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Impact of Nonbank Financial Institutions on systemic risk. Do Banks mitigate it?

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Abstract

The financial and economic crisis of recent years highlighted not only the importance of systemic risk and its management, but also the growing relevance of nontraditional financial institutions, commonly referred to as Nonbank financial institutions (NBFI). These institutions played a significant role in the propagation of systemic risk during the global financial crisis (2007-2009) as well as during the recent turmoil in 2020. Since then, NBFI have expanded significantly and now account for approximately 60% of the total assets of the euro financial system and 49,10% of the total global financial assets.

This research investigates the contribution of NBFI, explores the interconnectedness of banks, and examines the characteristics underlying the systemic contribution of these institutions, motivated by their increased relevance within the financial system and the lack of research focused on them. Using a sample of 100 institutions from the STOXX Europe 600 Financials index over the period 2014-2023, systemic risk is assessed through a modified CoVaR methodology, while connectedness is analyzed using advanced spillover techniques.

The results show that although banks contribute more to systemic risk, NBFIs exhibit greater volatility and internal connectedness, making them key channels for the propagation of financial shocks. Furthermore, we found that banks are constantly receiving shocks coming from NBFI, highlighting the interdependency nature of systemic risk and underscoring the importance of incorporating NBFIs into macroprudential regulation and monitoring frameworks.

Key words: Nonbank Financial Institutions (NBFI), Banks, Systemic risk, Connectedness, interconnectedness, Systemic contribution, determinants, CoVaR.

JEL Codes: C22, C23, C26, C31, G01, G20, G23, G28

Abstract (Português)

A crise financeira e económica dos últimos anos destacou não só a importância do risco sistémico e da sua gestão, mas também a crescente relevância das instituições financeiras não tradicionais, vulgarmente designadas de instituições financeiras não bancárias (IFNB). Estas instituições desempenharam um papel significativo na propagação do risco sistémico durante a crise financeira global (2007-2009) bem como na recente crise de 2020. Desde então, as IFNB têm crescido significativamente e, atualmente representam cerca de 60% do total de ativos do sistema financeiro da zona euro e cerca de 49,10% dos ativos financeiros globais.

A presente dissertação investiga a contribuição das IFNB para o risco sistémico, explora a interconexão com os bancos e analisa as características por detrás da contribuição sistémica das instituições, motivado pelo aumento da relevância das instituições financeiras não bancárias no sistema e pela escassez de estudos focados nelas. Utilizando uma amostra de 100 instituições retirada do índice "STOXX Europe 600 Financials", no período de 2014 a 2023, o risco sistémico é avaliado através da metodologia CoVaR modificada, enquanto as interligações entre instituições são avaliadas com recurso a técnicas de *spillover* avançadas.

Os resultados demonstram que, embora os bancos contribuam mais para o risco sistémico, as IFNB apresentam uma maior volatilidade e uma interconectividade interna mais acentuada, tornando-se canais cruciais na propagação de choques financeiros. Além disso, verificámos que os bancos são recorrentemente recetores de choques provenientes de IFNB, o que evidencia a natureza interdependente do risco sistémico e reforça a importância de incluir as IFNB nos mecanismos de regulação e supervisão macroprudencial.

Palavras-chave: Instituições Financeiras Não Bancárias (IFNB), Bancos, Risco sistémico, Conectividade, Interligação, Contributo sistémico, determinantes, CoVaR.

Códigos JEL: C22, C23, C26, C31, G01, G20, G23, G28

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1. Introduction

Although its importance is widely recognized, there is no one definition for systemic risk. According to the Financial Stability Board (FSB) and the European Central Bank (ECB), systemic risk can be defined as the disruption of financial stability caused by an impairment of the financial system that can have serious adverse effects on the broader economy (ECB, 2009; FSB, 2009).

The financial and economic crisis of recent years has highlighted the importance of systemic risk and its management due to its significant influence on the economy and financial markets. There are several studies done in this area, for example, Serwa (2010) studied the cost of banking crisis by evaluating the relationship between banking crisis and GDP growth and found that crises are costly for the economy and that they cause deceleration in its growth.

Nevertheless, there are other reasons as to why we should pay attention to systemic risk and consequently focus on its management. For example, as highlighted by research undertaken by the World Bank, crises have social consequences, with the lives of many families and individuals being impacted. As illustrated in the paper, following the financial crisis of 2007, millions fell or were at risk of falling into poverty. Besides that, the income distribution was also worsened following the crisis, and the "*Millennium Development Goals*" progress slowed by 2015. As such, as demonstrated, a financial crisis can rapidly transform into a social crisis, hindering the development of a country and putting livelihoods at stake (Ötker-Robe & Podpiera, 2013).

In addition to that, the financial crisis of 2007 provided us with relevant insights into systemic risk and its contributors. As was demonstrated, nonbank financial institutions (NBFI) played a significant role in the propagation of systemic risk. As such, evidence called for a shift in regulations that until then, focused on regulating the action of banks, as it was believed that only banks impacted systemic risk and consequently the stability of the financial system and the economy. Thus, as a consequence of the global financial crisis, regulators strengthened the regulation of NBFI and created oversight bodies such as the Financial Stability Board (FSB) and the Financial Stability Oversight Council (FSOC). The Financial Stability Board, established at the international level, has the goal of promoting global financial stability and achieve this by monitoring and addressing emerging forms of systemic risks that could affect the global financial system. Whereas the Financial Stability Oversight Council was created with the same goal in mind but with a specific focus on the US economy, aiming to identify emerging forms of systemic risk within the United States, address them, and promote stability in the financial system (Kress et al., 2019).

Over the last few years, the Financial Stability Board has assessed the risks for global stability of the financial system and consequently identified the risk posed by the NBFI sector. They developed a program to enhance the resilience of this sector as the assets of nonbank financial institutions have grown significantly, and with it their importance to systemic risk, which was verified by the recent turmoil in 2020 ("*dash for cash*") (FSB, 2024a).

The relevance of studying nonbank financial institutions can also be examined through their growing influence on the economy. Since the global financial crisis of 2008, their sector (non-bank financial intermediation) has grown in size, with the total assets increasing from €23 trillion in 2008 to €54 trillion as of the end of 2023, representing close to 60% of the total assets of the euro area financial system. The global values also illustrate the growth of this sector with the total assets increasing from $97 trillion in 2008 to $239 trillion by the end of 2023, representing close to 49,10% of the total global financial assets. Additionally, according to the FSB, this sector has grown at a higher pace than other financial institutions (FSB, 2024b). With the increase in size, its role in financing the real economy has also increased, with these institutions providing credit to corporations and households. Despite the potential benefits that these institutions bring to the system, we also have to consider their vulnerabilities since, as was shown in previous crises, NBFIs can contribute to market disruption and financial systemic risk. The main sources of vulnerabilities introduced by the ECB comprise "excessive exposure to liquidity risk", "excessive leverage and interconnectedness across the financial system", and the interaction between them (ECB, 2024, p.6).

Furthermore, the crisis of 2007 also showed that only mitigating the individual risk of each financial institution was not enough, thanks to the contagion resulting from the increased interconnectedness of the financial system. In addition, recent research has highlighted that the level of interconnectedness of the global financial system has increased in recent years, which poses a challenge to systemic risk regulation (Atasoy et al., 2024; Huang et al., 2016). As a consequence, and with the recognition that systemic risk is greatly impacted by NBFI and by the interconnectedness of the system, policymakers have been challenged to make regulations that ensure financial stability.

However, despite recognizing the NBFI´s importance and growing influence in the economy, research in this area remains scarce, with the majority of the literature focusing on the contribution and determinant characteristics of banks to systemic risk. Additionally, studies on the interconnectedness of the financial system are sparse and don´t focus on the effects of the overall network on systemic risk. Furthermore, the relationship between the systemic contribution of banks and NBFI remains largely unexplored, particularly in the context of how interdependencies between these institutions influence the propagation of systemic risk during times of financial stress.

Consequently, the main purpose of the present dissertation is to delve into the contributions and determining characteristics of NBFIs to systemic risk in Europe. Simultaneously, we aim to test the connection of NBFIs with traditional banks as well as the financial network between the institutions to assess whether banks, with their central role in the economy, act as stabilizers in the financial system, thereby mitigating the systemic risk arising from NBFIs. Therefore, the present dissertation helps to fill the gap in understanding the contribution of NBFIs to systemic risk and further enriches the expanding literature on the interconnectedness of financial institutions.

To support this analysis, we follow Karimalis & Nomikos (2018) in the selection of data, and use the STOXX Europe 600 Financials index, which includes institutions from three different super sectors: Banks, Financial Services, and Insurance. From the initial sample of 111 institutions, we excluded 11 due to the lack of historical information over the time period that we wanted to analyze (2014-2023). Thus, the final dataset was retrieved from Datastream by Refinitiv and is composed of daily prices for the institutions (2567 observations) as well as measures for their profitability, leverage, size, international activity, and liquidity. We also retrieved economic variables in order to controls retrieved from Datastream by Refinitiv and the world bank. Furthermore, in the current dissertation, we use the methodology proposed by Adrian & Brunnermeier (2016) with the modifications proposed by Girardi & Tolga Ergün (2013) to calculate our systemic risk measure. Then, to assess the connectedness of the financial institutions, we will follow the methodology proposed by Diebold & Yilmaz (2012) and the consequent innovations of Gabauer & Gupta (2018) and Stenfors et al. (2022).

The results of this study can be dissected into three main insights. First, we found that banks show an overall higher contribution to systemic risk than NBFI, although the gap narrows in turbulent periods. Additionally, we found that CoVaR was consistently higher than VaR, which emphasizes the role of institutional interconnectedness in systemic risk contribution. Finally, NBFI contributions show greater volatility, which highlights their more uncertain contribution.

The second group of insights is related to the determinants of the systemic risk contributions. The analysis showed that inflation and regulatory quality are negatively associated with systemic risk, while GDP growth and interest rates are positively associated with systemic risk. On the institutional side, profitability shows a weak but significant negative effect on systemic risk, whereas leverage is positively associated with systemic risk. For banks, leverage and liquidity are positively associated with systemic risk.

Finally, the last group of insights is related to the analysis of the connectedness of the financial system. The connectedness analysis revealed a balanced pattern of risk transmission across groups. However, when we decompose the Total Connectedness Index (TCI) into internal and external spillovers, we concluded that nonbanks have a consistently higher internal TCI, which suggests that connections within the nonbank network are stronger. Moreover, during periods of stress, there was a spike in the external TCI of banks, indicating that banks contribute significantly to the increase in systemic risk during these periods. Finally, our last analysis led us to conclude that banks persistently exhibit negative values for the net total group-specific index, meaning that this sector is receiving shocks originating from the NBFI sector. This finding has serious implications for macroeconomic regulation since it shows that systemic risk propagation is extremely interdependent.

This dissertation will thus be structured as follows. Following this introduction, in Chapter 2, a literature review will be conducted. Chapter 3 is divided into three subsections, starting with the formulation of the research questions, followed by the data analyzed and presentation of the methodology that will be employed. Finally, in Chapter 4, the empirical results will be presented and discussed in light of theory and past research. Chapter 5 will conclude the dissertation, highlighting the main conclusions and limitations of the analysis, as well as suggesting directions for future research.

2. Literature Review

The literature on systemic risk is divided into three main focuses: institutional-characteristics contributions to systemic risk, measures of systemic risk, and spillovers within the financial system that could affect the financial system as a whole, thereby influencing systemic risk. Accordingly, this chapter is structured around these three areas with an additional subchapter addressing the role of nonbank financial institutions and their contributions to systemic risk. The literature on the systemic risk measures and their determinants is then summarized in the appendix (Table i, Table ii, Table iii and Table iv).

2.1 Systemic risk and its measures

Research on systemic risk was intensified after its importance was unveiled by the 2007 financial crisis. However, researchers and regulators have yet to agree on a single definition for systemic risk.

The definitions seem to be divided into two types. On one hand, several authors define systemic risk with a focus on the financial system as a whole (Abdymomunov, 2013; BCBS, 2018; Patro et al., 2013). Thus, the characterization involves assessing the effect that a shock has on a financial institution's soundness. On the other hand, some authors define systemic risk as the impact that a failure of an institution and its risk has on the overall systemic risk (ECB, 2009; FSB, 2009). As such, this definition considers the contribution of one single institution and its interconnectedness to the financial system and its systemic risk.

The European Central Bank (ECB) characterizes systemic risk as the disruption of financial stability caused by an impairment of the financial system that can have serious adverse effects on the broader economy (ECB, 2009). From their 2009 report, we can read, "one perspective is to describe it as the risk of experiencing a strong systemic event. Such an event adversely affects a number of systemically important intermediaries or markets (including potentially related infrastructures)" (ECB, 2009, p.134). In the same line, the Financial Stability Board (FSB) uses a similar definition and introduces the systemic importance concept (FSB, 2009). From their 2009 report, they define systemic importance as "an institution, market or instrument as systemic if its failure causes widespread distress, either as a direct impact or as a trigger for broader contagion" (FSB, 2009, p.7). A systemic event is then characterized as "the disruption to the flow of financial services that is (i) caused by an impairment of all or parts of the financial system; and (ii) has the potential to have serious negative consequences for the real economy" (FSB, 2009, p.7-8).

In turn, Abdymomunov (2013) defines systemic risk as the probability of the financial system and the economy as a whole being affected by a negative shock. Patro et al. (2013) has a similar vision, viewing systemic risk as the likelihood of financial markets and the economy being affected by a systemic failure induced by a strong systemic event. Similarly, the Basel Committee on Banking Supervision (BCBS) views systemic risk "in terms of the impact that a bank´s failure can have on the global financial system and wider economy, rather than the risk that a failure could occur" (Committee on Banking Supervision, 2018, p.8).

Given these differing definitions, several different methodologies were created. And, to this day, there is an ongoing debate among researchers and practitioners on the best and most effective way to measure systemic risk.

Until the global financial crisis of 2007, researchers and practitioners believed that simple measures such as balance sheet information, equity prices, and credit default swaps could be used to measure systemic risk.

Brownlees & Engle (2017) in their paper examine the relation between balance sheet variables and their importance to understand crisis. They provide several policy implications to manage balance sheet variables in order to mitigate a crisis.

Lehar (2005) proposes a systemic risk measure calculated based on bank asset portfolios. In their work, he explained that at the time, the current regulatory framework considered that managing banks´ individual risk was sufficient to maintain systemic risk low, which failed to consider the interdependencies among banks. Their approach would help to address this problem by adding interdependencies for consideration. As such, his measure considered three key inputs: correlation between banks´ asset portfolios, financial soundness since shocks can impact banks in different ways (banks with bigger dimensions can accommodate shocks more easily), and volatility as more volatile banks are more likely to default. Considering these inputs, they use a put option to calculate the measure of systemic risk to represent the "present value of the expected future shortfall" (Lehar, 2005, p.3).

Chan-Lau & Gravelle (2005) measure was based on the expected number of defaults (END indicator) constructed based on price information of financial securities and balance sheet data. Once again, they identify that traditional measures of risk do not take into account the interconnectedness of banks and aim to tackle this problem with their measure.

In contrast, Avesani et al. (2006) suggests a measure based on default probabilities calculated using a basket of credit default swaps (CDS) of large and complex financial institutions. They deviate from balance sheet-based measures since these measures were limited because of the lack of regular information available. To this end, they identify the role that large financial institutions have in the stability of the financial system and create a measure of systemic risk around them.

However, the crisis proved that these indicators failed to incorporate the complexity of the financial system and its interconnectedness. As identified by Avesani et al. (2006) balance sheet-based measures of systemic risk have problems because the availability of this information is scarce and is only published once a year in some cases. This makes accompanying the developments of systemic risk and managing promptly difficult.

Despite the drawbacks of measuring systemic risk using CDS, several authors continued to use it as a measure since it had higher predictive power than measures such as Granger causality (Rodríguez-Moreno & Peña, 2013). For example, Huang et al. (2009), propose a measure of systemic risk based on the credit default swap (CDS) spreads and individual banks´ equity prices. They then calculate the probability of default and correlations between banks based on these indicators. After that, they assess the systemic risk of the financial system by comparing the price of insurance against the default losses based on the probabilities calculated before.

To respond to the drawbacks and inability of the systemic risk measures used until the global financial crisis, new measures were created with the goal of improving the measurement and monitoring of systemic risk.

Adrian & Brunnermeier, (2016) applied the measure introduced by Tyrrell Rockafellar & Uryasev (1999) in the systemic literature, introducing a new way to measure systemic risk called the delta conditional value at risk (ΔCoVaR). Tyrrell Rockafellar & Uryasev (1999) introduced the conditional value at risk as a way of measuring risk in 1999 as a result of all the drawbacks identified within the VaR methodology, namely the fact that this measure was not coherent. Adrian & Brunnermeier, (2016) then builds on this measure and introduces the delta conditional value at risk which is defined as "the change in the value at risk of the financial system conditional on an institution being under distress relative to its median state" (Adrian & Brunnermeier, 2016, p.1) and calculated through returns and losses on the equity market. With this measure, the authors intended to build on the value at risk (VaR) approach and overcome one of its shortcomings related to the fact that the approach only considered financial institutions in isolation without considering the spillovers that might happen due to the interconnectedness of the financial system. Their methodology can be adapted in order to use quantile regressions, GARCH models, copula methods, as well as Bayesian models in order to accommodate specific characteristics.

Their approach begins by estimating the value at risk (VaR) of the system and its institutions. Then, they proceed to calculate the Conditional Value at Risk (CoVar), which represents the VaR of the system conditional on the existence of an extreme event at a financial institution. Finaly, they calculate the difference between the CoVaR of the system when the institution is under stress and the CoVaR of the system when the institution is in its median (normal) state in order to calculate the delta conditional value at risk (ΔCoVaR) that represents the added risk an institution introduces in the system. As such, the higher the value of the ΔCoVaR, the higher the contribution of the institution to the systemic risk of the system. This measure has the advantage of building upon the standard regulatory tool (VaR) used by regulators. Girardi & Tolga Ergün (2013) built upon this measure to make it more robust and align with reality by considering that an institution is under stress when it is at or below its VaR, rather than only when it is exactly at its VaR.

Acharya et al. (2016) introduced the systemic expected shortfall (SES) and the marginal expected shortfall (MES) as systemic risk measures. To calculate their measures, the authors use data from the equity market and data on credit default swaps. They define the systemic expected shortfall as the probability of an institution being undercapitalized when the system is undercapitalized. In turn, the marginal expected shortfall is calculated taking into account the 5% worst days of the market and accounts for how much a specific firm is exposed to aggregate tail shocks.

The SES is then calculated, taking into account the impact that a certain systemic event has on financial institutions. Thus, as higher the projected losses in case of a financial crisis, the higher the SES. As such, this measure conceptually is different from the CoVaR since it examines the "financial firm´s stress conditional on systemic risk" instead of "the system stress conditional on an individual firm´s stress" (Acharya et al., 2016, p.6).

Finally, Brownlees & Engle (2016) developed the systemic risk measure (SRISK). This measure is calculated using both balance sheet (size of the firm and degree of leverage) and equity data and is defined as "the expected capital shortfall of a financial entity conditional on a prolonged market decline" (Brownlees & Engle 2016, p.49). Thus, it provides us with the overall systemic risk when we sum the SRISK across all firms and can be thought of as the total amount that a government would need to inject into the financial system in case of a crisis.

In their work, Brownlees & Engle (2016) compare its measure with the one developed by Acharya et al. (2016) pointing out the limitations in using the systemic expected shortfall (SES) to measure systemic risk. According to the authors, because the SES is based on structural assumptions and requires the observation of a systemic crisis in order to make estimations, it cannot be used as an ex-ante measure of systemic risk. This fact significantly impacts its predictive power, decreasing its utility for estimating systemic risk.

Given the several measures identified before, some authors have focused their research on their comparison, as well as examining their advantages and drawbacks. Bernard et al. (2012) have focused on the comparison between the CoVaR and SES measures as well as on the identification of their strengths and weaknesses. Starting their analysis with the CoVaR measure proposed by Adrian & Brunnermeier, (2016), the authors identified as a drawback the calculation of the ΔCoVaR as the difference between the CoVaR at its VaR with the CoVaR in the medium state, since they consider that a better representation would be to calculate it as the difference between the CoVaR at or below its VaR with the CoVaR in the medium state. Over time, this drawback ceased to exist, which, according to the authors, is a significant improvement and should be used when calculating the ΔCoVaR. Furthermore, the use of copulas to better accommodate marginal distributions for individual losses and better model extreme dependencies is also considered to be an improvement in the CoVaR and SES measures.

As for the comparison between these two measures, with the adjustments in the CoVaR measure to consider losses beyond the VaR level, the sensitivity to skewness and heavy tails becomes similar for both measures. In addition, CoVaR does not take into account the marginal distribution of an individual institution. However, because standard capital requirements could be thought of as a proxy, it does not influence the measure as much. Finally, and to conclude, the authors found that the SES seems to overestimate risk in some cases (small companies and companies with risky marginals), concluding that the CoVaR methodology seems more appropriate to calculate systemic risk.

Benoit et al. (2013) expanded in this line of research by also analyzing the SRISK measure proposed by Brownlees & Engle (2016). In their research, the author highlights the need for the development of a more comprehensive measure of risk since all the measures presented (SES, SRISK and ΔCoVaR) demonstrate a highly correlation with specific factors (beta in the case of SES, market capitalization and liabilities in the SRISK case and VaR in the ΔCoVaR case). Thus, they argue that these measure, while useful in certain contexts, fall short in capturing the multifaceted nature of systemic risk.

More recently, Zhou et al. (2020) studied systemic risk in China and made a comparison between the measures mentioned before, as well as an evaluation of the contributions of banks, insurance companies, and securities firms. By looking at the difference responses of the measures during the financial crisis that affected the Chinese economy during the global financial crisis of 2008 and 2015 they founded that while ΔCoVaR and MES exhibited abnormal spikes during crises, SRISK showed steady growth but did not adequately reflect risk peaks during critical moments, due to its strong reliance on market capitalization and liabilities. Furthermore, they show that ΔCoVaR and MES were identified as the highest contributors to systemic risk banks in 2008 and insurance companies in 2015, while SRISK identifies banks as the highest contributors in both periods, failing to incorporate the growing significance of other financial institutions over the years.

2.2 Determinants of systemic risk

Over the years, several authors have studied the determinants of systemic risk. However, the majority of the authors have focused their research on bank determinants.

Several authors have focused on the relationship between **bank size** and its contribution to systemic risk as a result of the collapse of Lehman Brothers and the consequent trigger of the financial crisis. Many studies have found a positive relationship between size and systemic risk, for example, according to the study of Laeven et al. (2016), systemic risk increases with bank size due to the fact that larger banks typically have lower capital ratios and at the same time higher exposure to risky activities. Similarly, Varotto & Zhao (2018) reached equivalent conclusions, attributing this relationship to the fact that governments tended to bail out large institutions in case of need, which leads them to take on excessive risk, highlighting the overriding concern for *"too-big-to-fail"* institutions. However, some studies argue a contrary view, having found that systemic risk is negatively associated with size (Knaup & Wagner, 2012) or that size does not play a relevant role in systemic risk contribution (López-Espinosa et al. 2013).

Another significant risk factor that has been identified and studied within the literature is the relationship between **bank capital** and systemic risk. Anginer & Demirguç-Kunt (2014) studied this relationship, and although they found that the effects varied according to the size of the banks, quality of the capital, and supervision of these institutions, they concluded that there is a negative relation between bank capital and systemic risk. In the same line, Laeven et al. (2016) found that systemic risk is negatively related to bank capital.

Additionally, systemic risk is also affected by the **profitability** of financial institutions. Its influence on systemic risk has been studied by several authors through different perspectives, reaching different results. Williams (2016) analyzed the impact of non-interest income, which can increase the profitability of institutions but in turn increase systemic risk since these activities involve taking on more risk. Lehar (2005) studied the impact of profitability on systemic risk through the lens of the impact that higher profits have on the behavior of the institution, finding that higher profits lead banks to engage in less risky activities, which in turn leads to lower systemic contribution.

Furthermore, another key determinant is the **leverage**. The relevance of this determinant is illustrated by the fact that high leverage is identified as the main driver behind financial instability and subsequent financial crisis, including the global financial crisis of 2009 (Schularick & Taylor, 2012). Several studies have studied the impact of leverage on systemic risk and found that higher leverage leads banks to engage in riskier operations, which in turn creates higher volatility and leads to higher systemic risk contribution. As a result, it is identified in those studies that one way to promote financial stability is to introduce higher capital requirements (Acharya & Thakor, 2016; Acosta-Smith et al., 2024; Kuzubaş et al., 2016). On the other hand, banks with high leverage typically have a better loan portfolio, which in turn might help in reducing their systemic contribution (Diamond & Rajan, 2001) .

Moreover, **liquidity** is also another determinant of systemic risk. The idea is that higher liquidity makes the bank stronger and more able to deal with a crisis and absorb shocks. Consequently, it is believed that there is a negative relation between liquidity and systemic risk. Lu & Wang (2023) studied the relation between liquidity hoarding and the banks contribution to systemic risk and found, as expected, that higher levels of liquidity hoarding improve the banks stability and reduced the systemic contribution. This effect was found to be higher in periods of uncertainty. However, liquidity hoarding was also found to harm economic growth. As a consequence, the authors suggest that policymakers focus on incentivizing the creation of liquidity rather than excessive liquidity hoarding. It is on this line that the research of Davydov et al. (2021) and Louhichi et al. (2024) builds upon previous findings to assess the link between the creation of liquidity and systemic risk. Davydov et al. (2021) found that liquidity creation decreases systemic contribution of individual banks and increases the link between institutions, which in turn may cause problems in times of stress. Louhichi et al. (2024), however, found that although in normal times, liquidity creation does not increase the systemic contribution of each bank, in times of stress, it exacerbates it.

Finally, several authors have focused their research on the study of the determinants identified above jointly rather than in isolation. That is the case of López-Espinosa et al. (2013) that studied the determinants of bank contributions to systemic risk and based their choice of parameters on the criteria set by the Basel Committee for Banking Supervision (size, interconnectedness, substitutability, cross boarder activity and complexity of the bank) and found that funding risk, the business model and cross border activities are the main determinant of systemic risk. Furthermore, they found that differences attributable to substitutability do not seem to play a relevant role in the systemic risk contribution of banks. Zeb & Rashid (2019) also studied the determinants of systemic risk, but included other financial institutions in their analysis, such as financial services and insurance firms. They conclude that size, liquidity ratio, operating profit margin, and market-to-book value are statistically significant in determining systemic risk contribution.

In the same line as the previous studies, Karimalis & Nomikos (2018) analyzed the effect of bank-specific characteristics such as size, liquidity, leverage, and equity beta, and enriched the literature by analyzing the contribution of macroeconomic variables such as unemployment, industrial production, stock market index, and GDP on systemic risk. They found that liquidity, size, and leverage were the most important determinants of systemic risk contribution and that the rise in unemployment, decrease in the stock market index, and GDP contribute significantly to increase systemic risk.

Qin & Zhou (2019) then extended the existing literature by studying the relation between the involvement of banks in non-traditional services and systemic risk and found that banks engaged in non-traditional banking activities increase systemic risk. Furthermore, they found that the effect was stronger when financial markets had higher importance than banks in the economy.

2.3 Nonbank financial institutions' contribution to systemic risk

Given nonbank financial institutions growing importance in recent years and their rising importance in the global financial system, some researchers have been focusing on the contribution of these institutions to systemic risk. Although studies on this topic remain limited, this subsection aims to explore the existing literature in this field.

Bernal et al. (2014) aimed at assessing the contribution of several financial institutions to systemic risk and ranking them according to that contribution. According to their study, in the eurozone between 2004 and 2012, the “other financial services sector” contributed the most to systemic risk, followed by banks and finally insurance companies. In the US, for the same period, the results were in accordance with the financial sector being the riskiest and banks the least risky.

Rahman et al. (2022) studied the contribution of banks and nonbank financial institutions in Australia across different frequencies using the CoVaR methodology as well as the determinants of these contributions. In their analysis, they found that overall, the systemic contribution of banks was larger than that of other financial institutions and that the systemic risk seems to be higher in the short term compared to the medium or long term. Furthermore, they assessed the determinants of the contributions of the institutions following the criteria set by the Basel Committee for Banking Supervision (size, interconnectedness, substitutability, cross boarder activity and complexity of the bank) and found that VaR, size, liquidity, housing price growth, cash rate and profitability explain both bank and nonbank financial institution contribution while banks contribution is also explained by leverage, intangible assets, exchange rate and economic growth.

In the same line, Soo Hong et al. (2024) analyzed the systemic risk evolution over time by sector in South Korea as well as the impact of the issuance of derivative-linked securities (ELS) on systemic risk. They concluded that the systemic risk within the different sectors increased during the global financial crisis, whereas the relation between the sectors varied.

During the margin call crisis in 2020, the difference between the sectors decreased, which underscores the more substantial role of nonbank financial institutions in the overall financial system. Furthermore, they concluded that the issuance of ELS increased the systemic risk.

Zheng et al. (2025) assessed how the expansion of nonbank financial institutions within the financial sector affected the short- and long-term financial stability, as well as the impact of these institutions on the financial system resilience in China. They concluded that the NBFIs initially destabilize the system but positively influence financial stability over time. Additionally, they found that NBFIs play an increasingly significant role in financial stability in the medium to long term, with their impacts varying across different time dimensions.

2.4 Contagion within the financial system

With the increasing complexity and interconnectedness of the financial system, studying the contagion that might happen and that ultimately leads to the spread of systemic risk is something that has been of interest for both researchers and regulators. Thus, several authors address this in their research. The methods employed in these studies are diverse, ranging from connectedness measures, GARCH DCC, Granger causality, and network analysis.

Billio et al. (2012) studied the interconnectedness of the financial system using principal component analysis and Granger Causality Networks. They found that banks, hedge funds, brokers, and insurance companies have become more interrelated over the years, which in turn has increased the systemic risk of the system. However, he found that at the time, banks still played the most prominent role in transmitting systemic risk.

Building upon this idea, Huang et al. (2016) examine the contributions of financial institutions to systemic risk by evaluating the dynamic evolution contribution and the financial network structure. The network structure is created by using both the GARCH DCC model and minimum dynamic spanning trees, which allows us to understand how risk is disseminated within the system, taking into account the changing interconnectedness of financial institutions within the system. Furthermore, to assess the role of each institution, they use metrics of node strength, node betweenness centrality, node closeness centrality, node occupation layer, and node clustering coefficient, calculated for each institution. They found that the sectors that had the largest contribution to systemic risk were in descending order: insurance companies, commercial banks, security broker-dealers, and other financial institutions. The institutions with higher systemic risk contribution were characterized by greater node strength, betweenness centrality, closeness centrality, and clustering coefficient.

Gong et al. (2019) also analyzed the connectedness of the financial system through a financial network created using Granger Causality Networks and principal component analysis while filtering out market risk using the CAPM model. They analyzed the connectedness across banks, insurance, and security companies in the Chinese financial market and found that the connections increase in times of turmoil, indicating a stronger connection among companies during crisis and that while banks are the most interconnected to other institutions, the systemic contribution of brokers, dealers and insurance companies dominated.

Zhang et al. (2023), however, studied the systemic risk spillover among financial institutions in China using GARCH-DCC models in order to capture the dynamic correlation among the institutions. They found that the bank sector was the one that produced higher systemic risk spillovers, followed by the security and real estate sectors. Furthermore, they identify the real estate sector as the one that produces the highest spillovers, highlighting its importance in the financial system.

More recently, Atasoy et al. (2024) studied the contagion between institutions through a different lens by evaluating the determinants of the connection between institutions. In their study, they found that in their period of analysis (2004-2021), the contagion was mainly driven by credit risk and leverage, and that the impact of size and capital adequacy on contagion has been decreasing since 2012. Furthermore, the impact of funding structure and profitability was relevant in contributing to contagion during the period of COVID-19 and from 2014 to 2017.

Henriques & Sadorsky (2025) analyzed the connectedness between FinTech and traditional financial stocks in the US by estimating connectedness measures through the TP-VAR model and found that FinTech and insurance stocks were net receivers of shocks, while large banks were a source of shocks. Thus, given that the FinTech sector was a receiver of shocks, they concluded that it was not a driver of systemic risk and, as such, did not need a more stringent regulation.

3. Research Questions, Data and Methodology

3.1 Research Questions

As was previously mentioned, empirical evidence on the contribution of nonbank financial institutions has remained scarce despite the recognition of its importance. In light of this fact, the first objective of the present study is to analyze the contribution of these institutions to systemic risk:

Q.1: *What is the contribution of NBFI to systemic risk?*

Additionally, it is also relevant to assess the characteristics that are driving systemic risk to be able to adapt the regulations, diminish systemic risk crises, and promote stability.

Q.1.1: *What characteristics are driving systemic risk?*

Furthermore, due to the growing interconnectedness of the financial system observed over the years, driven by advances in technology, globalization of financial markets, and the diversification of financial services, systemic risk has been affected. In addition, its relevance during the global financial crisis of 2007 highlights the need to assess the evolution and impact that the growing interconnectedness of the financial system influences systemic risk. This goal leads to the formulation of the following research question:

Q.2: *How do financial networks influence systemic risk, and how have they changed over the years?*

Building on these ideas, it is essential to evaluate both trends identified above and assess whether the increased interconnectedness and the rise of non-traditional participants in the financial sector have amplified systemic risk. Thus, this reasoning resulted in the following sub-question:

Q.2.1*: Has the increased interconnectedness and rise of non-traditional participants (e.g, fintech, investment banks) in the financial sector heightened systemic risk?*

Ultimately, answering the questions above sets the stage for our primary research question. Consequently, with the insights gained from the answers to the questions formulated above, the study seeks to evaluate whether traditional banks, as core institutions in the financial system, can stabilize the economy and mitigate the systemic risks arising from nonbank financial institutions. Thus, we culminate with the following question:

Q.3 *Do traditional banks mitigate the risk arising from nonbank financial institutions?*

3.2 Data

In order to answer the questions mentioned in the previous section and to perform the empirical analysis, we follow Karimalis & Nomikos (2018) and focus on the STOXX Europe 600 Financials, which is a sub-index derived from the STOXX Europe 600, composed of the largest six hundred companies in Europe. The index from which the STOXX Europe 600 Financials is derived is composed of companies across 18 countries from 19 subsectors according to the ICB classification, including the financial sector. The STOXX Europe 600 Financials is, therefore, composed of 111 institutions across 16 countries from three different super sectors: Banks, Financial Services, and Insurance. These companies, due to their size, cross-border exposure, and activity, play a crucial role in Europe and thus can be seen as a good representation of the financial sector.

From the initial 111 institutions composing the STOXX Europe 600 Financials index, we excluded 11 institutions due to the lack of historical financial information over the time period that we wanted to analyze. As a consequence, our final dataset is composed of 100 institutions, starting on 02/01/2014 and ending on 29/12/2023 (2567 observations for each institution). The time period selected offers a solid foundation for us to assess the systemic contribution of the different institutions in Europe as it encompasses several major events, such as the aftermath of the European sovereign debt crisis, the COVID-19 pandemic and the war in Ukraine, and the consequent energy and inflation crisis. Moreover, these institutions are distributed across 16 countries, represented in Figure 1 by dots that indicate both the super sector of the institutions present in each country and their relative number, with larger dots representing a higher concentration of institutions in the database.

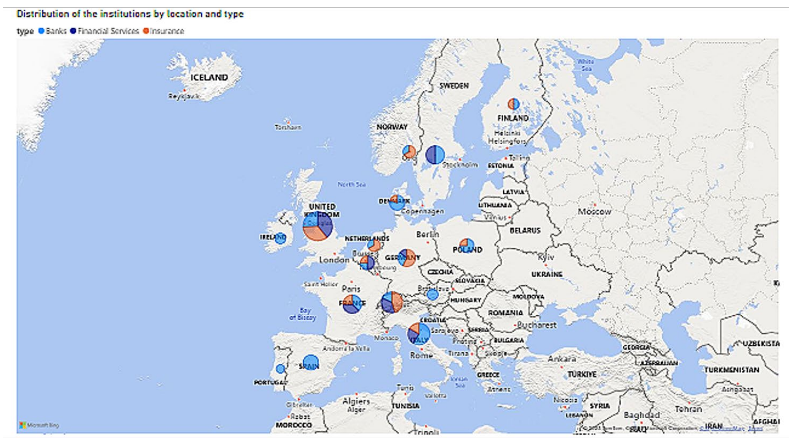


Figure 1 Distribution of the institutions by location and type. Own elaboration

Moreover, the 100 institutions are divided across three large sectors: Banks, Financial services and Insurance. Figure 2 illustrates the division of the institutions across these sectors. As we can conclude, banks represent 46% of the sample with a total of 46 institutions while the remaining institutions fall under the category of Nonbank Financial Institutions (NBFIs) representing 54% of the sample with a total of 54 institutions. It is relevant to also note that the Nonbank Financial Institutions are subdivided into multiple sectors including Investment Banking, Diversified Investment Services, Insurance (Multiline Insurance, Property & Casual Insurance, Life and Health Insurance and Reinsurance), Investment Holding Companies and Financial and Commodity Market Operators.

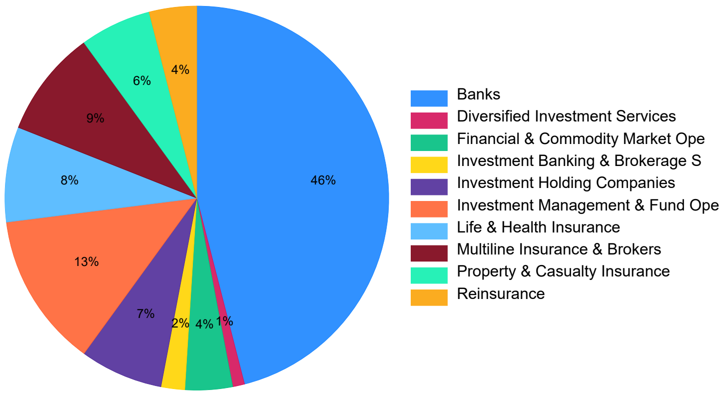
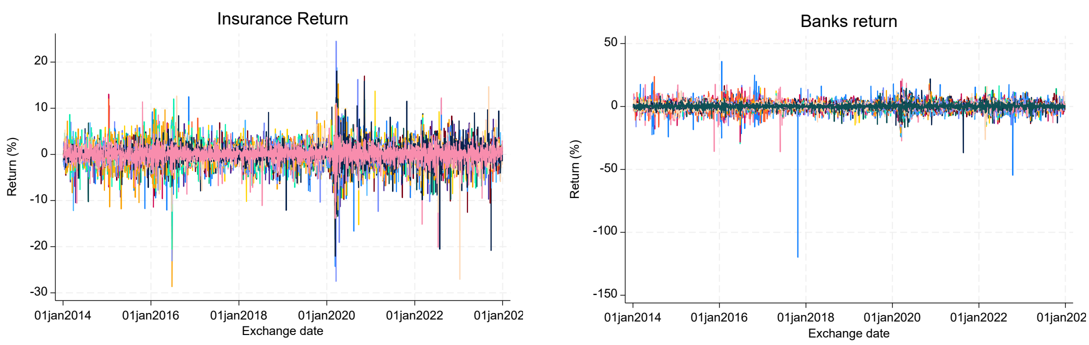


Figure 2 Distribution of the financial institution. Own elaboration

After defining the institutions of interest, we retrieved daily stock data for the 100 institutions that compose our database from Refinitiv DataStream, which aligns with other studies on systemic risk, such as Laeven et al. (2016) and Rahman et al. (2022), among others. Following that, we calculated the daily return for each institution by calculating the logarithmic return $(\ln\left(\frac{P_t}{P_{t-1}}\right) * 100)$. The summary of the individual returns of the institutions can be seen in the appendix (Table v, Table vi, Table vii).



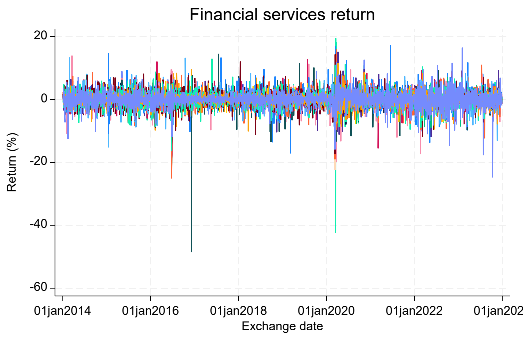


Figure 3 Evolution of returns for banks, insurance, and financial services companies. Own elaboration

As can be seen in Figure 3, the returns of insurance and financial services companies exhibit high dispersion over the period being analyzed, with the returns ranging from -30% to 20% for the insurance sector and -60% to 20% for the financial services sector. This behavior suggests the existence of high volatility among these sectors, which may have implications for systemic risk. In contrast, the banking sector offers a lower dispersion in returns, most of the time experiencing episodes of extreme negative returns at certain points in time. This suggests that banks might be more exposed to systemic (left tail) events often associated with financial crises and liquidity shocks. As a consequence, studying the joint dynamics of nonbank financial institutions, represented by the insurance and financial services sector, and banks is crucial to understand how systemic risk propagates across the financial system, given the central role of banks in the financial system.

Finally, to represent the system, we will calculate a market-value-weighted portfolio with the remaining companies.

Furthermore, to assess the determinants of the systemic contribution of each institution, we are going to use the following variables retrieved from Datastream by Refinitiv (Table 1):

Table 1 Variables and their description. Own elaboration

Variables	Description
Total assets	Measures the size of an institution.
Loans /Deposits	Is a proxy for the liquidity of banks.
Cash and Short-term Investments / Short Term Liabilities	Is a proxy for the liquidity of nonbank financial institutions.
ROA (Net Income/ Total Assets)	Is a proxy for the profitability of both banks and nonbank financial institutions.
Leverage ratio (Total Debt/Total assets)	Is a proxy for the leverage of both banks and nonbank financial institutions.

The selection of these variables is based on literature already presented in the present work, as well as the economic theory and the sometimes-contradictory empirical evidence regarding their role in systemic risk, summarized in Table iii and Table iv. Moreover, the limited number of studies analyzing the impact of these characteristics on nonbank financial institutions further justifies their inclusion in the present analysis. In this sense, to analyze the determinants of the institutions' contribution to systemic risk, we used four variables.

The first variable that we use is **size,** represented by the total assets. The economic theory says that larger institutions are sometimes protected by governments due to their role in the financial system and their interconnectedness. This leads them to engage in riskier activities, which in turn exacerbate systemic risk (Too-big-to-fail theory). Thus, economic theory predicts that there is a positive relationship between size and systemic risk. However, empirical evidence found two contrary views. On one hand, many studies found a positive relationship between size and systemic risk as predicted (Laeven et al., 2016; Varotto & Zhao, 2018). On the other hand, some studies have found the contrary effect (Knaup & Wagner, 2012).

The second variable being considered assesses the effect of **liquidity,** which is proxied by the ratio between loans and deposits in the case of banks and cash and short-term investments and short-term liabilities for nonbank financial institutions. According to economic theory, institutions with lower levels of liquidity in periods of stress can be obligated to sell their assets fast. This leads them to accept lower values, which in turn increases systemic risk. As such, economic theory suggests that there is a negative relationship between liquidity and systemic risk. This is corroborated within the literature by Lu & Wang (2023) and Davydov et al. (2021). However, some studies have found the contrary effect, which is the case of Rahman et al. (2022).

The third variable assesses the effect of **leverage,** proxied by the ratio between total debt and total assets. According to economic theory, higher leverage increases an institution´s vulnerability to asset price shocks. As such, in distress situations, highly leveraged institutions are more likely to deleverage by selling assets, potentially triggering fire sales and contagion effects, thus increasing systemic risk. On one hand, literature corroborates economic theory finding that there is a positive relation between leverage and systemic risk (Acharya & Thakor, 2016; Acosta-Smith et al., 2024; Schularick & Taylor, 2012). On another hand, some authors argue that leverage might decrease systemic contribution since institutions with higher leverage have a better loan portfolio and thus are more resilient during a crisis (Diamond & Rajan, 2001).

The fourth variable, **profitability**, is measured by the ROA. Economic theory suggests that higher profitability reflects better risk management, efficient asset allocation, and stronger capital buffers, making institutions more resilient during downturns. According to buffer theory, profitable institutions are more likely to retain earnings, which can be used to absorb losses in times of financial stress, thereby reducing their contribution to systemic risk. Additionally, under moral hazard theory, less profitable institutions may take excessive risks in pursuit of higher returns, potentially increasing their systemic relevance. Thus, economic theory suggests a negative relation between profitability and systemic risk. On one hand, this theory is corroborated within the literature (Lehar, 2005; Varotto & Zhao, 2018). However, on the other hand, if the higher profitability stems from non-interest income, increased profitability can, contrarily, increase the systemic contribution of an institution (Williams, 2016).

Table 2 represents the descriptive statistics of the variables that are going to be used as well as its decomposition regarding the between-group (measures the differences in value of the variable across groups, in this case, institutions keeping time constant) and within-group (measures differences from the group average within one institution over time) variation which provides valuable insights into the data. The sample includes annual observations for the variables across 100 different institutions from 2014 to 2023. The **total assets** variable has an overall mean of 328 billion euros, which indicates that the sample is composed of big companies, which was to be expected since we selected them from the STOXX Europe 600 Financials. Its variability is high (493 billion) with total assets ranging from a minimum of 662 million to 2.76 trillion, which means that we have a high variability in terms of the size of the companies within our sample. Furthermore, as we can see, the between-group variation (489 billion) is significantly higher than the within-group variation (73,5 billion), indicating that the size differences between the institutions are greater than each institution´s size evolution over time.

Concerning the **liquidity ratios** that we are going to use we can see that they exhibit a significantly lower volatility compared to the size of the institutions and that the proxy of liquidity used for banks (loans to deposit ratio) has a significantly lower variability than the one used for nonbank financial institutions (cash and short-term investments to short term liabilities) which suggests that banks tend to maintain a more stable liquidity position over time while nonbank financial institutions experience greater fluctuations. Furthermore, the loans-to-deposit ratio has an overall mean of 1.02 and a standard deviation of 0.43. The within-group variation is on average 0.14 with a standard deviation of 0.34, which suggests that the institutions maintain a relatively stable level of liquidity over time. The between-group variation, however, is higher with a mean of 0.41 and a standard deviation of 0.19. The lower between-group standard deviation indicates that the liquidity across institutions does not differ significantly. On the other hand, the proxy of liquidity used for nonbank financial institutions (cash and short-term investments to short-term liabilities), exhibits higher variability, indicating a less stable liquidity position when compared to banks. The mean of this variable is 1.29, with a standard deviation of 9.79 encompassing values ranging from 0.000003 to 183.02. Its average between-group variation is 4.98 with a standard deviation of 0.002, while the within-group variation has a mean variation of 8.48 and a standard deviation of 149.58, with the lowest within-group variation being -32.76. This decomposition leads us to conclude that although nonbank financial institutions do not differ significantly in their liquidity positions at a given time, their individual liquidity positions fluctuate significantly over time, occasionally displaying abrupt shifts in their patterns.

With respect to the proxy used for **profitability** (ROA), its overall mean is 0.02 with a significantly low standard deviation of 0.06 and with values ranging from -0.24 to 0.51. The between-group variation has a mean of 0.05 with a standard deviation of 0.27, with the lowest observed between-group variation being -0.007. As for the within-group variation, the mean is at 0.03 with a standard deviation of 0.05, and the lowest observed within-group variation is -0.29.

Additionally, the **leverage** indicator (Total Debt/Total Assets) has an overall mean of 0.833 with a relatively low standard deviation of 0.226 and with values ranging from 0.030 to 1. Regarding its decomposition, the between-group variation has a mean of 0.222 and a standard deviation of 0.039, while the within-group variation exhibits a mean of 0.054 with a higher standard deviation of 0.440. These results suggest that leverage positions tend to differ more within the same institution over time than across different institutions.

Table 2 Descriptive statistics of panel data. Own elaboration

Variable		Mean	Std. Dev.	Min	Max	Observations
Total Assets						
	Overall	3.28e+11	4.93e+11	6.62e+08	2.76e+12	N=996
	Between		4.89e+11	1.12e+09	2.40e+12	n=100
	within		7.35e+10	9.86e+09	9.24e+11	T-bar=9.96
Loans/Deposits						
	Overall	1.0224	.4324	.0014	3.3505	N=458
	Between		.4118	.1864	2.6398	n=46
	within		.1415	.3363	1.7331	T-bar=9.956
Cash/Short term liabilities						
	Overall	1.2891	9.7955	2.86e-06	183.0163	N=484
	Between		4.9835	.0020171	34.7239	n=54
	within		8.479	-32.7592	149.5815	T-bar=8.96
ROA						
	Overall	.02438	.05881	-.240356	.5156	N=996
	Between		.0474	-.0073	.2679	n=100
	within		.0350	-.2878	.0468	T-bar=9.96
Total Debt/Total Assets						
	Overall	.8330	.2261	.0030	1	N=996
	Between		.2216	.0386	.989	n=100
	within		.0537	.4396	1.25	T-bar=9.96

Additionally, we also included economic variables in order to not only use them to control observable heterogeneity but also to give us an insight into which economic variables contribute to systemic risk. These variables are described in the table below and were retrieved from Refinitiv and the World Bank:

Table 3 Economic variables and their description. Own elaboration

Variables	Description
Interest rate	Reflects the monetary policy stance which is influences and is being influenced by systemic risk.
Regulatory Quality	Reflects the effectiveness of institutional frameworks and the enforcement of regulations which are crucial for mitigating systemic risk.
Credit spread	Measures the risk premium required by investors which is often linked to systemic risk perceived.
Real estate return	Indicates the performance of the real estate market which can be a source of systemic risk especially during bubbles.
Inflation	Represents price stability which affects purchasing power, interest rates and policy responses.
GDP growth	Reflects the overall economic activity and can serve as a proxy for economic resilience or vulnerability.

Table 3 represents the descriptive statistics of the economic variables as well as their decomposition regarding the between-group and within-group variation, which provides valuable insights into the data. The **interest rate** variable has an overall mean of 0.392 with a relatively high standard deviation of 1.343 and with values ranging from -0.750 and 6.437. The within-group variation (sd=1.198) is higher than the between-group variation (sd=0.566), which means that the interest rates differ more within a country over time rather than across countries, which reflects the coordination of economic policies within Europe, especially within the Eurozone.

With respect to the **regulatory quality**, our sample has an overall mean of 1.433 with a relatively low volatility, as the standard deviation is at 0.416. In contrast to interest rates, the between standard deviation (sd=0.404) is higher than the within standard deviation (sd=0.109), indicating that institution quality tends to remain stable within a country over time, with more substantial differences observed across countries.

As for the **credit spread,** which serves as a market-based measure of perceived credit risk, our sample has an overall mean of 0.352 with a low standard deviation and with values ranging from 0.0001 and 0.0526. In this case, since a single proxy was used for the European credit spread, there is no cross-sectional variation, resulting in a between-group standard deviation of 0. All observed variation stems from changes over time (within group). The same happens for the **real estate** proxy. This variable has an overall mean of $-6.50e^{06}$ with a relatively low standard deviation of 0.001 and with values ranging from -0.0020 and 0.008.

With respect to **inflation**, it has an overall mean of 2.18 with a relatively high standard deviation of 2.62 and with values ranging from -1.144 and 14.429. In this case, the between-group standard deviation (sd=0.788) is lower than the within-group standard deviation (sd=2.501), which means that the differences between inflation rates are a result of differences within one country over time rather than differences between different countries.

Finally, the **GDP growth** variable has an overall mean of 1.691 with a relatively high standard deviation of 3.429 and with values ranging from -10.940 to 8.931. The between-group variation, on the contrary to what happens with inflation, has a higher standard deviation (sd=0.574) than the within-group variation (sd=3.381), meaning that GDP growth experiences significant fluctuations over time within countries.

Table 4 Descriptive statistics of economic data. Own elaboration

Variable		Mean	Std. Dev.	Min	Max	Observations
Interest rate						
	Overall	0.3920	1.3235	-.75	6.4375	N=1000
	Between		.5658	1.12e+09	2.2591	n=100
	within		1.1976	-1.476	4.5704	T-bar=10
Regulatory Quality						
	Overall	1.4333	.4163	.4877	2.0405	N=1000
	Between		.4037	.6567	1.8409	n=100
	within		.1088	1.2259	1.7195	T-bar=10

Credit spread						
	Overall	.03519	.01519	.0001	.0526	N=1000
	Between		0	.0352	.0352	n=100
	within		.01519	.0001	.0526	T-bar=10
Real estate						
	Overall	-6.50e-06	.0008	-.0020	.0008	N=1000
	Between		0	-6.50e-06	-6.50e-06	n=100
	within		.0008	-0.0020	.0008	T-bar=10
Inflation						
	Overall	2.179	2.6213	-1.1439	14.4294	N=1000
	Between		.7883	.5068	3.9019	n=100
	within		2.5011	-2.5967	12.7069	T-bar=10
GDP growth						
	Overall	1.6916	3.4292	-10.940	8.9310	N=1000
	Between		.5739	.8936	3.7648	n=100
	within		3.3812	-11.2831	9.5824	T-bar=10

3.3 Methodology

As we have seen, in the literature, there is no one definition of systemic risk. However, there are several ways to calculate it. Despite that, comparing these measures seems to be difficult, with each presenting upsides and downsides. Nonetheless, ΔCoVar seems to be ahead of other indicators, according to some studies and according to the Google Scholar citations[1]. Having said that, in the present dissertation, we are going to follow the delta conditional value at risk approach (ΔCoVaR).

Nevertheless, we are going to introduce some modifications to the traditional measure to better reflect the situation where the financial institution is under stress by changing the way that we calculate the ΔCoVaR. Instead of an institution being in stress when its returns are at its VaR, we will consider that an institution is in stress when its returns are at or below its VaR level, following Girardi & Tolga Ergün (2013). By doing this, we are considering more severe distress events that are further into the tail of the earnings distribution. As identified by Bernard et al. (2012) this change allows us to achieve better accuracy in calculating the systemic risk.

Furthermore, we will also use a Copula-GARCH model to calculate our measure. This choice is based on the superior knowledge that these models provide, according to the literature. The use of copulas, as mentioned by Bernard et al. (2012), allows us to better

[1] 4586 citations for the Adrian & Brunnermeier, (2016) measure, 1688 for the Brownlees & Engle (2016) measure and 3880 for the Acharya et al. (2016) measure. (Information retrieved on 10/06/2025)

accommodate marginal distributions for individual losses and better model extreme dependencies of multivariate distributions, improving the predictive ability of the model. Furthermore, their use is also motivated by the fact that, according to Fritzsch et al. (2024), they provide higher flexibility in the multivariate setting, making them essential for accurately modeling the dependence structure of financial variables. Importantly, the study demonstrated that the choice of copula is extremely correlated with model risk (defined as the relation between the model and estimation uncertainty). In addition, they show that the choice of the copula is of extreme importance since it is economically significant and the main source of model risk, especially in financial crises, arises from their selection. Furthermore, they conclude that the copula choice can reduce uncertainties amplified by higher volatilities during turbulent times. Thus, their selection can help increase the forecast accuracy of financial risk since it helps decrease model risk, which is crucial for our study.

The use of the GARCH DCC model is driven by its ability to dynamically capture the evolving interconnections between financial institutions and the broader financial system over time. Thus, this model provides valuable insights into the propagation of systemic, reflecting shifts in correlations during stress and stability. As such, their use enhances our ability to model systemic risk by accounting for its multidimensional and time-varying nature, ultimately improving the robustness and accuracy of risk assessments (Girardi & Tolga Ergün, 2013).

We will merge these two models in order to be able to capture both the dynamically evolving interconnection of the system and to better model extreme dependencies of multivariate distributions, thus improving the predictive ability of our model. This hybrid approach enhances the robustness and predictive power of the systemic risk model.

3.3.1 Delta Conditional Value at Risk (CoVaR) approach

The measure proposed by Adrian & Brunnermeier, (2016) builds upon the value at risk (VaR) approach and intends to surpass some of its shortcomings, as was already mentioned. Its goal is to provide a measure of the downside risk and its spillovers of individual financial institutions to the whole financial sector. To do that, this approach begins by estimating the VaR of each institution. This can be represented as:

$$\Pr\left(X^i \leq VaR_q^i\right) = q\% \quad (3.3.1.1)$$

Equation (3.3.1.1), therefore, presents the maximum loss of a given institution with a probability of q% with X^i, being the continuous compounded stock returns of a given financial institution i. Following this calculation, the authors present the conditional value at risk (CoVaR), which represents the VaR of the system conditional on the existence of an extreme event at a financial institution. However, we will follow Girardi & Tolga Ergün (2013) modification of the calculation in order to achieve better accuracy in calculating the systemic risk. Thus, we will calculate the CoVaR by:

$$\Pr\left(X^i \leq CoVaR_q{}^{X \leq VaR_q^X} | X \leq VaR_q^X\right) = q\% \quad (3.3.1.2)$$

This formula (3.3.1.2) gives us the VaR of the system conditional on institution X being under stress, which is defined as the institution being at or below its VaR. Finaly, the authors calculate the difference between the CoVaR of the system when an institution is under stress and the CoVaR of the system when the institution is at its median (normal) state in order to calculate the delta conditional value at risk (ΔCoVaR) that represents the added risk an institution introduces in the system.

$$\Delta CoVaR_q^{\leq} = CoVaR_q{}^{X \leq VaR_q^X} - CoVaR_q^{X = VaR_{50\%}^X} \quad (3.3.1.3)$$

Formula 3.3.1.3 provides the additional risk introduced by an institution to the system when institution X is under stress compared to the situation where the institution is in a normal state, representing an institution's systemic contribution. The normal state is represented by the median VaR ($X = VaR_{50\%}^X$), which serves as a baseline since it reflects the typical or central behavior of the institution.

Adrian & Brunnermeier (2016) was first introduced using a quantile approach, however, this method lacks the ability to model time-varying and joint dependence structure effectively. Thus, we will use copulas to better accommodate marginal distributions for individual losses and better model extreme dependencies of multivariate distributions, improving the predictive ability of the model and GARCH models to dynamically capture the evolving interconnections between financial institutions and the broader financial system over time.

By computing the delta conditional value at risk for the institutions within our database, we are able to assess the contribution of nonbank financial institutions to the systemic risk and thus be able to answer question 1.

3.3.2 Determinants of systemic risk

In order to be able to evaluate the determinants of systemic risk and thus be able to respond to question 1.1, we employ a regression-based approach. The general models that are going to be implemented to assess the determinants of systemic risk have the logarithm of ΔCoVaR as the dependent variable, and the specific regression models are as follows:

$$\ln(\Delta CoVaR_{i,t}) = \alpha + \beta_1 * \ln(\Delta CoVaR_{i,t-1}) + \beta_2 * \ln(Liquidity_{i,t}) + \beta_3 * \ln\left(\frac{Deposits}{Assets}_{i,t}\right) + \beta_4 * \ln(ROA_{i,t}) + \beta_5 * \ln(Total\ Assets_{i,t}) + \beta_6 * Is_{Bank} + \beta_7 * Internacional\ activity + \beta_{10} * \ln(Interest\ rate_{i,t}) + \beta_{11} * \ln(Credit\ spread_{i,t}) + \beta_{12} * \ln(Regulatory\ Quality_{i,t}) + \beta_{12} * \ln(Real\ estate_{i,t}) + \beta_{14} * \ln(Inflation_{i,t}) + \beta_{16} * \ln(GDP\ growth\ _{i,t}) + \alpha_c + \gamma_t + \epsilon_{i,t} \quad (3.3.2.1)$$

$$\ln(\Delta CoVaR_{i,t}) = \alpha + \beta_1 * \ln(\Delta CoVaR_{i,t-1}) + \beta_2 * \ln(Liquidity_{i,t}) + \beta_3 * (\ln(Liquidity_{i,t}) * Is_{bank}) + \beta_4 * \ln\left(\frac{Deposits}{Assets}_{i,t}\right) + \beta_5 * \left(\ln\left(\frac{Deposits}{Assets}_{i,t}\right) * Is_{bank}\right) + \beta_6 * \ln(ROA_{i,t}) + \beta_7 * (\ln(ROA_{i,t}) * Is_{bank}) + \beta_8 * \ln(Total\ Assets_{i,t}) + \beta_9 * (\ln(Total\ Assets_{i,t}) * Is_{bank}) + \beta_6 * Is_{Bank} + \beta_7 * Internacional\ activity + \beta_8 * \ln(Interest\ rate_{i,t}) + \beta_9 * \ln(Credit\ spread_{i,t}) + \beta_{10} * \ln(Regulatory\ Quality_{i,t}) + \beta_{11} * \ln(Real\ estate_{i,t}) + \beta_{12} * \ln(Inflation_{i,t}) + \beta_{13} * \ln(GDP\ growth\ _{i,t}) + \alpha_c + \gamma_t + \epsilon_{i,t} \quad (3.3.2.2)$$

3.3.3 Connectedness measures

To answer the remaining questions, we will follow the methodology employed by Diebold & Yilmaz (2012) and consequent innovations of Gabauer & Gupta (2018) and Stenfors et al. (2022).

Diebold et al. (2009) first proposed a way to measure connectedness based on the decomposition of forecast error variances (FEVD) derived from a VAR model. In their approach, they employ the moving average representation of VAR to decompose the variance of forecast errors for a forecast horizon H based on the Cholesky factorization of the residual covariance matrix. This framework, although useful, had the drawback that the order of the variables and returns affected the results. As such, the measures then presented to evaluate the connectedness (e.g., Total Spillover Index) were biased. To overcome this issue and produce better results, in 2012, the same authors improved their methodology by using the generalized FEVD developed by Koop et al. (1996) and Pesaran & Shin (1998), which makes the decomposition invariant to variable ordering. This generalized approach allows for correlated shocks, accounting for them using the historically observed distribution of the errors. As a result, the shocks are not orthogonalized, leading the sum of the variance decomposition to not be equal to one (Diebold & Yilmaz, 2012).

To calculate the measures of connectedness, the authors start by defining the "*own variance shares*" which are equal to the H-step ahead error variances in forecasting x_i due to shocks to x_i (i=1,2, …, N) and the "*cross variance shares*" also referred as "*spillovers*" as the fraction of H-step ahead variances in forecasting x_i due to shocks to x_j (i≠j). It's from this definition that they apply the generalized FEVD developed by Koop et al. (1996) and Pesaran & Shin (1998) and calculate the H-step-ahead forecast error variance decomposition ($\theta_{jj}^{g}(H)$):

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \quad (3.3.3.1)$$

In formula (3.3.3.1), $\sum$ is the variance matrix for the error vector ε, σ_{jj} represents the standard deviation of the error term for the *j*th equation and e_i is the selection vector, with one as the *i*th element and zeros otherwise. As explained before, as a result of the application of the FEVD, the shocks are not orthogonalized, and the sum of the variance decomposition is not equal to one. As such, to calculate the spillover index, we need to normalize each entry of the variance decomposition matrix calculated through formula (3.3.3.1), as follows:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \quad (3.3.3.2)$$

After getting the normalized variance decomposition matrix, we are able to compute the connectedness measures. First, we compute the total volatility spillover index, which provides us with information about the contribution of spillovers of volatility shocks across asset classes to the total forecast error variance.

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} * 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} * 100 \quad (3.3.3.3)$$

After that, in order to understand the direction of volatility spillovers across major asset classes, we can calculate the directional spillovers received from other markets (Equation 3.3.3.4) and the directional spillovers transmitted to other markets (Equation 3.3.3.5) by using the normalized elements of the generalized variance decomposition matrix.

$$S_{i \leftarrow \cdot}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} * 100 = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} * 100 \quad (3.3.3.4)$$

$$S^g_{i\to\cdot}(H) = \frac{\sum_{\substack{j=1\\ i\neq j}}^{N} \tilde{\theta}^g_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ji}(H)} * 100 = \frac{\sum_{\substack{j=1\\ i\neq j}}^{N} \tilde{\theta}^g_{ji}(H)}{N} * 100 \text{ (3.3.3.5)}$$

Finaly, we can calculate the net spillovers (Equation 3.3.3.6) which is given by the difference between the spillovers transmitted to other markets and the spillovers received from other markets and the net pairwise spillovers (Equation 3.3.3.7), providing us information regarding the contribution of one market to the volatility of others, in net terms.

$$S^g_i(H) = S^g_{i\to\cdot}(H) - S^g_{i\leftarrow\cdot}(H) \text{ (3.3.3.6)}$$

$$S^g_{ij}(H) = \left(\frac{\tilde{\theta}^g_{ji}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}^g_{ik}(H)} - \frac{\tilde{\theta}^g_{ij}(H)}{\sum_{j,k=1}^{N} \tilde{\theta}^g_{jk}(H)}\right) * 100 = \left(\frac{\tilde{\theta}^g_{ji}(H) - \tilde{\theta}^g_{ij}(H)}{N}\right) * 100 \text{ (3.3.3.7)}$$

Gabauer & Gupta (2018) delve into the connectedness measures proposed by Diebold & Yilmaz (2012) and introduce a novel extension into the dynamic directional connectedness. In their paper, they are interested in analyzing the spillovers from one country to another. With this in mind, they wanted to see how much of the spillovers were transmitted within the respective countries and how much of the spillovers were transmitted from one country to another. Thus, they introduced a novel approach – Connectedness decomposition, represented by Equation 3.3.3.8.

$$\phi(J) = \left[\tilde{\phi}\right]_{ij,t}(J) = \begin{bmatrix} C_{11} & C_{12} & \cdots & C_{1k} \\ C_{21} & C_{22} & \cdots & C_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ C_{k1} & C_{k2} & C_{32} & C_{kk} \end{bmatrix} \text{ (3.3.3.8)}$$

In the matrix represented by Equation 3.3.3.8, the diagonal includes the internal spillovers, which represent the spillovers transmitted within the country, and the rest represents the external spillovers, which are the spillovers transmitted from one country to another. After the decomposition, we can calculate the connectedness measures and get a better representation of the dynamic directional connectedness.

$$To_{ij} = \sum_{n=1}^{k} C_{ij,nm} \text{ (3.3.3.9)}$$

$$From_{ij} = \sum_{m=1}^{k} C_{ji,nm} \text{ (3.3.3.10)}$$

$$NET_{ij} = To_{ij} - From_{ij} \text{(3.3.3.11)}$$

$$NI_{ij} = \sum_{n=1}^{k} \sum_{m=1}^{k} C_{ij,nm} - \sum_{n=1}^{k} \sum_{m=1}^{k} C_{ji,nm} \text{ (3.3.3.12)}$$

Equation 3.3.3.9 provides the total country-specific connectedness to others, while equation 3.3.3.10 provides the total country-specific connectedness from others, and equation 3.3.3.11 provides the net total country-specific connectedness. Equation 3.3.3.12 presents the net international total country-specific connectedness.

Stenfors et al. (2022), in the same line as Gabauer & Gupta (2018), delve into aggregated connectedness measures, introducing the conditional connectedness approach, which allows for a focus on specific groups. In their paper, they are studying the dynamic interactions between currencies and their maturities. With the introduction of their novel approach, they can detangle the network and focus on the movements between currencies in one given maturity or the connectedness between different maturities of one currency. Thus, this approach allows us to investigate the transmission mechanism of shocks, focusing on a particular maturity or currency while avoiding the bias that could arise from over-aggregating data across dimensions. For example, the approach allows us to focus solely on the 2-year maturity and obtain a connectedness matrix that reflects how different currencies influence each other at this horizon, allowing us to infer on the transmitting and receiving currencies, eliminating distortions that would result from including irrelevant maturities in the estimation. The conditional connectedness measures are given through the following equations:

$$C_{ij,t|m} = \frac{G_{ij,t}}{\sum_{j \in k_m} G_{ij,t}} \quad (3.3.3.13)$$

$$C_{i\to\bullet,t|m} = \sum_{j \in k_m, j \neq i} C_{ji,t|m} \quad (3.3.3.14)$$

$$C_{i\leftarrow\bullet,t|m} = \sum_{j \in k_m, j \neq i} C_{ij,t|m} \quad (3.3.3.15)$$

$$C_{i,t|m} = C_{i\to\bullet,t|m} - C_{i\leftarrow\bullet,t|m} \quad (3.3.3.16)$$

$$C_{t|m} = \frac{n(k_m)}{n(k_m)-1} \sum_{i=1}^{n(k_m)} C_{i\to\bullet,t|m} \equiv \frac{n(k_m)}{n(k_m)-1} \sum_{i=1}^{n(k_m)} C_{i\leftarrow\bullet,t|m} \quad (3.3.3.17)$$

Equation 3.3.3.13 represents the conditional connectedness given a group k_m while equation 3.3.3.14 provides us with the conditional total group-specific connectedness to others, which gives us insight, in the paper, of how much a currency/maturity is transmitting to another currency/maturity. Equation 3.3.3.15 provides us with the conditional total group-specific connectedness from others, which provides us with insight into how much a currency/maturity is absorbing from another currency/maturity. Finally, equation 3.3.3.16 gives us insight into the currency/maturity that is driving the connectedness or being driven, and equation 3.3.3.17 illustrates the interconnectedness of currencies/maturities given a certain maturity/currency. This approach allows us to assess how a given currency/maturity (or any subgroup) transmits or receives shocks, while isolating its contribution from the rest of the system.

For the purpose of the current dissertation, the methodology employed by Diebold & Yilmaz (2012) will provide us with insight into the overall network of the financial institutions. Gabauer & Gupta (2018) approach will then allow us to gather insight on the transmissions between banks and NBFI as well as within each sector. Finally, Stenfors et al. (2022) will allow us to examine the aggregate dynamics while isolating the impact of specific subgroups of the connections between banks and NBFI and allow us to conclude whether banks are in fact driving NBFI and thus have the ability to control the systemic contribution of these institutions or conversely whether NBFI are driving banks and thus exacerbating systemic risk.

4. Empirical results and discussion

4.1 Systemic risk contribution by sector

This subsection presents the empirical findings as well as the calculation of the systemic risk contribution of both banks and NBFI. Thus, it intends to respond to the first question of the present dissertation.

As was already mentioned, we will be applying the modified methodology of the delta conditional value at risk of Girardi & Tolga Ergün (2013) and apply GARCH and copula models in the forecast of the CoVaR measures. Thus, we started by modeling the dynamically and evolving interconnections between financial institutions and the broader financial system over time using the GARCH framework, and then to capture the dependency structure between the institutions and the system, we employed copula models. At this stage, several copulas were tested (Student, Gaussian, Clayton, Frank, Gumbel, Joe, Dynamic Gaussian, Dynamic Student, Dynamic Gumbel, Dynamic Rot. Gumbel, and Plackett) and then compared and selected according to the Akaike Information Criterion (AIC). After applying all these models, the corresponding VaR, CoVaR, and Delta Conditional Value at Risk were calculated.

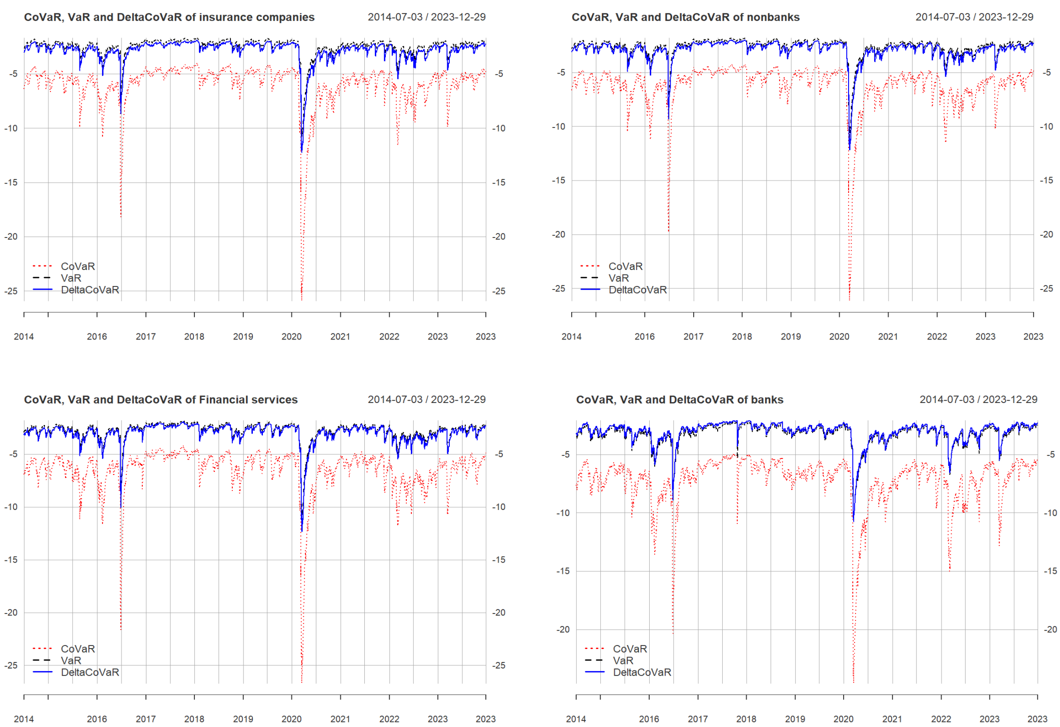


Figure 4 VaR, CoVaR and DeltaCoVaR by group. Own elaboration

The results shown in Figure 4 show a significant increase in ΔCoVaR during the COVID-19 crisis, which is consistent with the concept of systemic risk. Moreover, there also seems to be a significant increase in the measures for the period of 2016, which is possibly explained by the uncertainty created by the Brexit referendum in the European markets. Additionally, these results show that all sectors increase their ΔCoVaR, which signifies an increase in the overall financial system risk reflected in the increase of bankruptcy risks of individual institutions and correlation between the financial system index and individual institutions.

Furthermore, upon examining the statistics of the estimates in the whole sample period from 2014 to 2023 (Table 5) we can see that the average contribution to the systemic risk represented by the ΔCoVaR is higher for banks (-3.9%) than for nonbank financial institutions (-2.9%), although their values are close. This means that when the daily return of the sectors (banks, NBFI) falls to the bottom 5%, the daily 5% value at risk for the financial system increases, on average, by 3.9 and 2.9 percentage points. By decomposing the ΔCoVaR of NBFI into ΔCoVaR of financial services and insurance companies, we can see that, on average, financial services contribute more to the systemic risk than insurance companies. Moreover, we can also conclude that the standard deviation of the systemic contribution of banks is lower than the standard deviation of the systemic contribution of NBFI. This indicates that the systemic contribution of NBFIs varies more over time than that of banks, suggesting that the impact of these institutions is less predictable.

Concerning the summary statistics of VaR and CoVaR for all sectors, we can conclude that the CoVaR is significantly higher than the VaR, suggesting that the systemic risk is mainly driven by the interconnections among institutions rather than their individual risk profiles. Thus, an institution may adopt a risk-averse stance and have a high contribution to systemic risk due to its connections within the system, which underscores the importance of studying contagion effects that may happen and the network of institutions. Furthermore, the standard deviation of the CoVaR measures is also significantly higher than that of the VaR, indicating that the transmission of risk is more uncertain and highly dependent on the evolving network of financial linkages. Moreover, it is also worth mentioning that in the same line as what happens with the ΔCoVaR, banks present the highest value for the CoVaR and VaR, which highlights their central role in systemic risk propagation. Within the NBFI sector, financial services companies are the ones with the highest indicators, highlighting their systemic importance.

Table 5 Summary statistics VaR, CoVaR and DeltaCoVaR whole sample. Own elaboration.

	Mean	Median	SD
CoVaR banks	-7,22	-6,64	2,17
CoVaR financial services	-6,5	-5,97	2,16
CoVaR insurance companies	-5,98	-5,44	2,16
CoVaR Nonbank financial institutions	-6,22	-5,7	2,13
VaR banks	-3,25	-3	0,95
VaR financial services	-2,77	-2,55	0,91
VaR insurance companies	-2,48	-2,26	0,9
VaR Nonbank financial institutions	-2,62	-2,4	0,89
DeltaCoVaR banks	-3,06	-2,81	0,96
DeltaCoVaR financial services	-2,99	-2,75	1
DeltaCoVaR insurance companies	-2,83	-2,57	1,02
DeltaCoVaR Nonbank financial institutions	-2,9	-2,66	1

During the COVID-19 crisis, as expected, the measures for systemic risk show elevated values compared with those of the entire sample (Table 6). Looking at the ΔCoVaR, we can see that banks remain the largest contributors to systemic risk, with an average value for the ΔCoVaR of 4.25%. However, NBFI is not that far with their contribution being only 25bp less than that of banks. Within the NBFI, in contrast to what happens for the whole sample, insurance companies are the ones that are contributing more to the systemic risk. This shift highlights the increased vulnerability of insurance firms during the crisis, which is likely due to heightened market volatility and exposure to pandemic-related claims. Looking at the VaR and CoVaR, we can conclude that once again, banks have higher indicators than NBFI, which highlights their central role and importance in systemic risk. However, as can be seen, NBFIs are not too far behind and also show significant systemic exposure. Furthermore, these institutions have a notably higher standard deviation for both VaR, CoVaR, and ΔCoVaR, reinforcing the idea that their systemic risk transmission is more volatile and uncertain. Additionally, it is also relevant to note that, in the same line with what happens for the whole sample, the CoVaR measure exhibits significantly higher values than those of VaR, highlighting the growing importance of network interconnections and contagion effects.

Overall, both these tables (Table 5 and Table 6) reinforce that banks play a central role in the transmission of systemic risk, as their contribution remains the largest during both crisis and on average throughout the entire period being analyzed. It also reinforces the significance of the interconnections among institutions, as evidenced by CoVaR levels consistently exceeding VaR levels, which reflect individual risk levels. Finally, the higher standard deviation of the systemic risk measure for NBFI highlights their greater uncertainty and more volatile contribution, emphasizing the importance of studying their contribution as well as the key determinants that drive it.

These results were consistent with Rahman et al. (2022) and Soo Hong et al. (2024). However, we found that banks exhibited a larger contribution, which goes against the finding of Bernal et al. (2014) that the "other financial service sector" was the largest contributor.

Table 6 Summary statistics VaR, CoVaR and DeltaCoVaR Covid-19. Own elaboration.

	Mean	Median	SD
CoVaR banks	-9,89	-8,68	3,87
CoVaR financial services	-8,58	-6,91	4,49
CoVaR insurance companies	-8,84	-7,19	4,58
CoVaR Nonbank financial institutions	-8,72	-7,02	4,53
VaR banks	-4,41	-3,86	1,69
VaR financial services	-3,67	-2,97	1,89
VaR insurance companies	-3,67	-2,98	1,91
VaR Nonbank financial institutions	-3,67	-2,95	1,9
DeltaCoVaR banks	-4,25	-3,72	1,71
DeltaCoVaR financial services	-3,95	-3,17	2,08
DeltaCoVaR insurance companies	-4,18	-3,42	2,16
DeltaCoVaR Nonbank financial institutions	-4,07	-3,28	2,12

4.2 Systemic risk determinants

In this subsection, we present the empirical findings related to the firm-specific and market-wide characteristics that influence an institution´s contribution to systemic risk. This analysis directly addresses research question 1.1.

As a starting point for the analysis, we employ the regression framework introduced in section 3.3.2. However, before that, it is important to choose which method we are going to employ in our panel data. There are different methods that can be used in panel data, including fixed effects (FE) and random effects (RE) models. The main difference between these methods is the treatment of unobservable individual heterogeneity. The fixed effects model assumes that individual-specific characteristics (observed and unobserved) are correlated with the independent variable. As a result, fixed effect models include individual-specific intercepts, allowing for the control of such unobserved heterogeneity. On the other hand, random effects models treat individual-specific effects as uncorrelated with the observed covariates, considering them as random variables with specific variance. Thus, to determine which model to use, the Hausman test will be performed (Table viii). Under the null hypothesis, the random effect model is preferred to the fixed effect model. Since the p-value is below 5% for both of our equations, we reject the null hypothesis, meaning that the fixed effect model is preferred.

Following the choice of the model and to ensure the reliability and validity of the regression results, we begin by testing the classical hypothesis. To start, we need to make sure that we do not have a multicollinearity issue among our variables. To do that, we need to analyze the VIF statistics (Table ix). Since our VIF statistics were above 5, we have to drop variables due to multicollinearity. As a result, our VIF statistics mean was below 5 (Table x) and the equations were now:

$$\ln(\Delta CoVaR_{i,t}) = \alpha + \beta_1 * \ln(\Delta CoVaR_{i,t-1}) + \beta_2 * \ln(Liquidity_{i,t}) + \beta_3 * \ln\left(\frac{Deposits}{Assets}_{i,t}\right) + \beta_4 * \ln(ROA_{i,t}) + \beta_5 * \ln(Interest\ rate_{i,t}) + \beta_6 * \ln(Regulatory\ Quality_{i,t}) + \beta_7 * \ln(Inflation_{i,t}) + \beta_8 * \ln(GDP\ growth_{\ i,t}) + \beta_9 * Is_{bank} + \beta_{10} * International_{activity} + \alpha_c + \gamma_t + \epsilon_{i,t} \quad (4.2.1)$$

$$\ln(\Delta CoVaR_{i,t}) = \alpha + \beta_1 * \ln(\Delta CoVaR_{i,t-1}) + \beta_2 * \ln(Liquidity_{i,t}) + \beta_3 * (\ln(Liquidity_{i,t}) * Is_{bank}) + \beta_4 * \ln\left(\frac{Deposits}{Assets}_{i,t}\right) + \beta_5 * \left(\ln\left(\frac{Deposits}{Assets}_{i,t}\right) * Is_{bank}\right) + \beta_6 * (\ln(ROA_{i,t}) * Is_{bank}) + \beta_7 * \ln(Interest\ rate_{i,t}) + \beta_8 * \ln(Regulatory\ Quality_{i,t}) + \beta_9 * \ln(Inflation_{i,t}) + \beta_{10} * \ln(GDP\ growth_{\ i,t}) + \beta_{11} * Is_{bank} + \beta_{12} * International_{activity} + \alpha_c + \gamma_t + \epsilon_{i,t} \quad (4.2.2)$$

Moving on, we do not have to worry about specification due to the decision to lean our research on extensive past research, namely the Rahman et al. (2022) contribution.

Moreover, homoscedasticity is a classical hypothesis describing a situation where the variance of disturbances associated with the dependent variable is constant across all observations. To test for the presence of homoscedasticity, we performed the Wald test for groupwise heteroscedasticity (Table xi) in a fixed effect model and concluded that equation (4.2.2) rejected the null hypothesis for a p-value of 5% of presence of homoscedasticity whereas equation (4.2.1) did not. Thus, for equation (4.2.2) there was a need to use robust standard errors in order to correct the presence of heteroscedasticity. Moving forward with the classical hypothesis testing, we tested for the presence of autocorrelation and concluded that both equations had the presence of both cross-sectional and serial autocorrelation (Table xii). To correct the presence of serial autocorrelation, we estimated the models using the Newey-West estimator, whereas to correct the cross-sectional autocorrelation, we employed a regression with the Driscoll-Kraay standard errors. It is important to note that the regression with the Driscoll-Kraay standard errors corrects both cross-sectional and serial correlation as well as heteroscedasticity.

Finally, we analyzed the presence of endogeneity, which is often a result of simultaneity, reverse causality, omitted bias, or measurement errors, and concluded that for equations (4.2.1) and (4.2.2), inflation was endogenous. This outcome was to be expected since inflation affects the purchasing power, which in turn pressures the interest rate and can result in systemic risk amplification. In turn, systemic risk directly influences interest rates, which in turn influence inflation. To solve this issue, we used an IV estimation and used the logarithmic value for the credit spread, which, according to Kleibergen-Paap rk Wald F statistic, was a strong instrument for our variable (Table xiii). After testing the classical hypothesis, the final models were estimated. The results can be seen below:

Table 7 Effect of macro-financial and institutional characteristics on Systemic risk. Own elaboration

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
Lag_LogDeltaCoVar	-0.15184*** (0.05155)	-0.15406*** (0.04728)	0.86208*** (0.08240)	0.85313*** (0.09076)	-0.12139 (0.09394)	-0.12728 (0.08311)
LogLiquidity	0.00728 (0.02528)	-0.01315 (0.02262)	0.01154 (0.00991)	0.00365 (0.00716)	0.01452 (0.00930)	0.00518 (0.01781)
LogLiquidity_b		0.06052** (0.02458)		0.03446* (0.01920)		0.02311 (0.01890)
LogDA	0.04130 (0.06604)	0.06033 (0.05557)	0.01165 (0.03319)	0.02203 (0.03119)	0.06954** (0.02214)	0.08294* (0.03791)
LogDA_b		11.34317*** (1.92631)		1.86656** (0.91509)		7.27289*** (1.60721)
LogROA_b		-0.05961 (0.05382)		-0.00779 (0.04461)		-0.05555 (0.03554)
Is_Bank			-0.04886 (0.04533)	0.07819 (0.27636)		
International activity			-0.02059 (0.05402)	-0.04354 (0.04954)		
LogIR	0.05998*** (0.01845)	0.04820*** (0.01646)	0.07935*** (0.02219)	0.07792*** (0.02269)	0.05194** (0.01645)	0.04522** (0.01664)
LogRQ	-1.30074*** (0.19664)	-0.94661*** (0.17908)	0.14566*** (0.05367)	0.13334** (0.05463)	-0.68213*** (0.13742)	-0.52744*** (0.13682)
LogInflation	-0.13867*** (0.02900)	-0.11414*** (0.02553)	-0.07760** (0.03904)	-0.06037 (0.03847)	3.25715 (2.09017)	2.87071 (2.05799)
LogGDP	0.05309** (0.02065)	0.05020*** (0.01764)	0.09927*** (0.01845)	0.09844*** (0.01902)	0.03430 (0.03152)	0.03427 (0.02898)
LogROA	-0.04080* (0.02319)		-0.01573 (0.01505)		-0.03012 (0.01701)	
Constant			0.04621 (0.11123)	0.12379 (0.11527)	-0.54513 (1.24295)	-0.14856 (1.23193)

Notes: ***p<0.01, **p<0.05, *p<0.1. Model (1) and (2) applies the OLS method with unit fixed effects, endogeneity correction and robust standard errors in parenthesis. Model (3) and (4) applies the Newey West estimation and endogeneity correction. Model (5) and (6) apply the Driscoll-Kraay standard errors regression with unit fixed effects and endogeneity correction.

Table 7, columns 1, 3, and 5 represent the results of the estimation of equation (4.2.1) with the different models presented before. As we can see, inflation is only significant in columns 1 and 3. According to column 1, an increase of 1% in **inflation** above the average level for a given entity provokes a decrease of 0.13% in the systemic risk measured through the ΔCoVaR, ceteris paribus. Similarly, a 1% increase in inflation leads to a decrease of 0.07% in the systemic risk, ceteris paribus, according to column 3. This inverse relationship may reflect the countercyclical nature of inflationary periods, which often trigger accommodative monetary policy interventions aimed at stabilizing financial markets. The momentum is accounted for while analyzing the β associated with the **lagged ΔCoVaR.** According to column 1, an increase of 1% in the lagged systemic risk above the average level for a given entity provokes a decrease of 0.15% in systemic risk, ceteris paribus, suggesting a mean-reversion phenomenon. Column 3, however, appoints for systemic risk persistence, concluding that past systemic conditions can amplify current vulnerabilities since a 1% increase in the variable is associated with a 0.86% increase in systemic risk, ceteris paribus.

Moreover, an increase of 1% on the **interest rates** above the average level for a given entity provokes an increase of 0.06% on systemic risk, ceteris paribus, according to column 1 and an increase of 0.05% according to column 5. Column 3 suggests that an increase of 1% in the interest rates provokes an increase of 0.07% in systemic risk, ceteris paribus. This result is in line with the study of Nguyen et al. (2023) that found that when a rise in interest rates is introduced, systemic risk increases. This relationship inverts its signal in the long term, where systemic risk decreases as a result of the introduction of higher interest rates. Furthermore, an increase of 1% in the **regulatory quality** above the average level for a given entity of a country is associated with a decrease of 1.3% in systemic risk, ceteris paribus, according to column 1 and 0.68% according to column 5. This finding highlights the importance of the credibility associated with regulatory governance in promoting financial stability. However, column 3 finds that an increase of 1% in the regulatory quality is associated with an increase in systemic risk of 0.14%, ceteris paribus.

An increase of 1% in the **growth rate of the GDP** above the average for a given entity is associated with an increase of 0.05% in systemic risk, ceteris paribus, according to column 1. Column 3 suggests that an increase in 1% of the growth rate of the GDP is associated with an increase of 0.1% in systemic risk, ceteris paribus. This result suggests that economic expansions, while generally positive, may lead to an increase in systemic risk, possibly due to the increase in risk-taking and greater interconnectedness within the financial system. Finally, the only institution specific characteristic that is statistically and at a 10% level, in column 1, suggests that an increase of 1% in the **profitability** above the average for a given institution, proxied by the return on assets (ROA) is associated with the decrease of systemic risk of 0.04%, ceteris paribus, suggesting a weak but possibly meaningful relationship between financial performance and systemic vulnerability. Additionally, according to column 5, an increase of 1% in the **leverage** (proxied by the ratio between debt and assets) above the average for a given institution leads to an increase of systemic risk of 0.07%, ceteris paribus.

Table 7, columns 2, 4, and 6 represent the results of the estimation of equation (4.2.2), with the different models mentioned before introducing multiplicative effects through the interaction terms between institution-specific characteristics and a dummy variable identifying banks to equation (4.2.1). As we can see from the analysis of the columns, the coefficients analyzed before remaining statistically significant and retain their sign and magnitude. However, in addition to that, two new coefficients related to institution-specific characteristics emerge as statistically significant. These are the coefficients associated with the **leverage position of banks** and the **liquidity position of banks**. Starting with the **leverage position of banks**, as we can see, an increase of 1% in the leverage of banks above the average for a given entity is associated with an increase in systemic risk of 11%, ceteris paribus, according to column 2 and 7% according to column 6. As for column 4, an increase of 1% in the leverage position of banks is associated with an increase of 2% in systemic risk, ceteris paribus. Furthermore, a 1% increase in the **liquidity of banks** above the average for a given entity is associated with an increase in systemic risk of 0.05%, ceteris paribus, according to column 2. Finally, at a 10% level, according to column 4, a 1% increase in the liquidity of banks is associated with an increase of 0.03% in systemic risk, ceteris paribus. This finding reflects the potential that liquidity has on risk-taking and speculative behaviors. Additionally, if there is a mismatch between the maturity of assets and liabilities, banks might enter into fire sales even though, in theory, they have enough liquidity, which in turn, increases systemic risk (Brunnermeier & Pedersen, 2008).

These results are in line with Acharya & Thakor (2016), Acosta-Smith et al. (2024) and Schularick & Taylor (2012) that found that leverage is found to have a positive relation to systemic risk. This link is associated with the fact that institutions might have to deleverage in cases of stress, which implies fire sales of assets below their actual value. Furthermore, the research is also aligned with Lehar (2005) that found a negative relation between profitability and systemic risk. Additionally, Rahman et al. (2022) found a positive relation between liquidity and systemic risk, and Davydov et al. (2021) found that liquidity increases the interconnections within the system, which, in the case of stress, can exacerbate systemic risk.

To conclude, based on our results, we conclude that both macroeconomic conditions and institution-specific characteristics play a role in explaining an institution's contribution to systemic risk. Overall, the analysis shows that inflation and regulatory quality are negatively associated with systemic risk, while GDP growth and interest rates are positively associated with systemic risk. On the institutional side, profitability and leverage show a negative and positive effect on systemic risk, respectively. As for the interactional terms added in equation (4.2.2), they reveal that for banks, leverage and liquidity are positively associated with systemic risk. Thus, our analysis suggests that effective systemic risk mitigation strategies must account not only for market-wide dynamics but also for the structural and financial attributes of institutions, particularly within the banking sector.

4.3 Connectedness

This subsection presents the empirical findings regarding the evolution of the interconnections within the system as well as the identification of key metrics that will help address research questions 2, 2.1, and 3 of the dissertation.

Specifically, we analyze the dynamics of systemic risk contributions of institutions measured through ΔCoVaR in order to understand how they are interconnected. To this end, we follow the methodology proposed by Diebold & Yilmaz (2012) using a Vector Autoregressive (VAR) model with a 10-day forecast horizon and a 250-day rolling window to compute the connectedness measures.

We started by calculating the average connectedness table (Table xiv, Table xv, Table xvi). The results revealed that the "ING Groep NV", a bank, exhibits the highest net spillover (42,68), indicating that this institution is the largest transmitter of systemic risk within the network. Additionally, we concluded that there were 27 NBFI that displayed a positive net transmission, meaning that they were transmitters of systemic risk, while another 27 NBFI were receivers (negative net spillover). On the other hand, we had 25 banks that were transmitters and 19 that were receivers. These results suggest a relatively balanced distribution of systemic risk contributions within both groups—banks and nonbanks—which may imply a degree of mutual dependence and complexity in the risk transmission dynamics of the financial system.

To be able to better illustrate the network of connectedness within the financial system, we created a graph that shows the connections between different participants (Figure 5). The nodes are color-coded according to their role in risk transmission: institutions that act as transmitters (dynamic net pairwise directional connectedness (NPDC)>0) are represented in blue, while institutions that receive risk (NPDC<0) are represented in yellow. Their border color represents the group of institutions that they belong with the border being blue for nonbank entities and black for banks. The links not only represent the direction of risk transmission but also the relationship between the institutions: blue for bank-to-bank transmissions, dark green for bank-to-nonbank, dark orange for nonbank-to-bank, and light gray for connections between nonbanks. Furthermore, the thickest of each link reflects the strength of the connection, with thicker links indicating a stronger transmission of risk.

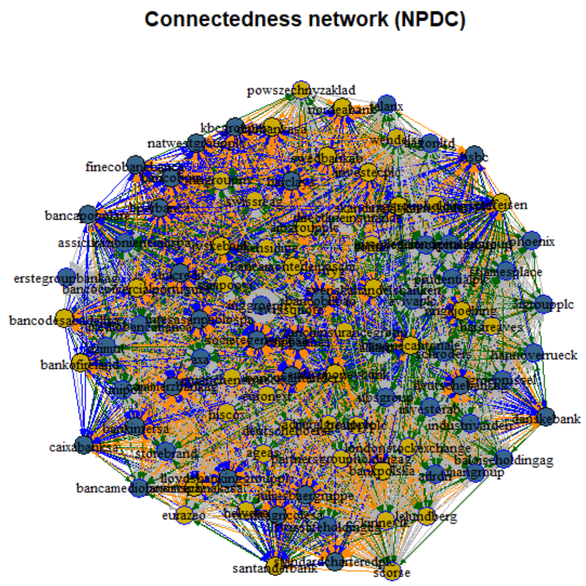


Figure 5 Connectedness network. Own elaboration.

In order to be able to analyze which part of connectedness could be attributed to internal shocks within a specific group or between those groups, we applied the connectedness decomposition approach of Gabauer & Gupta (2018). As a result of this approach, two figures were generated, the left image in Figure 6 shows the total connectedness index (TCI) in black, the TCI without the external shocks in red, and the TCI without external shocks for both banks and nonbanks, in green and blue, respectively. While the right image in Figure

6 shows the total connectedness index in black, the TCI without internal shocks in red, and the TCI without internal shocks for both banks and nonbanks in green and blue, respectively.

As shown in Figure 6 the total connectedness index varies over time, peaking between 2016 and 2018 and in 2020. These peaks are consistent with the results that we got before when we were analyzing the results for the ΔCoVaR, and are consistent with the Brexit referendum, which created uncertainty in the European markets, and the COVID-19 crisis. The average TCI connectedness for the sample is 92,96, indicating that on average 92,96% of the ΔCoVaR forecast error variance comes from spillovers. This means that the financial sector is extremely interconnected, which exacerbates systemic risk since a shock in one institution can rapidly spread. These conclusions are in line with previous research of Billio et al. (2012), Gong et al. (2019) and Zhang et al. (2023).

By decomposing the TCI into internal and external spillovers, we concluded that the internal TCI has an average of 51,04 while the average external TCI is 45,60. This way, we can conclude that internal spillovers account on average for 51,04% of ΔCoVaR forecast error variance while external spillovers account on average for 45,60%. Although internal spillovers seem to account for an overall higher percentage of ΔCoVaR forecast error variance, external spillovers remain substantially high, which underscores the importance of cross-sector linkages. Furthermore, we can see that the internal TCI of NBFI is consistently higher than the internal TCI of banks, meaning that the connections within the nonbank network are stronger, and that the external TCI of nonbanks seems to be more volatile than the external TCI of banks. This also implies that the existence of NBFI is exacerbating and increasing the interconnectedness of the system.

Looking more closely at the periods of stress (between 2016 and 2018 and 2020) we can see that the external TCI increased more than the internal TCI, which suggests that during crisis, cross-group contagion (between banks and NBFI) intensifies more rapidly than internal ones, which underscores the importance of monitoring inter-group spillovers. Specifically, during these periods we can see a spike in the external TCI of banks, which suggests that in these moments they are contributing significantly to the increase of systemic risk. However, we cannot conclude whether banks are receiving or transmitting shocks to nonbanks. Thus, this metric alone does not allow us to determine whether banks are primarily transmitting or receiving shocks from NBFI. To answer this, a further directional decomposition is necessary and will be explored in the next step.

Overall, by analyzing the internal and external decomposition of the total connectedness index, we can see that nonbank financial institutions have a consistently higher internal TCI, which suggests that connections within the nonbank network are stronger. Furthermore, the TCI of NBFI seems more volatile, which indicates that NBFI play a central role in the propagation of financial stress across the system. Finally, we can also see that in periods of stress, there is a spike in the external TCI of banks, indicating that banks contribute significantly to the increase in systemic risk during these periods. Nevertheless, to fully understand the drivers behind these dynamics, particularly the directionality of cross-group interactions, further analysis is necessary.

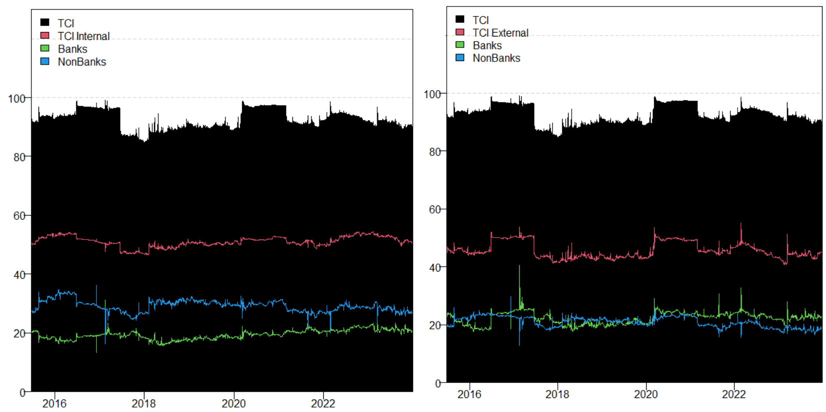
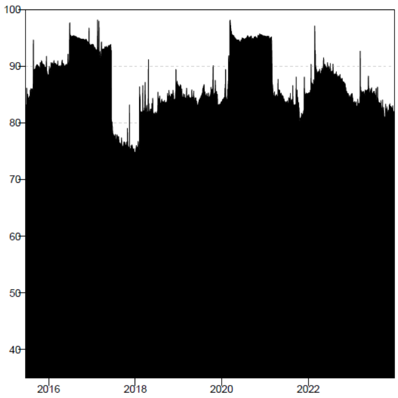


Figure 6 Dynamic total connectedness with internal and external decomposition. Own elaboration.

Building upon these insights and in order to fully understand the links between these two groups (banks and NBFI), we followed the approach of Stenfors et al. (2022). These authors extended the connectedness approach by introducing the conditional and aggregate approaches. The conditional approach intends to give further insight into the connectedness within one group, which in this case allows us to see the connectedness dynamic within banks and NBFI. The aggregate approach intends to give us further insight into the connectedness between two groups instead of looking at the individual connectedness of the institutions belonging to each group. By applying the aggregate approach, we are able to see if banks are affecting NBFI or if, otherwise, NBFI are affecting banks.

Starting with the conditional approach in Figure 7, and Figure 8, we can see the connectedness within NBFI and the bank sector. As expected from the previous results, the connectedness between NBFI is slightly higher through the period analyzed however, these differences are not significant during crisis (between 2016 and 2018 and 2020). Furthermore, since the overall connectedness (average TCI) is higher than the connectedness observed when conditioning only on banks, we can infer that NBFIs contribute significantly to the interconnectedness of the financial system.



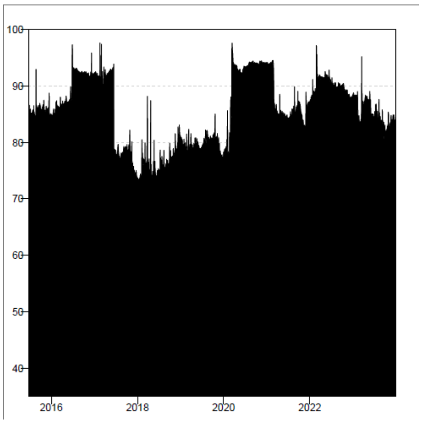


Figure 7 Conditional Connectedness NBFI. Own elaboration

Figure 8 Conditional Connectedness Banks. Own elaboration.

With the aggregate approach, we can see which sector is being influenced and which sector is influencing another by looking at the aggregate values for the net total group-specific connectedness index. If this index has a positive value, it means that the sector is transmitting shocks to the system, while if it has a negative value, it means that the sector is being influenced and, as such, is absorbing shocks of the system. By looking at Figure 9 we can see that banks persistently exhibit negative values for the net total group-specific index, meaning that this sector is actually receiving shocks originating from the NBFI sector. This finding is particularly relevant as it indicates that the larger ΔCoVaR of banks is not solely due to their own individual positions on risk but also a result of their continuous absorption of shocks coming from the NBFI sector. Thus, this insight provides further insight into the systemic contribution of banks and builds upon the findings of existing literature.

This finding has serious implications for macroeconomic regulation since it shows that systemic risk propagation is extremely interdependent. Hence, even though banks are subject to a more stringent prudential regulation, their indirect exposure originating from less regulated entities undermines the effectiveness of isolated policy measures. This reinforces the need for coordinated and comprehensive macroprudential approaches that account for intersectoral spillovers in regulatory decisions.

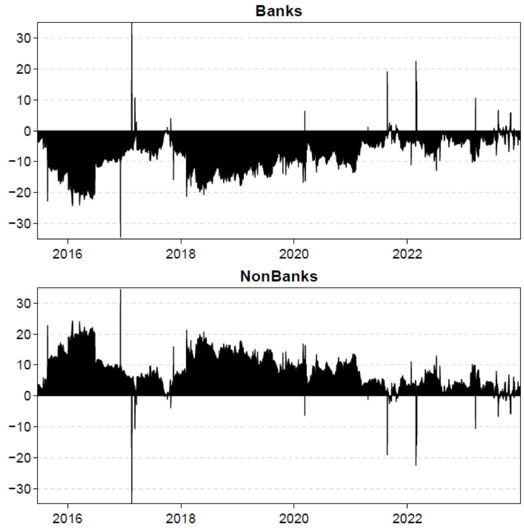


Figure 9 Net Total group-specific connectedness. Own elaboration.

4.4 Robustness

This study intends to extract knowledge on the influence of NBFI on systemic risk and its relationship with banks. Even though we consider the ΔCoVaR methodology to extract a systemic risk measure, there is no consensus on its use. Thus, one could say that our results are biased and a result of our choice. Thus, in order to test our hypothesis and see if we reached the same results, we applied the connectedness measures directly to the returns of the institutions as Billio et al. (2012), Zhang et al. (2023) and Henriques & Sadorsky (2025).

The results of this approach are presented in Figure i and are very similar to the ones that we got before. The average TCI for the sample is 94,04, the average internal TCI is 54,66, and the average external TCI is 43,65. These results, although slightly different by 2 bp lead us to the same conclusions as those presented before. Additionally, as we can see periods of stress (between 2016 and 2018 and 2020) the external TCI increased more than the internal TCI which suggests that during crisis, in the same line as what happened before, cross-group contagion (between banks and NBFI) intensify more rapidly than internal ones which underscores the importance of monitoring inter-group spillovers. Finally, the conclusion that banks persistently exhibit negative values for the net total group-specific index, meaning that this sector is actually receiving shocks originating from the NBFI sector, remains the same.

Furthermore, we estimated the Vector autoregressive model for different time windows, which according to Antonakakis et al. (2020) their average is similar to the results of the TP-VAR.

The results for the estimation using 125 days as a rolling window are shown in Figure ii and are very similar to the ones that we got before. The average TCI for the sample is at 97,52, the average internal and external TCI is 52,29 and 50,39, respectively. These results, although slightly different by 5 bp on the average and external TCI and 1 bp on the internal TCI, led us to the same conclusions as those presented before. Finally, the conclusion that banks persistently exhibit negative values for the net total group-specific index, meaning that this sector is actually receiving shocks originating from the NBFI sector remains the same.

To test the robustness of the results that we got regarding the characteristics that influence systemic risk, we added lagged variables of the economic conditions to the equations tested above. The results are shown in Table xvii. Comparing these results with the baseline models estimated, we find that the effect of inflation, leverage of banks, profitability, and interest rates remain consistent, supporting the robustness of these relationships. However, the coefficient for the lagged systemic risk measure and the coefficient associated with the GDP growth change its signal. These results indicate that an increase of 1% in the lagged systemic risk above the average introduces 0.2% in the systemic risk, indicating that systemic risk exhibits persistence and that past systemic conditions can amplify current vulnerabilities. Likewise, a 1% increase in the GDP growth above the average provokes a decrease of 0.1% in systemic risk, indicating that stronger economic performance contributes to financial stability. Finally, the models also introduce significance in three variables, overall liquidity and lagged interest rates, and inflation. According to the results, a 1% increase in liquidity over the average leads to a 0.03% decrease in systemic risk, while a 1% increase in the lagged interest rate and inflation above their averages leads to a decrease of 0.26% and 0.2% in systemic risk, respectively.

5. Conclusion

The present dissertation provides a comprehensive analysis of the systemic risk contribution of financial institutions as well as their determinants and the role of NBFI in the transmission of systemic risk within the European Financial System. Furthermore, it provides valuable insights into the link between Banks and NBFI. The motivation for the study stemmed from the increasing relevance of NBFI in the financial landscape, illustrated by their growth in size as well as in percentage of the total assets of the euro area and globally, and by their relevance in the recent crisis (2007 and 2020). Additionally, it was also motivated by the scarce literature on NBFI and their importance in modern financial networks and limited research on the relationship between banks and NBFI. By tackling the objectives of the present dissertation, we are able to understand the dynamics of the financial system as a whole, which is crucial for informing macroprudential policies.

In this context. a comprehensive empirical analysis was conducted using a sample of 100 institutions, retrieved from Datastream by Refinitiv, belonging to the STOXX Europe 600 Financials index covering the period from 2014 to 2023. The sample was divided between banks and NBF (Financial services and Insurance companies). To tackle the first goal of assessing the systemic contribution of both banks and NBFI, we employed the methodology proposed by Adrian & Brunnermeier (2016) with the modifications proposed by Girardi & Tolga Ergün (2013). The second objective was tackled by the application of econometric models, whereas the interconnectedness between institutions was assessed by following the methodology proposed by Diebold & Yilmaz (2012) and the consequent innovations of Gabauer & Gupta (2018) and Stenfors et al. (2022).

Regarding our findings, they can be divided into three areas. The first area, which accounts for the systemic contribution of the financial institutions, showed that banks exhibited a higher systemic contribution throughout our sample relative to NBFI, though the gap between the contributions narrowed in turbulent periods (e.g., 2020). These conclusions were consistent with the studies of Rahman et al. (2022) and Soo Hong et al. (2024). Furthermore, we found that CoVaR values were consistently higher than VaR levels, which suggests that the systemic risk is mainly driven by the **interconnections among institutions** rather than their individual risk profiles.

The second area of our results accounts for the market-wide and institution-specific characteristics of the systemic risk contributions of the institutions. In this part, we concluded that both macroeconomic conditions and institution-specific characteristics play a role in explaining an institution's contribution to systemic risk. Overall, the analysis shows that inflation and regulatory quality are negatively associated with systemic risk, while GDP growth and interest rates are positively associated with systemic risk. On the institutional side, profitability and leverage show a negative and positive effect on systemic risk, respectively. As for the interactional terms added in equation (4.2.2), they reveal that for banks, leverage and liquidity are positively associated with systemic risk. Thus, our analysis suggests that effective systemic risk mitigation strategies must account not only for market-wide dynamics but also for the structural and financial attributes of institutions, particularly within the banking sector. These results were in line with the literature (Acharya & Thakor, 2016; Acosta-Smith et al., 2024; Lehar, 2005; Rahman et al., 2022; Schularick & Taylor, 2012).

Finally, the third area of our results focused on studying the interconnectedness within the financial system. By analyzing the internal and external decomposition of the total connectedness index (TCI), we can see that NBFI has a consistently higher internal TCI, which suggests that connections within the nonbank network are stronger. Additionally, since the overall connectedness is higher than the connectedness observed when conditioning only on banks, we can infer that NBFIs contribute significantly to the interconnectedness of the financial system. Finally, we can also see that in periods of stress, there is a spike in the external TCI of banks, indicating that banks contribute significantly to the increase in systemic risk during these periods. These results of increased interconnectedness were consistent with the studies of Billio et al. (2012), Gong et al. (2019) and Zhang et al. (2023). Nevertheless, to fully understand the drivers behind these dynamics, particularly the directionality of cross-group interactions, further analysis was necessary. With this in mind, we adapted and implemented the approach of Stenfors et al. (2022). Through this analysis, we concluded that banks persistently exhibit negative values for the net total group-specific index, meaning that this sector is actually receiving shocks originating from the NBFI sector. This finding is particularly relevant as it indicates that the larger ΔCoVaR of banks is not solely due to their own individual positions on risk but also a result of their continuous absorption of shocks coming from the NBFI sector.

Overall, our results emphasize the critical need to monitor the interconnectedness within the system and to implement a more holistic macroprudential framework that fully integrates the role of NBFI. Given their growing prominence and influence, central banks must not only track their systemic impact but also introduce targeted policies to mitigate the vulnerabilities they introduce.

Nonetheless, despite comprehensive, like any other research, our study presents limitations. To begin with, our measure of systemic risk requires values for stock prices, as such, private institutions are not analyzed despite belonging to the financial system and being able to influence the systemic risk contribution of other institutions. Furthermore, to represent the system, we used an index composed of the 100 institutions that composed our sample instead of calculating an index for each of our institutions in order to mitigate possible correlations of the institution with the system. Despite this limitation, our risk is low since the largest compositor had a 7.9% contribution to the "financial system".

Another limitation of our work is the fact that, due to computational constraints, we used a Vector autoregressive model (VAR) in which we need to manually set a rolling window, which can in turn affect our measurements. This limitation was controlled in the robustness part, in which we estimated the VAR model with different time windows, since according to Antonakakis et al. (2020) their average is similar to the results of the TP-VAR approach. Nonetheless, the VAR model does not adapt as quickly to underlying events.

Last but not least, we also limited our analysis to the ΔCoVaR measure of systemic risk, and since there is no one agreed-upon methodology for the systemic risk calculation, complementing the study by using different methods could have been valuable.

To conclude, future research could be focused on the determinants of the connectedness of the financial institutions in order to determine which factor would need to be controlled to mitigate systemic risk contagion. This would contribute to the development of more targeted and effective macroprudential policies aimed at enhancing the resilience of the financial system. Additionally, it would also be interesting to analyze the impact of evolving market structures and regulatory regimes on the systemic contribution of NBFIs.

Appendix

Author	Systemic risk measure	Advantages	Drawbacks
Until the global financial crisis			
Brownlees & Engle (2017)	Balance sheet information	Easy to compute	By only using balance sheet data, it becomes difficult to compute an accurate and recorrent systemic risk measure since the institutions only provide information regaring their balance sheet once or twice a year (lack of regular information available). Additionaly, by only using balance sheet information we are disregarding the interconnectedness of the system.
Lehar (2005)	Systemic risk is measured though the banks asset portolio using a put option	Introduced in order to consider the interdependencies that only using balance sheet data disregards.	Difficult to compute.
Chan-Lau & Gravelle (2005)	END indicator which is based on balance sheet indicators and price information of financial securities	Takes into account the interconnectedness of institutions	Fails to consider the interconnectedness of the system. Additionaly, by using balance sheet data, it becomes difficult to compute an accurate and recorrent systemic risk measure since the institutions only provide information regaring their balance sheet once or twice a year.
Avesani et al. (2006)	Uses credit default swaps to measure systemic risk	Credit default swaps provide regular information as such it is possible to compute an accurate and recorrent systemic risk measure	CDS focus mainly on credit risk, potentially ignoring other sources of systemic risk such as liquidity shocks or indirect contagion.

Table i Systemic risk measures summary – until Global Financial Crisis. Own elaboration.

Author	Systemic risk measure	Advantages	Drawbacks
After the global financial crisis			
As a result of the inability of the measures used until the global financial crisis to provide an accurate and recorrent way to measure systemic risk, several new approaches were developed in the aftermath of the global financial crisis with the aim of improving the measurement of systemic risk.			
Adrian & Brunnermeier, (2016)	Delta conditional value at risk which is defined as the change in the value at risk of the financial system conditional on an institution being under stress relatively to its median state.	Starts taking into account the connectedness of institutions. Uses market returns to compute the measure which means that there is always data available.	Disregards the systemic risk coming from private interprises since there are no public returns that can be used to calculate the systemic risk measure.
Acharya et al. (2016)	Systemic expected shortfall (SES)	Uses daily data from the equity market and data on credit default swaps and as such there isn´t lack of data available	Disregards the systemic risk coming from private interprises since there are no public returns that can be used to calculate the systemic risk measure. Because they define systemic risk as the probablity of an institution being undercapitalized when the system is undercapitalized, their calculation involves the observation of systemic risk in the market and as such can´t be used as an ex-ante measure of systemic risk.
Brownlees & Engle (2016)	SRISK	Uses both balance sheet and equity data	Lack of regular availability of balance sheet data. Additionaly, due to their reliability on maket capitalization and total liabilities it can sometimes underestimate the systemic contribution of small institutions and fail to capture peaks of systemic risk as demonstrated by Zhou et al. (2020)

Table ii Systemic risk measures summary – after Global Financial Crisis. Own elaboration.

Author	Determinant being analyzed	Finding	Economic explanation
Laeven et al. (2016)	Bank Size	Positive relationship between bank size and systemic risk	Larger banks typically have lower capital rations and at the same time higher exposure ro risky activities
Varotto & Zhao (2018)			Larger banks are typically bailed out by governments due to the possible effects that they can provoke on society. As such, larger banks tend to engage in riskier situations
Knaup & Wagner (2012)		Negative relation between bank size and systemic risk	Larger banks can cover the losses more easily do to their structure
López-Espinosa et al. 2013		No relevant contribution of bank size	
Anginer & Demirguç-Kunt (2014)	Bank Capital	Negative relation between bank capital and systemic risk	Banks with larger capital can cover their loses in case of a systemic crisis as such they contribute less to systemic risk
Laeven et al. (2016)			
Williams (2016)	Profitability	Positive relation between non-interest income and systemic risk	Banks that engage in risky activities and in turn increase their non-interest income thus incrising their profitability exacerbate systemic risk
Lehar (2005)		Negative relationship between profitability and systemic risk	Banks that have higher profitabilities tend to engage in less risky activities and thus have a lower systemic contribution.

Table iii Determinants literature summary. Own elaboration.

Author	Determinant being analyzed	Finding	Economic explanation
Acharya & Thakor (2016); Acosta-Smith et al. (2024); Kuzubaş et al. (2016)	Leverage	Positive relation between leverage and systemic risk	Higher leverage leads banks to engage in riskier operations which in turn increases their systemic contribution
Diamond & Rajan (2001)		Negative relation between leverage and systemic risk	Banks with higher leverage have a better loan portfolio which helps reducing their systemic contribution
Lu & Wang (2023)	Liquidity	Negative relationship between liquidity and systemic risk	Higher liquidity makes banks stronger to deal with crisis and absorb shocks which decreases their systemic contribution.
Davydov et al. (2021)	Liquidity creation	Liquidity creation decreases systemic contribution of individual banks	
Louhichi et al. (2024)		Although in normal times, liquidity creation does not increase the systemic contribution of each bank, in times of stress it exacerbates it	

Table iv Determinants literature summary (2). Own elaboration.

Variable	Obs	Mean	Std. Dev.	Min	Max
Allianz	2565	.025	1.482	-16.638	14.673
Zurichinsurancegroup	2565	.032	1.325	-14.624	12.229
MuenchenerRueck	2564	.034	1.508	-19.531	18.378
Axa	2565	.016	1.707	-16.82	16.181
Swissreag	2564	.017	1.468	-16.759	15.168
assicurazionienera~a	2565	.005	1.536	-18.354	10.49
Swisslifeholdingag	2564	.056	1.409	-15.837	14.447
prudentialplc	2564	-.01	2.202	-19.469	16.989
sampooyj	2564	.01	1.43	-16.201	14.898
legalandgeneralgroup	2564	.003	2.149	-28.652	16.501
avivaplc	2564	-.002	1.866	-23.065	15.135
hannoverrueck	2564	.049	1.492	-19.594	15.761
nngroupnv	2438	.021	1.693	-20.821	10.267
admiralgroupplc	2446	.03	1.653	-20.103	12.247
ageas	2446	.011	1.699	-17.185	12.036
aegonltd	2446	-.009	2.255	-24.307	16.383
baloiseholdingag	2446	.02	1.271	-11.632	13.061
tryg	2446	.025	1.318	-9.774	7.506
beazleyplc	2446	.031	1.964	-15.254	15.135
powszechnyzaklad	2565	0	1.837	-13.076	8.582
helvetia	2564	.021	1.416	-15.287	12.031
phoenix	2564	-.004	1.69	-16.255	18.796
talanx	2564	.037	1.536	-18.185	13.897
unipol	2564	.006	2.12	-20.549	16.323
storebrand	2564	.021	2.162	-21.652	16.007
hiscox	2564	.012	1.884	-27.514	24.534
directlineinsurance	2564	-.005	1.804	-27.083	14.694
scorse	2564	.001	1.986	-22.083	18.085
gkensidige	2564	.009	1.575	-13.868	11.378

Table v Descriptive statistics Insurance return. Own elaboration

Variable	Obs	Mean	Std. Dev.	Min	Max
UBSgroup	2564	.028	1.77	-13.943	11.729
LondonStockExchange	2565	.067	1.743	-15.491	12.773
InvestorAB	2565	.048	1.51	-13.902	10.539
DeutscheBoerse	2565	.044	1.424	-12.598	12.314
iGroupPLC	2565	.07	1.899	-16.4	16.897
partnersgrouphold	2564	.074	1.616	-15.069	14.088
euronext	2446	.061	1.698	-8.788	15.127
intermediatecapita	2446	.056	2.527	-42.313	19.426
mediobancabanca	2446	.016	2.098	-23.847	13.025
stjamesplace	2565	-.004	2.077	-24.683	12.582
groeprussel	2564	.002	1.245	-22.375	6.515
industrivarden	2564	.027	1.542	-13.267	10.843
hargreaves	2564	-.026	2.282	-22.741	13.925
IGgroupholdingsp	2564	.006	2.029	-48.417	14.418
swissquote	2564	.075	2.338	-17.042	17.105
schroders	2564	-.003	1.859	-18.947	10.017
sofina	2564	.039	1.449	-11.507	10.668
lelundberg	2564	.045	1.508	-14.922	10.157
eurazeo	2564	.021	1.687	-15.296	15.11
adrdn	2565	-.029	2.197	-25.008	15.803
mangroup	2565	.037	2.11	-14.834	13.27

azimut	2565	.007	2.16	-17.308	14.299
bancamediolanum	2565	.012	1.972	-16.31	11.409
wendelse	2565	-.01	1.635	-14.214	11.51
kinnevik	2565	-.013	2.208	-15.868	16.448

Table vi Descriptive statistics Financial services. Own elaboration

Variable	Obs	Mean	Std. Dev.	Min	Max
HSBC	2565	-.003	1.605	-10.014	10.731
BancoSantander	2565	-.012	2.153	-22.172	17.582
juliusbaergruppe	2564	.014	1.836	-15.127	16.746
IntesaSanpaoloSpA	2565	.015	2.128	-26.059	13.493
Unicredit	2565	-.004	2.663	-27.166	14.777
BNPParibas	2565	.005	2.005	-19.117	16.535
BancoBilbao	2565	.002	2.112	-17.649	15.404
INGgroepNV	2565	.011	2.119	-21.532	18.645
Barclays	2565	-.024	2.295	-25.463	15.276
LloydsBankinggroup	2565	-.021	2.087	-29.579	12.894
nordeabank	2565	.006	1.689	-15	8.498
natwestgroupplc	2565	-.015	2.289	-25.908	13.083
deutschebankag	2565	-.033	2.437	-20.378	12.133
standardcharteredplc	2565	-.027	2.216	-13.775	15.817
societegeneralesa	2565	-.021	2.366	-23.034	16.898
Skandinaviskaenski	2564	.011	1.747	-16.482	8.899
caixabanksa	2564	.003	2.151	-20.001	13.957
erstegroupbankag	2564	.015	2.147	-17.924	12.851
danskebank	2564	.015	1.744	-12.108	11.309
swedbankab	2564	-.004	1.753	-16.592	10.253
kbcgroepnv	2564	.014	2.019	-21.246	13.159
dnbbankasa	2564	.015	1.864	-18.422	10.751
Svenskahandelsbank	2564	-.006	1.67	-14.355	8.214
commerzbankag	2564	-.002	2.61	-23.844	16.572
creditagricolesa	2564	.013	2.014	-18.469	13.022
powszechnakasa	2564	.008	2.131	-19.273	12.46
bancoBPM	2564	-.02	2.99	-26.527	16.857
finecobankbanca	2438	.05	2.031	-12.969	11.212
bancodesabadellsa	2564	-.014	2.701	-21.434	21.987
AIBgroupplc	2564	-.078	3.643	-36	22.014
bankofireland	2446	.002	2.815	-23.516	14.374
bancamontedeipasch	2565	-.313	4.648	-119.824	35.863
bperbanca	2565	-.013	2.906	-28.251	20.216
bankpolska	2565	-.008	2.187	-23.077	15.698
bankintersa	2564	.018	1.965	-17.135	18.15
ringkjoebing	2564	.059	1.319	-10.339	7.882
bancocomercialport	2564	-.061	2.985	-16.468	23.855
investecplc	2564	.019	2.298	-24.362	15.411
santanderbank	2564	.008	2.354	-20.508	14.594
jyskebank	2565	.02	1.783	-11.429	16.453
bancapopolare	2565	.021	2.228	-21	12.733
avanza	2565	.058	2.316	-16.105	14.929
raiffeisen	2565	-.01	2.461	-26.317	15.974
cembramoneybank	2564	.015	1.57	-36.81	13.898
banquecantonale	2564	.042	1.166	-7.996	17.203
sydbank	2565	.028	1.844	-14.234	14.443

Table vii Descriptive statistics Banks. Own elaboration

	Model 1	**Model 2**
	Coef.	Coef.
Chi-square test value	128.68	499.98
P-value	0	0

Table viii Hausman Test. Own elaboration.

	Model 1		**Model 2**	
Variable	VIF	1/VIF	VIF	1/VIF
Log_RE	961.84	0.001040	1103.04	0.000907
Log_CS	824.97	0.001212	847.26	0.001180
Log_TotalAssets	324.07	0.003086	404.06	0.00245
Log_ROA	8.66	0.1155	44.75	0.022344
Log_ROA_b			6.76	0.1479
Log_LagDeltaCoVaR	4.71	0.2121	3.97	0.2519
Log_Inflation	3.99	0.2508	3.81	0.2625
Log_GDP	2.94	0.3405	2.85	0.3514
Log_RC	2.82	0.3550	2.41	0.4156
Log_IR	2.61	0.3825	2.64	0.3793
Log_Liquidity	1.94	0.5155	2.42	0.4126
Log_Liquidity_b			1.16	0.8586
Log_D/A	1.56	0.6428	1.67	0.5981
Log_D/A_b			4.95	0.2018
Mean VIF	198.97		175.54	

Table ix VIF statistics before correction. Own elaboration.

	Model 1		**Model 2**	
Variable	VIF	1/VIF	VIF	1/VIF
Log_ROA	8.66	0.1155		
Log_ROA_b			6.76	0.1479
Log_LagDeltaCoVaR	4.71	0.2121	3.97	0.2519
Log_Inflation	3.99	0.2508	3.81	0.2625
Log_GDP	2.94	0.3405	2.85	0.3514
Log_RC	2.82	0.3550	2.41	0.4156
Log_IR	2.61	0.3825	2.64	0.3793

Log_Liquidity	1.94	0.5155	2.42	0.4126
Log_Liquidity_b			1.16	0.8586
Log_D/A	1.56	0.6428	1.67	0.5981
Log_D/A_b			4.95	0.2018
Mean VIF	3.65		3.26	

Table x VIF statistics. Own elaboration.

	Model 1	**Model 2**
Chi2	157.57	84.15
Prob >Chi2	0	0.7076

Table xi Wald test. Own elaboration.

	Model 1	**Model 2**
Wooldridge test for autocorrelation in panel data – focused on the within variation component		
F	36.602	38.229
Prob >F	0	0
Pesaran CD test – focused on the between variation component (cross sectional independence)		
CD-test	27.774	17.006
p-value	0	0

Table xii Autocorrelation tests for panel data. Own elaboration

	Model 1	**Model 2**
Underidentification test		
Kleibergen-Paap rk LM statistic	54.590	63.526
Chi-sq(1) P-val	0	0
Weak identification		
Cragg-Donald Wald F statistic	121.108	161.323
Kleibergen-Paap rk LM statistic	129.864	164.704
Stock-yogo weak ID test critical values:		
10% maximal IV size	16.38	16.38
15% maximal IV size	8.96	8.96
20% maximal IV size	6.66	6.66
25% maximal IV size	5.53	5.53

Hansen J statistic (overidentification test of all instruments)	0	0
Endogeneity test of endogenous regressors	35.869	30.474
Chi-sq(1) P-val	0	0

Table xiii Endogeneity test. Own elaboration.

BANKS	NONBANKS	Transmiters (NET >0)	Receivers (net<0)
HSBC	UBS group	HSBC	Zurich insurance group
Banco Santander	London Stock Exchange	Allianz	London Stock Exchange
Intesa Sanpaolo SpA	Investor AB	UBS group	Muenchener Rueck
Unicredit	Deutsche Boerse	Banco Santander	Deutsche Boerse
BNP Paribas	3i Group PLC	Intesa Sanpaolo SpA	Swiss re ag
Banco Bilbao	partners group holding ag	Axa	nordea bank
ING groep NV	euronext	Unicredit	partners group holding ag
Barclays	intermediate capital group	BNP Paribas	Skandinaviska enskilda
Lloyds Banking group plc	mediobanca banca	Banco Bilbao	sampo oyj
nordea bank	st james place	ING groep NV	swedbank ab
natwest group plc	groep russel	Investor AB	dnb bank asa
deutsche bank ag	industrivarden	Barclays	svenska handelsbanken
standard chartered plc	hargreaves	3i Group PLC	powszechna kasa
societe generale sa	IG group holdings plc	Lloyds Banking group plc	nn group nv
Skandinaviska enskilda	swissquote	natwest group plc	banco de sabadell sa
caixabank sa	schroders	deutsche bank ag	AIB group plc
erste group bank ag	sofina	assicurazioni enerali spa	euronext
danske bank	l e lundberg	standard chartered plc	admiral group plc
swedbank ab	eurazeo	societe generale sa	bank of ireland
kbc groep nv	adrdn	Swiss life holding ag	ageas
dnb bank asa	man group	prudential plc	tryg
svenska handelsbanken	azimut	caixabank sa	beazley plc
commerzbank ag	banca mediolanum spa	erste group bank ag	powszechny zaklad
credit agricole sa	wendel se	danske bank	banca monte dei paschi
powszechna kasa	kinnevik	kbc groep nv	bank polska
banco BPM	Allianz	legal and general group	helvetia
finecobank banca	Zurich insurance group	commerzbank ag	hargreaves
banco de sabadell sa	Muenchener Rueck	aviva plc	IG group holdings plc
AIB group plc	Axa	hannover rueck	hiscox
bank of ireland	Swiss re ag	credit agricole sa	ringkjoebing
banca monte dei paschi	assicurazioni enerali spa	julius baer gruppe	banco comercial portugues
bper banca	Swiss life holding ag	banco BPM	swissquote
bank polska	prudential plc	finecobank banca	direct line insurance
bankinter sa	sampo oyj	aegon ltd	scor se
ringkjoebing	legal and general group	baloise holding ag	investec plc
banco comercial portugues	aviva plc	intermediate capital group	santander bank
investec plc	hannover rueck	mediobanca banca	sofina
santander bank	nn group nv	bper banca	gkensidige
jyske bank	admiral group plc	st james place	l e lundberg
banca popolare	ageas	groep russel	eurazeo
avanza	aegon ltd	phoenix	jyske bank
raiffeisen	baloise holding ag	talanx	raiffeisen
cembra money bank	tryg	industrivarden	cembra money bank
banque cantonale	beazley plc	bankinter sa	banque cantonale
sydbank	powszechny zaklad	unipol	wendel se
julius baer gruppe	helvetia	storebrand	kinnevik
	phoenix	schroders	
	talanx	adrdn	
	unipol	man group	
	storebrand	banca popolare	
	hiscox	azimut	
	direct line insurance	banca mediolanum spa	
	scor se		
	gkensidige		

Table xiv Overview net receivers and net transmitters. Own elaboration.

	TO	FROM	NET	NPT
HSBC	101,38	93,77	56	56
Allianz	128,2	95,03	85	85
UBS group	120,05	95,21	80	80
Zurich ins	35,06	94,45	3	3
London St	73,59	88,17	27	27
Banco Sar	126,51	95,44	91	91
Muencher	54,42	85,87	7	7
Intesa Sar	130,32	94,07	94	94
Axa	120,82	94,58	83	83
Unicredit	126,15	94,89	91	91
BNP Parib	133,86	96,09	95	95
Banco Bill	124,72	93,92	88	88
ING groep	138,34	95,65	96	96
Investor A	123,66	94,04	80	80
Barclays	113,81	94,58	75	75
Deutsche	63,12	88,19	14	14
3i Group F	96,86	93,08	47	47
Lloyds Bar	102,1	93,53	59	59
Swiss re a	78,68	92,32	25	25
nordea ba	92,47	92,91	43	43
natwest gr	97,49	93,55	53	53
deutsche l	112,49	93,54	78	78
assicuraz	96,92	93,8	55	55
partners g	67,32	91,77	20	20
standard	108,05	93,38	74	74
societe ge	132,45	94,93	93	93
Swiss life	98,09	95,58	52	52
Skandinav	79,18	91,56	23	23
prudentia	118,84	95,2	75	75
sampo oy	71,46	92,78	20	20
caixabank	97,32	93,01	53	53
erste grou	104,99	93,93	72	72
danske ba	93,09	89,66	51	51
swedbank	77,12	91,74	29	29
kbc groep	108,92	94,93	70	70
dnb bank	89,09	92,61	38	38
legal and	116,18	95,45	75	75
svenska h	68,46	91,56	23	23
commerzb	120,06	95,03	83	83
aviva plc	124,15	95,25	85	85
hannover	104,31	94,04	58	58
credit agri	114,07	92,55	76	76
julius bae	103,76	93,59	63	63
powszech	83,42	92,21	39	39
banco BPI	111,95	94,04	75	75
nn group i	87,25	93,12	41	41
finecoban	102,1	93,65	60	60
banco de	80,81	91,86	29	29
AIB group	51,25	85,65	11	11
euronext	60,15	90,15	8	8
admiral gi	64,56	87,84	22	22
bank of ire	90,44	93,52	45	45
ageas	78,24	92,49	35	35
aegon ltd	102,43	94,08	60	60
baloise ho	96,23	93,54	49	49
intermedi	112,7	92,97	71	71
mediobar	115,8	94,22	79	79
tryg	51,45	88,54	6	6
beazley pl	74,12	90,48	18	18
powszech	84,37	88,67	44	44
banca mo	50,51	85,96	10	10
bper banc	105,47	93,07	69	69
bank pols	77,86	91,85	32	32
st james p	111,76	93,75	71	71
helvetia	87,95	93,37	40	40
groep russ	112,67	94,34	71	71
phoenix	102,72	94,49	50	50
talanx	94,59	93,22	44	44
industriva	111,07	93,99	63	63
bankinter	107,22	93,28	68	68
hargreave	70,78	88,64	25	25
unipol	108,6	94,01	74	74
storebran	102	94,49	59	59
IG group h	55,61	79,74	9	9
hiscox	59,79	88,64	16	16
ringkjoebi	70,41	92,38	27	27
banco cor	76,28	91,9	29	29
swissquot	44,68	84,19	4	4
direct line	64,95	89,21	18	18
scor se	84,76	91,16	41	41
schroders	121,75	95,26	81	81
investec p	78,36	92,74	28	28
santander	86,62	91,32	40	40
sofina	66,76	89,58	17	17
gkensidig	54,79	88,04	11	11
l e lundbe	88,24	92,09	42	42
eurazeo	81,89	92,07	36	36
adrdn	98,89	94,46	54	54
jyske banl	65,99	88,17	18	18
man grou	107,94	93	65	65
banca po	93,74	92,47	43	43
azimut	93,09	92,93	54	54
raiffeisen	88,43	92,01	40	40
cembra m	49,15	86,87	10	10
banca me	98,67	93,66	53	53
banque ca	56,53	89,74	12	12
wendel se	93,27	93,67	46	46
kinnevik	82,15	89,12	33	33

Table xv Net, From, To and NPT measures of connectedness. Own elaboration.

	Maximum		Minimum	
TO	138,34	ING groep NV	35,06	Zurich insurance group
NET	42,68	ING groep NV	-59,39	Zurich insurance group
NPT	96	ING groep NV	3	Zurich insurance group
FROM	96,09	BNP Paribas	79,74	IG group holdings plc

Table xvi Measures of connectedness analysis. Own elaboration.

	Model 7	Model 8
LogInflation	-0.17876*** (0.03840)	-0.24683*** (0.04917)
LogDA_b		12.85522*** (4.67891)
LogROA_b		-0.06854 (0.05777)
Lag_LogDeltaCoVar	0.29426** (0.11532)	0.19855* (0.10918)
LogLiquidity	-0.03953* (0.02116)	-0.03007* (0.01788)
LogLiquidity_b		0.80564*
LogDA	-0.02326 (0.08634)	0.01362 (0.05561)
LogIR	0.35252*** (0.05029)	0.33418*** (0.05265)
Lag_LogIR	-0.26149*** (0.05029)	-0.25814*** (0.05265)
Lag_LogRC		-2.40439*** (0.58022)

Lag_LogInflation	-0.21310*** (0.02899)	-0.27654*** (0.02953)
LogGDP	-0.09713*** (0.03330)	-0.12669*** (0.03532)
Lag_LogGDP	-0.04615 (0.03880)	-0.19648*** (0.05457)
LogROA	-0.04394* (0.02395)	

Table xvii Characteristics robustness. Own elaboration.

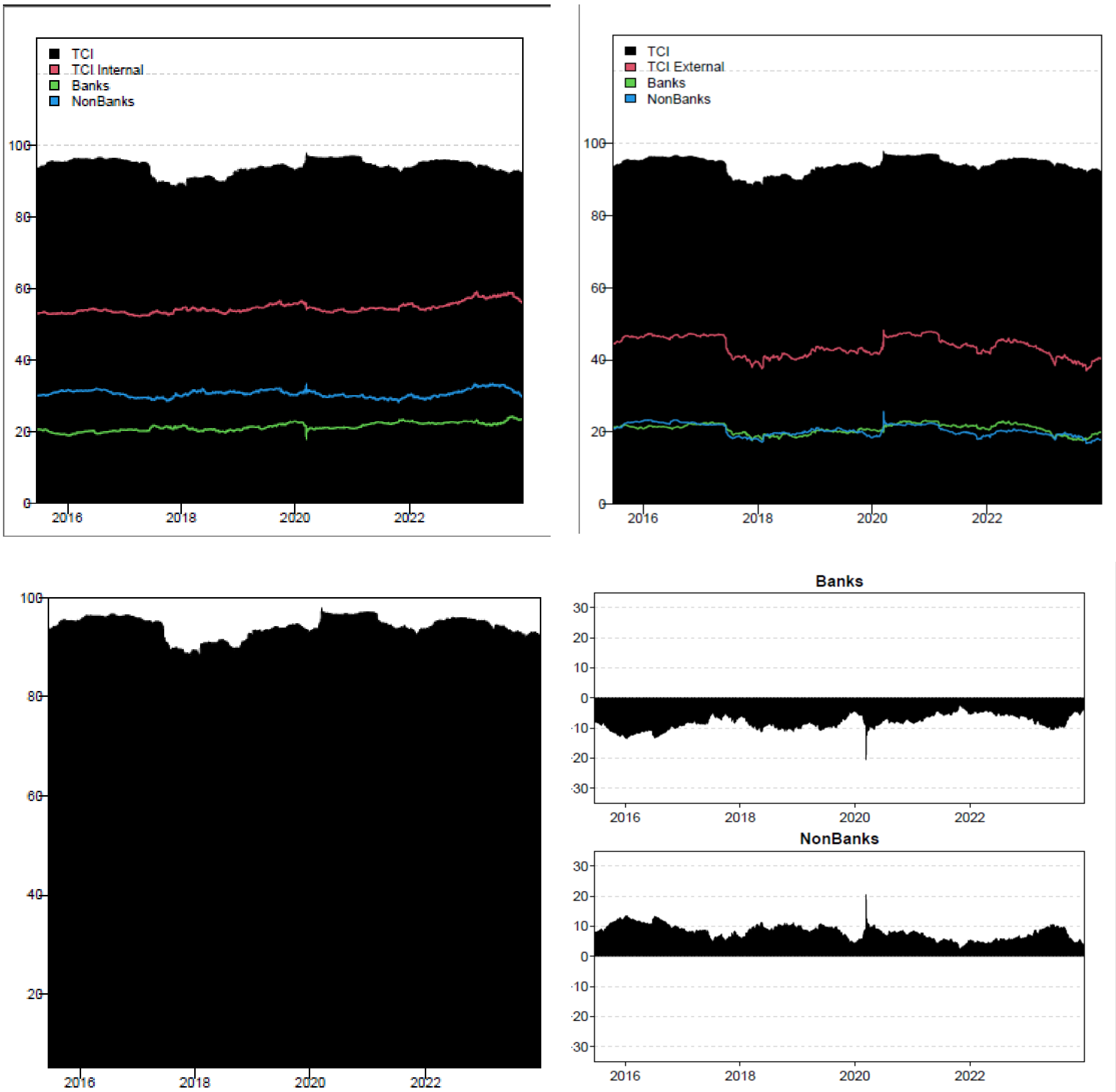


Figure i Robustness figures - external and internal decomposition, TCI and aggregated net connectedness. Own elaboration.

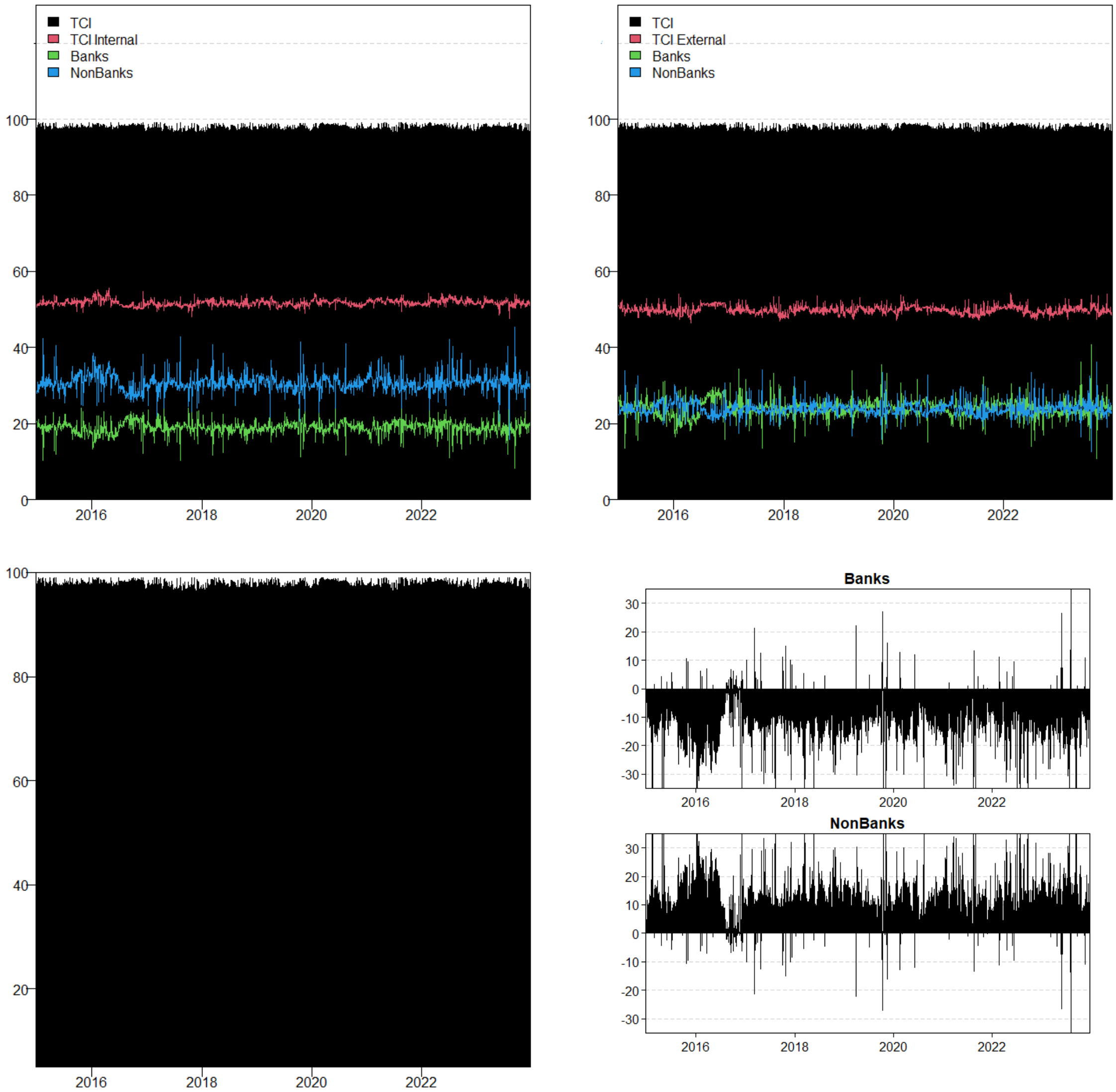


Figure ii Robustness with a 125 rolling window. Own elaboration.

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