significant portion of votes to exert effective control and influence banks' decision-making. Based on this threshold, we consider a bank as controlled if it has at least one shareholder with 10% or more of shares and, as widely-held if it has no controlling shareholder. As a robustness check, we also consider a 20% control threshold.

In our empirical analysis, we use two indicators to capture banks' ownership concentration. The first measure, denoted thereafter Concentration1, is the percentage of shares held by the largest controlling shareholder. The second measure is the sum of ownership percentages held

[8] Similarly, Adrian and Brunnermeier (2016) calculate quarterly values of ΔCoVaR by averaging the weekly observations within each quarter of the period.

[9] Ownership structure is collected for only one year and not for the whole sample period because of data unavailability. This is not a serious concern for our study because ownership is known to be relatively stable across time (La Porta et al., 1999; Laeven and Levine, 2008).

by all controlling shareholders of each bank (Concentration2).[10] This allows us to capture possible coalitions among several shareholders. In both cases ownership concentration is set equal to zero if the bank is widely held, i.e. if it has no controlling shareholder. For regressions analysis, we also capture ownership concentration using a binary variable d(Concentration1) [d(Concentration2)] which takes a value of one if Concentration1 (Concentration2) is greater than the median value, and zero otherwise. d(Widely) is a dummy variable which takes a value of one if the bank has no controlling shareholder, and zero otherwise.

In line with the aim of our analysis, beyond ownership concentration we also consider the type of the largest controlling shareholder of each bank. We hence classify banks' controlling shareholders into five categories: banks (Bank); institutional investors including insurance companies, mutual and pension funds, and financial companies (Institutional); industrial companies (Industry); individuals or family investors (Family); and States or public authorities (State). Based on these categories, we define a set of dummy variables [d(OwnershipType)] to capture the category of the bank's largest shareholder: d(Bank), d(Institutional), d(Industry), d(Family), and d(State) which take a value of one if the largest shareholder is of that category, and zero otherwise.[11]

2.2.2.3. Control variables

We include in our estimations a set of bank-specific and country-level control variables (X) as well as a vector of regulatory variables (Regulation) that are expected to affect banks' systemic risk contribution.

The Basel Committee on Banking Supervision argued that systemically important banks can be identified using a number of attributes like size, lack of substitutability, interconnectedness, diversification and complexity. We then include in the model a set of bank-level variables that reflect these attributes.

Considering bank level variables, we follow previous studies on systemic risk contribution (e.g., Acharya and Thakor, 2011; Brunnermeier et al., 2012 Anginer et al., 2014; Anginer et al., 2014b; Mayordomo et al., 2014; De Jonghe et al., 2015; Jamshed et al., 2015 ; Laeven et al., 2016; Bostandzic and Weiß, 2018) and include in our regressions the following variables: the natural logarithm of bank total assets (LnTA) as a proxy for bank size as well as the

[10] Concentration2 is the sum of ownership percentages held by owners having 10% or more of bank shares. Formally, Concentration2=$\sum_{i=1}^{n}\text{Concentration}1_i$ if $\text{Concentration}1_i \geq 10\%$, where n is the number of owners for each bank. For robustness checks, we also calculate the variable Concentration2 by setting 20% as a control threshold.

[11] Unlike other studies on ownership structure (e.g., Caprio et al., 2007; Laeven and Levine, 2008; Saghi-Zedek and Tarazi, 2015), in our sample no bank is classified as controlled by a foundation/research institute.

square term of LnTA (LnTA2) to take into account potential non-linearity effects of bank size on systemic risk contribution; the ratio of equity to total assets (EQTA) to account for banks' capitalization; the ratio of net income to total assets (ROA) to account for differences in the level of bank profitability and its ability to efficiently generate profits throughout the business cycle; the ratio of net loans to total assets (LOTA) as a proxy for differences in banks' business models and complexity; the ratio of loan loss provisions to net loans (LLP) to account for differences in credit risk among banks and the quality of their loan portfolio; and the market to book ratio defined as the market value of equity divided by the book value of equity (MTB) to account for banks' growth opportunities.

Regarding country level variables, we include the growth rate of the real gross domestic product (GDPGrowth) to take into account differences in the macroeconomic environment within countries as well as the natural logarithm of the number of banks in each country [Ln(Number of banks)] as a proxy for the banking system concentration (Anginer et al., 2014).

Finally, we also include a vector of regulatory variables (Regulation) characterizing the design of the regulatory regimes implemented in the sample banks' home countries (Anginer et al., 2014) and including the deposit insurance schemes index (DIS), capital stringency index (CAP) and asset diversification index (DIV).

[Insert Table 3 about here]

2.2.3. Model specification

To test the effect of ownership structure on systemic risk, we estimate the following model (thereafter referred to as baseline model) including a set of bank and country control variables (X) as well as vectors of regulatory variables (Regulation), year (Year) dummies and bank specification (Specification) dummies to allow for different intercepts for commercial banks, investment banks, saving banks, and diversified banking institutions:

$$\begin{aligned} \mathrm{SRISK}_{it} = {} & \alpha_1 * \mathrm{OwnershipConcentration}_i + \alpha_2 * \mathrm{OwnershipType} + \beta' X \\ & + \sum_{j=1}^{3} \beta_j * \mathrm{Regulation}_{it}^{j} + \beta_0 + \sum_{t=2005}^{2016} \omega_t \,\mathrm{Year}_i^t \\ & + \sum_{s=2}^{4} \gamma_s \,\mathrm{Specification}_i^s + \varepsilon_{it} \end{aligned} \tag{4}$$

The dependent variable in Eq.(4) is the systemic risk contribution measured by the ΔCoVaR for bank i at time t. OwnershipConcentration refers to one of the ownership measures described above [Concentration1; Concentration2; d(Concentration1); d(Concentration2)]. We further account for differences in ownership types (Barry et al., 2011) by including OwnershipType vector; a set of dummy variables which reflect the type of the largest controlling shareholder as previously defined [d(Bank), d(Institutional); d(Family), d(State), and d(Industry) with the category of widely held banks, d(Widely), considered as the benchmark group]. X is a vector of bank and country level control variables as defined above.[12] Regulation is the vector of regulatory variables: DIS, CAP and DIV.

The coefficient α_1 measures the effect of greater ownership concentration on banks' systemic risk contribution. Controlling owners –especially of the same category– may have homogeneous behavior and objectives in terms of risk-taking. Banks under the control of those shareholders may therefore behave similarly and take correlated risks, increasing their systemic contribution. Consistent with this risk culture view, we expect the coefficient α_1 to be negative and statistically significant indicating that higher ownership concentration is associated with greater systemic risk contribution.

The effect of ownership concentration may be exacerbated for some categories of shareholders. For this purpose, we go further by studying the effect of the ownership type of the largest shareholders. Consistent with the *risk culture hypothesis*, our main results indicate that ownership concentration exposes banks to higher systemic risk, potentially because controlling shareholders encourage banks to take similar and correlated risks, making them more fragile. However, risk-taking incentives and culture may vary across different shareholder categories. For instance, diversified owners like banking institutions and other institutional investors may have stronger incentives to undertake risky strategies and to encourage risk-shifting behavior. Moreover, because they have expertise and experience in several activity areas, such shareholders may also encourage their banks to invest in different areas and to choose much diversified asset portfolios. Such a behavior may allow for risk diversification at the individual level but for greater risk correlation at the aggregate level. State-owned banks could also have higher systemic risk contribution because they should be subject to risk-shifting behavior. Black et al.(2016) explain how State ownership can be perceived as a government support and how it leads to an increase in systemic risk. In

[12] Table B.1 in Appendix B shows the correlation coefficients among the main independent variables used in our regressions. On the whole, the correlation coefficients are low except for bank size as measured by the natural logarithm of total assets (LnTA) and the ratio of equity to total assets (EQTA). We introduce separately LnTA and EQTA in the regressions and the results are not affected by high correlation.

contrast, atomistic shareholders like families or manager controlled banks (i.e., widely-held ones) may be less willing to undertake risky strategies to preserve their human capital skills and private benefits of control. Also, family controlled banks may choose less diversified portfolios and invest in few areas where they have enough expertise. Such a behavior may lead banks to take concentrated risks at the individual level but less correlated risks at the aggregate level.

Given these arguments, we expect banks controlled by other banking institutions or any institutional investor as well as State-owned banks to contribute more to systemic risk compared to their counterparts. To test this hypothesis, we estimate this augmented version of Eq.(4) where we introduce interaction terms Concentration*OwnershipType among the ownership concentration variable and the dummy capturing the category of the largest controlling shareholder:

$$\begin{aligned}\mathrm{SRISK}_{it} = {} & \alpha_1 * \mathrm{OwnershipConcentration}_i + \alpha_2 * \mathrm{OwnershipType} \\ & + \alpha_3 * \mathrm{OwnershipConcentration}_i * \mathrm{OwnershipType}_i + \beta' X \\ & + \sum_{j=1}^{3} \beta_j * \mathrm{Regulation}_{it}^{j} + \beta_0 + \sum_{t=2005}^{2016} \omega_t \, \mathrm{Year}_i^t + \sum_{s=2}^{4} \gamma_s \, \mathrm{Specification}_i^s \\ & + \varepsilon_{it}\end{aligned} \tag{5}$$

Where OwnershipType is a row vector including a set of dummy variables capturing the category of the largest controlling owner of each bank: d(Bank); d(Institutional); d(Family); d(State); and d(Industry).

2.3. Sample characteristics and univariate analysis

We first present the ownership characteristics of the sample banks. Then, using univariate mean tests we look into banks' characteristics and systemic contribution depending on their ownership concentration.

2.3.1. Ownership characteristics of the sample banks

We present in Table 4 information on ownership type and percentage held by each shareholder category.

Considering the control threshold of 10%, our sample includes controlled banks (around 70% of the observations) and widely-held banks (30% of the observations). The number of direct controlling shareholders for each bank ranges from one to five. The data also show that industrial companies, other banking institutions and institutional investors are the predominant largest controlling shareholders of banks in our sample. Family and State owners are also present as largest controlling shareholders but at a lower extent compared to other categories. Banks in our sample are very rarely controlled by foundations.

2.3.2. Ownership structure and banks' characteristics: univariate analysis

We analyze the characteristics of the sample banks depending on their ownership concentration. To achieve this, we divide the sample banks into two groups based on the median value of ownership concentration measure (Concentration1)[13]: Banks with high ownership concentration are banks for which the ownership concentration variable is above the median value and banks with low ownership concentration are banks for which the ownership concentration measure is below the median value.

Table 5 compares the key financial characteristics and systemic risk contribution of concentrated and dispersed banks.

In terms of general financial characteristics (Panel A of Table 5), the results do not display significant differences across concentrated and dispersed banks. Specifically, the data show that banks with high ownership concentration are smaller but have greater growth opportunities compared to banks with dispersed ownership.

Regarding systemic risk contribution (Panel B of Table 5), the table mainly shows that concentrated banks are associated with higher systemic risk contribution (lower values of ΔCoVaR) suggesting that ownership concentration increases banks' systemic risk contribution. This result is consistent with the risk culture view suggesting that controlling owners –especially if they are of the same category– may encourage their banks to take similar risky activities increasing the correlation of their risk-taking behavior and making them simultaneously vulnerable to shocks.

To better emphasize the characteristics of the sample banks, we further analyze the data across sound times and distress times i.e. the financial crisis (2008-2009) and the foreign debt crisis (2010-2011). Not surprisingly, the data (Table 6) show that systemic exposure of our banks has increased during the financial crisis of 2008-2009 and the debt crisis 2010-2011. The results also show that banks become smaller (lower LnTA), are less profitable (lower ROA) and have lower growth opportunities during the two crises. Moreover, the table

[13] We also use the Concentration2 variable to divide the sample into two groups. The main results of Table5 hold when we use the Concentration2 variable.

indicates that banks have increased their provisions (higher LLP) during the financial crisis and the debt crisis.

To analyze the pattern of our systemic risk measure (ΔCoVaR), we report in Table 7 the average systemic contribution by country. The table shows that systemic risk contribution is higher for banks located in countries like Greece and Ireland.

2.4. Econometric results

We first examine the effect of ownership structure (i.e., ownership concentration and ownership structure) on European banks' systemic risk contribution. We then go deeper and test the effect of the regulatory environment on banks' systemic risk contribution.

We perform several tests to choose the appropriate method to estimate the coefficients of Eq. (4) and Eq. (5). The Fischer test points to the presence of individual effects and the Hausman test indicates that random individual effects are more suitable for our dataset. As a consequence, we estimate the coefficients of the model presented in Eq. (4) and (5) using the random effects panel techniques.

2.4.1. Ownership structure and bank systemic risk contribution

Tables 8 and 9 report respectively the baseline estimation (Eq.4) results and the interaction model's results (Eq.5). Columns 1-2 of Table 8 report the results using a continuous variable for ownership concentration (Concentration1 and Concentration2) and columns 3-4 present the estimation results using a binary variable to capture ownership concentration [d(Concentration1) and d(Concentration2)]. We also control for the largest controlling owner category using a row vector variable (OwnershipType) which includes a set of dummy variables capturing the category of the largest controlling owner of each bank: d(Bank); d(Institutional); d(Family); d(State); and d(Industry).

The results show that ownership concentration is associated with higher systemic contribution and this result holds in all the regressions regardless of the ownership measure we use: the coefficient α_1 associated to the ownership concentration variable is negative and statistically significant in all the regressions. Our results are then consistent with the *risk culture hypothesis* and suggest that ownership concentration exposes banks to similar sources of credit or any other risk and results in a herding behavior and greater correlated risk taking, making the banking system more fragile to shocks.

Consistent with our predictions, the results of Table 9 show that the effect of ownership concentration on systemic contribution is enhanced when the controlling shareholder is another banking institution, an institutional investor or a State: the coefficient α_3 associated to the interaction term is negative and statistically significant, suggesting that these categories of shareholders strengthen the banks' systemic contribution, potentially because of the risk-shifting behavior as explained before (Wald tests are displayed on the bottom of Table 9).

Regarding the control variables, few of them are significant. More specifically, consistent with prior studies, the results show that highly capitalized banks (higher EQTA) contribute less to systemic risk. In line with previous studies, the results also indicate that banking systems with a large number of banks [higher Ln(Number of banks)] are more contributing to the overall risk compared to their counterparts. The remaining control variables including those capturing the type of the largest controlling are generally non-significant.

On the whole, our results are consistent with the *risk culture hypothesis* indicating that shareholder-controlled banks should be subject to similar risk-taking behavior and, as a consequence, ownership concentration leads to a common individual risk exposure making the banking sector vulnerable to systemic shocks. Our results also show that ownership concentration have a strong impact on banks' systemic risk contribution if those banks are controlled by other banks, institutions or State owned.

[Insert Tables 8 and 9 about here]

2.4.2. Ownership concentration and bank systemic risk: the impact of regulatory variables

In this section, we test the effect of regulatory environment and country supervision on the observed relationship between systemic risk and ownership structure. The variables we consider are deposit insurance schemes, capital stringency and asset diversification (see Table 3 for variables definition).

To achieve that, we conduct a set of regressions using various subsamples. For each regression, we split the sample into two parts according to the median value of each regulatory variable [deposit insurance schemes (DIS), capital stringency (CAP) and asset diversification (DIV)]; the first (second) subsample consists of observations for which the regulatory variable is above (below) its median value. Then we run regressions separately on subsamples using the following equation[14]:

$$\mathrm{SRISK}_{it} = \alpha_1 * \mathrm{OwnershipConcentration}_i + \alpha_2 * \mathrm{OwnershipType} + \beta_0 + \beta' X + \sum_{j=1, j\neq k}^{3} \beta_j * \mathrm{Regulation}_{it}^{j} + \sum_{t=2005}^{2016} \omega_t \, \mathrm{Year}_i^t + \sum_{s=2}^{4} \gamma_s \, \mathrm{Specification}_i^s + \varepsilon_{it} \quad (6)$$

For each regulatory variable, we run Eq.(6) using two subsamples: when $\mathrm{Regulation}_{it}^{j}$ is less than its median value [$\mathrm{d}(\mathrm{Regulation}_{it}^{k})$=0] and when $\mathrm{Regulation}_{it}^{j}$ is greater than its median value [$\mathrm{d}(\mathrm{Regulation}_{it}^{k})$=1]; where $\mathrm{d}(\mathrm{Regulation}_{it}^{k})$ is a dummy equal to one if the value of $\mathrm{Regulation}_{it}^{k}$ is greater than its median value and zero otherwise with $k \in \{1,2,3\}$; $\mathrm{Regulation}_{it}^{j}$ denotes one of the following regulatory variables: deposit insurance schemes index (DIS when k=1), capital stringency index (CAP when k=2) and asset diversification index (DIV when k=3).[15]

2.4.2.1. Deposit insurance schemes

Deposit insurance schemes are adopted to prevent broad banks runs and enhance systemic stability. However, deposit insurance schemes may be costly as they can increase the risk taking incentives in banks (Barth et al., 2004). Consistent with Demirgüç-Kunt and Detragiache (2002), Barth et al., (2004) argue that the generosity of the deposit insurance scheme is positively related to bank fragility; that is, generous deposit insurance schemes allow bank owners to engage in higher risky activities. In this line, we test whether the DIS in European countries affect the relationship between systemic risk and ownership structure. To achieve that, we construct a DIS index using the DIS database provided by Asli Demirgüç-Kunt et al. (2014). Since the database is constructed for 2003, 2010 and 2013 only and the deposit insurance schemes tend to be relatively stable across time, we update missing data points with the most recent data that is available to us. We thus use the deposit insurance scheme database of 2003 for years 2004-2009, the survey of 2010 for years 2010-2012 and the survey of 2013 for years 2013-2016. We construct the DIS index by adding the answers of the following 9 questions that take one if the answer is yes and zero otherwise: 1. Is the

[14] We only focus on Eq.(4) in our deeper analysis because of the few number of observation we obtain after splitting the data into two subsamples; including the interaction term of the ownership concentration and ownership type [Eq. (5)] in the splitting operation reduces the number of observations.

[15] For each subsample regression, we do not include the regulatory variable used to split the sample in the regression as an independent variable because there is no variety among its values and to avoid the co-linearity bias.

scheme legally separate? 2. Is the scheme administered jointly? 3. Is the scheme paybox plus? 4. Are there multiple schemes? 5. Are local branches of any foreign banks covered? 6. Is funding ex-ante? 7. Does any form of government support exist in case of a shortfall of funds explicitly? 8. Are premiums adjusted for risk? 9. Are covered deposits the base over which premiums is assessed?[16]

While we found that ownership concentration is associated with greater systemic risk contribution, we find now that this relationship is related to a higher DIS index; higher systemic risk contribution is associated with concentrated ownership for banks with more deposit insurance schemes. Consistent with the moral hazard behavior, Table 10 shows that the coefficient associated to the ownership concentration is no more significant for banks in countries who adopt lower deposit insurance schemes whereas this coefficient is negative and statistically significant for banks located in countries with higher deposit insurance index. These results suggest that controlling shareholders tend to take more risky incentives in countries with higher deposit insurance schemes.

[Insert Table 10 about here]

2.4.2.2. Capital stringency

Capital requirements have been a focus of regulators to promote the safety of banking system. Banks owners are required to increase their capital at risk. As discussed previously, banks, like any limited liability firm, tend to engage in higher risky activities, which engender a higher amount of capital at risk. Traditionally, capital reserves serve as a buffer against losses and failures. Indeed, stringent capital requirements may reduce contagion and encourage banks to control their risk taking incentives and thus higher monitoring. The existing BIS regulations concerning the capital requirements addressed only the individual risk of banks, thus banks may reduce their individual failure risk while the systemic risk remains unaffected (Acharya, 2009b). Authors argue that the individual risk taking incentives could be translated into a systemic risk by risk-shifting phenomenon after collecting funds from bondholders. In this context, capital requirements are important to protect banks from joint failures.

[16] While various papers include the existence of an explicit deposit insurance scheme and the coverage ratio in their studies (e.g., Anginer et al., 2014b; Weiß et al., 2014), we do not include these two variables in our analysis since all the banks of the sample present an explicit deposit insurance schemes and there is no significant variety among the deposit insurance coverage ratio.

The capital stringency index (CAP) used in this study is a variable that captures the overall as well as the initial capital stringency.[17] We use Bank Regulation and Supervision surveys of years 2004, 2007 and 2011 from World Bank. We use the 2004's survey for years 2004-2006, the survey of 2007 for years 2007-2010 and the survey of 2011 for years 2011-2016. The capital stringency index ranges from zero to eight with higher values indicating higher capital stringency. The questions used to build this index are the following: 1. Is the minimum capital-asset ratio requirement risk weighted in line with the Basel guidelines? 2. Does the minimum ratio vary as a function of market risk? 3. Are market values of loan losses not realized in accounting books deducted? 4. Are unrealized losses in securities portfolios deducted? 5. Are unrealized foreign exchange losses deducted? 6. Are the sources of funds to be used as capital verified by the regulatory/supervisory authorities? 7. Can the initial disbursement or subsequent injections of capital be done with assets other than cash or government securities? 8. Can initial disbursement of capital be done with borrowed funds? Considering these questions, the capital stringency index measures thus the regulatory approach to assessing and verifying the degree of capital and risk instead of measuring the statutory capital requirements. We expect that the relationship between systemic risk and ownership concentration would be stronger in banks with lower capital stringency index.

The results of the regression are reported in Table 11. Results show that the concentrated ownership structure negatively affects systemic risk in countries with lower capital requirements. These results suggest that stringent capital requirements may reduce the systemic risk contribution of banks by controlling the amount of their capital at risk.

[Insert Table 11 about here]

2.4.2.3. Asset diversification

In this section we aim to study the effect of asset diversification on the relationship we found between systemic risk and ownership structure. While asset diversification may allow for a risk diversification at individual level, it may increase the probability of overlapping activities across banks. Such a behavior elevates the aggregate risk as the risk is not eliminated but rather reallocated (Acharya, 2009b; Wagner, 2011).

To account for asset diversification across banks, we use the database conducted by Bank Regulation and Supervision Survey in WorldBank to construct a diversification index (DIV)

[17] The overall capital stringency measures the extent of regulatory requirements regarding the amount of capital banks must hold. The initial capital stringency measures whether the source of funds that count as regulatory capital can include assets other than cash or government securities, borrowed funds, and whether the regulatory/supervisory authorities verify the sources of capital. The capital stringency index incorporates the previous two measures of capital stringency (Barth et al., 2004).

that measures whether regulations support geographical asset diversification. It questions whether there are explicit, verifiable, and quantifiable guidelines for asset diversification (e.g., are banks required to have some minimum diversification of loans among sectors, or are their sectoral concentration limits?) and whether banks are allowed to make loans abroad. These questions take one if the answer is yes and zero otherwise. Higher values of diversification index (DIV) indicate more diversification. We expect higher systemic risk to be associated with higher ownership concentration (i.e. negative ΔCoVaR) in countries with asset diversification guidelines (Anginer et al., 2014) as the joint failure may increase by the asset pooling phenomenon (Winton, 1997).

The regression results are reported in Table 12. The results show that the coefficient associated to the ownership concentration is negative and significant for banks with banks in more diversified market suggesting that the more the asset diversification the more the systemic risk contribution for controlled banks.

[Insert Table 12 about here]

2.5. Robustness checks

In this section, we perform various regressions to check the robustness of the results obtained in subsections 4.1 and 4.2. We test if our results are robust during different time periods and by using alternative measures of systemic risk and ownership structure.

Our sample period includes sound and distress times. To ensure that our results are not affected by the financial crisis of 2008-2009 and/or the European debt crisis of 2010-2012, we run regressions separately on subsamples of normal times and distress times. Our results remain unchanged (see Table C.1).

We include also an interaction term of the ownership concentration and the financial crisis and/or the debt crisis; we still have the same results (see Table C.2).

Besides performing regressions during various periods, we test the robustness of our results using alternative measures of systemic risk and ownership structure. Until now, the annual ΔCoVaR we use in our analyses is measured as the mean value of weekly ΔCoVaRs. To check whether the use of mean value has not biased our results, we compute the annual ΔCoVaR as the median value of weekly ΔCoVaRs ($\Delta CoVaR_{med}$). Our results remain unchanged (see Tables C.3 and C.4).

Until now, our systemic risk measure is computed at the 99% confidence level. To check whether our results identically hold regardless of the confidence level we consider, we also run regressions using a ΔCoVaR computed at the 95% level. The results are qualitatively the same (see Table C.5).

Additionally, we change the control threshold and compute again ownership variables with a control level of 20% instead of 10%. This new control threshold increases the proportion of banks considered as widely held and decreases the proportion of family- and State-owned banks in our sample. Nevertheless, our main results are unchanged (see Table C.6).

Finally, to account for global country effect, we run the regressions by substituting the regulatory variables with country dummies; binary variables that indicate the bank's country. Our main results hold (see Tables C.7 and C.8).

2.6. Conclusion

The aim of this study is to empirically test the impact of ownership structure on banks' systemic risk. More specifically, we investigate whether banks' systemic contribution depends on their ownership concentration and test how this effect may vary across different shareholders categories. For this purpose, we construct a dataset on ownership concentration and accounting and market data of 79 banks based in 16 European countries during the 2004-2016 period. We estimate systemic risk using the ΔCoVaR which measures the contribution of each bank to the overall risk. Then we define ownership structure indicators that capture the controlling shareholder ownership percentages and types. Finally we establish a link between systemic risk and ownership structure by running panel regressions.

Our results show that ownership concentration is associated with greater systemic contribution, potentially because the presence of controlling shareholders leads banks to take highly correlated risks making them more vulnerable. A deeper analysis shows that such a relationship is even stronger for banks where institutional investors and States are the largest controlling owners.

Additionally, we argue that the effect of regulatory environment and institutional factor may reduce or increase the graveness of the ownership effect on the systemic risk. More specifically, our results suggest that the relationship we found is more important in countries with more deposit insurance schemes, less restrictions on banks' activities, and finally higher asset diversification.

On the whole, our findings contribute to the post-crisis debate on systemic fragility. Our paper supports the regulatory perspective arguing that the contribution of an individual financial institution to the system's risk may be more relevant than the individual risk of that institution. Our results also address the concerns of the Basel Committee on Banking Supervision (BIS, 2010) highlighting the importance of sound corporate governance schemes in the banking industry and requiring the disclosure of banks' ownership for further monitoring.

Table 1
Distribution of European banks by country
This table shows the breakdown of the 79 European banks and the number of observations in the final sample for each country.

Country	Number of sample banks	Number of observations
Austria	4	29
Belgium	2	24
Denmark	14	79
Finland	2	20
France	5	55
Germany	8	38
Greece	1	11
Ireland	1	5
Italy	9	67
Netherlands	3	15
Norway	9	52
Portugal	1	4
Spain	5	47
Sweden	3	12
Switzerland	6	21
United Kingdom	6	49
Total	**79**	**528**

Table 2
Distribution of observations by year
This table shows the number of observations in the final sample for each year from 2004 to 2016.

Year	Number of observations	Percentage of observations
2004	26	4.92
2005	48	9.09
2006	49	9.28
2007	34	6.44
2008	32	6.06
2009	40	7.58
2010	34	6.44
2011	52	9.85
2012	33	6.25
2013	40	7.58
2014	41	7.77
2015	40	7.58
2016	59	11.17
Total	**528**	**100**

Table 3

Variables definition and summary statistics

This table provides the definition and summary statistics for all the variables used in our regressions. The sample consists of 79 European banks corresponding to 528 year observations during the 2004-2016 period.

Variable name	Definition	Source	Mean	Median	Standard deviation	Minimum	Maximum	Number of observations
Systemic risk variable								
ΔCoVaR	Mean of weekly ΔCoVaRs defined as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median (50% percentile) (%)	Bloomberg	-1.452	-1.170	1.107	-8.268	1.407	528
$\Delta CoVaR_{med}$	Median of weekly ΔCoVaRs defined as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median (50% percentile) (%)	Bloomberg	-1.194	-0.975	0.870	-5.809	1.187	528
Ownership structure variables								
Concentration1	The percentage of shares held by the largest controlling shareholder (%)	Orbis	23.272	17.590	24.567	0	100	528
Concentration2	The sum of ownership percentages held by all controlling shareholders of each bank (%)	Orbis	29.473	20.830	28.380	0	100	528
d(Concentration1)	Dummy equal to one if Concentration1 is greater than the median value; and zero otherwise	Orbis	0.4750	0	0.3428	0	1	528
d(Concentration2)	Dummy equal to one if Concentration2 is greater than the median value; and zero otherwise	Orbis	0.3484	0	0.4769	0	1	528
d(Bank)	Dummy equal to one if the largest controlling owner is a bank; and zero otherwise	Orbis	0.188	0	0.391	0	1	528
d(Institutional)	Dummy equal to one if the largest controlling owner is a financial company, an insurance company, a mutual or a pension fund; and zero otherwise	Orbis	0.123	0	0.329	0	1	528
d(Family)	Dummy equal to one if the largest controlling owner is an individual or a family; and zero otherwise	Orbis	0.083	0	0.277	0	1	528
d(State)	Dummy equal to one if the largest controlling owner is a State, a government or a public	Orbis	0.057	0	0.232	0	1	528

Table 3 (*continued*)

Variable name	Definition	Source	Mean	Median	Standard deviation	Minimum	Maximum	Number of observations
	authority; and zero otherwise							
d(Industry)	Dummy equal to one if the largest controlling owner is an industrial company; and zero otherwise	Orbis	0.235	0	0.424	0	1	528
d(Widely Held)	Dummy equal to one if the bank is widely held (i.e., with no controlling owner); and zero otherwise	Orbis	0.303	0	0.46	0	1	528
Bank characteristics								
LnTA	Natural logarithm of total assets (Million of Euros)	Bloomberg	9.816	9.929	3.046	2.966	14.627	528
EQTA	Ratio of total equity to total assets (%)	Bloomberg	9.038	6.767	9.771	0.863	89.675	528
ROA	Return on assets defined as the ratio of net income to total assets (%)	Bloomberg	0.366	0.507	1.341	-6.93	6.789	528
LOTA	Ratio of net loans to total assets (%)	Bloomberg	59.278	63.041	21.341	0.164	94.517	528
LLP	Loan loss provisions defined as the amount of loan loss provisions divided by net loans (%)	Bloomberg	0.493	0.261	0.732	-0.733	6.072	528
MTB	Market to book defined as the ratio of the market value of equity to the book value of equity (%)	Bloomberg	117.89	86.509	97.029	0.451	675.691	528
Country variables								
GDPGrowth	Growth rate of real GDP (Gross Domestic Product) (%)	Bloomberg	1.176	1.500	2.498	-10.100	26.600	528
Ln(Number of banks)	Natural logarithm of the number of banks (with active and inactive trading status) in each country	Bloomberg	4.952	4.905	0.974	2.890	7.163	528
Regulatory variables								
DIS	Deposit insurance schemes index. All countries of our sample present explicit deposit insurance schemes. The sum of the answers of nine questions. It ranges from zero to seven with higher value indicating more insurance. The following questions take zero if the answer is no and one if the answer is yes: 1. Is the scheme legally separate? 2. Is the scheme administered jointly? 3. Is the scheme paybox plus? 4. Are there multiple schemes?	Asli Demirgüç-Kunt et al.,(2014)	4.9412	5	1.2206	1	7	528

Table 3 (*continued*)

Variable name	Definition	Source	Mean	Median	Standard deviation	Minimum	Maximum	Number of observations
	5. Are local branches of any foreign banks covered? 6. Is funding ex-ante? 7. Does any form of government support exist in case of a shortfall of funds explicitly? 8. Are premiums adjusted for risk? 9. Are covered deposits the base over which premiums is assessed?							
CAP	Capital stringency index. The sum of the answers of eight questions that capture the overall capital stringency and the initial capital stringency. It ranges from zero to eight with higher values indicating higher capital stringency. The following questions take zero if the answer is no and one if the answer is yes: 1. Is the minimum capital-asset ratio requirement risk weighted in line with the Basel guidelines? 2. Does the minimum ratio vary as a function of market risk? 3. Are market values of loan losses not realized in accounting books deducted? 4. Are unrealized losses in securities portfolios deducted? 5. Are unrealized foreign exchange losses deducted? 6. Are the sources of funds to be used as capital verified by the regulatory/supervisory authorities? 7. Can the initial disbursement or subsequent injections of capital be done with assets other than cash or government securities? 8. Can initial disbursement of capital be done with borrowed funds?	WorldBank: Bank Regulation and Supervision Survey	5.5852	6	0.9819	3	8	528
DIV	Asset diversification index. The sum of the answers of two questions. It ranges from zero to two, with higher values indicating more diversification. The following questions take a value of 1 if the answer is yes and zero if the answer is no: 1. Are there explicit, verifiable, and quantifiable guidelines regarding asset diversification? For example are banks required to have some minimum diversification of loans among sectors, or are their sectoral concentration limits? 2. Are banks permitted to make loans abroad?	WorldBank: Bank Regulation and Supervision Survey	0.5246	1	0.4998	0	1	528

Table 4

Ownership characteristics of the sample banks

This table reports information on ownership type for the sample banks. We differentiate banks according to the type of their owners: a bank (Bank); a financial company, an insurance company, a mutual or a pension fund (Institutional); an individual or a family (Family); a State, a government or a public authority (State); an industrial company (Industry). Widely Held refers to banks with no controlling shareholder.

Owner type	Percentage of observations	Number of observations	Number of banks	Percentage of ownership
Bank	18.750	99	17	36.403
Institutional	13.450	71	10	31.528
Family	8.330	44	7	28.554
State	5.680	30	7	63.967
Industry	23.480	124	18	26.370
Widely Held	30.310	160	20	0

Table 5

Financial characteristics, systemic risk and ownership concentration: univariate analysis

This table compares the financial characteristics of dispersed and controlled banks over the 2004-2016 period. Using a control threshold of 10%, we classify a bank with a high ownership concentration (low ownership concentration) if the percentage held by the largest shareholder is greater (lower) than the median value. d(Concentration1) is a dummy equal to one if Concentration1 is greater than its median, and zero otherwise; Concentration1 is the percentage of shares held by the largest controlling shareholder. LnTA is the natural logarithm of total assets; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP is the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity; ΔCoVAR is the mean of the weekly ΔCoVaRs defined as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median;. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

Variable	Banks with high ownership concentration [d(Concentration1)=1]	Banks with low ownership concentration [d(Concentration1)=0]	T-statistics
Panel A: General financial characteristics			
LnTA	9.296	10.088	-2.8574***
EQTA	9.652	8.718	1.0421
ROA	0.452	0.321	1.0659
LOTA	58.357	59.759	-0.7163
LLP	0.533	0.471	0.9241
MTB	139.491	106.622	3.7398***
Panel B: Systemic risk			
ΔCoVAR	-1.623	-1.363	-2.5706**

Table 6

Characteristics of sample banks during normal and distress times

This table compares the characteristics of banks during several periods. We split the sample into four groups: (1) normal times (2004-2007; 2013-2016); (2) the financial crisis period (2008-2009); (3) the foreign debt crisis (2010-2012); and (4) the financial and debt crises. ΔCoVAR is the mean of the weekly ΔCoVaRs defined as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median; LnTA is the natural logarithm of total assets; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP is the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity. T-statistics are based on the difference between each crisis period and normal times. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

Variable	(1) Normal times: 2004-2007, 2013-2016	(2) Financial crisis: 2008-2009	T-statistics	(3) Foreign debt crisis: 2010-2012	T-statistics	(4) Financial and debt crises: 2008-2012	T-statistics
ΔCoVAR	-1.234	-2.041	5.9350***	-1.712	4.4759***	-1.836	6.2189***
LnTA	10.004	8.717	3.3436***	9.947	0.1789	9.484	1.8925*
EQTA	8.824	9.945	-0.8885	9.092	-0.2645	9.414	-0.6659
ROA	0.518	0.090	2.6669**	0.099	2.8969**	0.096	3.5113***
LOTA	59.588	60.719	-0.4067	57.528	0.9004	58.731	0.4429
LLP	0.448	0.774	-4.6430***	0 .622	-3.1200***	0.679	-4.4967***
MTB	134.954	86.570	3.8137***	88.513	4.4163***	87.781	5.5158***

Table 7

Banks' systemic risk by country

This table presents the average of systemic risk contribution as measured by the ΔCoVaR in each country. ΔCoVAR is the mean of the weekly ΔCoVaRs defined as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median.

Country	ΔCoVAR
Austria	-0.8391
Belgium	-1.5734
Denmark	-1.1248
Finland	-1.2433
France	-1.0481
Germany	-1.3313
Greece	-4.3178
Ireland	-3.3337
Italy	-1.6278
Netherlands	-1.7788
Norway	-1.3216
Portugal	-1.2603
Spain	-1.7382
Sweden	-0.7567
Switzerland	-1.8710
United Kingdom	-1.6130

Table 8

Ownership concentration and banks' systemic risk

This table reports the estimation results of the model presented in Eq.(4) for the sample of 79 banks over the 2004-2016 period. The dependent variable is the ΔCoVaR defined as the mean of weekly ΔCoVaRs calculated as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median. Our variable of interest is the OwnershipConcentration defined as follow: (1) Concentration1 is the percentage of shares held by the largest controlling shareholder, (2) Concentration2 is the sum of ownership percentages held by all controlling shareholders of each bank, (3) d(Concentration1) is a dummy variable equal to one if the Concentration1 variable is more than its median; and zero otherwise, (4) d(Concentration2) is a dummy variable equal to one if the Concentration2 variable is more than its median; and zero otherwise. The four models are performed on the sample of 79 banks of 528 observations. LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity; d(Bank)-d(Industry) is a set of dummy variables representing the type of the largest controlling shareholder (Widely is the benchmark group); GDPGrowth is the real GDP (Gross Domestic Product) growth rate; Ln(Number of banks) is the natural logarithm of the number of banks in each country; DIS is the deposit insurance schemes index; CAP is the capital stringency index; DIV is the asset diversification index. Bank specification is a set of dummy variables to account for banks type (commercial banks, investment banks, saving banks, and diversified banking institutions). P-Values (reported in parentheses) are based on robust standard errors. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	(1) Concentration1	(2) Concentration2	(3) d(Concentration1)	(4) d(Concentration2)
OwnershipConcentration	-0.0095*	-0.0106**	-0.4030*	-0.3961**
	(0.0824)	(0.0147)	(0.0774)	(0.0428)
LnTA	0.0789	0.0609	0.1541	0.0937
	(0.7813)	(0.8247)	(0.6434)	(0.7562)
LnTA2	-0.0067	-0.0055	-0.0102	-0.0071
	(0.6637)	(0.7119)	(0.5705)	(0.6630)
EQTA	0.0112	0.0126	0.0163	0.0147
	(0.3659)	(0.2911)	(0.2099)	(0.2386)
ROA	0.0190	0.0170	0.0138	0.0153
	(0.5802)	(0.6194)	(0.6977)	(0.6649)
LOTA	-0.0086	-0.0087	-0.0094	-0.0093
	(0.1707)	(0.1607)	(0.1423)	(0.1469)
LLP	-0.1302	-0.1291	-0.1345	-0.1256
	(0.3069)	(0.3107)	(0.2848)	(0.3207)
MTB	0.0007	0.0007	0.0007	0.0007
	(0.5284)	(0.5323)	(0.5447)	(0.5465)
d(Bank)	0.2415	0.3046	0.1068	0.1100
	(0.3304)	(0.1859)	(0.6193)	(0.5932)
d(Institutional)	-0.1305	-0.0061	-0.0704	-0.0410
	(0.7600)	(0.9880)	(0.8800)	(0.9294)
d(Family)	-0.2944	-0.1844	-0.1883	-0.1423
	(0.4685)	(0.6484)	(0.6011)	(0.6568)
d(State)	0.2214	0.2837	0.0464	0.0529
	(0.6912)	(0.5825)	(0.9218)	(0.9102)
d(Industry)	0.3973	0.5676**	0.3721*	0.3969*
	(0.1104)	(0.0328)	(0.0838)	(0.0660)
GDPGrowth	0.0244	0.0237	0.0273	0.0272
	(0.5335)	(0.5467)	(0.4893)	(0.4893)
Ln(Number of banks)	-0.0665	-0.0778	-0.1078	-0.0907
	(0.4701)	(0.3797)	(0.2501)	(0.3119)
DIS	0.0629	0.0725	0.0841	0.0764
	(0.2835)	(0.1879)	(0.1606)	(0.2101)
CAP	-0.0062	-0.0106	0.0012	-0.0047
	(0.9356)	(0.8867)	(0.9878)	(0.9525)
DIV	0.0557	0.0671	0.0551	0.0610
	(0.5389)	(0.4569)	(0.5398)	(0.4929)
Intercept	-0.6320	-0.5392	-0.8975	-0.6456
	(0.6438)	(0.6796)	(0.5530)	(0.6470)
Year dummies	Yes	Yes	Yes	Yes
Bank specification	Yes	Yes	Yes	Yes
Number of observations	528	528	528	528
Number of banks	79	79	79	79
R-Square	0.2673	0.2818	0.2512	0.2579

Table 9

Ownership concentration and bank systemic risk: impact of the largest shareholder category

This table reports the estimation results of the model presented in Eq.(4) for the sample of 79 banks over the 2004-2016 period. The dependent variable is the ΔCoVaR of each bank defined as the mean of weekly ΔCoVaRs calculated as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median. OwnershipConcentration is defined as follow: (1) Concentration1 is the percentage of shares held by the largest controlling shareholder, (2) d(Concentration1) is a dummy variable equals to one if the Concentration1 variable is more than its median; and zero otherwise. LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP is the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity; d(Bank)-d(Industry) is a set of dummy variables representing the type of the largest controlling shareholder (Widely is the benchmark group); GDPGrowth is the real GDP (Gross Domestic Product) growth rate; Ln(Number of banks) is the natural logarithm of the active and inactive banks in each country; DIS is the deposit insurance schemes index; CAP is the capital stringency index; DIV is the asset diversification index. Ownership type is a dummy variable to control banks owners' type; Bank specification is a dummy variable to control banks type (commercial banks, investment banks, saving banks, and diversified banking institutions). P-Values based on robust standard errors are reported in parentheses. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	(1) Concentration1	(2) d(Concentration1)
OwnershipConcentration	0.0188***	1.9095**
	(0.0012)	(0.0142)
OwnershipConcentration *d(Bank)	-0.0324***	-2.4264***
	(0.0005)	(0.0082)
OwnershipConcentration *d(Institutional)	-0.1309***	-2.9575**
	(0.0000)	(0.0178)
OwnershipConcentration *d(Family)	0.0212	-1.5355*
	(0.5749)	(0.0968)
OwnershipConcentration *d(State)	-0.0327**	-2.2121**
	(0.0315)	(0.0176)
OwnershipConcentration *d(Industry)	-0.0202	-2.2609***
	(0.1514)	(0.0047)
LnTA	0.3305	0.1938
	(0.2412)	(0.5711)
LnTA2	-0.0207	-0.0118
	(0.1725)	(0.5220)
EQTA	0.0189	0.0192
	(0.1161)	(0.1754)
ROA	0.0063	0.0147
	(0.8328)	(0.6723)
LOTA	-0.0118*	-0.0117*
	(0.0501)	(0.0871)
LLP	-0.1211	-0.1270
	(0.3074)	(0.3205)
MTB	0.0011	0.0008
	(0.3207)	(0.5147)
GDPGrowth	0.0109	0.0258
	(0.7506)	(0.4973)
Ln(Number of banks)	-0.0216	-0.0575
	(0.7550)	(0.5726)
DIS	0.0074	0.0526
	(0.9214)	(0.5043)
CAP	-0.0454	-0.0092
	(0.5329)	(0.9053)
DIV	0.0771	0.1075
	(0.4075)	(0.2186)
Intercept	-2.0649	-1.5577
	(0.1583)	(0.3619)

Ownership type	Yes	Yes
Year dummies	Yes	Yes
Bank specification	Yes	Yes
Number of observations	528	528
Number of banks	79	79
R-Square	0.4160	0.2829
Wald tests: Bank	-0.0136**	-0.5168*
	(0.03482)	(0.0844)
Institutional	-0.1120***	-1.0479*
	(0.0000)	(0.0989)
Family	0.0400	0.3740
	(0.2608)	(0.3129)
State	-0.0138	-0.3025
	(0.3521)	(0.5270)
Industry	-0.0013	-0.3514
	(0.9085)	(0.2651)

Table 10

Ownership structure and banks' systemic risk: the impact of deposit insurance schemes

This table reports the estimation results of a modified model presented in Eq.(6), for the sample of 79 banks over the 2004-2016 period. The dependent variable is the ΔCoVaR defined as the mean of weekley ΔCoVaRs calculated as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median. Our variable of interest is the OwnershipConcentration defined as follows: (1) Concentration1 which is the percentage of shares held by the largest controlling shareholder; (2) Concentration2 is the sum of ownership percentages held by all controlling shareholders of each bank. d(DIS) is a dummy equals to one (zero) if the DIS is greater (less) than its median value. DIS is the deposit insurance schemes index; CAP is the capital stringency index; DIV is the asset diversification index; LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP is the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity; Ln(Number of banks) is the natural logarithm of the active and inactive banks in each country; Ownership type is a set of dummy variables to control owners type; Bank specification is a dummy variable to control the banks type (commercial banks, investment banks, saving banks, and diversified banking institutions). P-Values (reported in parentheses) are based on robust standard errors. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	d(DIS)=0		d(DIS)=1	
	(1)	(2)	(3)	(4)
	Concentration1	Concentration2	Concentration1	Concentration2
OwnershipConcentration	0.0001	-0.0084	-0.0158**	-0.0115**
	(0.9897)	(0.5750)	(0.0316)	(0.0284)
CAP	-0.3200	-0.4154	0.0020	0.0536
	(0.2820)	(0.1817)	(0.9859)	(0.6292)
DIV	-0.2617	-0.5136	0.1952	0.0889
	(0.6616)	(0.3847)	(0.1425)	(0.4678)
LnTA	0.8856	0.9384	0.1877	0.0627
	(0.2409)	(0.2334)	(0.4184)	(0.7708)
LnTA2	-0.0423	-0.0492	-0.0144	-0.0076
	(0.2509)	(0.1655)	(0.2585)	(0.5090)
EQTA	0.0708***	0.0660***	0.0098	0.0088
	(0.0001)	(0.0006)	(0.2225)	(0.2588)
ROA	-0.0214	-0.0140	0.0100	0.0197
	(0.7109)	(0.8099)	(0.7700)	(0.5810)
LOTA	-0.0225***	-0.0217**	-0.0108	-0.0123
	(0.0026)	(0.0201)	(0.1991)	(0.1593)
LLP	0.3996	0.3824	-0.1543	-0.1519
	(0.4191)	(0.4352)	(0.1521)	(0.1566)
MTB	0.0002	0.0002	0.0007	0.0006
	(0.9470)	(0.9445)	(0.5927)	(0.6297)
GDPGrowth	0.0922**	0.0872**	0.0429	0.0446
	(0.0254)	(0.0420)	(0.4493)	(0.4504)
Ln(Number of banks)	-0.0304	0.4168	0.0599	-0.0007
	(0.9577)	(0.4443)	(0.5844)	(0.9947)
Intercept	-1.3938	-3.3907	-2.2403	-0.5396
	(0.7257)	(0.3660)	(0.1362)	(0.7052)
Ownership type	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Bank specification	Yes	Yes	Yes	Yes
Number of observations	131	131	397	397
Number of banks	23	23	56	56
R-Square	0.5747	0.5734	0.3162	0.3027

Table 11

Ownership concentration and banks' systemic risk: impact of the capital stringency

This table reports the estimation results of a modified model presented in Eq.(6), for the sample of 79 banks over the 2004-2016 period. The dependent variable is the ΔCoVaR defined as the mean of weekley ΔCoVaRs calculated as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median. Our variable of interest is the OwnershipConcentration defined as follows: (1) Concentration1 which is the percentage of shares held by the largest controlling shareholder; (2) Concentration2 is the sum of ownership percentages held by all controlling shareholders of each bank. d(CAP) is a dummy equals to one (zero) if CAP is greater (less) or equal its median value. CAP is the capital stringency index; DIS is the deposit insurance schemes index; DIV is the asset diversification index. LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP is the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity; GDPGrowth is the real GDP (Gross Domestic Product) growth rate; Ln(Number of banks) is the natural logarithm of the active and inactive banks in each country; Ownership type is a set of dummy variables to control owners type; Bank specification is a dummy variable to control the banks type (commercial banks, investment banks, saving banks, and diversified banking institutions). P-Values (reported in parentheses) are based on robust standard errors. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	d(CAP)=0		d(CAP)=1	
	(1) Concentration1	(2) Concentration2	(3) Concentration1	(4) Concentration2
OwnershipConcentration	-0.0175**	-0.0139***	-0.0774	-0.0169
	(0.0326)	(0.0043)	(0.9203)	(0.8052)
DIS	0.0027	0.0901	0.2747	0.6767
	(0.9710)	(0.1107)	(0.8590)	(0.8877)
DIV	0.1496	0.0764	0.8944	0.0161
	(0.1856)	(0.5033)	(0.9199)	(0.9967)
LnTA	0.1736	0.1553	-0.0210	-0.0210
	(0.4668)	(0.5131)	(0.9986)	(0.9986)
LnTA2	-0.0111	-0.0100	-0.0368	-0.0368
	(0.3903)	(0.4261)	(0.9266)	(0.9266)
EQTA	0.0196	0.0219	-0.1270	-0.1270
	(0.1326)	(0.1016)	(0.7645)	(0.7645)
ROA	0.0034	0.0040	0.4823	0.4823
	(0.9185)	(0.9072)	(0.7736)	(0.7736)
LOTA	-0.0105	-0.0116	-0.0376	-0.0376
	(0.1555)	(0.1203)	(0.1312)	(0.1312)
LLP	-0.1664	-0.1648	0.8540	0.8540
	(0.1269)	(0.1257)	(0.4023)	(0.4023)
MTB	0.0008	0.0008	-0.0027	-0.0027
	(0.5120)	(0.4889)	(0.8929)	(0.8929)
GDPGrowth	0.0244	0.0236	0.0382	0.0382
	(0.5223)	(0.5470)	(0.8529)	(0.8529)
Ln(Number of banks)	-0.0169	-0.0650	0.9774	0.9632
	(0.8684)	(0.4805)	(0.9365)	(0.9395)
Intercept	-1.8097	-1.0888	-0.001	-0.0120
	(0.1550)	(0.3655)	(0.2513)	(0.513)
Ownership type	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Bank specification	Yes	Yes	Yes	Yes
Number of observations	181	181	347	347
Number of banks	46	46	60	60
R-Square	0.2981	0.3044	0.5292	0.5382

Table 12

Ownership concentration and banks' systemic risk: impact of asset diversification

This table reports the estimation results of a modified model presented in Eq.(6), for the sample of 79 banks over the 2004-2016 period. The dependent variable is the ΔCoVaR defined as the mean of weekley ΔCoVaRs calculated as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median. Our variable of interest is the Ownership Concentration defined as follows: (1) Concentration1 which is the percentage of shares held by the largest controlling shareholder; (2) Concentration2 is the sum of ownership percentages held by all controlling shareholders of each bank. d(DIV) is a dummy equals to one (zero) if the DIV is greater (less) or equal its median value. DIV is the asset diversification index; DIS is the deposit insurance schemes index; CAP is the capital stringency index. LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP is the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity; GDPGrowth is the real GDP (Gross Domestic Product) growth rate; Ln(Number of banks) is the natural logarithm of the active and inactive banks in each country; Ownership type is a set of dummy variables to control owners type; Bank specification is a dummy variable to control the banks type (commercial banks, investment banks, saving banks, and diversified banking institutions). P-Values (reported in parentheses) are based on robust standard errors. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	d(DIV)=0		d(DIV)=1	
	(1)	(2)	(3)	(4)
	Concentration1	Concentration2	Concentration1	Concentration2
OwnershipConcentration	-0.0092	-0.0132**	-0.0170***	-0.0168
	(0.3013)	(0.0051)	(0.0015)	(0.7744)
DIS	0.1582	0.0809	0.0099	0.3682
	(0.1436)	(0.1924)	(0.9357)	(0.5432)
CAP	0.0146	0.0645	0.0292	0.9998
	(0.9523)	(0.4954)	(0.7000)	(0.9488)
LnTA	0.1442	0.1682	0.0770	-0.0210
	(0.7613)	(0.4657)	(0.7737)	(0.9986)
LnTA2	-0.0119	-0.0105	-0.0044	-0.0368
	(0.6429)	(0.3828)	(0.7573)	(0.9266)
EQTA	0.0254	0.0216	0.0098	-0.1270
	(0.2123)	(0.1061)	(0.5609)	(0.7645)
ROA	0.0001	0.0028	0.0087	0.4823
	(0.9977)	(0.9349)	(0.8649)	(0.7736)
LOTA	0.0051	-0.0114	-0.0138**	-0.0376
	(0.6554)	(0.1260)	(0.0324)	(0.1312)
LLP	-0.1362	-0.1758	-0.1720	0.8540
	(0.3159)	(0.1006)	(0.2086)	(0.4023)
MTB	0.0003	0.0007	-0.0001	-0.0027
	(0.7480)	(0.5416)	(0.9640)	(0.8929)
GDPGrowth	0.0110	0.0252	0.1303	0.0382
	(0.5780)	(0.5141)	(0.1576)	(0.8529)
Ln(Number of banks)	0.1834	-0.0132***	-0.0111	-0.1322
	(0.3195)	(0.0051)	(0.9003)	(0.9766)
Intercept	-3.1348	0.0809	-1.4406	0.0072
	(0.2206)	(0.1924)	(0.3609)	(0.1082)
Ownership type	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Bank specification	Yes	Yes	Yes	Yes
Number of observations	277	277	251	251
Number of banks	55	55	55	55
R-Square	0.2181	0.3033	0.4402	0.5292

Appendix A

This Appendix explains how to use quantile regressions to estimate the value at risk (VaR), the conditional value at risk (CoVaR) and the delta conditional value at risk (ΔCoVaR). Koenker (2005) present a detailed description about the general quantile regressions.

While OLS regression models the relationship between a set of independent variables (X_i)i=1,…,n and the conditional mean of the dependent variable Y, quantile regression estimates the conditional quantiles of the independent variable Y given certain values of (X_i). Quantile regression can be viewed as an extension of linear regression; it allows for a more complete picture of the conditional distribution of Y given (X_i) when one is interested in the lower or upper quantile. Particularly, in finance, quantile regression is useful to estimate the Value at Risk (VaR) and risk measures where the lowest 1% or 5% quantiles are of interest.

Suppose that the returns X_t^i have the following linear factor structure:

$$X_{t+1}^j = \phi_0 + \phi_1 M_t + \phi_2 X_{t+1}^i + (\phi_3 + \phi_4 M_t)\Delta Z_{t+1}^j$$

where M_t is a vector of state variables; ΔZ_{t+1}^j is the error term assumed to be i.i.d. with zero mean and unit variance and $E\left[\Delta Z_{t+1}^j \middle| M_{t-1}, X_{t+1}^i\right] = 0$. The conditional expected return is given by $\mu^j[X_{t+1}^j | M_t, X_{t+1}^i] = \phi_0 + \phi_1 M_t + \phi_2 X_{t+1}^i$ and the conditional volatility is given by $\sigma_t^{jj}\left[X_{t+1}^j \middle| M_t, X_{t+1}^i\right] = (\phi_3 + \phi_4 M_t)$. Instead of estimating the coefficients ϕ_0, ϕ_1, ϕ_2, ϕ_3 and ϕ_4 using OLS regression that require a distributional assumptions, quantile regressions are used to estimates these coefficients for different percentiles.

Let F be the cumulative distribution function of the error term ΔZ^j with the inverse distribution function $F_{\Delta Z^j}^{-1}(q)$ for the q-quantile.

We can immediately obtain the inverse distribution function of X_{t+1}^j:

$$F_{X_{t+1}^j}^{-1}(q | M_t, X_{t+1}^i) = \alpha_q + \gamma_q M_t + \beta_q X_{t+1}^i$$

where $\alpha_q = \phi_0 + \phi_3 F_{\Delta Z^j}^{-1}(q)$, $\gamma_q = \phi_1 + \phi_4 F_{\Delta Z^j}^{-1}(q)$ and $\beta_q = \phi_2$ for $q \in (0,1)$.

$F_{X_{t+1}^j}^{-1}(q | M_t, X_{t+1}^i)$ is referred to as the conditional quantile function.

VaR is then obtained by solving the following equation:

$$VaR^{j}_{q,t+1} = \inf_{VaR^{j}_{q,t+1}} \left\{ \Pr\left(X_{t+1} | \{M_t, X^{i}_{t+1}\} \le VaR^{j}_{q,t+1}\right) \ge q \right\} = F^{-1}_{X^{j}_{t+1}} (q|M_t, X^{i}_{t+1})$$

By conditioning on $X^{i}_{t+1} = VaR^{i}_{q,t+1}$ we obtain the $CoVaR^{j|i}_{t+1}$ using the quantile function:

$$\begin{aligned} CoVaR^{j|i}_{q,t+1} &= \inf_{VaR^{j}_{q,t+1}} \left\{ \Pr\left(X_{t+1} \middle| \{M_t, X^{i}_{t+1} = VaR^{i}_{q,t+1}\} \le VaR^{j}_{q,t+1}\right) \ge q \right\} \\ &= F^{-1}_{X^{j}_{t+1}} (q|M_t, X^{i}_{t+1} = VaR^{i}_{q,t+1}) \end{aligned}$$

The quantile function is estimated by predicting the q-quantile regressions of X^{i}_{t+1} on M_t and X^{j}_{t+1} by solving

$$\min_{\alpha_q, \beta_q, \gamma_q} \sum_t \begin{cases} q \left| X^{j}_{t+1} - \alpha_q - \beta_q X^{i}_{t+1} - \gamma_q M_t \right| & \text{if } (X^{j}_{t+1} - \alpha_q - \beta_q X^{i}_{t+1} - \gamma_q M_{t-1}) \ge 0 \\ (1-q) \left| X^{j}_{t+1} - \alpha_q - \beta_q X^{i}_{t+1} - \gamma_q M_t \right| & \text{if } (X^{j}_{t+1} - \alpha_q - \beta_q X^{i}_{t+1} - \gamma_q M_{t-1}) < 0 \end{cases}$$

Adrian and Brunnermeier (2016) provide detailed discussion about quantile regression properties.

Appendix B

Table B.1

Correlations table

This table shows the correlations among the explanatory variables used in the regressions. Concentration1 is the percentage of shares held by the largest controlling shareholder; Concentration2 is the sum of ownership percentages held by all controlling shareholders of each bank; LnTA is the natural logarithm of total assets; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP is the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity; GDPGrowth is the real GDP (Gross Domestic Product) growth rate; Ln(Number of banks) is the natural logarithm of the number of banks (with active and inactive trading status) in each country; DIS is the deposit insurance schemes index; CAP is the capital stringency index; DIV is the asset diversification index. In parenthesis below the correlations are their corresponding p-values. DIV is the asset diversification index.

	Concentration1(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Bank level variables												
Concentration2 (2)	0.9172	1										
	(0.000)											
LnTA (3)	-0.0706	-0.1054	1									
	(0.1052)	(0.0154)										
EQTA (4)	0.0157	0.0885	-0.4624	1								
	(0.7186)	(0.0420)	(0.000)									
ROA (5)	-0.001	-0.0187	-0.0001	-0.0321	1							
	(0.9818)	(0.6681)	(0.9991)	(0.4612)								
LOTA(6)	-0.0616	-0.0949	-0.2143	-0.3076	0.0117	1						
	(0.1577)	(0.0293)	(0.000)	(0.000)	(0.7892)							
LLP (7)	-0.004	-0.0018	-0.1303	0.0195	-0.4562	0.2226	1					
	(0.9262)	(0.9665)	(0.0027)	(0.6550)	(0.000)	(0.000)						
MTB(8)	0.1798	0.1536	-0.077	0.0498	0.1554	-0.2298	-0.2046	1				
	(0.000)	(0.0004)	(0.0772)	(0.2538)	(0.0003)	(0.000)	(0.000)					
GDPGrowth (9)	0.0604	0.0382	0.0575	-0.026	0.1517	0.0268	-0.3166	0.2225	1			
	(0.1655)	(0.3815)	(0.1873)	(0.5506)	(0.0005)	(0.539)	(0.000)	(0.000)				
Ln(Number of banks) (10)	-0.0698	-0.167	0.0082	0.2435	-0.103	-0.3807	-0.072	0.2047	0.0063	1		
	(0.1092)	(0.000)	(0.8516)	(0.000)	(0.0179)	(0.000)	(0.0986)	(0.000)	(0.8853)			
Panel B: Regulatory level variables												
DIS (11)	-0.1803	-0.1266	-0.173	0.1162	-0.0392	-0.1922	0.1584	-0.0679	-0.1469	0.1583	1	
	(0.000)	(0.0036)	(0.0001)	(0.0075)	(0.3683)	(0.000)	(0.0003)	(0.1192)	(0.0007)	(0.0003)		
CAP (12)	-0.0386	-0.1224	-0.0377	-0.0127	-0.0458	-0.0066	0.1819	0.0408	-0.1657	0.0668	0.0746	
	(0.3757)	(0.0048)	(0.3873)	(0.7713)	(0.2933)	(0.8794)	(0.000)	(0.3500)	(0.000)	(0.1252)	(0.0867)	1
DIV (13)	0.0831	0.149	0.108	-0.0358	-0.044	-0.065	-0.0614	-0.1361	-0.0545	-0.1345	0.0941	0.1388
	(0.0564)	(0.0006)	(0.0131)	(0.4121)	(0.3129)	(0.1355)	(0.1586)	(0.0017)	(0.2113)	(0.0019)	(0.0306)	(0.0014)

Appendix C

Table C.1

Ownership concentration and banks' systemic risk during sound and distress times

This table reports the estimation results of the model presented in Eq.(4) over three period scenarios: (1) the financial crisis of 2008-2009; (2) the debt crisis of 2010-212; and (3) the financial and debt crises. We run regressions separately on six subsamples: normal times (if the time period doesn't belong to the crisis period) and crisis times (if the time period belongs to the crisis period). The dependent variable is the ΔCoVaR defined as the mean of weekly ΔCoVaRs. Our variable of interest is the OwnershipConcentration defined as the percentage of shares held by the largest controlling shareholder (Concentration1). LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity; d(Bank)-d(Industry) is a set of dummy variables representing the type of the largest controlling shareholder (Widely is the benchmark group); GDPGrowth is the real GDP (Gross Domestic Product) growth rate; Ln(Number of banks) is the natural logarithm of the number of banks in each country; DIS is the deposit insurance schemes index; CAP is the capital stringency index; DIV is the asset diversification index. Bank specification is a set of dummy variables to account for banks type (commercial banks, investment banks, saving banks, and diversified banking institutions). P-Values (reported in parentheses) are based on robust standard errors. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	Financial crisis		Debt crisis		Financial and debt crises	
	Normal times	Crisis times	Normal times	Crisis times	Normal times	Crises times
OwnershipConcentration	-0.0085*	-0.0268*	-0.0081*	-0.0151**	-0.0061**	-0.0157*
	(0.0695)	(0.1000)	(0.0952)	(0.0288)	(0.0132)	(0.0831)
LnTA	0.2059	0.4925	0.2131	-0.0837	0.1065	-0.0672
	(0.4818)	(0.4035)	(0.4587)	(0.8054)	(0.7330)	(0.8653)
LnTA2	-0.0119	-0.0292	-0.0130	0.0002	-0.0061	-0.0023
	(0.4576)	(0.3974)	(0.4264)	(0.9926)	(0.7187)	(0.9177)
EQTA	0.0097	-0.0617***	0.0116	-0.0024	0.0023	-0.0025
	(0.3261)	(0.0057)	(0.3567)	(0.8942)	(0.8547)	(0.8530)
ROA	0.0346	0.3275	0.0023	0.0836	0.0047	0.1264
	(0.2026)	(0.1802)	(0.9521)	(0.4262)	(0.8910)	(0.2789)
LOTA	-0.0059	-0.0334**	-0.0087	-0.0130	-0.0058	-0.0151**
	(0.2988)	(0.0434)	(0.1425)	(0.1245)	(0.3413)	(0.0424)
LLP	-0.1798	0.3089**	0.0177	-0.3037*	-0.0880	-0.0840
	(0.1402)	(0.0339)	(0.8681)	(0.0955)	(0.3993)	(0.6306)
MTB	0.0016*	-0.0064	0.0015	0.0003	0.0018*	-0.0023
	(0.0628)	(0.1729)	(0.1657)	(0.7657)	(0.0561)	(0.1052)
d(Bank)	0.2183	1.5262**	0.1269	0.8369**	0.0648	0.8641**
	(0.3883)	(0.0419)	(0.6312)	(0.0192)	(0.8091)	(0.0198)
d(Institutional)	-0.2269	0.8139	-0.2356	0.3753	-0.4534	0.6554
	(0.5885)	(0.2048)	(0.5492)	(0.5168)	(0.3021)	(0.1989)
d(Family)	-0.4690	1.8264	-0.4702	-0.0927	-0.5656*	0.5538
	(0.2047)	(0.1894)	(0.2251)	(0.9157)	(0.0902)	(0.3943)
d(State)	0.0551	0.4775	-0.0865	0.7397	0.0055	0.8633
	(0.9156)	(0.6997)	(0.8936)	(0.2143)	(0.9915)	(0.2047)
d(Industry)	0.2542	0.6372	0.2291	0.3779	0.1953	0.5577
	(0.2806)	(0.2870)	(0.3564)	(0.3153)	(0.4176)	(0.1025)
GDPGrowth	0.0466*	-0.3459***	0.0697*	0.0701**	-0.0226	0.1003***
	(0.0964)	(0.0095)	(0.0536)	(0.0118)	(0.2556)	(0.0013)
Ln(Number of banks)	-0.1198	0.7040*	-0.1207	-0.0386	-0.1840*	0.1425

	(0.2156)	(0.0644)	(0.1994)	(0.7575)	(0.0504)	(0.2922)
DIS	0.0900**	0.1445	0.0974	0.0891	0.0933	0.0295
	(0.0498)	(0.4266)	(0.1124)	(0.2823)	(0.1154)	(0.7906)
CAP	-0.0242	-0.0595	-0.0629	-0.0194	-0.0246	-0.0989
	(0.7774)	(0.7617)	(0.4565)	(0.8339)	(0.7906)	(0.4214)
DIV	-0.2064	0.7555	-0.1228	-0.2028	-0.2474	0.0128
	(0.2300)	(0.3844)	(0.3563)	(0.1010)	(0.2929)	(0.9434)
Intercept	-1.5320	-6.0335*	-1.2409	0.0414	-0.6236	-0.0271
	(0.3524)	(0.0995)	(0.3805)	(0.9826)	(0.7300)	(0.9893)
Bank specification	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	456	72	409	119	337	191
Number of banks	78	42	78	58	75	67
R-Square	0.2219	0.5908	0.1437	0.5259	0.1754	0.3943

Table C.2

Ownership concentration and banks' systemic risk: the effect of crises periods

This table reports the estimation results of a modified version of Eq.(4). We run three regressions separately by including an interaction term of the ownership concentration and crises dummies (OwnershipConcentration *Crisis) for the sample of 79 banks: (1) the financial crisis of 2008-2009; (2) the debt crisis of 2010-212; and (3) the financial and debt crises. The dependent variable is the ΔCoVaR defined as the mean of weekly ΔCoVaRs. Our variable of interest is the OwnershipConcentration defined as the percentage of shares held by the largest controlling shareholder (Concentration1). LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity; d(Bank)-d(Industry) is a set of dummy variables representing the type of the largest controlling shareholder (Widely is the benchmark group); GDPGrowth is the real GDP (Gross Domestic Product) growth rate; Ln(Number of banks) is the natural logarithm of the number of banks in each country; DIS is the deposit insurance schemes index; CAP is the capital stringency index; DIV is the asset diversification index. Crisis dummy is a set of dummy variable to account for each crisis period. Bank specification is a set of dummy variables to account for banks type (commercial banks, investment banks, saving banks, and diversified banking institutions). P-Values (reported in parentheses) are based on robust standard errors. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	(1) Financial crisis	(2) Debt crisis	(3) Financial and debt crises
OwnershipConcentration	-0.0099*	-0.0098*	-0.0092*
	(0.0659)	(0.0625)	(0.0768)
OwnershipConcentration *Crisis	-0.0007	-0.0013	-0.0018
	(0.9297)	(0.6488)	(0.6932)
LnTA	0.1905	0.2543	0.1495
	(0.4726)	(0.3881)	(0.5885)
LnTA2	-0.0133	-0.0156	-0.0106
	(0.3740)	(0.3408)	(0.4875)
EQTA	0.0122	0.0146	0.0131
	(0.3276)	(0.2157)	(0.3238)
ROA	0.0186	0.0228	0.0192
	(0.5824)	(0.4381)	(0.4968)
LOTA	-0.0086	-0.0091	-0.0092
	(0.1547)	(0.1281)	(0.1426)
LLP	-0.0962	-0.0725	-0.0705
	(0.4089)	(0.5149)	(0.5451)
MTB	0.0016	0.0012	0.0010
	(0.1227)	(0.2298)	(0.2993)
d(Bank)	0.2713	0.2535	0.2409
	(0.2932)	(0.3283)	(0.3511)
d(Institutional)	-0.0515	-0.0557	-0.0277
	(0.8960)	(0.8842)	(0.9425)
d(Family)	-0.4217	-0.3564	-0.3820
	(0.3128)	(0.3825)	(0.3614)
d(State)	0.1050	0.0729	0.1394
	(0.8516)	(0.9055)	(0.8136)
d(Industry)	0.2890	0.2893	0.3071
	(0.2539)	(0.2552)	(0.2221)
GDPGrowth	0.0383	0.0835***	0.0480**
	(0.1925)	(0.0029)	(0.0441)
Ln(Number of banks)	-0.0983	-0.0799	-0.0854
	(0.3366)	(0.4119)	(0.3792)
DIS	0.0734	0.0683	0.0542
	(0.1808)	(0.2296)	(0.3160)
CAP	-0.0576	-0.0547	-0.0456
	(0.4331)	(0.4615)	(0.5283)
DIV	-0.0366	-0.0680	-0.0250
	(0.7107)	(0.5272)	(0.7971)

Intercept	-0.9773	-1.4855	-0.7779
	(0.4842)	(0.3142)	(0.5939)
Crisis dummy	Yes	Yes	Yes
Bank specification	Yes	Yes	Yes
Number of observations	528	528	528
Number of banks	79	79	79
R-Square	0.1994	0.1952	0.2127

Table C.3

Ownership concentration and banks' systemic risk: alternative measure of systemic risk contribution

This table reports the estimation results of the model presented in Eq.(4) for the sample of 79 banks over the 2004-2016 period. The dependent variable is the ΔCoVaR defined as the median of weekly ΔCoVaRs calculated as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median. Our variable of interest is the OwnershipConcentration defined as follow: (1) Concentration1 is the percentage of shares held by the largest controlling shareholder, (2) Concentration2 is the sum of ownership percentages held by all controlling shareholders of each bank, (3) d(Concentration1) is a dummy variable equal to one if the Concentration1 variable is more than its median; and zero otherwise, (4) d(Concentration2) is a dummy variable equal to one if the Concentration2 variable is more than its median; and zero otherwise. The four models are performed on the sample of 79 banks of 528 observations. LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity; d(Bank)-d(Industry) is a set of dummy variables representing the type of the largest controlling shareholder (Widely is the benchmark group); GDPGrowth is the real GDP (Gross Domestic Product) growth rate; Ln(Number of banks) is the natural logarithm of the number of banks in each country; DIS is the deposit insurance schemes index; CAP is the capital stringency index; DIV is the asset diversification index. Bank specification is a set of dummy variables to account for banks type (commercial banks, investment banks, saving banks, and diversified banking institutions). P-Values (reported in parentheses) are based on robust standard errors. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	(1) Concentration1	(2) Concentration2	(3) d(Concentration1)	(4) d(Concentration2)
OwnershipConcentration	-0.0082**	-0.0085***	-0.3643**	-0.3880***
	(0.0482)	(0.0077)	(0.0326)	(0.0081)
LnTA	0.1550	0.1344	0.2232	0.1728
	(0.4626)	(0.5144)	(0.3520)	(0.4212)
LnTA2	-0.0093	-0.0080	-0.0124	-0.0099
	(0.4220)	(0.4756)	(0.3426)	(0.4041)
EQTA	0.0121	0.0132	0.0167*	0.0154*
	(0.1923)	(0.1415)	(0.0847)	(0.0992)
ROA	0.0226	0.0211	0.0186	0.0198
	(0.3926)	(0.4256)	(0.4932)	(0.4668)
LOTA	-0.0073	-0.0073	-0.0082	-0.0082
	(0.1396)	(0.1363)	(0.1069)	(0.1085)
LLP	-0.0892	-0.0885	-0.0927	-0.0851
	(0.3205)	(0.3235)	(0.2979)	(0.3393)
MTB	0.0010	0.0010	0.0009	0.0009
	(0.2092)	(0.2068)	(0.2195)	(0.2178)
d(Bank)	0.1501	0.1801	0.0431	0.0612
	(0.4562)	(0.3329)	(0.7953)	(0.7012)
d(Institutional)	-0.0814	0.0043	-0.0476	0.0034
	(0.7816)	(0.9877)	(0.8794)	(0.9912)
d(Family)	-0.3150	-0.2383	-0.2037	-0.1479
	(0.3320)	(0.4553)	(0.4784)	(0.5427)
d(State)	-0.0221	-0.0060	-0.1569	-0.1265
	(0.9649)	(0.9899)	(0.7148)	(0.7655)
d(Industry)	0.2132	0.3309*	0.2182	0.2620
	(0.2521)	(0.0942)	(0.1794)	(0.1032)
GDPGrowth	0.0559***	0.0558***	0.0572***	0.0571***
	(0.0022)	(0.0024)	(0.0018)	(0.0016)
Ln(Numberofbanks)	-0.0929	-0.1043	-0.1286*	-0.1131
	(0.2032)	(0.1360)	(0.0807)	(0.1070)
DISIndex	0.0505	0.0583	0.0691	0.0635
	(0.2484)	(0.1530)	(0.1248)	(0.1647)
Capitalstringency	-0.0678	-0.0710	-0.0625	-0.0688
	(0.2814)	(0.2461)	(0.3297)	(0.2808)
DiversificationIndex	-0.0264	-0.0181	-0.0277	-0.0223
	(0.7537)	(0.8282)	(0.7411)	(0.7910)

Intercept	-0.7740	-0.6741	-1.0048	-0.7921
	(0.5030)	(0.5477)	(0.4112)	(0.4895)
Year dummies	Yes	Yes	Yes	Yes
Bank specification	Yes	Yes	Yes	Yes
Number of observations	528	528	528	528
Number of banks	79	79	79	79
R-Square	0.1997	0.2113	0.1845	0.1932

Table C.4

Ownership concentration and bank systemic risk: impact of the largest shareholder category

This table reports the estimation results of the model presented in Eq.(4) for the sample of 79 banks over the 2004-2016 period. The dependent variable is the ΔCoVaR of each bank defined as the median of weekly ΔCoVaRs calculated as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median. OwnershipConcentration is defined as follow: (1) Concentration1 is the percentage of shares held by the largest controlling shareholder, (2) d(Concentration1) is a dummy variable equals to one if the Concentration1 variable is more than its median; and zero otherwise. LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP is the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity; d(Bank)-d(Industry) is a set of dummy variables representing the type of the largest controlling shareholder (Widely is the benchmark group); GDPGrowth is the real GDP (Gross Domestic Product) growth rate; Ln(Number of banks) is the natural logarithm of the active and inactive banks in each country; DIS is the deposit insurance schemes index; CAP is the capital stringency index; DIV is the asset diversification index. Ownership type is a dummy variable to control banks owners' type; Bank specification is a dummy variable to control banks type (commercial banks, investment banks, saving banks, and diversified banking institutions). P-Values based on robust standard errors are reported in parentheses. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	(1) Concentration1	(2) d(Concentration1)
OwnershipConcentration	-0.0018	1.0156*
	(0.7832)	(0.0995)
OwnershipConcentration *d(Bank)	-0.0112	-1.5066**
	(0.1578)	(0.0351)
OwnershipConcentration *d(Institutional)	-0.0777***	-1.9075**
	(0.0000)	(0.0284)
OwnershipConcentration *d(Family)	0.0225	-0.7669
	(0.4008)	(0.2651)
OwnershipConcentration *d(State)	-0.0072	-1.5024*
	(0.5882)	(0.0589)
OwnershipConcentration *d(Industry)	-0.0016	-1.3004*
	(0.9041)	(0.0646)
LnTA	0.3921*	0.2811
	(0.0510)	(0.2473)
LnTA2	-0.0221**	-0.0151
	(0.0448)	(0.2560)
EQTA	0.0206**	0.0202*
	(0.0310)	(0.0624)
ROA	0.0115	0.0179
	(0.6418)	(0.5093)
LOTA	-0.0107**	-0.0108*
	(0.0415)	(0.0653)
LLP	-0.0773	-0.0844
	(0.3560)	(0.3435)
MTB	0.0012	0.0010
	(0.1176)	(0.1825)
GDPGrowth	0.0513***	0.0574***
	(0.0036)	(0.0015)
Ln(Number of banks)	-0.0596	-0.0947

	(0.2741)	(0.2232)
DIS	0.0683	0.0817*
	(0.1038)	(0.0620)
CAP	-0.0829	-0.0654
	(0.2019)	(0.3162)
DIV	-0.0526	-0.0170
	(0.5509)	(0.8404)
Intercept	-1.7804	-1.3713
	(0.1054)	(0.2772)
Ownership type	Yes	Yes
Year dummies	Yes	Yes
Bank specification	Yes	Yes
Number of observations	528	528
Number of banks	79	79
R-Square	0.3223	0.2131
Wald tests: Bank	-0.0129*	-0.4909**
	(0.0052)	(0.0427)
Institutional	-0.0794***	-0.8918*
	(0.0000)	(0.0538)
Family	0.0207	0. 2487
	(0.4348)	(0.3061)
State	-0.0089	-0. 4867
	(0.4782)	(0.2583)
Industry	-0. 0033	-0. 2847
	(0.7420)	(0.2554)

Table C.5

Ownership concentration and banks' systemic risk at 5%

This table reports the estimation results of the model presented in Eq.(4) for the sample of 79 banks over the 2004-2016 period. The dependent variable is the ΔCoVaR defined as the mean of weekly ΔCoVaRs calculated as the difference between the VaR of the system when the institution is at the 5% percentile and the VaR of the system when the institution is at its median. Our variable of interest is the OwnershipConcentration defined as follow: (1) Concentration1 is the percentage of shares held by the largest controlling shareholder, (2) Concentration2 is the sum of ownership percentages held by all controlling shareholders of each bank, (3) d(Concentration1) is a dummy variable equal to one if the Concentration1 variable is more than its median; and zero otherwise, (4) d(Concentration2) is a dummy variable equal to one if the Concentration2 variable is more than its median; and zero otherwise. LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity; d(Bank)-d(Industry) is a set of dummy variables representing the type of the largest controlling shareholder (Widely is the benchmark group); GDPGrowth is the real GDP (Gross Domestic Product) growth rate; Ln(Number of banks) is the natural logarithm of the number of banks in each country; DIS is the deposit insurance schemes index; CAP is the capital stringency index; DIV is the asset diversification index. Bank specification is a set of dummy variables to account for banks type (commercial banks, investment banks, saving banks, and diversified banking institutions). P-Values (reported in parentheses) are based on robust standard errors. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	(1) Concentration1	(2) Concentration2	(3) d(Concentration1)	(4) d(Concentration2)
OwnershipConcentration	-0.0046*	-0.0041**	-0.1741*	-0.1313
	(0.0502)	(0.0335)	(0.0717)	(0.1230)
LnTA	0.1020	0.0833	0.1284	0.0772
	(0.4270)	(0.5154)	(0.4103)	(0.5747)
LnTA2	-0.0062	-0.0051	-0.0074	-0.0047
	(0.3816)	(0.4715)	(0.3933)	(0.5392)
EQTA	0.0022	0.0029	0.0049	0.0036
	(0.6105)	(0.4792)	(0.2910)	(0.4006)
ROA	0.0291	0.0281	0.0276	0.0302
	(0.1677)	(0.1776)	(0.2007)	(0.1748)
LOTA	-0.0063***	-0.0063***	-0.0066***	-0.0064***
	(0.0042)	(0.0045)	(0.0037)	(0.0048)
LLP	-0.0368	-0.0359	-0.0395	-0.0346
	(0.5285)	(0.5362)	(0.4903)	(0.5538)
MTB	0.0007	0.0007	0.0007	0.0007
	(0.1917)	(0.1954)	(0.2057)	(0.2039)
d(Bank)	0.0959	0.0889	0.0221	0.0059
	(0.3759)	(0.3951)	(0.7982)	(0.9452)
d(Institutional)	-0.2239	-0.1984	-0.2184	-0.2417
	(0.2718)	(0.3135)	(0.3358)	(0.2738)
d(Family)	-0.0830	-0.0514	-0.0279	-0.0454
	(0.6271)	(0.7628)	(0.8463)	(0.7325)
d(State)	-0.0946	-0.1225	-0.2017	-0.2284
	(0.7496)	(0.6667)	(0.4159)	(0.3502)
d(Industry)	0.0610	0.1018	0.0466	0.0277
	(0.5565)	(0.3912)	(0.5883)	(0.7503)
GDPGrowth	0.0467**	0.0469**	0.0479**	0.0477**
	(0.0329)	(0.0330)	(0.0301)	(0.0304)
Ln(Number of banks)	-0.0529	-0.0595	-0.0698	-0.0600
	(0.3236)	(0.2526)	(0.2079)	(0.2653)
DIS	0.0299	0.0333	0.0387	0.0353
	(0.2205)	(0.1628)	(0.1250)	(0.1666)
CAP	-0.0491	-0.0516	-0.0441	-0.0467
	(0.2303)	(0.2013)	(0.3003)	(0.2794)
DIV	-0.0171	-0.0104	-0.0185	-0.0147
	(0.7485)	(0.8430)	(0.7241)	(0.7826)
Intercept	-0.2679	-0.1769	-0.3776	-0.1809
	(0.6338)	(0.7468)	(0.5390)	(0.7481)
Year dummies	Yes	Yes	Yes	Yes
Bank specification	Yes	Yes	Yes	Yes
Number of observations	528	528	528	528
Number of banks	79	79	79	79
R-Square	0.2250	0.2274	0.2128	0.2158

Table C.6

Ownership concentration and bank systemic risk: the effect of control threshold

This table reports the estimation results of the model presented in Eq.(4) for the sample of 79 banks over the 2004-2016 period. The dependent variable is the ΔCoVaR of each bank defined as the mean f weekly ΔCoVaRs. OwnershipConcentration is defined as follow: (1) Concentration1 is the percentage of shares held by the largest controlling shareholder, (2) d(Concentration1) is a dummy variable equals to one if the Concentration1 variable is more than its median; and zero otherwise. We set an ownership control threshold of 20% instead of 10%. LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP is the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity; d(Bank)-d(Industry) is a set of dummy variables representing the type of the largest controlling shareholder (Widely is the benchmark group); GDPGrowth is the real GDP (Gross Domestic Product) growth rate; Ln(Number of banks) is the natural logarithm of the active and inactive banks in each country; DIS is the deposit insurance schemes index; CAP is the capital stringency index; DIV is the asset diversification index. Ownership type is a dummy variable to control banks owners' type; Bank specification is a dummy variable to control banks type (commercial banks, investment banks, saving banks, and diversified banking institutions). P-Values based on robust standard errors are reported in parentheses. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	(1) Concentration1	(2) Concentration2	(3) d(Concentration1)	(4) d(Concentration2)
OwnershipConcentration	-0.0074**	-0.3823**	-0.0183***	-0.2345
	(0.0349)	(0.0290)	(0.0000)	(0.1127)
LnTA	0.1847	0.2371	0.5033	0.1002
	(0.3840)	(0.2965)	(0.1948)	(0.6374)
LnTA2	-0.0109	-0.0136	-0.0269	-0.0063
	(0.3483)	(0.2806)	(0.2316)	(0.5930)
EQTA	0.0123	0.0144	0.0329**	0.0118
	(0.1862)	(0.1176)	(0.0218)	(0.2095)
ROA	0.0219	0.0201	-0.0152	0.0282
	(0.4025)	(0.4393)	(0.6995)	(0.3107)
LOTA	-0.0074	-0.0077	-0.0092	-0.0070
	(0.1377)	(0.1277)	(0.5049)	(0.1487)
LLP	-0.0894	-0.0900	-0.2166*	-0.0836
	(0.3180)	(0.3118)	(0.0542)	(0.3465)
MTB	0.0010	0.0010	0.0007	0.0010
	(0.2022)	(0.1935)	(0.6543)	(0.1895)
d(Bank)	0.0751	0.0517	-0.0436	-0.1458
	(0.6800)	(0.7704)	(0.8609)	(0.3932)
d(Institutional)	-0.1632	-0.1309	-0.8898***	-0.4218
	(0.5724)	(0.6437)	(0.0006)	(0.2611)
d(Family)	-0.3962	-0.2369	-0.7571**	-0.4990
	(0.2329)	(0.4260)	(0.0432)	(0.1756)
d(State)	-0.0900	-0.1610	-0.0620	-0.4549
	(0.8492)	(0.7126)	(0.3279)	(0.2853)
d(Industry)	0.1573	0.2310	-0.0140	-0.0772
	(0.3655)	(0.2001)	(0.9031)	(0.6761)
GDPGrowth	0.0559***	0.0565***	0.0661***	0.0557***
	(0.0021)	(0.0018)	(0.0053)	(0.0019)
Ln(Number of banks)	-0.1025	-0.1310*	0.6107***	-0.1103
	(0.1484)	(0.0629)	(0.0002)	(0.1550)
DIS	0.0530	0.0648	0.3479***	0.0595
	(0.2194)	(0.1452)	(0.0000)	(0.2104)
CAP	-0.0674	-0.0637	-0.1915**	-0.0655
	(0.2858)	(0.3223)	(0.0313)	(0.3159)
DIV	-0.0279	-0.0295	-0.1354	-0.0316
	(0.7417)	(0.7278)	(0.5276)	(0.7117)
Intercept	-0.8536	-1.0063	-5.3946***	-0.3117
	(0.4590)	(0.3960)	(0.0038)	(0.7963)
Year dummies	Yes	Yes	Yes	Yes
Bank specification	Yes	Yes	Yes	Yes
Number of observations	528	528	152	528
Number of banks	79	79	24	79
R-Square	0.2017	0.1949	0.6191	0.1923

Table C.7

Ownership concentration and banks' systemic risk: Country factors effect

This table reports the estimation results of a modified version of Eq.(4) by substituting the regulatory variables with country dummies for the sample of 79 banks over the 2004-2016 period. The dependent variable is the ΔCoVaR defined as the mean of weekly ΔCoVaRs calculated as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median. Our variable of interest is the OwnershipConcentration defined as follow: (1) Concentration1 is the percentage of shares held by the largest controlling shareholder, (2) Concentration2 is the sum of ownership percentages held by all controlling shareholders of each bank, (3) d(Concentration1) is a dummy variable equal to one if the Concentration1 variable is more than its median; and zero otherwise, (4) d(Concentration2) is a dummy variable equal to one if the Concentration2 variable is more than its median; and zero otherwise. LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity; d(Bank)-d(Industry) is a set of dummy variables representing the type of the largest controlling shareholder (Widely is the benchmark group); GDPGrowth is the real GDP (Gross Domestic Product) growth rate; Ln(Number of banks) is the natural logarithm of the number of banks in each country. Bank specification is a set of dummy variables to account for banks type (commercial banks, investment banks, saving banks, and diversified banking institutions). P-Values (reported in parentheses) are based on robust standard errors. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	(1) Concentration1	(2) Concentration2	(3) d(Concentration1)	(4) d(Concentration2)
OwnershipConcentration	-0.0111**	-0.0106***	-0.3937**	-0.4740***
	(0.0199)	(0.0080)	(0.0401)	(0.0034)
LnTA	0.1947	0.1682	0.2434	0.2363
	(0.4819)	(0.5256)	(0.4310)	(0.4136)
LnTA2	-0.0098	-0.0084	-0.0117	-0.0114
	(0.5144)	(0.5599)	(0.4819)	(0.4666)
EQTA	0.0214**	0.0232**	0.0239**	0.0238**
	(0.0332)	(0.0171)	(0.0293)	(0.0219)
ROA	0.0006	-0.0010	-0.0061	-0.0074
	(0.9835)	(0.9725)	(0.8431)	(0.8113)
LOTA	-0.0054	-0.0050	-0.0055	-0.0057
	(0.3781)	(0.4041)	(0.3833)	(0.3629)
LLP	-0.0979	-0.0986	-0.1048	-0.1022
	(0.4267)	(0.4248)	(0.3945)	(0.4076)
MTB	0.0009	0.0008	0.0009	0.0008
	(0.5152)	(0.5461)	(0.5233)	(0.5319)
d(Bank)	0.3568	0.3704	0.1661	0.2142
	(0.2244)	(0.1828)	(0.5469)	(0.4144)
d(Institutional)	0.4666	0.5310*	0.5439*	0.5718*
	(0.1315)	(0.0932)	(0.0990)	(0.0693)
d(Family)	0.1947	0.3232	0.1533	0.3869
	(0.5399)	(0.3478)	(0.6067)	(0.1306)
d(State)	0.6512	0.6142	0.3315	0.3951
	(0.1076)	(0.1046)	(0.3853)	(0.2885)
d(Industry)	0.1803	0.3090	0.1341	0.2491
	(0.4134)	(0.1948)	(0.5182)	(0.2603)
GDPGrowth	0.0391	0.0392	0.0398	0.0398
	(0.2867)	(0.2868)	(0.2773)	(0.2781)
Ln(Number of banks)	-3.1236*	-3.3153**	-3.3089**	-3.1456*
	(0.0839)	(0.0316)	(0.0457)	(0.0561)
Intercept	13.3676	14.4141*	13.9523*	13.2243*
	(0.1304)	(0.0551)	(0.0828)	(0.0981)
Country dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Bank specification	Yes	Yes	Yes	Yes
Number of observations	528	528	528	528
Number of banks	79	79	79	79
R-Square	0.4680	0.4714	0.4595	0.4649

Table C.8

Ownership concentration and bank systemic risk: impact of the largest shareholder category-country factors

This table reports the estimation results of a modified version of Eq.(5) by substituting the regulatory variables with country dummies for the sample of 79 banks over the 2004-2016 period. The dependent variable is the ΔCoVaR of each bank defined as the mean of weekly 1% ΔCoVaRs. OwnershipConcentration is defined as follow: (1) Concentration1 is the percentage of shares held by the largest controlling shareholder, (2) d(Concentration1) is a dummy variable equals to one if the Concentration1 variable is more than its median; and zero otherwise. LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP is the amount of loan loss provisions divided by net loans; MTB is the ratio of the market value of equity to the book value of equity; d(Bank)-d(Industry) is a set of dummy variables representing the type of the largest controlling shareholder (Widely is the benchmark group); GDPGrowth is the real GDP (Gross Domestic Product) growth rate; Ln(Number of banks) is the natural logarithm of the active and inactive banks in each country. Bank specification is a set of dummy variables to account for banks type (commercial banks, investment banks, saving banks, and diversified banking institutions). P-Values based on robust standard errors are reported in parentheses. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	(1) Concentration1	(2) d(Concentration1)
OwnershipConcentration	0.0196***	2.2000***
	(0.0046)	(0.0045)
OwnershipConcentration *d(Bank)	-0.0335***	-3.1875***
	(0.0022)	(0.0006)
OwnershipConcentration *d(Institutional)	-0.0875***	-3.8437***
	(0.0041)	(0.0001)
OwnershipConcentration *d(Family)	0.0163	-2.2122***
	(0.7618)	(0.0022)
OwnershipConcentration *d(State)	-0.0398***	-2.2741***
	(0.0005)	(0.0051)
OwnershipConcentration *d(Industry)	-0.0166	-2.2432***
	(0.1282)	(0.0098)
LnTA	0.2311	0.3284
	(0.4348)	(0.2684)
LnTA2	-0.0135	-0.0183
	(0.4010)	(0.2588)
EQTA	0.0184	0.0236**
	(0.1136)	(0.0319)
ROA	-0.0033	-0.0024
	(0.9118)	(0.9363)
LOTA	-0.0079	-0.0086
	(0.2541)	(0.1933)
LLP	-0.1101	-0.1008
	(0.3702)	(0.4075)
MTB	0.0010	0.0011
	(0.4539)	(0.4048)
GDPGrowth	0.0392	0.0396
	(0.2790)	(0.2747)
Ln(Number of banks)	-2.3557	-2.5259
	(0.1597)	(0.1071)
Intercept	9.7994	10.1355
	(0.2296)	(0.1849)
Ownership type	Yes	Yes
Country dummies	Yes	Yes
Year dummies	Yes	Yes
Bank specification	Yes	Yes
Number of observations	528	528
Number of banks	79	79
R-Square	0.4844	0.4931
Wald tests: Bank	-0.0139**	-0.9875***
	(0.0348)	(0.0079)
Institutional	-0.0679**	-1.6436***
	(0.0144)	(0.0008)
Family	0.0359	-0.0122
	(0.5148)	(0.9869)
State	-0.0202**	-0.0740
	(0.0547)	(0.8292)
Industry	0.0030***	-0.0431
	(0.6779)	(0.8730)

CHAPTER 3

Systemic risk and liquidity creation in European banks: the impact of excess liquidity creation

ABSTRACT

In this paper we test the effect of high liquidity creation on systemic risk in European banks over the 2004-2016 period. Our results show that high liquidity creation is associated with high systemic risk exposure and contribution. Additionally, we found that systemic risk contribution and exposure increase when there was an excessive liquidity creation during the crisis of 2008. Our findings contribute to the literature by suggesting that regulators should pay more attention on high liquidity creators as they may cause an aggregate financial fragility.

JEL Classification: *G21, G28, G32, G33*
Keywords: systemic risk, liquidity creation, illiquidity.

3.1. Introduction

The concept of systemic risk became one of the most important topics in the economic and financial regulatory debates after the recent financial crisis of 2008. This crisis showed how a negative failure in one financial institution in one country can propagate not only to the domestic institutions but also to other countries. Financial institutions, especially banks are the main contributors to systemic risk as they are considered the major players in the financial and economic sectors. Therefore, banks regulators and supervisors are paying attention to analyze and measure the systemic risk. Yet, the literatures of bank specific determinants affecting systemic risk are still burgeoning. Despite the large literature that investigates the factors behind systemic risk, the relationship between systemic risk and liquidity creation is not yet examined. Systemic risk literature mainly focuses on finding measures and estimates to capture the risk (e.g., Huang et al., 2012; Adrian and Brunnermeier, 2016; Acharya et al., 2017; Brownlees and Engle, 2017). Other researches investigate some factors affecting the systemic risk. According to these studies, institutions' size, non-interest income and diversification, competition, corporate governance and regulation are some of the factors that affect the systemic risk (e.g., Brunnermeier et al., 2012; Anginer et al., 2014; Mayordomo et al., 2014; Weiß et al., 2014; De Jonghe et al., 2015; Jamshed et al., 2015; Laeven et al., 2016). However, the literature on systemic risk and liquidity creation is not investigated yet. In this regard, the main motivation of this study is to investigate a bank specific attribute- liquidity creation- that may affect the level of systemic risk.

In fact, to finance their assets, banks must create liquidity. Banks create liquidity by financing illiquid assets (e.g., long-term loans) with liquid liabilities (e.g., short-term deposits). Banks also create liquidity off the balance sheet through loan commitments and other claims (Berger and Bouwman, 2009). Indeed, the more banks create liquidity, the more they are exposed to the risk of being unable to meet unexpected withdrawals from customers (Distinguin et al., 2013). By increasing their liquidity creation, the probability to meet the liabilities decreases making the probability of bank failure increasing (Thakor, 2005; Acharya and Naqvi, 2012; Dell'ariccia et al., 2012). Recently, Berger and Bouwman (2017) argue that high liquidity creation is a good predictor of a future systemic financial crisis. Authors found that liquidity creation has been particularly high before the subprime mortgage crisis in 2007. Another theoretical related research is the study of Acharya and Thakor (2016) who argued that excessive leverage-based liquidity creation may led to a higher probability of inefficient bank liquidation that can give a wrong risk information. More precisely, authors argued that not all creditors of a bank have the same information about the risk; they may receive a wrong message about banks decisions by observing their behaviors. Thus they learn from each other in a noisy way because of the unclear information about idiosyncratic and systematic risks.

The objective of this paper is to extend the literature by empirically examining the effect of the liquidity creation on banks' systemic risk. More precisely, we investigate whether high liquidity creation in the banking sector is positively related to a high systemic risk and we focus on this relationship during the financial crisis of 2008 when the liquidity dried up quickly from the market.

We frame our empirical investigation around two famous hypotheses: *fire sale channel* and *lending channel*. First, banks create liquidity by transforming liquid liabilities into illiquid assets. This transformation makes banks flush with more illiquid assets which decreases their probability to meet their liabilities and cash payments. When facing liquidity problems to meet liquid liabilities, banks will liquidate their assets rapidly at a fire sale to collect some funds. This fire sale generated by a bank' asset liquidation engenders a decline in assets prices not only for this particular bank but also the prices of similar instruments for the banking sector. This fire sale will translated by a decline of the assets prices of other banks that find themselves obliged to liquidate some or the whole of their assets at a low price to avoid additional assets price decline. In this vein, Hull (2012) argued that a liquidity black hole is created when a price decline causes more market participants to sell, thus offers increase and eventually prices decline more.

Bank creditors learn from other banks' liquidation caused by the uncertainty about aggregate and information asymmetry which lead to contagious liquidations of other banks and therefore systemic risk. In this line, Basel Committee on Banking Supervision (2013) outlines that an attempt by a bank to raise liquidity by selling at fire sale prices may destroy not only the confidence in this individual banks, but also add liquidity pressure on other banks holding the similar instruments thus encouraging further fire sales and prices declines. Acharya and Thakor (2016) argue that a systemic risk can be generated from one or several banks' bailout through information spillover about asset-value impairment across banks. They find that one bank's liquidation can lead to contagious liquidations of other banks. This channel of propagation will be referred to as a "*fire sale channel*".

The second theoretical keystone of this study is "*lending channel*". Banks balance sheets are correlated via interbanking loans; the liabilities of one bank (e.g. loans from other banks) may be assets for other banks (e.g. loans to other banks). When banks create a lot of liquidity, they increase the amount of illiquid assets decreasing thus their probability to meet their cash payments to other banks. As liquidity creation increases, banks face difficulties to repay their cash payments and thus liquidate their assets to fund liabilities. The losses of one or several banks from liquidating at fire-sale don't allow them to repay their interbank loans in full (Krause and Giansante, 2012). This leads to losses above equity in one or many lending banks that may be liquidated in ulterior steps. Suppose that some lending banks may have sufficient equity to cover those losses and thus continue to exist but with lower equity than before. However, these banks may be able to cover losses from one bank individually but not from cumulative losses from banks that cannot cover their own losses. In their turn, these banks will be liquidated in a subsequent step.

Additionally, one can argue that banks may not be necessarily liquidated at the same time, but it could be that one bank is liquidated before other banks, and some banks may be able to cover losses arising from the liquidated bank, and continue with a lower equity, therefore if another bank is liquidated would eliminate the remaining equity of other banks and therefore face liquidation is some steps. This phenomenon leads to decrease the trust in the interbank lending market and freezes up the transactions. The joint failure thus impede to further failures in the banking system creating thus a systemic crisis. Thus an increase in liquidity requirements- controlling the liquidity creation- may reduce the impact of interbank shock on the financial sector (Corrado and Schuler, 2017). This propagation channel is referred to as "*lending channel*".

Based on these two theoretical hypotheses, in this article, we empirically investigate the impact of a high liquidity creation on systemic risk. We use a hand collected liquidity dataset of 75 banks in 16 European countries over the 2004-2016 period. We find that systemic risk exposure is highly affected by the liquidity creation and this result is more stronger during the financial crisis. We also found that banks systemic risk contribution increases when the liquidity creation increases during the 2008 crisis.

The remainder of this paper is structured as follows. In Section 2, we describe the sample, define our variables and present the model. In Section 3, we report the sample characteristics and univariate analyses. Section 4 reports the results. Alternative robustness checks are presented in Section 5 and finally Section 6 concludes the paper.

3.2. Sample and empirical method

In this section we describe the sample, define the variables and present the model.

3.2.1. Presentation of the sample

In this study we analyze a sample of 75 publicly traded banks over the 2004-2016 period. In our sample we focus in banks in 16 European banks: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Norway, Netherlands, Portugal, Sweden, Spain, Switzerland and the United Kingdom. In order to collect the data, we use Bloomberg database to gather the accounting and market data required for calculus. First we identify banks in the 16 listed countries for which Bloomberg report daily stock prices for the study period. To enable the systemic risk measures (MES and ΔCoVAR), we restrict our sample to banks with continuously traded stocks. This criterion leaves 134 European banks.

To compute liquidity creation indicator, we use a detailed breakdown of banks' balance sheets. For the 134 banks we then collect data about assets and liabilities to estimate the liquidity creation indicator. Similarly, to enable the liquidity creation indicator calculation, we restrict our sample to banks for which loans are classified by categories and deposits are reported by maturity. Unfortunately, Bloomberg does not report detailed information about banks' balance sheet. We complete the database manually from annual reports and banks websites. The dataset is then an intersection of the available data to calculate the systemic risk measures and the liquidity creation indicator. We winsorize all variables at 1 percent and 99 percent to mitigate the impact of outliers. We end up finally with a sample of 75 banks with 475 bank-year observations (see Tables 1 and 2 for a breakdown by country and year).[1]

[Insert Tables 1 and 2 about here]

3.2.2. Variables definition

This section provides information on the methods we use for estimating banks' systemic risk and banks' liquidity creation indicator and also defines the control variables. In this paper, we investigate the effect of banks' liquidity creation on their systemic risk exposure and contribution. To that end, we first define our dependent variable reflecting banks' systemic risk. Then we define our independent variable of interest (bank liquidity creation). Summary statistics of all variables are reported in Table 3.

3.2.2.1. Measuring banks' systemic risk

In our empirical analysis, we measure the systemic risk using two different measures: bank's systemic risk exposure measured by the marginal expected shortfall (MES) and bank's

[1] The intersection of the ΔCoVaR measure with the liquidity indicator gives us a dataset of 475 observations corresponding to 75 banks, while the intersection of the MES measure with the liquidity indicator gives us a dataset of 412 observations corresponding to 74 banks.

systemic risk contribution measured by the delta conditional value at risk (ΔCoVaR). The dependent variable in our study is bank's systemic risk (exposure and contribution).

Following Acharya et al. (2017), we define a bank's systemic risk exposure by the bank's so called marginal expected shortfall (MES) as the mean return of the bank during times of a market crash. Formally, the MES of bank *i* at time *t* is given by the following formula:

$$\mathrm{MES}_{i,t}(q) = E[R_{i,t} | R_{m,t} < \mathrm{VaR}_{m,t}(q)] \tag{1}$$

In Eq.(1), $R_{i,t}$ denotes the weekly stock return of bank i at time t, $R_{m,t}$ is the return of the market system[2] at time t. $VaR_{m,t}(q)$ denotes the q Value-at-Risk of the market m at time t, which is the maximum value such that the probability of loss that exceed this value equals to q. After calculating the weekly MES we use the mean of the values to estimate the annual systemic risk exposure. Lower values of MES indicate higher systemic risk as we do not use the absolute value of MES to differentiate between profits and losses.

Similarly, we follow Adrian and Brunnermeier (2016) who proposed the delta conditional value at risk (ΔCoVaR) as a measure of bank's risk contribution to the overall risk Formally, the ΔCoVAR of bank *i* at time *t* is given by the following formulas:

$$\mathrm{CoVaR}_{q,t}^{s/i} = \hat{\alpha}_q^{s/i} + \hat{\beta}_q^{s/i} * \mathrm{VaR}_{q,t}^{i} + \hat{\gamma}_q^{s/i} * \mathrm{M}_{t-1} \tag{2}$$

$$\Delta\mathrm{CoVaR}_{q,t}^{s/i} = \mathrm{CoVaR}_{q,t}^{s/i} - \mathrm{CoVaR}_{0.5,t}^{s/i} \tag{3}$$

In Eq.(2) we run a quantile regression of the following variables: $\mathrm{CoVaR}_{q,t}^{s/i}$ is the VaR of the system *s* conditional on the distress situation of the institution *i* (i.e., when it is at its $\mathrm{VaR}_{q,t}^{i}$) at time *t*; $\mathrm{VaR}_{q,t}^{i}$ is the VaR of the institution *i* at time *t;* following the prior literature, for instance Anginer et al. (2014) and Adrian and Brunnermeier (2016), M_{t-1} is a vector of lagged state variables that includes: volatility index (V2X) which captures the implied volatility in the stock market, liquidity spread which is the difference between the three-month repo rate and the three-month bill rate, the change in the three-month bill rate, the change in the slope of the yield curve which is the difference between German ten-year government bond yield and the German three-month Bubill rate, the change in credit spread measured by the spread between ten-year Moody's seasoned BAA-rated corporate bond, and finally the German ten-year government bond and the S&P 500 return index as a proxy for market equity

[2] The system is the set of all banks in the study.

returns.

We then measure the contribution of each bank on the system's risk using the ΔCoVaR defined in Eq.(3) as the difference between the VaR of the system when a particular institution *i* becomes financially stressed (i.e., at the qth percentile) and the VaR of the system when the institution is at its median (i.e., 50% percentile). Similarly, to estimate the annual systemic risk contribution, we compute the mean of the weekly ΔCoVaR of each year. Lower values of ΔCoVaR indicate higher systemic risk contribution.

In this paper, we set q at 5% to test the extreme values of losses of each bank that occur in a distress time for the 2004-2016 period. Setting q at 5% means that $MES_{i,t}(5\%)$ corresponds to the bank i's loss percentage in year t when the market experienced its worst 5% of outcomes. It also allows us to estimate the $\Delta \mathrm{CoVaR}_{\mathrm{q,t}}^{\mathrm{s/i}}(5\%)$ that gives the percentage change in the financial system's 5% VaR when a particular bank realizes its own 5% VaR. For robustness test, we calculate MES and ΔCoVaR by setting q at 1% (see Table 3 for a breakdown of systemic risk measures by country).

[Insert Table 3 about here]

3.2.2.2. Bank liquidity creation

The aim of this article is to test whether banks' liquidity creation affects their systemic risk exposure and contribution. To achieve that, we follow Berger and Bouwman (2009) to measure the liquidity created by banks. In their work, authors introduced the narrow liquidity creation indicator by using on-balance sheet information but also a broader indicator by adding off-balance sheet positions. In this paper we measure the liquidity created by banks from on-balance sheet items only as a detailed breakdown of off-balance sheets is not available in standard databases for European banks.

In order to construct the narrow liquidity creation indicator (LC) based on the on-balance sheet activities, we follow Berger and Bouwman (2009) and proceed a three steps method: first we classify all assets and liabilities into three categories: liquid, semi-liquid or illiquid. This classification of assets and liabilities is based on flexibility and ease banks present to create liquidity, the cost banks pay to provide liquidity to customers and the time banks need to produce liquidity for customers when requested. Another criterion to categorize bank's balance sheet activities is information on either maturity or product category.

According to Berger and Bouwman (2009), some assets can be sold quickly while other assets present some difficulties to be sold. Cash, securities, and other marketable assets are classified as liquid assets because bank can use these items without incurring major losses. Authors also distinguished between residential and customer loans; residential loans are classified as semi-illiquid assets as they can be easily traded in the market, while commercial loans are classified as illiquid assets as they are harder to be traded.

Considering the liability side of the balance sheet, while saving deposits are classified as liquid liabilities as customers can easily withdraw their fund without penalty, time deposits are slightly harder to be withdrawn without cost; they are classified then as semi-liquid. Also long-term liabilities-such as subordinated debt- are classified as illiquid because they generally cannot be withdrawn easily or quickly.

Finally, equity capital belongs to the illiquid liabilities category because, according to Berger and Bouwman (2009), investors cannot demand liquid funds from the bank, they are long term maturity, and finally the equity funds are related to the capital market rather to the bank.

In the second step, we attribute a weight to each item according to their liquidity status: positive (+0.5), negative (-0.5) and neutral (0) weights are assigned respectively to liquid, illiquid and semi-liquid items aforementioned. This weighting means that banks remove illiquid items to create liquid items. In this regard, banks can create maximum liquidity if all illiquid assets are financed by all liquid liabilities. Similarly, banks destroy liquidity if liquid assets are financed by illiquid liabilities (see Table 4 for balance sheet items classification and weights).

In the third step, we combine the first step (items classification) and the second step (items weighting) to construct the liquidity indicator using the following formula:

$$\begin{aligned}\mathrm{LC} = \; & 100 * (0.5 * \text{illiquid assets} + 0 * \text{semiliquid assets} - 0.5 * \text{liquid assets} + 0.5 \\ & * \text{liquid liabilities} + 0 * \text{semiliquid liabilities} - 0.5 * \text{illiquid liabilities}) \\ & / \,\text{Total Assets}\end{aligned} \tag{47}$$

LC denotes the narrow liquidity creation indicator. A positive (+0.5) weight is given to liquid liabilities and illiquid assets, and a negative (-0.5) weight is given to illiquid liabilities and equity capital and liquid assets and a neutral (0) weight is assigned to semi-liquid items. These weights suggest that $1 of liquidity is created when banks transform $1 of illiquid assets into $1 of liquid liabilities. Moreover, when a dollar of liquid liabilities is used to finance one dollar of illiquid assets, one dollar of liquidity is created: +0.5*$1+0*$1+0.5*$1= + $1.

Similarly, when a dollar of illiquid liabilities or equity is used to finance a dollar of liquid asset, one dollar of liquidity is destroyed: $-0.5*\$1-0*\$1-0.5*\$1= -\$1$. The higher the values of LC, the higher the bank illiquidity as banks invest more liquid liabilities into illiquid assets (See Table 4 for a description of the liquidity creation indicator).

[Insert Table 4 about here]

3.2.2.3. Control variables

Following the existing literature on systemic risk, we consider a set of bank-level variables and country-level indicators (X) that are expected to affect banks' systemic risk.

To account for bank size, we include the natural logarithm of bank total assets (LnTA) as well as the square term of LnTA to account for a non-linearity relationship between systemic risk and liquidity creation that may be presented (Anginer et al., 2014). Additionally, size may affect banks' systemic risk exposure and contribution; large banks are able to diversify their activities and thus their risk, but also this diversification may engender several risk (Laeven et al., 2016).

In our regressions we account for bank capitalization using the ratio of equity to total assets (EQTA). Consisting with Brunnermeier et al. (2012), Mayordomo et al. (2014), Jamshed et al. (2015), and Acharya and Thakor (2016), we assume that banks with higher capital ratio are less exposed to systemic risk.

We introduce in our models a bank level profitability indicator using the ratio of net income to total assets (ROA). We expect that banks with higher values of ROA are less exposed to systemic risk (Anginer et al., 2014; De Jonghe et al., 2015). Considering business activities, we include the ratio of net loans to total assets (LOTA) and the ratio of non interest income to total assets (NII). While engaging in non-traditional activities increases the exposure to risk, the effect of non-interest income on systemic risk varies with bank size (De Jonghe et al., 2015). Additionally, we include the ratio of loan loss provisions to total loans (LLP) to capture the effect of credit risk among banks. Higher values of LLP suggest higher credit risk and consequently higher systemic risk.

We also control for banks' growth opportunities using the ratio of market to book (MTB) by dividing the market value of equity by the book value of equity. Higher values of MTB indicate that banks have high franchise value and thus less systemic risk (Anginer et al., 2014). We finally include bank type dummy to control for banks types (commercial, investment and diversified).

As for country level variables, we use the growth rate of the real gross domestic product (GDPGrowth) to control for macroeconomic factors within countries. We also control for banking sector density using the number of banks in each country [Ln(Number of banks)].

[Insert Table 5 about here]

3.2.3. Model specification

The aim of this paper is to empirically investigate whether banks' liquidity creation affects their systemic risk exposure and contribution. To achieve that we run the following regressions:

$$\text{Systemic risk}_{it} = \alpha_1 \mathrm{LC}_{it} + \beta' \mathrm{X} + \beta_0 + \sum_{k=2}^{16} \varphi_k \mathrm{Country}_i^k + \sum_{t=2005}^{2016} \omega_t \mathrm{Year}_i^t + \sum_{s=2}^{3} \gamma_s \mathrm{Type}_i^s + \varepsilon_{it} \tag{5}$$

$$\text{Systemic risk}_{it} = \alpha_1 \mathrm{LC}_{it} + \alpha_2 \mathrm{LC}_{it} * \mathrm{Dcrisis2008} + \alpha_3 \mathrm{Dcrisis2008} + \beta' \mathrm{X} + \beta_0 + \sum_{k=2}^{16} \varphi_k \mathrm{Country}_i^k + \sum_{s=2}^{3} \gamma_s \mathrm{Type}_i^s + \varepsilon_{it} \tag{6}$$

The dependent variable is the systemic risk exposure measure by the MES and the systemic risk contribution measured by ΔCoVaR, LC_{it} is bank i's liquidity creation at time t, X is a vector of control variables defined in Table 5 above, Country and Year denote the country and the year dummies respectively, and finally, Type is a dummy that captures the bank type.

The coefficient α_1 in Eq.(5) measures the effect of the liquidity created by the bank on its systemic risk (exposure and contribution); we run the regressions separately, first using the systemic risk exposure MES and second using the systemic risk contribution ΔCoVaR. Lower values of MES correspond to greater systemic risk exposure; lower values of ΔCoVaR correspond to larger systemic risk contribution; and higher values of LC mean higher banks' liquidity creation thus higher illiquidity. We expect α_1 to be negative, which means that when banks create more liquidity, their exposure and contribution to the systemic risk become more important.

In Eq.(6) we include the Dcrisis2008 which is a dummy variable equal to one if the period is the 2008 crisis and zero otherwise. $LC_{it} * Dcrisis2008$ is the interaction term of the liquidity creation (LC) and the crisis dummy (Dcrisis2008). This interaction allows us to detect the effect of the crisis of 2008 on the relationship between the systemic risk and the liquidity creation. The coefficient α_2 measures the effect of the liquidity creation in the 2008 crisis period on the systemic risk exposure and contribution. We expect a significant negative sign assigned to this coefficient.

3.3. Univariate analysis

In this section we present the results of the univariate mean and quartile tests of banks' liquidity creation and systemic risk. We also analyze the data across sound times and crisis times.

We first analyze the characteristics of sample banks according to the liquidity creation indicator. For that end, we divide the sample into two categories. The first (respectively second) category consists of banks for which liquidity creation is lower (respectively greater) than the median of the liquidity creation.

We proceed the same method using the first quartile (25%), the third quartile (75%) and the 95% quartile to test the extreme values (see Table A.2 in Appendix A).

Panel A of table 6 shows that larger banks create more liquidity than smaller banks. This result is consistent with the findings of Berger and Bouwman (2009, 2017) who argue that small banks and large banks create liquidity in a different way.

As for banks capitalization, we find that higher capitalized banks (higher EQTA) create less liquidity than lower capitalized banks (lower EQTA). Recently, studies who analyze the relationship between banks capital and liquidity creation produce opposing predictions. Our results meet the suggestions of Diamond and Rajan (2000, 2001) who argued that bank capital may block liquidity creation by making the bank's capital structure less fragile. Capital may also reduce liquidity creation because it "crowds out" deposits. This theory is referred to by the "*financial fragility-crowding out*" hypothesis (Berger and Bouwman, 2009). While higher capital is associated with less liquidity creation due to a lower monitoring it may also crowd out deposits and thereby reduce the liquidity creation (Gorton and Winton, 2017).

Additionally, our results show that when banks create more liquidity they increase their provisions (higher LLP). We also find that banks with lower liquidity creation tend to engage in nontraditional activities as their non interest income ratio (NII) is higher than high liquidity creator banks.

Again, consistent with Berger and Bouwman (2009)[3], we find that banks with higher market value [higher market to book (MTB) value] create more liquidity than banks with relatively low MTB ratio. We find these results using the third quartile of the liquidity creation.

Regarding the systemic risk measures, panel B of Table 6 shows that systemic risk exposure is higher for banks with more liquidity creation indicator. This result holds when we use two levels of confidence (1% and 5%). As for the systemic risk contribution, the result is inversed; more systemic risk contribution is associated with lower liquidity creation. However, this result is not significant for the first and third quartile and 95% quartile.

Second we divide the sample period into two sub-periods, normal times and crisis times. Normal times are 2004-2007 and 2010-2016 and crisis times are 2008-2009 which corresponds to the financial subprime crisis. Considering banks liquidity creation, we found no direct significant difference between its value during sound and crisis times. As for financial variables, the results are consistent with the market behavior and show that banks' size, profitability, and growth decrease in that period while credit risk increases. Also, banks decrease their loan loss provisions during the crisis (Panel A of Table 7).

Panel B of Table 7 reports the systemic risk exposure and contribution during the crisis and normal times. Not surprisingly, systemic risk exposure (MES) and systemic risk contribution (ΔCoVAR) of the sample banks were significantly higher (in absolute value) in the crisis time.

[Insert Tables 6 and 7 about here]

3.4. Results and discussion

In this paper we aim to investigate the effect of the liquidity creation on systemic risk exposure and contribution. To that end, we run several panel regressions with random effect specification. This section describes the econometric results of this study.

Table 8 reports the estimation results of equations Eq.(5) and Eq.(6). The dependent variable of the model is the systemic risk. While in models (1) and (2) of Table 8, the dependent variable is systemic risk exposure measured by the marginal expected value

[3] Authors studied the correlation between the liquidity creation and the market-to-book ratio and the price-earnings ratio. They found a positive relationship between liquidity creation and the value of the firm. For more details see Berger and Bouwman (2009).

(MES95), in models (3) and (4) the dependent variable is the systemic risk contribution measured by ΔCoVaR. The independent variable of interest is the liquidity creation (LC). In Models (1) and (3), we test the effect of the liquidity creation on systemic risk exposure and contribution respectively. In Models (2) and (4) we include the interaction term of the liquidity creation indicator and the crisis dummy (DCrisis2008).

In Table 9, we present the results of the regressions of equations Eq.(5) and Eq.(6) by substituting the liquidity creation indicator (LC) with a dummy variable [d(LC)]; d(LC) is a dummy equal to one if the liquidity creation (LC) is higher than its median value and zero otherwise. Similarly, in models (1) and (2), the dependent variable is systemic risk exposure measured by the marginal expected value (MES95), in models (3) and (4) the dependent variable is the systemic risk contribution measured by ΔCoVaR. Models (2) and (4) test the impact of the interaction term of the liquidity creation dummy [d(LC)] and the crisis dummy (DCrisis2008). Tables 8 and 9 also report that the explanatory power of the models, the adjusted R^2, varies from 24% to 44%, suggesting that the independent variables are able to explain a substantial amount of variation in systemic risk measures.

Results show that high liquidity creation is associated with high systemic risk exposure (Column 1 of Table 9). In fact, high liquidity creator banks may not be able to meet their liabilities in case of systemic risk, thus their exposure to this overall risk will be greater than banks with liquidity reserve. While the coefficient associated to the systemic risk exposure was no significant when we use the liquidity creation percentage, the result became significant when we use the liquidity creation dummy [d(LC)]. This finding suggests that liquidity creation may affect systemic risk after a certain percentage threshold. As for the systemic risk contribution, results show that high liquidity creation is associated with lower systemic risk contribution (column 3 of Table 8). However, this results doesn't hold when we use the liquidity dummy [d(LC)] instead of the liquidity creation percentage. This result is consistent with the previous finding suggesting that systemic risk is only affected after a certain threshold percentage.

Models 2-4 of Tables 8 and 9 report results of the modified model presented in Eq.(6). Results show that there is a negative and significant coefficient associated to the interaction terms d(LC)*DCrisis2008. This result suggests that on balance sheet liquidity creation have a stronger and positive effect on the level of systemic risk exposure and contribution during the financial crisis. In other words, our results show that banks that created a lot of liquidity were not only more exposed to the overall risk, but they also contributed more to the systemic risk.

Our results are consistent with the existing literature on fire sales and freezing up of assets during systemic events. When macroeconomic risk increases, depositors tend to save their money in banks as deposits and avoid direct investments as they consider this is safer. This results an excessive banks liquidity which in his turn leads to an excessive lending leading thus to the formation of a bubble. Indeed, during uncertain times, when the deposits flow into banks, banks lower their lending standards and increase their lending. By this behavior, banks' liquidity creation increases. This phenomenon makes the banking sector more fragile due to the asset price bubbles described above.

3.5. Alternative tests

In this section we perform various alternative tests to check the robustness of our results.

First, we estimate our systemic risk measures- the marginal expected shortfall and conditional value at risk- at the 99% level (MES99 and ΔCoVAR99). While this computation reduces the number of observations from 475 to 394 and the number of banks from 75 to 74, the results of the regressions remain unchanged (see Table B.1 in Appendix B).

Small and large banks create liquidity in a different way. To account for banks size, we include the interaction term of the banks' size (LnTA) and the liquidity creation (LC) (see Table B.2 in Appendix B).

In an alternative test, we split the dataset into two subsamples using the median value of the banks of the sample. The first subsample includes small banks (banks whose size is smaller than the median value) and the second subsample consists of large banks (banks whose size is greater than the median value). Nevertheless, our results are unchanged (see Table B.3 in Appendix B). Noting that we do not include the size of banks (LnTA) as an independent variable when we split the sample according to banks' size to avoid the colinearity.

3.6. Conclusion

The purpose of this study is to test the relationship between systemic risk and liquidity creation. To that end we construct a dataset of 75 banks in 16 European countries during the 2004-2016 period. We first estimate the systemic risk using two alternative measures: the marginal expected shortfall (MES) which measures the exposure of each bank to the overall risk, and the Delta conditional value at risk (ΔCoVAR) which measures the contribution of each bank to the overall risk. Second we estimate a liquidity indicator measure from on-balance sheet positions. Finally, to find the relationship between systemic risk and liquidity creation, we run several panel regressions.

The main results show that banks that create a lot of liquidity are more exposed to the overall risk. This result is even stronger in crisis periods. Additionally, we analyze the effect of the liquidity creation on the systemic risk contribution. Our results show that while during normal times, high liquidity creation does not increase the contribution of each bank to the overall risk, it increases those banks' systemic risk contribution during crisis times.

Our findings offer several implications. First, we show that while liquidity creation presents core activities of the banking sector and an important factor for macro-economy, sometimes high liquidity creation may produce financial fragility. Second, we argue that excessive liquidity creation has negative externalities not only on the individual banks level by making them illiquid, but also on the banking system and more generally on the real economy. Finally, our findings suggest that regulators and supervisory authorities should tighten their monitoring activities and pay more attention to high liquidity creators in order to prevent systemic risk and lessen the likelihood of financial crises.

Table 1
Distribution of European banks by country
This table shows the breakdown of the 75 European banks and the number of observations in the final sample for each country.

Country	Number of observations	Number of observations	Percentage of observations
Austria	4	29	6.11
Belgium	2	24	5.05
Denmark	11	60	12.63
Finland	2	20	4.21
France	5	51	10.74
Germany	7	32	6.74
Greece	1	5	1.05
Ireland	1	5	1.05
Italy	9	64	13.47
Netherlands	3	15	3.16
Norway	9	38	8
Portugal	1	4	0.84
Spain	5	47	9.89
Sweden	3	12	2.53
Switzerland	6	21	4.42
United kingdom	6	48	10.11
Total	75	475	100

Table 2
Distribution of observations by year
This table shows the number of observations in the final sample for each year from 2004 to 2016.

Year	Number of observations	Percentage of observations
2004	18	3.79
2005	39	8.21
2006	44	9.26
2007	29	6.11
2008	27	5.68
2009	33	6.95
2010	30	6.32
2011	48	10.11
2012	31	6.53
2013	40	8.42
2014	40	8.42
2015	39	8.21
2016	57	12
Total	475	100

Table 3

Banks' systemic risk by country

This table presents the average of systemic risk exposure as measured by the MES and the systemic risk contribution measured by the ΔCoVaR in each country. MES is the average of weekly marginal expected shortfall calculated at 95% defined as the expected return of the bank when the market is at its $VaR_{95\%}$; ΔCoVaR is mean of weekly ΔCoVaRs defined as the difference between the VaR of the system when the institution is at the 5% percentile and the VaR of the system when the institution is at its median (50% percentile).

Country	MES	ΔCoVaR	MES99
Austria	-2.559	-0.839	-2.542
Belgium	-2.334	-1.573	-2.836
Denmark	-2.838	-1.189	-2.368
Finland	-1.880	-1.243	-3.610
France	-3.391	-0.997	-2.506
Germany	-3.266	-1.410	1.082
Greece	-11.214	-4.208	0.499
Ireland	-5.026	-3.333	-5.534
Italy	-5.892	-1.588	-3.072
Netherlands	-3.712	-1.778	-1.876
Norway	-1.774	-1.195	2.372
Portugal	-0.993	-1.260	-2.560
Spain	-3.505	-1.738	-2.670
Sweden	-2.479	-0.756	-4.122
Switzerland	-4.196	-1.870	-1.008
United kingdom	-2.404	-1.631	-2.542
Number of observations	412	475	394

Table 4
Balance sheet items and weights
This table reports the liquidity level and the weight of each item of the balance sheet used to calculate the liquidity creation indicator.

Balance sheet variables	Description	Liquidity level	Weights to calculate LC
Assets			
Cash and near cash	Cash and assets that can be quickly liquidated into cash (e.g. short term investments and no-risk certificate of deposits)	Liquid	-0.5
Interbank assets	Short term interbank assets	Semiliquid	0
Short-term marketable assets	Financial instruments to be sold or redeemed within a year. They can be easily converted to cash (e.g. government bonds, common stock or certificates of deposit)	Liquid	-0.5
Commercial loans	Loans given to companies	Illiquid	0.5
Consumer loans	Loans to retail clients	Semiliquid	0
Other loans	All other loans	Semiliquid	0
Long-term marketable assets	Assets held for longer than one year	Semiliquid	0
Fixed assets	Assets purchased for long-term use and are not likely to be converted quickly into cash (e.g. land, buildings, equipment)	Illiquid	0.5
Other assets	All other assets	Illiquid	0.5
Customer acceptances	Short-term instrument issued by a company that is guaranteed by a commercial bank	Semiliquid	0
Liabilities			
Demand deposits	Deposits of retail and small business customers that can withdrawn on demand	Liquid	0.5
Saving deposits	Deposits held with banks that pays interest but does not allow for direct withdrawal	Liquid	0.5
Time deposits	Deposits with maturity more than 1 year	Semiliquid	0
Other term deposits	All other deposits	Semiliquid	0
Short-term borrowings	Borrowing for a period less than 1 year	Liquid	0.5
Other-short term liabilities	All other short-term liabilities	Liquid	0.5
Long-term borrowings	Borrowings for a period exceeding 1 year	Semiliquid	0
Other long-term liabilities	All other long-term liabilities	Semiliquid	0
Subordinated debentures	Loans or securities that rank below other loans or securities with regard to claims on assets or earnings	Illiquid	-0.5
Preferred equity and minority interests	Preferred dividends and non-controlling interests	Illiquid	-0.5
Shareholder common capital	Owners claims	Illiquid	-0.5
Retained earnings	Banks' profits	Illiquid	-0.5

Table 5

Variables definition and summary statistics

This table provides the definition and summary statistics for all the variables used in our regressions. The sample consists of 75 European banks during the 2004-2016 period.

Variable name	Definition	Source	Mean	Median	Standard deviation	Minimum	Maximum	Number of observations
MES95	Average of weekly marginal expected shortfall calculated at 95% defined as the expected return of the bank when the market is at its 95 % VaR (%)	Bloomberg	-3.308	-2.162	4.297	-20.731	3.989	412
MES99	Average of weekly marginal expected shortfall calculated at 99% defined as the expected return of the bank when the market is at its 99 % VaR (%)	Bloomberg	-2.677	-1.317	5.090	-19.204	11.295	394
ΔCoVAR	Mean of weekly ΔCoVaRs defined as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median (50% percentile) (%)	Bloomberg	-1.430	-1.171	1.051	-6.547	1.406	475
LC	Total liquidity creation divided by total assets (%)	Bloomberg	45.983	45.526	25.175	-52.606	96.766	475
LnTA	Natural logarithm of total assets (Million of Euros)	Bloomberg	10.162	10.318	2.991	2.966	14.627	475
EQTA	Ratio of total equity to total assets (%)	Bloomberg	8.318	6.620	7.279	0 .862	80.087	475
ROA	Return on assets defined as the ratio of net income to total assets (%)	Bloomberg	0.396	0.503	1.214	-6.930	5.654	475
LOTA	Ratio of net loans to total assets (%)	Bloomberg	58.684	62.383	20.943	0.164	94.517	475
LLP	Loan loss provisions defined as the amount of loan loss provisions divided by net loans (%)	Bloomberg	0.460	0.248	0.670	-0.625	4.632	475
NII	Non-interest income defined the ratio of the non interest income to total assets (%)	Bloomberg	2.804	1.291	6.654	-0.224	68.535	475
MTB	Market to book defined as the ratio of the market value of equity to the book value of equity (%)	Bloomberg	120.400	87.239	99.245	0.451	675.691	475
GDPGrowth	Growth rate of real GDP (Gross Domestic Product) (%)	Bloomberg	1.209	1.500	2.456	-9.100	26.600	475
Ln(Number of banks)	Natural logarithm of the number of banks (with active and inactive trading status) in each country	Bloomberg	4.960	4.905	0.962	2.890	7.163	475

Table 6

Financial characteristics, systemic risk and liquidity creation: univariate analysis

This table compares the financial characteristics of banks with low liquidity creation and banks with high liquidity creation over the 2004-2016 period. Using the median of the total liquidity creation, we classify a bank as low liquidity creator bank (high liquidity creator bank) if its liquidity creation is lower (greater) than the median value. MES95 is the average of daily marginal expected shortfall calculated at 95% defined as the expected return of the bank when the market is at its $VaR_{95\%}$; ΔCoVaR is mean of weekly ΔCoVaRs defined as the difference between the VaR of the system when the institution is at the 5% percentile and the VaR of the system when the institution is at its median; MES99 is the average of daily marginal expected shortfall calculated at 99% defined as the expected return of the bank when the market is at its $VaR_{99\%}$; LnTA is the natural logarithm of total assets; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP is the amount of loan loss provisions divided by net loans; NII is the ratio of non interest income to total assets; MTB is the ratio of the market value of equity to the book value of equity. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

Variable	Low liquidity creator bank [LC < median(LC)]	High liquidity creator bank [LC > median(LC)]	T-statistics
Panel A: General financial characteristics			
LnTA	9.510	10.188	2.557***
EQTA	9.187	8.915	0.318
ROA	0.457	0.290	1.431
LOTA	58.028	60.303	-1.219
LLP	0.373	0.590	-3.413***
NII	3.474	2.531	1.573*
MTB	112.677	122.167	-1.1185
Panel B: Systemic risk			
MES95	-2.915	-3.657	1.814**
ΔCoVaR	-1.563	-1.361	2.095**
MES99	-2.188	-3.156	1.970**

Table 7

Characteristics of sample banks during normal and distress times

This table compares the characteristics of banks during normal times (2004-2007; 2009-2016) and distress period (2008). MES95 is the average of daily marginal expected shortfall calculated at 95% defined as the expected return of the bank when the market is at its $VaR_{95\%}$; ΔCoVaR is mean of weekly ΔCoVaRs defined as the difference between the VaR of the system when the institution is at the 5% percentile and the VaR of the system when the institution is at its median; MES99 is the average of daily marginal expected shortfall calculated at 99% defined as the expected return of the bank when the market is at its $VaR_{99\%}$; LnTA is the natural logarithm of total assets; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP is the amount of loan loss provisions divided by net loans; NII is the ratio of non interest income to total assets; MTB is the ratio of the market value of equity to the book value of equity. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

Variable	Normal Times	Crisis Time	T-statistics
Panel A: liquidity creation and general financial characteristics			
LC	45.894	47.4731	-0.315
LnTA	10.297	9.226	2.665***
EQTA	9.124	7.701	0.798
ROA	0.435	0.127	1.837**
LOTA	58.5055	60.451	-0.726
LLP	0.46166	0.4423	-2.681***
NII	2.876	2.3286	0.5951
MTB	124.393	93.336	2.273**
Panel B: Systemic risk			
ΔCoVaR	-1.394	-2.350	4.836***
MES95	-3.062	-7.234	4.926 ***
MES99	-2.578	-4.908	2.238**

Table 8

Liquidity creation indicator and banks' systemic risk

This table reports the estimation results of the model presented in Eq.(5) and Eq.(6) over the 2004-2016 period. The dependent variable is the systemic risk measure. In models (1) and (2) the dependent variable is the systemic risk exposure MES95 which is the marginal expected shortfall calculated at 95% defined as the expected return of the bank when the market is at its VaR_{95}. In models (3) and (4) the dependent variable is the systemic risk ΔCoVaR defined as the mean of weekly ΔCoVaRs calculated as the difference between the VaR of the system when the institution is at the 5% percentile and the VaR of the system when the institution is at its median. Our variable of interest is the liquidity creation defined in Eq.(4). Models (1) and (2) are performed on the sample of 74 banks of 412 observations. Models (3) and (4) are performed on the sample of 75 banks of 475 observations. DCrisis is a dummy equal to one if the period is the 2007-2008 and zero otherwise. LC*DCrisis is the interaction term of LC and DCrisis. LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP the amount of loan loss provisions divided by net loans; NII is the ratio of non-interest income on total assets; MTB is the ratio of the market value of equity to the book value of equity. Bank type is a set of dummy variables to account for banks type (commercial banks, investment or diversified banking institutions). P-Values (reported in parentheses) are based on robust standard errors. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	(1) MES95	(2) MES95	(3) ΔCoVAR	(4) ΔCoVAR
LC	-0.0121	-0.0109	0.0061**	0.0063**
	(0.2561)	(0.3356)	(0.0268)	(0.0194)
LC*DCrisis		-0.0621**		-0.0094**
		(0.0128)		(0.0457)
DCrisis		0.6212		-0.5366**
		(0.6320)		(0.0264)
LnTA	-0.1382	-0.4306	0.2357	0.2103
	(0.8820)	(0.6361)	(0.3394)	(0.3489)
LnTA2	0.0022	0.0074	-0.0123	-0.0129
	(0.9657)	(0.8843)	(0.3530)	(0.3057)
ROA	0.0840	0.0974	-0.0195	-0.0133
	(0.5305)	(0.5174)	(0.6357)	(0.7580)
LOTA	-0.0008	-0.0016	-0.0014	-0.0026
	(0.9678)	(0.9253)	(0.7887)	(0.6153)
LLP	-0.1880	-0.0557	-0.0812	-0.0785
	(0.6377)	(0.9083)	(0.4833)	(0.4560)
NII	-0.0250	-0.0961**	0.0215*	0.0091
	(0.6346)	(0.0122)	(0.0577)	(0.3650)
MTB	-0.0040	0.0029	0.0000	0.0015
	(0.3177)	(0.4383)	(0.9992)	(0.2512)
GDPGrowth	0.2930	0.3182	0.0048	0.0303*
	(0.2277)	(0.1494)	(0.8689)	(0.0752)
Ln(Number of banks)	-2.2149	-8.5208	-2.8992*	-4.1596**
	(0.7943)	(0.3202)	(0.0910)	(0.0138)
Intercept	11.6926	40.3696	11.9435	17.5663**
	(0.7713)	(0.3204)	(0.1452)	(0.0281)
Country dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	No	Yes	No
Bank type	Yes	Yes	Yes	Yes
Number of observations	412	412	475	475
Number of Banks	74	74	75	75
R-Square	0.3353	0.2409	0.4130	0.3570

Table 9

Liquidity creation dummy and banks' systemic risk

This table reports the estimation results of the model presented in Eq.(5) and Eq.(6) over the 2004-2016 period. The dependent variable is the systemic risk measure. In models (1) and (2) the dependent variable is the systemic risk exposure MES95 which is the marginal expected shortfall calculated at 95% defined as the expected return of the bank when the market is at its VaR_{95}. In models (3) and (4) the dependent variable is the systemic risk ΔCoVaR defined as the mean of weekly ΔCoVaRs calculated as the difference between the VaR of the system when the institution is at the 5% percentile and the VaR of the system when the institution is at its median. Our variable of interest is the liquidity creation dummy defined as follows: d(LC) is a dummy equals to one if the liquidity creation (LC) is greater than the median value and zero otherwise. Models (1) and (2) are performed on the sample of 74 banks of 412 observations. Models (3) and (4) are performed on the sample of 75 banks of 475 observations. DCrisis is a dummy equal to one if the period is the 2007-2008 and zero otherwise. LC*DCrisis is the interaction term of LC and DCrisis. LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP the amount of loan loss provisions divided by net loans; NII is the ratio of non-interest income on total assets; MTB is the ratio of the market value of equity to the book value of equity. Bank type is a set of dummy variables to account for banks type (commercial banks, investment or diversified banking institutions). P-Values (reported in parentheses) are based on robust standard errors. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	(1) MES95	(2) MES95	(3) ΔCoVAR	(4) ΔCoVAR
d(LC)	-0.7663*	-0.5767	0.1654	0.2059
	(0.0840)	(0.2114)	(0.2002)	(0.1214)
d(LC)*DCrisis		-3.4427**		-0.6194**
		(0.0170)		(0.0392)
DCrisis		-0.0265		-0.3796
		(0.9821)		(0.1144)
LnTA	-0.0752	-0.4312	-0.0172	-0.0557
	(0.9212)	(0.5562)	(0.9385)	(0.7776)
LnTA2	-0.0040	0.0059	0.0002	0.0011
	(0.9245)	(0.8918)	(0.9861)	(0.9232)
ROA	0.0120	0.0537	0.0096	0.0175
	(0.9448)	(0.7555)	(0.7519)	(0.5573)
LOTA	0.0005	0.0003	-0.0037	-0.0041
	(0.9763)	(0.9867)	(0.4676)	(0.3814)
LLP	-0.3804	-0.1284	-0.1262	-0.0985
	(0.4111)	(0.7886)	(0.2768)	(0.3439)
NII	0.0127	-0.0593	0.0065	-0.0033
	(0.8181)	(0.1620)	(0.5639)	(0.7295)
MTB	-0.0035	0.0031	0.0007	0.0016
	(0.3823)	(0.4083)	(0.6181)	(0.1626)
GDPGrowth	0.2904	0.2959	0.0373	0.0493*
	(0.2288)	(0.1618)	(0.2954)	(0.0563)
Ln(Number of banks)	-3.2264	-9.1694	-3.4168**	-4.1963***
	(0.6999)	(0.2792)	(0.0320)	(0.0068)
Intercept	15.6029	43.2336	15.6441**	19.2259***
	(0.6945)	(0.2837)	(0.0409)	(0.0092)
Country dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	No	Yes	No
Bank type	Yes	Yes	Yes	Yes
Number of observations	412	412	475	475
Number of Banks	74	74	75	75
R-Square	0.3415	0.2456	0.4423	0.4030

Appendix A

Table A.1
Correlations table

This table shows the correlations among the explanatory variables used in the regressions. LC is the total liquidity creation divided by total assets; LnTA is the natural logarithm of total assets; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP is the amount of loan loss provisions divided by net loans; NII is the ratio of non interest income to total assets; MTB is the ratio of the market value of equity to the book value of equity; GDPGrowth is the real GDP (Gross Domestic Product) growth rate; Ln(Number of banks) is the natural logarithm of the number of banks (with active and inactive trading status) in each country.

	LC (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LnTA (2)	0.192	1							
EQTA (3)	-0.393	-0.494	1						
ROA (4)	-0.091	-0.033	0.111	1					
LOTA (5)	0.084	-0.219	-0.214	-0.005	1				
LLP (6)	0.132	-0.099	0.020	-0.465	0.221	1			
NII (7)	-0.295	-0.361	0.748	-0.054	-0.441	-0.014	1		
MTB (8)	0.084	-0.138	0.133	0.171	-0.246	-0.219	0.422	1	
Ln(Number of banks) (9)	0.075	0.014	0.165	-0.120	-0.349	0.003	0.326	0.240	1
GDPGrowth (10)	-0.041	0.048	-0.020	0.113	0.0421	-0.234	0.024	0.214	-0.012

Table A.2

Financial characteristics, systemic risk and liquidity creation: univariate analysis according to quartiles

This table compares the financial characteristics of banks with low liquidity creation and banks with high liquidity creation over the 2004-2016 period. Using first, third and fourth quartile liquidity creation (Q_1, Q_3, Q_4) we classify a bank as low liquidity creator bank (high liquidity creator bank) if its liquidity creation is lower (greater) than the quartile value. MES95 is the average of daily marginal expected shortfall calculated at 95% defined as the expected return of the bank when the market is at its $VaR_{95\%}$; ΔCoVaR is mean of weekly ΔCoVaRs defined as the difference between the VaR of the system when the institution is at the 5% percentile and the VaR of the system when the institution is at its median; MES99 is the average of daily marginal expected shortfall calculated at 99% defined as the expected return of the bank when the market is at its $VaR_{99\%}$; LnTA is the natural logarithm of total assets; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP is the amount of loan loss provisions divided by net loans; NII is the ratio of non interest income to total assets; MTB is the ratio of the market value of equity to the book value of equity. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	Q_1			Q_3			Q_4		
Variable	Low liquidity creator bank [LC < Q_1(LC)]	High liquidity creator bank [LC > Q_1(LC)]	T-statistics	Low liquidity creator bank [LC < Q_1(LC)]	High liquidity creator bank [LC > Q_3(LC)]	T-statistics	Low liquidity creator bank [LC <Q_4(LC)]	High liquidity creator bank [LC > Q_4(LC)]	T-statistics
Panel A: General financial characteristics									
LnTA	9.0915	10.520	-4.7111***	10.211	10.0156	0.6285	10.169	10.0240	0.2323
EQTA	11.671	7.203	6.0005***	8.5366	7.6747	1.1143	8.4243	6.3212	1.351
ROA	0.5986	0.3287	2.1038**	0.4112	0.3513	0.4639	0.4002	0.3200	0.3083
LOTA	58.305	58.801	-0.2228	58.094	60.441	-1.054	59.0672	51.009	1.8025*
LLP	0.3476	0.4983	2.126**	0.4436	0.51168	-0.9540	0.4483	0.7013	-1.7669*
NII	5.5213	1.9001	5.277***	2.943	2.395	0.7751	2.768	3.577	-0.568
MTB	117.873	121.338	-0.329	114.842	137.4978	-2.156**	116.671	195.117	-3.7447***
Panel B: Systemic risk									
MES99	-1.775	-2.980	2.0457**	-1.775	-2.980	2.0457**	-2.4598	-6.5449	3.6333**
ΔCoVaR	-1.458	-1.4205	-0.3428	-1.458	-1.4205	-0.3428	-1.4329	-1.373	-0.263
MES95	-2.643	-3.5438	1.8671**	-2.643	-3.5438	1.8671**	-3.178	-6.025	2.9400***

Appendix B

Table B.1

Liquidity creation indicator and banks' systemic risk at 1% risk level

This table reports the estimation results of the model presented in Eq.(5) and Eq.(6) over the 2004-2016 period. The dependent variable is the systemic risk measure. In models (1) and (2) the dependent variable is the systemic risk exposure MES99 which is the marginal expected shortfall calculated at 99% defined as the expected return of the bank when the market is at its VaR_{99}. In models (3) and (4) the dependent variable is the systemic risk ΔCoVaR defined as the mean of weekly ΔCoVaRs calculated as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median. Our variable of interest is the liquidity creation defined in Eq.(4). Models (1) and (2) are performed on the sample of 74 banks of 412 observations. Models (3) and (4) are performed on the sample of 75 banks of 475 observations. DCrisis is a dummy equal to one if the period is the 2007-2008 and zero otherwise. LC*DCrisis is the interaction term of LC and DCrisis. LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP the amount of loan loss provisions divided by net loans; NII is the ratio of non-interest income on total assets; MTB is the ratio of the market value of equity to the book value of equity. Bank type is a set of dummy variables to account for banks type (commercial banks, investment or diversified banking institutions). P-Values (reported in parentheses) are based on robust standard errors. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	(1) MES99	(2) MES99	(3) ΔCoVAR99	(4) ΔCoVAR99
LC	0.0016	-0.0015	0.0067*	0.0056
	(0.8902)	(0.9117)	(0.0559)	(0.1629)
LC*DCrisis		-0.0567*		-0.0138*
		(0.0948)		(0.0821)
DCrisis		1.6065		-2.1724***
		(0.2687)		(0.0000)
LnTA	-0.7543	-0.9184	0.0592	-0.3111
	(0.4182)	(0.3927)	(0.8337)	(0.3918)
LnTA2	0.0471	0.0454	-0.0040	0.0071
	(0.3634)	(0.4444)	(0.7911)	(0.7250)
ROA	0.1066	0.0880	-0.0421	0.0010
	(0.5412)	(0.6182)	(0.3167)	(0.9888)
LOTA	0.0403*	0.0464**	0.0003	-0.0012
	(0.0535)	(0.0422)	(0.9644)	(0.8854)
LLP	-0.7382	-0.5395	-0.3040***	-0.1770
	(0.1465)	(0.4013)	(0.0057)	(0.1705)
NII	0.0703	-0.0461	0.0070	-0.0409
	(0.2640)	(0.5343)	(0.7505)	(0.1045)
MTB	0.0009	0.0090**	-0.0007	0.0042**
	(0.7811)	(0.0250)	(0.4259)	(0.0123)
GDPGrowth	0.0044	0.1402	-0.0371	0.0095
	(0.9864)	(0.6210)	(0.3550)	(0.8412)
Ln(Number of banks)	0.5963	-5.6849	-0.8300	-4.1736**
	(0.9412)	(0.4702)	(0.6821)	(0.0457)
Intercept	-3.4326	23.6634	0.4342	16.4120*
	(0.9264)	(0.5208)	(0.9641)	(0.0939)
Country dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	No	Yes	No
Bank type	Yes	Yes	Yes	Yes
Number of observations	394	394	475	475
Number of Banks	73	73	75	75
R-Square	0.3320	0.1431	0.6349	0.3724

Table B.2

Liquidity creation indicator and banks' systemic risk: the impact of bank's size

This table reports the estimation results of the model presented in Eq.(5) over the 2004-2016 period. The dependent variable is the systemic risk measure. In model (1) the dependent variable is the systemic risk exposure MES95 which is the marginal expected shortfall calculated at 95% defined as the expected return of the bank when the market is at its VaR_{95}. In models (2) the dependent variable is the systemic risk ΔCoVaR defined as the mean of weekly ΔCoVaRs calculated as the difference between the VaR of the system when the institution is at the 5% percentile and the VaR of the system when the institution is at its median. Our variable of interest is the liquidity creation defined in Eq.(4). Models (1) and (2) are performed on the sample of 74 banks. LC*LnTA is the interaction term of LC and LnTA; LnTA is the natural logarithm of total assets; LnTA2 is the squared term of LnTA; EQTA is the ratio of total equity to total assets; ROA is the ratio of net income to total assets; LOTA is the ratio of net loans to total assets; LLP the amount of loan loss provisions divided by net loans; NII is the ratio of non-interest income on total assets; MTB is the ratio of the market value of equity to the book value of equity. Bank type is a set of dummy variables to account for banks type (commercial banks, investment or diversified banking institutions). P-Values (reported in parentheses) are based on robust standard errors. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	(1) MES95	(2) ΔCoVAR
LC	-0.0011	-0.0107
	(0.9759)	(0.2076)
LC*LnTA	-0.0020	0.0020*
	(0.6308)	(0.0968)
LnTA	-0.6646	0.1574
	(0.5315)	(0.4824)
LnTA2	0.0363	-0.0130
	(0.5379)	(0.2990)
ROA	0.1178	-0.0291
	(0.4598)	(0.4595)
LOTA	0.0127	-0.0021
	(0.5209)	(0.6880)
LLP	-0.5356	-0.0922
	(0.4861)	(0.4008)
NII	-0.0515	0.0176
	(0.3885)	(0.1102)
MTB	-0.0024	-0.0001
	(0.5582)	(0.9682)
GDPGrowth	0.5367	0.0055
	(0.1966)	(0.8483)
Ln(Number of banks)	-1.7270	-2.9388*
	(0.8031)	(0.0855)
Intercept	9.3937	12.9052
	(0.7734)	(0.1110)
Country dummies	Yes	Yes
Year dummies	Yes	Yes
Bank type	Yes	Yes
Number of observations	412	475
Number of Banks	74	75
R-Square	0.3186	0.4221

Table B.3

Liquidity creation indicator and banks' systemic risk: the impact of bank's size

This table reports the estimation results of the model presented in Eq.(5) and Eq.(6) over the 2004-2016 period. In models (1), (2), (5) and (6) the dependent variable is the MES95. In models (3), (4), (7) and (8) the dependent variable is the 5% ΔCoVaR. D(Size) is a dummy equal to one if the bank's size is greater that its median value and zero otherwise. DCrisis is a dummy equal to one if the period is the 2007-2008 and zero otherwise. LC*DCrisis is the interaction term of LC and DCrisis. All control variables are already defined in Table 5. Bank type is a set of dummy variables to account for banks type. P-Values (reported in parentheses) are based on robust standard errors. ***, ** and * indicate significance respectively at 1%, 5% and 10%.

	D(size)=0				D(Size)=1			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MES95	MES95	ΔCoVAR	ΔCoVAR	MES95	MES95	ΔCoVAR	ΔCoVAR
LC	-0.0140	-0.0168	-0.0003	0.0006	-0.0005	0.0005	0.0128	0.0143*
	(0.2970)	(0.2536)	(0.8706)	(0.7505)	(0.9827)	(0.9820)	(0.1006)	(0.0683)
LC*DCrisis		-0.0772***		-0.0054*		0.0365		-0.0151*
		(0.0081)		(0.0921)		(0.6857)		(0.0937)
DCrisis		2.1352		-0.2215		0.3285		-0.8540*
		(0.2020)		(0.3744)		(0.9247)		(0.0748)
ROA	0.1158	0.0070	-0.0182	-0.0237	-0.9716	-0.1432	-0.0037	-0.0447
	(0.4510)	(0.9613)	(0.6291)	(0.6006)	(0.3247)	(0.8862)	(0.9846)	(0.7940)
LOTA	-0.0043	-0.0062	-0.0028	-0.0038	-0.0445	-0.0663	-0.0125	-0.0157
	(0.8737)	(0.8295)	(0.7022)	(0.5697)	(0.3658)	(0.2117)	(0.2563)	(0.2120)
LLP	-0.1040	-0.0218	-0.1182*	-0.1286**	-2.8951	-1.5682	-0.0773	-0.0363
	(0.8896)	(0.9801)	(0.0715)	(0.0392)	(0.1050)	(0.3386)	(0.8198)	(0.9055)
NII	0.0396	-0.0113	0.0164	0.0145	2.1181**	2.4574**	0.3747***	0.3761***
	(0.3650)	(0.6138)	(0.1218)	(0.2286)	(0.0409)	(0.0154)	(0.0009)	(0.0006)
MTB	-0.0076	-0.0040	0.0007	0.0008	-0.0151	0.0004	-0.0001	0.0026
	(0.2003)	(0.3649)	(0.5289)	(0.3939)	(0.1757)	(0.9752)	(0.9727)	(0.2262)
GDPGrowth	0.8511*	0.5950	-0.0098	0.0163	0.1507	0.3797	0.0383	0.0284
	(0.0694)	(0.1904)	(0.8215)	(0.5613)	(0.7258)	(0.3934)	(0.2598)	(0.1350)
Ln(Number of banks)	7.3939***	2.8329	-4.1458***	-4.0279***	-22.4579	-30.0258**	-3.3570**	-4.3726***
	(0.0054)	(0.4571)	(0.0018)	(0.0033)	(0.1756)	(0.0343)	(0.0195)	(0.0023)
Intercept	-36.8707***	-17.1354	18.6747***	17.8655***	109.4006	138.6245**	15.2359**	19.2230***
	(0.0030)	(0.3346)	(0.0019)	(0.0042)	(0.1585)	(0.0393)	(0.0268)	(0.0067)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	No	Yes	No	Yes	No	Yes	No
Bank Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	202	202	216	216	210	210	259	259
Number of Banks	39	39	40	40	39	39	39	39
R-Square	0.5318	0.4277	0.5940	0.5635	0.2671	0.1848	0.4965	0.4553

CHAPTER 4

Forecasting systemic risk in European banking sector: a machine learning approach

ABSTRACT

The aim of this article is to forecast the systemic risk contribution and exposure measured by the Delta conditional value at risk (ΔCoVaR) and the marginal expected shortfall (MES) respectively. We first estimate ΔCoVaR and MES for banks in 16 European countries for 2002-2016 period. We then predict systemic risk measures using machine learning techniques such as artificial neural network (ANN) and support vector machine (SVM) and using AR-GARCH specification. Finally we compare the methods' forecasting values and the actual values. Our results show that two hidden layers artificial neural networks perform efficiently in forecasting systemic risk.

JEL Classification: *C02, C53, G21, G32*

Keywords: European banking, systemic risk, artificial neural network, support vector machine.

4.1. Introduction

Last financial crises, especially the 2008-2009 crisis, have demonstrated that the stability of banking sectors is an important key to maintain the overall financial stability. Therefore, the prediction of failure of financial firms, especially banks, as they are key drivers and major players in any economic system, has been an extensively researched area for many economists, statisticians and mathematicians. A variety of statistical and econometric models were developed to track banks' failures. And because the major threat of the banking sector is the systemic risk and the contagion effect, many researches were made to measure, estimate and model the systemic risk and its determinants. However, predicting systemic risk in the banking sector, despite its importance not only at the individual banking institution level, but also at the overall level, is rarely implemented.

During the last decade, several researches have been implemented to estimate systemic risk (e.g., Acharya et al., 2017; Brownlees and Engle, 2012; Girardi and Tolga Ergün, 2013; Huang et al., 2012). One famous systemic risk measure is the conditional value at risk (CoVaR) developed by Adrian and Brunnermeier (2016). Unlike the value at risk (VaR) that measures the risk of a firm in isolation, the CoVaR measures the risk of a financial firm(s) conditioning on the financial distress of other institution(s) or of the overall distress of the system. Authors also proposed the Delta CoVaR (ΔCoVaR) that measures the contribution of each institution to the systemic risk. Besides measuring firms' systemic risk contribution, Acharya et al. (2017) measure the exposure of each bank to the overall systemic risk using the marginal expected shortfall (MES). In this paper we consider these two measures as risk proxies to capture the contribution and the exposure of each bank to the systemic risk.

The objective of this article is threefold. We first aim to measure the systemic risk contribution and exposure of European banks using the ΔCoVaR and the MES respectively from 2002 to 2016. Second, in order to account for any nonlinearity and unobservable characteristics of systemic risk time series, we aim to forecast the systemic risk using Artificial Neural Networks (ANNs) and Support Vector Machine (SVM), two of the most used learning machines methods recently and using generalized autoregressive conditional heteroscedasticity (GARCH), to consider the volatility clustering phenomenon. Finally we test the methods' adequacy by comparing the forecasting output and the actual estimated values.

Artificial neural networks (ANNs), initially developed by McCulloch and Pitts (1943)[1], are

[1] McCulloch and Pitts (1943) proposed the first notion of the simple neuron model.

quantitative models belonging to the field of artificial intelligence and are based on the human brain structure in order to imitate its behavior. The motivation behind ANNs was to create artificial systems able to do difficult and complicated computations analogous to those performed by the human brain, such as patterns recognitions.[2] ANNs are data processing techniques that are capable of detecting, learning and predicting complex relations between quantities by repeatedly presenting examples of the relationship to the network.

In recent years, neural networks have been successfully used for modeling financial time series. Neural network are data-driven[3], non-parametric models and they are specialized by their capability to learn complex systems with incomplete and corrupted data. In addition, they are flexible and have the ability to learn dynamic systems through a retraining process using new patterns of the data. These characteristics make the ANN more powerful to describe the financial time series rather than the traditional statistical models (Tay and Cao, 2001).

Another learning machines method belonging to the artificial intelligence area is the Support vector machines (SVMs) introduced by Vapnik (1995). SVMs are developed to resolve classification problems, but they are recently used as a regression tool.

The main idea of an SVM algorithm is to build a model that can assign new examples to one of two categories based on a set of training examples. In an SVM model, examples are represented as points in space in a way that points belonging to different categories are separated by a clear gap. This separation maps then the new examples into this space in their corresponding categories. When using SVM to estimate the regression, three distinct characteristics are satisfied. First, the regression is estimated using a set of linear functions defined in a high dimensional space.[4] Second, in SVMs, the regression estimation is established by minimizing the risk measure by the loss function. Thirdly, the risk function used by SVMs consists of the empirical error and the regularization term derived from structural risk minimization principle (Tay and Cao, 2001).

The last prediction method used in this study to model time series is the generalized autoregressive conditional heteroskedasticity (GARCH) process developed by Engle in 1982 as an econometric tool to estimate volatility in financial markets. The main idea behind the

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[2] Pattern recognition is classifying data based on knowledge already gained or using statistical information extracted from patterns.

[3] Data-driven modeling refers to the fact that the underlying relationship among measured data is estimated by the model itself rather than using a priori information about the data behavior.

[4] High-dimensional space occurs when modeling datasets is done with many attributes. In this case, the dataset may be represented by its coordinates in this space defined by these attributes.

GARCH specification is that observations, especially in finance, don't conform always to a linear pattern. Instead, they tend to cluster in irregular patterns having high error variation. GARCH models were introduced to deal with volatility variation among observations.

To our best knowledge, there is no article focused on forecasting systemic risk and comparing the effectiveness of these three algorithms we reviewed. In this study, we adopt this point of view by predicting the systemic risk contribution measured by the ΔCoVaR and the systemic risk exposure measured by the MES for European banking sector composed of 134 banks in 16 European countries from 2002 to 2016. We also focus on comparing the performance of the three models namely, BPNN, SVM, and AR-GARCH in predicting systemic risk of European banking sector.

Our results show that neural networks outperform the support vector machine regression and the GARCH specification in predicting systemic risk for our sample. Moreover we show that the two hidden layers neural network was more adequate than one hidden layer neural network. Our results contribute to the existing debate about predicting systemic risk by presenting an efficient tool to prevent, perhaps, or at least lessen, some systemic risk consequences.

This paper is organized as follows. Section 2 presents the methodology. In Section 3 we describe the sample and detailed the prediction elaboration. The results are discussed in Section 4. Finally, Section 5 concludes the paper.

4.2. Methodology

In this section, we present the details of measuring and forecasting systemic risk. Our methodology involves three steps. In the first step we estimate the systemic risk contribution by calculating VaR, CoVaR and ΔCoVaR using quantile regressions using a set of financial, market and state factors as explaining variables. We also estimate the systemic risk exposure using the marginal expected shortfall (MES). The second step is concerned with systemic risk forecasting. We use the results we obtain in the first step (i.e., ΔCoVaR and MES) to implement two artificial neural networks, a support vector machine regression and an AR-GARCH(1,1) specification model. Finally, in the last step, we estimate the accuracy of the forecasting methods by comparing the predicted values with the actual values.

4.2.1. Step 1: Measuring systemic risk

In this paper, we aim to forecast the systemic risk contribution and exposure of European banking sector. To measure systemic risk contribution of banks, we use the delta conditional value at risk (ΔCoVaR) proposed by Adrian and Brunnermeier (2016). Whereas we use the marginal expected shortfall (MES) proposed by Acharya et al. (2017) to estimate the exposure of each bank to the systemic risk.

We first estimate the system's conditional value at risk (CoVaR) which is the value at risk (VaR) of the system if a particular institution is under financial distress.[5] Following Adrian and Brunnermeier (2016), we collect the accounting variables and market data used in the following quantile regression equations:

$$\begin{cases} R_t^i = \alpha_q^i + \gamma_q^i * M_{t-1} + \varepsilon_{q,t}^i \\ R_t^{s|i} = \alpha_q^{s|i} + \beta_q^{s|i} * R_t^i + \gamma_q^{s|i} * M_{t-1} + \varepsilon_{q,t}^{s|i} \end{cases} \tag{1}$$

where R_t^i is the return of the bank *i* at time *t* defined as $\ln(\frac{P_t^i}{P_{t-1}^i})$ where P_t^i is the price of the stock *i* at time *t*; M_{t-1} is a vector of lagged state variables that includes: volatility index (V2X) which captures the implied volatility in the stock market, liquidity spread which is the difference between the three-month repo rate and the three-month bill rate, the change in the three-month bill rate, the change in the slope of the yield curve which is the difference between German ten-year government bond yield and the German three-month Bubill rate, the change in credit spread measured by the spread between ten-year Moody's seasoned BAA-rated corporate bond, and finally the German ten-year government bond and the S&P 500 return index as a proxy for market equity returns (Anginer et al., 2014; Adrian and Brunnermeier, 2016); $R_t^{s|i}$ is the return of the system *s* conditional on the return of the bank *i* at time *t*; and ε_t^i and $\varepsilon_{q,t}^{s|i}$ are the error terms.

We then use the predicted values from regression in Eq.(1) to obtain:

$$\begin{cases} VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^{s|i} * M_{t-1} \\ CoVaR_{q,t}^{s|i} = \hat{\alpha}_q^{s|i} + \hat{\beta}_q^{s|i} * VaR_{q,t}^i + \hat{\gamma}_q^{s|i} * M_{t-1} \end{cases} \tag{8}$$

[5] The financial system, in our analysis, is the set of all banks in the sample

where $\mathrm{VaR}^{i}_{q,t}$ is the VaR[6] of the institution *i* at time *t*; and $\mathrm{CoVaR}^{s|i}_{q,t}$ is the VaR of the system *s* conditional on the distress situation of the institution *i* (i.e., when it is at its $\mathrm{VaR}^{i}_{q,t}$) at time *t*.

Finally the contribution of each bank to the system's risk is obtained using the ΔCoVaR as follows:

$$\Delta\mathrm{CoVaR}^{s|i}_{q,t} = \mathrm{CoVaR}^{s|i}_{q,t} - \mathrm{CoVaR}^{s|i}_{0.5,t} \tag{3}$$

Eq.(3) points that the contribution of each bank to the systemic risk is the difference between the system's VaR when the bank *i* is at its q^{th} percentile and the VaR of the system when the bank *i* is at its median (i.e., normal situation). We compute ΔCoVaR at q=1% for each bank of the sample from 2002 to 2016.

Next, following Acharya et al. (2017), we measure bank's systemic risk exposure by the its marginal expected shortfall (MES) which is the mean return of the bank during times of a market crash. Formally, the MES of bank *i* at time *t* is given by the following formula:

$$\mathrm{MES}_{i,t}(q) = \mathrm{E}[\mathrm{R}_{i,t} | \mathrm{R}_{m,t} < \mathrm{VaR}_{m,t}(q)] \tag{4}$$

where $\mathrm{R}_{i,t}$ denotes the weekly stock return of bank *i* at time *t*, $\mathrm{R}_{m,t}$ is the return of the market system[7] at time *t*. $VaR_{m,t}(q)$ denotes the *q*-value-at-risk of the market *m* at time *t*, which is the maximum value such that the probability of loss that exceed this value equals to *q*. In other words, in Eq.(4), we take the *q*% worst days for the market returns in each given year, and we then compute the average return on each bank for these days.

4.2.2. Step 2: Forecasting systemic risk

After estimating systemic risk in the first step, in this paragraph we present the methods used to forecast the systemic risk contribution and exposure of each bank of the sample using artificial neural network, support vector machine regressions- two machine learning methods- and AR-GARCH specification- a volatility clustering tool. Further details about methods implementation are provided thereafter in Section 3.2.

[6] VaR is the maximum loss over a fixed time horizon at a certain level of confidence.
[7] The system is the set of all banks in the study.

4.2.2.1. Artificial neural network (ANN)

Neural networks are universal functions approximates that can map any non-linear function without a priori assumptions about the properties of the data (Haykin, 1994).[8] They learn from examples using a training set; in other words, the network is capable to connect inputs with outputs through estimated parameters, creating thus some sort of generalization beyond the training data. Networks are distinguished by their architectures, level of complexity[9], number of layers[10], presence of feedback loops[11], and the activation or transfer function.

Formally speaking, a neural network is a connection of elementary objects: inputs $(x_1, \dots, x_n)$, weights[12] $(w_1, \dots, w_n)$, $w_i \in [0,1]$ associated to each input, activation function f used to limit the output of the neuron, the combiner[13] and the final output[14] obtained after the application of such an activation function. The final output y is obtained by the following formula:

$$y = f(b + \sum_{i=1}^{n} w_i x_i) \tag{5}$$

where, in this paper, x_i are systemic risk values (i.e., ΔCoVaR and MES) calculated in the first step; f is the activation function; n is the number of observations in the training dataset; w_i are the weights associated to the nodes; and b is an external bias. We split our data into three parts: 70% for training, 15% for validation and 15% for testing. The first subset, the training data, consists of the estimated values of the ΔCoVaR and MES used to train the network and to fit the parameters of the classifier. The second subset, the validation data, used to tune the parameters of the classifier and to find the optimal number of hidden units or determine a stopping point for the back-propagation algorithm. The third subset, the test dataset, used to assess the performance of a fully-trained classifier, to estimate the error rate to calculate the level of accuracy. Choosing the number of hidden layers in a multilayer network is not an easy subject. While Lee et al. (2005) and Zhang et al. (1999) argue that constructing

[8] Traditional statistical techniques usually estimate the model's parameters after defining the structures of the model a priori, while using intelligent techniques, the structure of the model is learned directly from the data (Wang et al., 2014).

[9] The complexity theory of neural networks can be separated into learning complexity that determine the work needed to learn and performance or neural complexity which precise the number of neurons needed to implement a good approximation (Kon and Plaskota, 2003).

[10] A neural network consists of three levels of interconnected layers: input, hidden that may include more than one layer, and output.

[11] While in a feedback (or recurrent or interactive) networks, the signals travel in all directions by introducing loops in the network, in a feed-forward network, signals travel one way only: for inputs to output.

[12] Weights values are estimated in the learning process.

[13] The combiner is a linear combiner that adds the weighted inputs of the neuron. This model also includes an external bias (b) that is used to minimize or increase the net input of the activation function.

[14] Usually, the normalized output ranges between 0 and 1, or -1 and 1.

a network with one hidden layer may resolve most of the classification problems, Vasu and Ravi (2011) show that networks with two hidden layers ensure the complexity of networks architectures.

In our study, we implement a network composed of both one and two hidden layers to ensure the sufficiency of the complexity of the banking sector and examine which one performs better. Further details about the method are provided in Appendix A.

4.2.2.2. Support Vector Machine Regression (SVM)

The basic idea of support vector machine is constructing a separating hyper-plane with high level of accuracy.

Let $x_i = (x^1, \ldots, x^p)$ set of inputs and y_i the corresponding target values where i=1,…,n, and n is the size of the training set. Our goal is to find a function $f(x)$ that estimates the relation between the inputs and the target value.

The input vector in our study is systemic risk values: the contribution and the exposure of each bank to the systemic risk for the entire period. Regression uses a loss function $L(y, f(x))$ that shows how the estimated function f deviates from the true values y.[15]

While most of the traditional neural networks seek to minimize the training error[16] to obtain the optimal solution, the key idea behind SVM is to minimize the upper bound of the generalization error.[17] This induction principle is based on the fact that the generalization error is bounded by the sum of the training error and a confidence interval term. Another characteristic of SVMs is the using of a linearly constrained quadratic programming. This leads to a unique, optimal solution absent from local minima of SVMs, unlike other networks' trainings that require non-linear optimization thus running the danger of getting stuck in local minima.

In most of the cases, it is difficult to find a linear function that fits the model, hence the necessity of a non-linear SVM algorithm. In our study we use the Vapnick's loss function. Further details about the method are provided in Appendix B.

[15] There are many forms of loss functions: linear, quadric loss function, exponential, etc.

[16] Training error is the error obtained after running the trained model back on the training data that has already been used to train the model.

[17] The generalization error, also known as the out-of-sample error, measures how the algorithm is able to accurately predict outcome values for previously unseen data.

4.2.2.3. Auto-regressive-generalized autoregressive conditional heteroscedasticity (AR-ARCH)

The financial field, the most uncertain part of any event is the future fluctuations usually manifested by the volatility. ARCH/GARCH[18] models are used as a volatility clustering tool.

The main intuition behind fitting an ARMA in the equation of GARCH is to deal with the problem of serial correlation in the residuals.[19] In this section we describe the forecasting method to predict the systemic risk measures (ΔCoVaR and MES) using AR(1)-GARCH(1,1).

The general GARCH process involves three steps. In the first step, an autoregressive model is fitted. In the second step, the autocorrelations among the error terms are computed. And finally the third is for testing significance.

First to test the inputs, we examine the dependencies among the conditional mean and variance in the inputs (ΔCoVaR and MES in our study). The input values (ΔCoVaR and MES) are modeled using AR(1)-GARCH(1,1) specification described by the following equations:

$$X_t^i = \mu_t^i + \varepsilon_{j,t} \tag{6}$$

where X_t^i is the systemic risk of bank *i* at time *t*, $\mu_t^i = \alpha_0 + \alpha_1 X_{t-1}^i$ is the conditional mean of bank *i* at time *t*; the error term $\varepsilon_{i,t} = z_{i,t}\,\sigma_{i,t}$ where $z_{i,t}$ is i.d.d.[20] with zero mean and unit variance; $\sigma_{i,t}$ is the conditional standard deviation of bank *i* at time *t*; the conditional variance has the standard GARCH(1,1) specification:

$$\sigma_{i,t}^2 = \beta_0^i + \beta_1^i\,\varepsilon_{i,t-1}^2 + \beta_2^i\,\sigma_{t-1}^2 \tag{7}$$

We then obtain the inputs modeled as an AR(1)-GARCH(1,1) structure as function of their corresponding volatilities using the following equation:

$$X_t^i = \alpha_0 + \alpha_1\,X_{t-1}^i + z_{i,t}\sqrt{\beta_0^i + \beta_1^i\,\varepsilon_{i,t-1}^2 + \beta_2^i\,\sigma_{t-1}^2} \tag{8}$$

[18] ARCH: autoregressive conditional heteroskedasticity; GARCH: generalized autoregressive conditional heteroskedasticity.
[19] Once the serial correlation removing is confirmed by adding the required ARMA terms, GARCH can be applied to model the conditional volatility.
[20] The variables $z_{i,t}$ are independent and identically distributed.

4.2.3. Step 3: Methods performance and accuracy

After measuring systemic risk contribution and exposure and predicting their values for the last 12 months using ANN, SVM, and AR-GARCH, the performance of the forecasting methods needs to be evaluated using specific accuracy metrics. These metrics reflects the validity of the model, and are useful to compare the performance of the methods for each bank.

The most used metrics are the percentage error measures as they are easy to interpret. The commonly used metric of this type is the mean absolute percentage error (MAPE) defined as following:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - F_i|}{y_i} \times 100 \tag{9}$$

where n is the number of points or observations for each bank; y_i are the forecasted values of systemic risk (contribution and exposure) of bank *i*; and F_i are the actual values of systemic risk measures estimated using ΔCoVaR and MES. The formula in Eq.(9) requests a non-null values of the denominator y_i (ΔCoVaR and MES in our study), therefore we apply an adjusted MAPE (A-MAPE) proposed by Hoover (2006). The A-MAPE is expressed by the following formula:

$$A - MAPE = \frac{\frac{1}{n}\sum_{i=1}^{n}|y_i - F_i|}{\frac{1}{n}\sum_{i=1}^{n}|y_i|} \times 100 = \frac{\sum_{i=1}^{n}|y_i - F_i|}{\sum_{i=1}^{n}|y_i|} \times 100 \tag{10}$$

4.3. Data, results and discussion

In this section we describe the data used to measure the systemic risk, we also present the details of forecasting implementation.

4.3.1. Data description

In our analysis, we focus on publicly listed banks in 16 Western European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and United Kingdom. Our data spans the 2002-2016 period. We retrieve the weekly prices of sample banks' stocks to estimate systemic risk measures in Bloomberg database.

First we identify information about 290 banks for the time period and countries for which the Bloomberg database provides stock prices. Then we eliminate banks with discontinuously traded stocks for the sake of systemic risk calculus. We also eliminate banks with extreme values and outliers. We end up with a final sample of 134 banks corresponding to 744 weekly stocks' prices for each bank.[21] Our sample includes commercial banks, diversified banks and investment banking institutions. Considering the state variables used to estimate banks' systemic risk contributions, we also use Bloomberg terminal to collect the values raging form 2002 to 2016 for each country. Table 1 reports a breakdown of the sample by country and type.

[Insert Table 1 about here]

4.3.2. Elaboration of forecast

Forecasts are implemented for all 134 banks of the sample, using artificial neural networks, support vector machine and autoregressive conditional heteroscedasticity. This section reports the details of these forecasting methods and how we apply them on our sample.

In this work, we measure and forecast systemic risk values of European banks. Each bank has 744 weekly values of systemic risk ranging from January 2002 to December 2016. We first estimate the weekly systemic risk values for all banks during the whole period. For forecast, we use the values ranging from 2002 to 2015 to predict those of 2016 and compare them with the actual values.

First, two neural networks are constructed to test the performance of prediction and choose the convenient architecture. The first network consists of 4 input nodes, one hidden layer of 2 nodes and one output node. The second network is constructed with 4 inputs nodes, two hidden layers of 2 hidden nodes each and one output node.

Let the time series $\{S_i\}_{1\leq i\leq 774}$ denoting the time series of systemic risk value. We use four previous periods to predict the value of next period. More precisely, we consider $X_i = (S_i, S_{i+1}, S_{i+2}, S_{i+3})$ and $Y_i = S_{i+4}$ for $1 \leq i \leq 770$; that is, the four inputs are the values of systemic risk at the i weeks immediately preceding the target period. For example, to forecast the systemic risk of the first week of February 2002, we use the weekly values of systemic risk of the first, second, third and fourth weeks of January 2002. We then look at (X_i, Y_i) as one couple; i.e., X_i is the input and Y_i is its desired output. In this paper we consider the non-

[21] All banks of our sample have the same number of observations in order to maximize the prediction accuracy.

linear logistic activation function.[22] We use the back-propagation transfer information because of its ability to optimize the output by sending back the information into the network. Note that the inputs and the outputs are weekly basis, which may be effective to capture the monthly risk information.

Second, same as neural network, in the support vector machine, the four previous values of systemic risk are use as predictors. We use the ν-regression which is similar to the ϵ-regression but with specifying an additional parameter ν which allows us to control the number of support vectors. After several attempts to minimize the error rate, we set the cost parameter to 10. We test separately different kernel functions; linear, polynomial, radial basis and sigmoid on both pure and normalized data sets corresponding to each function. The most adequate kernel function is the radial basis function (RBF) with a parameter $\gamma = 0.1$.

Finally, in a basic regression framework, the common formulas used to estimate regression parameters and their corresponding standard errors are the OLSs. However, OLS formulas cannot be used if the error term in the regression is not uncorrelated and homoskedastic.[23] In order to check for any autocorrelations and heteroskedasticity among the residuals, we look at the autocorrelation function (ACF) and the Ljung-Box test. We test the results using the Ljung-Box multiple test statistic under the null hypothesis that assumes no correlation among the first mean lags using the following formula:

$$Q(m) = T(T+2)\sum_{i=1}^{m}\frac{\hat{\rho}_i^2}{T-1} \tag{11}$$

where the null hypothesis H_0: $\rho_1 = \rho_2 = \dots = \rho_m = 0$ assumes that there is no correlations among the first m lags, and $Q(m)$ is $\chi^2(m)$-distributed.

Since our data consists of 134 banks, we do not present the ACF plots and the Ljung-Box results for each bank; ACF's results show that there is an evidence for dependencies in the conditional mean and a much stronger one in the conditional variance and all p-values of the Ljung-Box are lower than 0.05. An autoregressive structure AR(1) is thus implemented after detecting the presence of linear dependence in the residual series. We also test the presence of any correlations in the squared residuals using the AFC. We clearly see volatility clusters in the time series in Figure C.1 in the Appendix C; similarly, since our data consists of 134

[22] The logistic activation function also known by sigmoid function is defined by $f(x) = 1/(1+e^{-x})$; this assumes that the normalized output values belong to [0,1]; we then using an denormalization method to estimate the values of systemic risk.

[23] Homoskedastic means that the variance of the residual, or error term, in a regression model is constant.

banks, presenting the time series plots for each bank is not reasonable, we thus present the time series of the average values which gives us a general idea about values repartitions during time. Results suggests the adoption of a GARCH(1,1) process. Therefore the AR-GARCH(1,1) is used for systemic risk values (ΔCoVaR and MES) ranging from 2002 to 2015 in order to forecast their values for the 12 next months of 2016. [24]

4.4. Results and discussion

In this section, we report the main results on our systemic risk measures, the results obtained after the implementation of the neural networks, the support vector machine, and the AR-GARCH fitting model, and finally we discuss the predictions accuracy and methods performance.

First, we use the weekly[25] stocks returns to calculate the weekly systemic risk contribution and exposure measured by the ΔCoVaR and MES respectively for each bank of the sample. Table 2 reports the summary statistics of the ΔCoVaR and the MES; noting that the descriptive statistic are calculated on yearly basis; the data consists of 134 banks on the 2002-2016 period: 15 years x 134 banks = 2010 observations. The mean of ΔCoVaR is about -2.105 means that, in average, when the bank is at its 1% VaR, it increases the 1%VaR of the system by 2.105% during the 2002-2016 period. The minimum of ΔCoVaR is about -8.427 and the maximum is about 3.675 with a standard deviation of 4.169 pointing that the systemic risk contribution measure in our study is relatively dispersed. As for the systemic risk exposure, the average of the MES is about -2.771% meaning that, in average, the loss of each bank during the 2002-2016 period is about 2.771% when the system experiences its worst 1% times.

Table 3 lists the average of systemic risk contribution and exposure for each year. Results show that systemic risk contribution was higher in crises periods; ΔCoVaR was around -2.7% in 2002 (the introduction of the Euro as the single currency of the European Union), around

-2.6% during the 2007-2009 period (the financial subprime crisis), around -2.3% during the 2010-2011 period (the European sovereign debt crisis) and in 2016 (the Greek government-debt crisis). Similarly, the systemic risk exposure, MES, reaches its maximum value,

-6.892%, during the 2008 year (the subprime financial crisis). MES was also relatively high

[24] We use the Akaike information criterion (AIC=2 k-2 Ln(L); where k is the number of estimated parameters and L is the maximum likelihood function) to choose the best model parameters.

[25] We transform daily stock prices to weekly data using the average of daily prices of each week for each bank.

(-5.792%) during the European debt crisis of 2011.

Table 4 reports the average of the systemic risk contribution and exposure for each country. Results show that systemic risk contribution and exposure were relatively high in countries like Greece and Ireland.

[Insert Tables 2, 3 and 4 about here]

After estimating the systemic risk measures using the ΔCoVaR and MES for all banks of the sample for the 2002-2016 period, we split the observations into three sets; from January 2002 to June 2012 (70% of the data for training) for training and the implementing the networks, from July 2012 to August 2014 (15% of the data for validation) to validate the model, and from September 2014 to December 2016 (15% of the data for testing) to test the accuracy of the artificial neural network and the support vector.

Table 5 compares the mean values of ΔCoVaR and MES predicted using the one and two hidden layers ANNs, the SVM and the AR-GARCH(1,1) with the estimated values of ΔCoVaR and MES calculated using the quantile regression and Eq.(4) respectively.

To estimate the accuracy of each method, we estimate the adjusted error of the methods using the A-MAPE defined in Eq.(9). Table 5 reports the forecasted values of the two systemic risk measures for the last 12 months of the sample period: from January 2016 to December 2016. As mentioned before, the actual values of the systemic risk contribution (ΔCoVaR) and exposure (MES) of the 2016 year are not included in the architectures of the neural networks (with one and two hidden layers) nor in the support vector machine or GARCH specification in order to test the efficiency of these methods in forecasting their values.

Panel A of table 5 reports the results of the systemic risk contribution. Results show that the artificial neural network doesn't perform in the same way using one and two hidden layers. While the adjusted error (A-MAPE) of the value forecasted via one hidden layer is about 82.11%, the two hidden layers neural network performs better with an adjusted error of 11.5%. The support vector machine presents also an effective performance having an error of 10.267% only. While the AR-GARCH(1,1) specification model forecast values with a 57.932% error rate, it may be considered best than the one hidden layer neural network. This result suggests that the neural network architectures may not always capture the volatility among the observations and choosing the number of hidden layers may a real subject in this case.

The forecasting results of the systemic risk exposure are reported in Panel B of Table 5. Results show that, despite the little difference in the error rates, again, the artificial neural network performs better when we use two hidden layers architectures. The error rates were 15.224% and 13.019% for one hidden layer and two layers respectively. In contrast, the support vector machine and the AR-GARCH models fail to efficiently forecast the systemic risk measures of our sample.

Briefly, our results show that the artificial neural networks are effective tools in predicting systemic risk contribution and exposure as their mean error terms were 10.26% and 15.224% and outperform other prediction tools. Our results also show that while support vector machine performs efficiently using the systemic risk contribution values, it mispredicts the values of the marginal expected shortfall.

4.5. Conclusion

This paper proposes an empirical study on the prediction of systemic risk contribution and exposure in banking sector. We proceed a three steps methodology to forecast the systemic risk in European banks. First, we estimate the systemic risk contribution and exposure for 134 banks in 16 European countries during the 2002-2016 period. We use the delta conditional value at risk (ΔCoVaR) and the marginal expected shortfall (MES) to respectively account for systemic risk contribution and exposure. Next, we implement two artificial neural networks (ANN), with one and two hidden layers, a support vector machine (SVM) and an autoregressive conditional heteroscedasticity (GARCH) to forecast the systemic risk for the last 12 months of the sample period. Finally, we test the feasibility of these methods by comparing the actual and the forecasted values of systemic risk and estimate the accuracy level of each method using the adjusted mean absolute percentage error (A-MAPE).

Our results show that artificial neural network with two hidden layers perform effectively in forecasting systemic risk in European banking sector. Its misprediction error varies from a minimum of 10.26% and a maximum of 15.224%. Results also show that support vector machine (SVM) may not always give accurate prediction values. As for the GARCH specification, results show that it performs less than the ANN and SVM methods suggesting that machine learning techniques may be considered as a promising tool for regulators and supervisors to develop early warning of banks' systemic risk.

Table 1
Distribution of European banks by country
This table shows the breakdown of the 134 European banks of the sample and the type of sample's banks.

Country	Number of sample banks
Austria	6
Belgium	5
Denmark	15
Finland	3
France	10
Germany	14
Greece	3
Ireland	2
Italy	13
Netherlands	4
Norway	12
Portugal	2
Spain	6
Sweden	3
Switzerland	11
United Kingdom	25
Total	**134**
Banks type	
Commercial banks	58
Diversified banks	45
Investment banks	31
Total	**134**

Table 2
Systemic risk summary statistics
This table provides the summary statistics for the systemic risk measures used in our study. The sample consists of 134 European banks during the 2002-2016 period.

	ΔCoVaR	MES
	Definition: Mean of weekly ΔCoVaRs defined as the difference between the VaR of the system when the institution is at the 1% percentile and the VaR of the system when the institution is at its median (50% percentile) (%) Source: Bloomberg, own. calc.	Definition: Mean of weekly MESs defined as the return of the institution when the system is at its 1% percentile worst days (%) Source: Bloomberg, own. calc.
Mean	-2.105	-2.771
Median	-1.329	-0.849
Standard deviation	4.169	7.177
Minimum	-8.427	-18.320
Maximum	3.675	11.955
Number of observations	2010	2010

Table 3
Distribution of observations by year
This table shows the average of systemic risk measures, ΔCoVaR and MES for each year from 2002 to 2016.

Year	ΔCoVaR	MES
2002	-2.701	-3.071
2003	-2.320	-1.778
2004	-1.761	-1.393
2005	-1.448	-0.949
2006	-1.537	-1.896
2007	-1.690	-2.932
2008	-2.692	-6.892
2009	-2.452	-3.965
2010	-2.303	-2.858
2011	-2.381	-5.792
2012	-2.152	-1.996
2013	-1.866	-0.979
2014	-1.176	-1.907
2015	-2.079	-2.935
2016	-3.028	-2.235

Table 4
Distribution of observations by country
This table shows the average of systemic risk measures, ΔCoVaR and MES for each country of the sample.

Country	ΔCoVaR	MES
Austria	-1.113	-1.866
Belgium	-2.345	-2.274
Denmark	-1.158	-1.392
Finland	-1.079	-2.167
France	-1.273	-2.461
Germany	-2.299	-2.473
Greece	-4.321	-5.375
Ireland	-3.414	-5.926
Italy	-2.314	-3.530
Netherlands	-1.563	-3.763
Norway	-1.343	-1.485
Portugal	-2.411	-1.041
Spain	-2.276	-2.300
Sweden	-0.934	-3.416
Switzerland	-1.274	-2.279
United Kingdom	-1.992	-2.596

Table 5
Systemic risk forecasting results
This table reports the average of actual and forecasted values of systemic risk contribution (ΔCoVaR) and exposure (MES).

	Panel A: ΔCoVaR					Panel B: MES				
	Actual	ANN		SVM	AR-GARCH	Actual	ANN		SVM	AR-GARCH
Month		1 hidden layer	2 hidden layers				1 hidden layer	2 hidden layers		
January	-2.983	-2.172	-3.142	-2.825	-1.404	-1.367	-1.462	-1.497	-2.210	-1.531
February	-3.713	-2.274	-3.603	-2.859	-1.342	-1.197	-1.118	-1.089	-2.088	-1.618
March	-3.064	-2.145	-3.379	-3.138	-1.318	0.1953	0.095	-0.250	-2.067	-1.650
April	-2.941	-2.152	-3.338	-3.173	-1.308	-1.777	-1.678	-1.543	-2.237	-1.661
May	-2.997	-2.072	-3.328	-3.099	-1.304	-0.216	-0.366	-0.289	-2.154	-1.665
Jun	-3.035	-2.067	-3.173	-2.971	-1.302	-2.917	-2.998	-2.881	-2.269	-1.667
July	-2.346	-2.280	-3.117	-2.957	-1.301	0.820	0.737	0.775	-2.290	-1.652
August	-3.105	-2.165	-3.419	-3.488	-1.300	-5.655	-5.603	-5.813	-2.119	-1.680
September	-2.987	-1.499	-3.379	-3.298	-1.310	-3.972	-3.293	-3.397	-2.277	-1.368
October	-2.983	-2.022	-3.359	-3.233	-1.209	-3.678	-3.529	-3.569	-2.309	-1.599
November	-3.101	-2.060	-3.269	-3.100	-1.023	-6.043	-5.729	-5.570	-2.201	-1.781
December	-3.091	-2.086	-3.118	-2.982	-1.169	-1.013	-0.005	-0.057	-2.456	-1.038
Mean	-3.028	-2.082	-3.300	-3.093	-1.274	-2.235	-2.079	-2.098	-2.223	-1.575
A-MAPE		82.11%	11.504%	10.267%	57.932%		15.224%	13.019%	112.147%	109.563%

Appendix A

In this appendix we report details about the neural network model used in our empirical study.

A.1. Artificial neural network

This paragraph presents the prediction method and the Back-propagation algorithm.

For simplicity, let consider an example of a simple neural network composed of 2 inputs, 1 hidden layer and 1 output represented in figure 1 as follows:

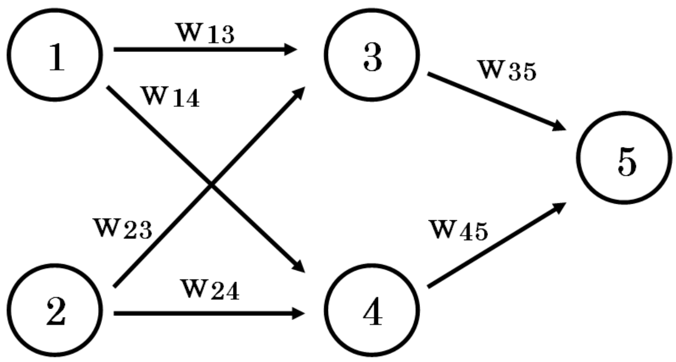

Figure A.1: Neural network composed of 2 inputs (1 and 2), 1 hidden layer (3 and 4) and 1 output (5)

Let n_i, $i = 3, \ldots, 5$, the computed output of each neuron i

x_1 and x_2 are the inputs of the network

w_{ij} the weight connecting neuron i to neuron j

y the expected output

η the learning rate

First, we compute the output of the network n_5

$$n_3 = f(\, x_3\,) = f(\, w_{13}\ x_1 + \ w_{23}\ x_2\,)$$

$$n_4 = f(\, x_4\,) = f(\, w_{14}\ \ x_1 + \ w_{24}\ \ x_2\,)$$

$$n_5 = f(\, x_5\,) = f(\, w_{35}\ \ n_1 + \ w_{45}\ \ x_4\,)$$

Where the activation function f is the logistic function defined as follows:

$$f(x) = \frac{1}{1 + e^{-x}}$$

The error term of neuron 5(n_5) is: $e_5 = y - n_5$

The error signal:

$$\delta_5 = \frac{\partial f(x_5)}{\partial x_5} \cdot e_5 = \ n_5\ (1 - n_5) \cdot (y - n_5)$$

First, we estimate the updated values of w_{35} and w_{45} as follows:

The updated value is $\Delta w_{ij} = \eta\ \delta_j n_i$ and the new weight is $w'_{ij} = \ w_{ij} + \Delta w_{ij}$.

To find the updated value to the other weights, the error signal of the hidden neurons should be calculated, so the error signal δ_5 is propagated back through the layer using the weights (old weights):

$$\delta_3 = w_{35} \cdot \delta_5$$

Then the updated values and the new weights are calculated as described before.

A.2. The resilient Back-Propagation Algorithm

The main idea behind the resilient back-propagation algorithm was to reduce the impact of the partial derivative of the activation function on the weight adjustment. As a result, only the sign of the derivative is taking into account to determine the direction of weight update.

$$\Delta w_{ij}^{(t)} = \begin{cases} -\Delta_{ij}^{(t)} , & if \ \frac{\partial f^{(t)}}{\partial x} > 0 \\ \Delta_{ij}^{(t)} , & if \ \frac{\partial f^{(t)}}{\partial x} < 0 \\ 0 , & else \end{cases}$$

Where

$$\Delta_{ij}^{(t)} = \begin{cases} \eta^{+} \cdot \Delta_{ij}^{(t-1)} , & if \ \frac{\partial f^{(t-1)}}{\partial x} \cdot \frac{\partial f^{(t)}}{\partial x} > 0 \\ \eta^{-} \cdot \Delta_{ij}^{(t-1)} , & if \ \frac{\partial f^{(t-1)}}{\partial x} \cdot \frac{\partial f^{(t)}}{\partial x} < 0 \\ \Delta_{ij}^{(t-1)} , & else \end{cases}$$

where $0 < \eta^{-} < 1 < \eta^{+}$. Each time the partial derivative's sign is changed, indicating that the last update was too big, $\Delta_{ij}^{(t)}$ is decreased by η^{-} to correct this update. When the algorithm starts, it takes an initial value Δ_0 that is chosen according to the initial values of weights.

Appendix B

In this appendix we report details about the support vector machine regression used in our empirical study.

B.1. Support vector machine

This appendix reports the details of the support vector machine used in this study.

The Vapnick's loss function is used in the support vector machine regression (SVM), also known as ϵ- insensitive loss function, is defined as follows:

$$L\big(y, f(x)\big) = \begin{cases} 0 & , \quad \text{if } |y - f(x)| \leq \epsilon \\ |y - f(x)| - \epsilon & , \quad \text{otherwise} \end{cases}$$

where $\epsilon > 0$ is a constant that controls the error. So the aim is to find a function $f(x)$ that has the most ϵ difference from the actual values y, and to be as flat as possible.

If the function is linear, $f(x) = \langle \omega, x \rangle + b$, flatness means $\| \omega \|$ is small.

Where $\langle \cdot,\cdot \rangle$ denotes the dot product in $\mathbb{R}^p$

$\|\cdot\|$ is the Euclidean norm

$\omega \in \mathbb{R}^p$ are the weights

$x \in \mathbb{R}^p$ is the inputs vector

$b \in \mathbb{R}$ is the bias

The optimization problem is summarized as:

$$\text{Minimize} \quad \frac{1}{2}||\omega||^2$$

$$\text{Subject to} \begin{cases} y_i - \langle w, x_i \rangle + b \leq \epsilon \\ \langle w, x_i \rangle + b - y_i \leq \epsilon \end{cases}$$

This assumes the existence of such function f that estimates the relation between $(x_i)_{i=1,\dots,n}$

and y_i with ϵ accuracy. This optimization problem may not always be "feasible", and such function may not always exist.

To deal with this problem, slack variables ζ_i and ζ_i^* are added, to allow for some error or miscalculations. The optimization problem is then defined as follows:

$$\text{minimize} \quad \frac{1}{2}||\omega||^2 + C\sum_{i=1}^{n}(\zeta_i + \zeta_i^*)$$

$$\text{subject to} \begin{cases} y_i - \langle w, x_i\rangle + b \leq \epsilon + \zeta_i \\ \langle w, x_i\rangle + b - y_i \leq \epsilon + \zeta_i \\ \zeta_i \geq 0 \quad , \quad \zeta_i \geq 0 \end{cases}$$

where C is a cost parameter > 0 that includes the trade-off between the flatness of f and the amount up to which deviations larger than ϵ are acceptable.

B.2. Dual Problem and Lagrange Multipliers

The minimization problem shown above is called "the primal function" and is solved by defining a dual set of variables and transforming it to a Lagrange function as follows:

$$L = \frac{1}{2}||\omega||^2 + C\sum_{i=1}^{n}(\zeta_i + \zeta_i^*) - \sum_{i=1}^{n}(\lambda_i \zeta_i + \lambda_i^* \zeta_i^*) - \sum_{i=1}^{n}\alpha_i(\epsilon + \zeta_i - y_i + \langle\omega, x_i\rangle + b)$$
$$- \sum_{i=1}^{n}\alpha_i^*(\epsilon + \zeta_i^* - y_i + \langle\omega, x_i\rangle + b)$$

Where L is the Lagrangian and α_i, α_i^*, λ_i, and λ_i^* are Lagrange multipliers ≥ 0 (dual variables). This function has a saddle point with respect to the dual and primal variables $(\omega, b, \zeta_i, \zeta_i^*)$ at the solution point. Thus:

$$\partial_b L = \textstyle\sum_{i=1}^{n}(\alpha_i^* + \alpha_i) = 0 \quad , \quad \partial_\omega L = \omega - \displaystyle\sum_{i=1}^{n}(\alpha_i^* + \alpha_i)x_i = 0$$

$$\partial_{\zeta_i} L = C - \alpha_i - \lambda_i = 0 \quad , \quad \partial_{\zeta_i^*} L = C - \alpha_i^* - \lambda_i^* = 0$$

We can deduce the dual optimization problem when substituting these equations into the Lagrangian:

$$\text{maximize} \quad -\frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)\langle x_i,y_i\rangle-\epsilon\sum_{i=1}^{n}(\alpha_i+\alpha_i^*)+\sum_{i=1}^{n}y_i(\alpha_i-\alpha_i^*)$$

$$\text{subject to} \quad \begin{cases}\sum_{i}^{n}(\alpha_i-\alpha_i^*)=0\\ \alpha_i,\ \alpha_i^* \in [0,C]\end{cases}$$

The dual variables λ_i and λ_i^* are replaced by $C-\alpha_i$ and $C-\alpha_i^*$.

A proper algorithm introduced by Smola and Schölkopf (1998) is used to solve the previous optimization problem and find the values of α_i and α_i^*.

The saddle point condition allows us to write:

$$\omega\sum_{i}^{n}(\alpha_i-\alpha_i^*)x_i \quad \text{and thus}, \qquad f(x)=\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)\langle x_i,x_i\rangle+b$$

This is called the "support vector expansion", ω is described as a linear combination of the data points. Computing b is based on the Karush-Kuhn-Tucker (KKT) conditions that at the solution point, the product between dual variables and constraint is zero:

$$\alpha_i(\epsilon+\zeta_i-y_i+\langle\omega,x_i\rangle+b)=0 \quad , \quad \alpha_i^*(\epsilon+\zeta_i^*-y_i+\langle\omega,x_i\rangle+b)=0$$

$$(C-\alpha_i)\zeta_i=0 \quad , \quad (C-\alpha_i^*)\zeta_i^*=0$$

In order to satisfy these conditions, $\alpha_i,\alpha_i^*=C$ for all (x_i,y_i) samples that are outside the $\epsilon-$tube, and they are equal to zero for all the samples inside the $\epsilon-$tube ($|f(x_i)-y_i|<\epsilon$).

For $\alpha_i,\alpha_i^* \in]0,C[$, we have $\zeta_i,\zeta_i^*=0$ and thus we can deduce:

$$b=y_i-\langle\omega,x_i\rangle-\epsilon \ \text{ for } \alpha_i \in]0,C[$$

$$b=y_i-\langle\omega,x_i\rangle+\epsilon \ \text{ for } \alpha_i^* \in]0,C[$$

α_i, α_i^* can't be simultaneously non-zero, because that will lead to non-zero slacks in both directions.

A final note, not all data samples are used to describe ω, only the ones that has non-zero value for α_i or α_i^*, therefore we have a sparse expansion of ω in terms of x_i, these samples are called "support vectors".

B.3 Non-Linear Regression

Most of the cases, it is difficult to find a linear function that fits the model, so it is necessary to find a non-linear SVM algorithm. This is done by mapping the inputs in another feature space $\mathcal{F}$ of higher dimension where they are linearly separable using a mapping function $\Phi(x)\colon \mathbb{R}^p \longrightarrow \mathcal{F}$. As noted before, the SVM algorithm only depends on the dot products between data points, hence it is sufficient to define a function $k(x,y) = \langle \Phi(x), \Phi(y) \rangle$ without the need to explicitly find $\Phi(x)$ because it may be too complicated.

This is known as "the Kernel trick". The most used Kernel function is the radial basis function:

$$k(x, y) = \exp(\frac{-\parallel x - y \parallel^2}{2\gamma})$$

The expansion is therefore written as:

$$\omega = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*)\, \Phi(x_i) = \sum_{i=1}^{m} v_i\, \Phi(x_i)$$

$$\text{and} \quad f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) k(x_i, x) + b = \sum_{i=1}^{m} v_i\, k(x_i, x) + b$$

where $v_i = \alpha_i - \alpha_i^*$ when α_i and α_i^* are not simultaneously zero (the sparse expansion).

Appendix C

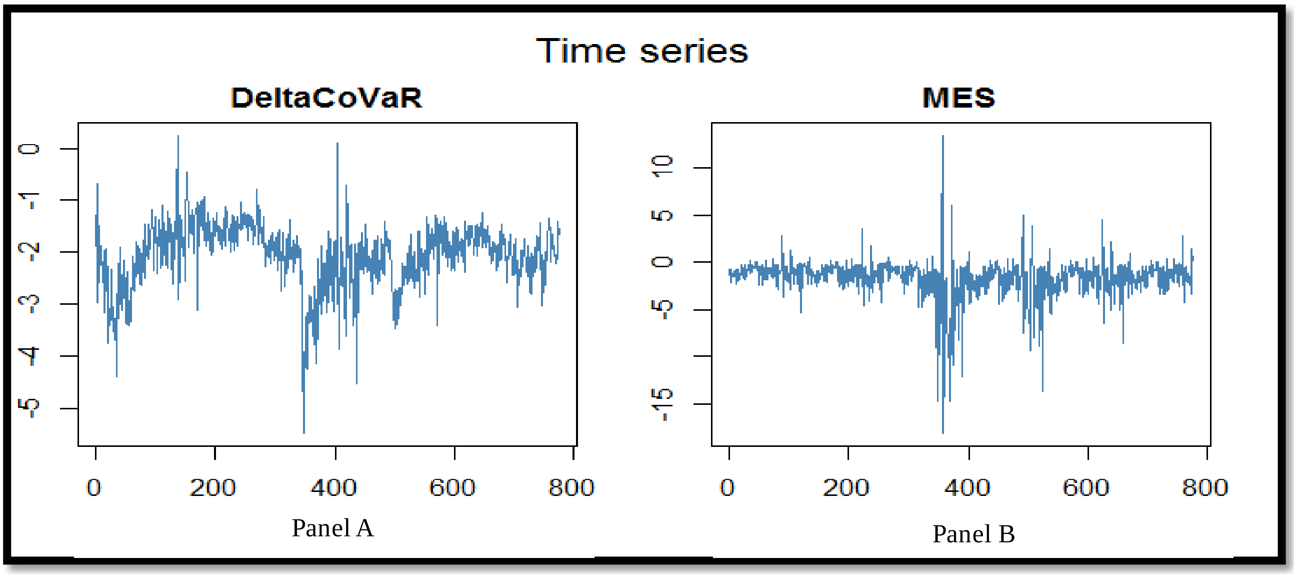

Figure C.1: The times series plot for systemic risk measures. Panel A presents the time series of the average value of ΔCoVaR of 134 banks which is the average of banks' contribution to the systemic risk; Panel B presents the time series of the average value of MES of 134 banks which is the average exposure of banks to the systemic risk; the abscissa axes are the time period ranging from 2002 to 2016; while the ordinate axes are the systemic risk values (ΔCoVaR and MES).

GENERAL CONCLUSION

The past decades have been considerably noticed by a succession of financial crises that demonstrated the instability of the banking sector and its mechanisms. And recently, the global financial crisis of 2007-2008 has renewed the debate on systemic risk and the factors behind it. In addition, financial regulators argued that banks risk taking strategies could be more important at an aggregate level than at individual level. This gives great importance to the analysis of the ownership structure and liquidity creation as determinants of risk-taking behavior and performance design. The aim of this dissertation is to investigate the impact of these two factors, the ownership structure and the liquidity creation, that have been ignored during the past years. Besides testing the effect of these two systemic risk determinants, we present a novel approach to forecast future systemic risk values using artificial intelligence methods.

In the first chapter we recall systemic risk's literature and review its different facets. We began by listing the possible definitions of the systemic risk. Then we presented the empirical and theoretical works that have been elaborated to capture the systemic risk. We also reported authors' findings and recommendations. After that, we reported the relationship between systemic risk and corporate governance and the liquidity creation. We also list the researches related to the application of the network theory on the systemic risk. Finally we show how regulators and supervisory authorities treat the systemic risk subject.

The objective of Chapters 2, 3 and 4 has been to provide empirical support to fill the gap in the literature mentioned in Chapter 1 by applying it to European databases.

While corporate governance constitutes one of the most crucial phenomena in the financial and non-financial sectors, surprisingly yet its impact on the systemic risk is rarely investigated. The first empirical framework of this thesis, Chapter 2, is devoted to this end. More precisely, we investigate the impact of the ownership structure on the systemic risk. We explain a possible existence of a relationship between systemic risk and ownership structure using two principal keystones. First, controlled banks and diversified-owned banks tend to be riskier than widely held banks and non-diversified owned banks. Those risk incentives at the individual level may result in a herding behavior and could directly translate into greater systemic risk of banking institutions. Second, diversified owners are known to have prior experience in loans syndication, securities and insurance underwriting, brokerage and mutual fund activities and, as a consequence, banks may find it easier to invest in different areas and to choose very diversified portfolios. Such a behavior may allow for risk diversification at the individual level but for higher risk correlation at the aggregate level because activity diversification increases the likelihood of overlapping strategies across banks. We thus assume that ownership structure can affect the systemic risk. Using a sample of 79 banks in 16 European countries during the 2004-2016 period, we investigate whether banks' systemic contribution depends on their ownership concentration and test how this effect may vary across different shareholders categories. First, we estimated the systemic risk contribution of sample's banks using the Delta conditional value at risk (ΔCoVaR) which measures the contribution of each bank to the overall risk. Then we define ownership structure indicators that capture the controlling shareholder ownership percentages and types. Finally we establish a link between systemic risk and ownership structure by running panel regressions.

Our results suggest that higher ownership concentration increases the contribution of banks to the systemic risk. This result may be caused by the fact that controlling owners tend to engage banks in highly correlated risks making them more vulnerable. We also found that banks controlled by institutional investors and State are more concerned with this relationship we found. We go deeper in our analysis and test the effect of regulatory variables on the relationship between systemic risk and ownership structure. We investigate the effect of deposit insurance schemes, restrictions on banks activities and asset diversification. Our results show that the relationship we found is even stronger in countries with more deposit insurance schemes, less restrictions on banks activities, and finally higher asset diversification. Our findings address also the regulatory side and the post-crisis debate on systemic fragility.

The third chapter investigates the impact of liquidity creation on banks' systemic risk contribution and exposure. The aim of this chapter is to study the impact of another risk taking factor that may affect the systemic stability. We test the relationship during normal times and distress times to shed light on whether such effect is different according to the soundness of the banking industry. To finance their assets, banks create liquidity by financing illiquid assets with liquid liabilities. Indeed, the more banks create liquidity, the more they are exposed to the risk of being unable to meet unexpected withdrawals from customers increasing thus their probability of failure. Thus banks will liquidate their assets at a fire sale to collect some funds. In his turn, the fire sale engenders a decline in the assets prices not only for this particular bank but also for the banking sector making prices decline. Based on this argument, additionally to the interbanking lending phenomenon, we construct our framework.

To that end we construct a dataset of 75 banks in 16 European countries during the 2004-2016 period. We first estimate the systemic risk using two alternative measures: the marginal expected shortfall (MES) which measures the exposure of each bank to the overall risk, and the Delta conditional value at risk (ΔCoVaR) which measures the contribution of each bank to the overall risk. Second we estimate a liquidity creation indicator measure from on-balance sheet positions. Finally, to find the relationship between systemic risk and liquidity creation, we run several panel regressions.

The results show that banks that create a lot of liquidity are more exposed to the overall risk. This result is even stronger in crisis periods. Moreover, we analyze the effect of the liquidity creation on the systemic risk contribution of banks. Our results show that during normal times, high liquidity creation does not increase the contribution of each bank to the overall risk. However, we found an opposite result during crisis times. Our findings offer several implications. First, we show that while liquidity creation presents core activities of the banking sector and an important factor for macro-economy, sometimes especially during financial crisis, high liquidity creation may reduce the financial stability. Second, we argue that excessive liquidity creation has negative externalities not only on the individual banks level by making them illiquid, but also on the banking system and more generally on the real economy.

After analyzing the impact of both the shareholder structure and the liquidity creation on systemic risk, we tackle a different angle of the subject. In Chapter 4, the third empirical is devoted to forecast the future values of systemic risk using different methods. Two of these methods belong to the artificial intelligence area and the third one belongs to variance clustering and volatility estimating field. The artificial intelligence methods we used are the artificial neural network and the support vector machine. These methods are widely used recently due to their ability of learning data behavior using the data itself without a priori assumptions about the data distribution. In recent years, neural networks and support vector machine have been successfully used for modeling financial time series. However, there are no studies that use these methods to forecast the systemic risk of banking sector using historical time series. This chapter is devoted to this end. Additionally, we estimate the forecasts also using the AR-GARCH specification after detecting the presence of volatility clusters in the values.

To that end, we use a sample of 134 banks in 16 European countries from 2002 to 2016. We first estimate the systemic risk measures using the MES and the ΔCoVaR to respectively account for the exposure and the contribution of each bank to the systemic risk. Then, we construct two neural networks with one and two hidden layers to be able to choose the best architecture. We also run a support vector machine regression and establish an AR-GARCH(1,1) specification. By applying these three methods on the dataset raging from 2002 to 2015, we forecast systemic risk values for the 12 months of 2016. Finally we compared the performance of the three models in predicting systemic risk of European banking sector. Our results show that artificial neural network with two hidden layers effectively outperforms the rest of the methods in forecasting systemic risk in European banking sector. Its misprediction error varies from a minimum of 10.26% and a maximum of 15.224% which is relatively low and effective. Results also show that support vector machine (SVM) may not always give accurate prediction values. As for the GARCH specification, results show that it performs less than the ANN and SVM methods. On the whole, our findings suggest that machine learning techniques are promising tools for regulators and supervisors to develop early warning of banks' systemic risk.

Our findings give rise to several policy implications. First, our results suggest that the ownership structure is a key driver of systemic risk; controlled banks contribute more to the systemic risk than widely held banks. To face such an impact, controlled banks should draw a convenient risk taking behavior. Our results support the regulatory perspective arguing that the contribution of an individual financial institution to the system's risk may be more relevant than the individual risk of that institution. Our results also address the concerns of the Basel Committee on Banking Supervision (BIS, 2010) highlighting the importance of sound corporate governance schemes in the banking industry and requiring the disclosure of banks' ownership for further monitoring.

Second, regarding another risk taking incentive, our results suggest that a high liquidity creation may negatively affect the performance of the banking system. Thus, regulators and supervisory authorities should tighten their monitoring activities and pay more attention to high liquidity creators in order to prevent systemic risk and lessen the likelihood of financial crises.

Finally, our findings suggest that besides detecting the factors that may affect the systemic risk, we should also learn from historical behavior of banks and their reaction in a case of systemic event to build a prediction method that can capture future comportment. We suggest that artificial intelligence methods are promising tools to detect such designs due to their abilities to learn from networks' reactions and structures.

Our work gives rise to several managerial implications for banks and for regulatory policies and authorities. We examined the role of banks' ownership structure and liquidity creation as instruments of risk taking. We exposed a fundamental link between banks' specific attributes and their contribution end exposure to the systemic risk. First, while concentrated and diversified ownership create stronger stability and discipline at the individual level, it leads to greater systemic risk induced by contagious runs explained by *systemic risk-shifting* and *systemic diversification* phenomena. Banks and regulatory policies should take into consideration the consequences of these findings as they could destabilize the aggregate stability. First, regulatory reforms must shed light on the necessity of building and adjusting a convenient framework that investigates the optimal ownership structure of banks and force banks to implement a sound corporate governance schemes. Second, banks should pay attention not only on their individual risks induced by their own risky activities, but also on risks that may propagate to sector's members; differently said, banks must construct prudent strategies that account for the aggregate contagion that may diffuse from other institutions. However, there are several limitations in this framework that should be addressed in the future. First, we use a sample of 79 European banks, which may be considered relatively small; bigger database that includes international banks may allow us to go deeper and generalize our findings. Moreover, the study is investigated during the 2004-2016 period, which can be considered as a set of consecutive crises and financial distress times, thus a longer sample period would allows us to examine the relationship we found during several financial situations.

Our second contribution is that we provide theoretical evidence justified by empirical evidence that banks should pay more attention on their role as liquidity creator; we determine the magnitude of bank liquidity creation and the characteristics of high and low liquidity creators, and examine the relationship between liquidity creation and systemic risk contribution and exposure. This approach helped us to investigate an issue of significant research area and policy relevance. While recent studies have argued that the bank liquidity creation is positively associated with bank value, we prove that this liquidity creation increases bank risk and its effects on the system. From this perspective, our results may be used to address interesting issues that are beyond the scope of this thesis. Does liquidity creation present a critical point at which banks' performance may reform? How does liquidity creation differ across countries? How do regulatory policy reforms affect liquidity creation and what role should central banks play to maintain the stability of financial markets? All these questions, and much more, may be considered as future potential projects to get investigated. However, this framework presents also several limitations. First, a clear and complete database on liquidity creation factors is not available; the database must be collected manually to be able to estimate the liquidity indicators. Banks websites are used and financial reports are adopted to collect a minimum amount of information to estimate the needed indicators. Second, our results are drawn for European banks, thus a study on dataset of mixed countries and nations would be more realistic. Similarly, a more extended period would allow us to generalize the results.

Finally, we present a novel approach to predict systemic risk values using artificial intelligence and clustering methods. While these methods present reliable and promising tools to forecast risk values, predicting future values based on historical time series may not always be convenient and reasonable. More precisely, it would be some unexpected external factors that affect the behavior of the series we use. This limitation must be taken into consideration when estimating quantities and interpreting results.

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TABLE OF CONTNENTS

Title: Modeling and analyzing systemic risk in European banking sector

Key words: systemic risk, ownership structure, liquidity creation, artificial intelligence.

Résumé: This dissertation investigates the systemic risk subject in three different empirical frameworks. Besides listing the existing works related to the systemic risk in the first chapter, we examine the impact of two risk-taking factors in affecting the systemic risk level of European banks. The second chapter investigates the impact of the ownership structure on systemic risk contribution of 79 banks in 16 western European countries during the 2004-2016 period. The results show that higher ownership concentration is associated with greater banks' systemic risk contribution. Moreover, we found that banks' systemic risk contribution is even stronger for banks where institutional investors and States are the largest controlling owners. We go deeper and investigate the effect of regulatory variables on the relationship between systemic risk and ownership structure. We find that higher ownership concentration increased banks' systemic risk contribution in countries with high deposit insurance, lower capital stringency and higher asset diversification. The third chapter explores the effect of another risk-taking incentive, the liquidity creation, on banks systemic risk contribution end exposure. We use the same sample consisting of 79 European banks during the 2004-2016 period. The findings emphasize that during normal time, systemic risk exposure of banks are exacerbated by high liquidity creation. Moreover we show that, during distress times, high liquidity creation affects negatively not only banks exposure to systemic risk but also their contribution. Chapter four investigates a different facet of the systemic risk. Using a sample of 134 banks in 16 European countries ranging from 2002 to 2016, we construct three forecasting methods to predict systemic risk contribution and exposure values. We use artificial neural network, support vector machine and generalized autoregressive conditional heteroscedasticity specification. Our results show that two hidden layers artificial neural networks outperform other models in effectively predicting systemic risk.

Titre : Modélisation et analyse du risque systémique des établissements bancaires Européens

Mots clés : risque systémique, structure actionnariale, création de liquidité, intelligence artificielle

Résumé: Cette thèse examine le sujet du risque systémique dans trois cadres empiriques différents. A part de citer la liste des travaux existants liés au risque systémique dans le premier chapitre, nous examinons l'impact de deux facteurs de prise de risque sur le niveau de risque systémique des banques européennes. Le deuxième chapitre étudie l'impact de la structure de propriété sur la contribution du risque systémique de 79 banques de 16 pays Européens sur la période 2004-2016. Les résultats montrent qu'une concentration plus élevée de la propriété est associée à une plus hausse contribution du risque systémique des banques. De plus, nous avons constaté que la contribution des banques au risque systémique était encore plus forte pour les banques où les investisseurs institutionnels et les États étaient les principaux actionnaires majoritaires. Nous allons plus loin et étudions l'effet des variables réglementaires sur la relation entre le risque systémique et la structure de propriété. Nous constatons que la concentration de la propriété accroît la contribution du risque systémique des banques dans les pays où la garantie des dépôts est élevée, où les fonds propres sont moins exigeants et où la diversification des actifs est plus grande. Le troisième chapitre explore l'effet d'une autre incitation à la prise de risque, la création de liquidités, sur l'exposition et la contribution des banques au risque systémique. Nous utilisons le même échantillon composé de 79 banques européennes au cours de la période 2004-2016. Les conclusions soulignent que, en temps normal, l'exposition au risque systémique des banques est aggravée par une forte création de liquidités. De plus, nous montrons que, en période de crise, une forte création de liquidité affecte négativement non seulement l'exposition des banques au risque systémique, mais également leur contribution. Le chapitre quatre examine une autre facette du risque systémique. En utilisant un échantillon de 134 banques dans 16 pays européens pendant la période 2002-2016, nous avons construit trois méthodes de prévision pour prédire la contribution et l'exposition des banques au risque systémique. Nous utilisons un réseau neurone artificiel, support vecteur machine et la spécification generalized autoregressive conditional heteroscedasticity. Nos résultats montrent que les réseaux de neurones artificiels à deux couches cachées surpassent les autres modèles en ce qui concerne la prévision du risque systémique.