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At the origin of banking systemic risk: investigation of macro and micro factors affecting systemic risk level in European banking sector

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Thesis background: Introduction to systemic risk, purpose of the study and literature contribuition

Introduction

The past two decades have been characterized by a series of financial crises that have compelled policymakers and regulators to strengthen bank controls and supervise financial platforms. All these crises share a common feature: their systemic impact. From the 2008 crisis to the recent COVID-19 and Russian-Ukrainian issues, the effects have not remained confined to specific regions but have reverberated globally and have involved a great part of the finanial sector players. And this is always true for both financial originated crisis and non-finacial originated crisis (as the COVID-19 and Russian-Ukraine ones). This transnational potential united to the non-isolated nature of the crisis has underscored the need to develop globally harmonized and effective countermeasures.
Drawing from this premise, the study offers an experimental assessment of the key variables that empirically influence individual banks and hold systemic relevance. This understanding of risk origins could pave the way for more targeted solutions, preventing the imposition of punitive regulations or adverse consequences, and thus preserving the pivotal role of banks in the economy. This role primarily encompasses monetary transmission and intermediation functions.
Hence, the dissertation aims to investigate the sources of systemic risk by analysing respectively:

- The role of energy commodities on banking system stability (Chapter 1)
- The plurality of macrofactors affecting market bank performances and contribuition to overall banking systemic risk (Chapter 2)
- The relevance of microfactors affecting the systemic risk level of banks. (Chapter 3)

From the methodological standpoint, the underlying *leitmotiv* that inspires all the pages is the model selection approach. It is acknowledged that this risk could be determined by a plurality of concurrent causes, but only recognizing the limited set of drivers that concretely influence and determine the banking systemic risk could help to glean the fundamental dynamics behind the systemic disruptions; thus avoiding the risk of creating noise and disturbances in the analysis due to disordered misspecification of the phenomenon within the data.
The analysis conducted has revealed significant insights. It has underscored the critical

role of market volatility as a determinant of losses for both the system and banks. Furthermore, the gold price has emerged as a key disruptor, influencing bank performance even during stable periods. Notably, the aspect of interconnectedness in the financial market has been highlighted, emphasizing the importance of cross-market dependencies (as represented by the CISS intermediaries driver (Hollo et al. (2012))) and the interconnectedness within the banking sector. This market feature has been demonstrated as one of the primary drivers of contagion during crisis periods, even more than the size per se.

What systemic risk means?

The concept of systemic risk has been under investigation since its first introduction in the work of Eisenberg and Noe (2001), which linked this concept to the propensity of a given firm in the system to default alongside other firms. Referring to the regulatory definition, as cited by the IMF, systemic risk is defined as follows:

"risk of disruption to 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"

Therefore, for systemic risk to materialize, two factors should coexist: the declining comovement of financial firms and the impactful effect on the real economy. This definition, in contrast to the one proposed by Eisenberg and Noe (2001) , which focuses on the individual firm within an interconnected network, is primarily related to the system's health. However, the interpretation of *'impairment'* can vary depending on the perspective. From this contrapposed visions, the evolution of the literature on systemic risk can be narrated. Indeed, the academic literature, in an attempt to synthesize regulatory prescriptions in empirical analyses, has developed a synthesis of these two visions, defining a quantifiable metric to observe the impairment of firms while retaining the concept of contagion initially proposed by Eisenberg and Noe (2001). According to Benoit et al. (2017), who provided a comprehensive literary review on this topic, the most widely used definition of systemic risk in literature is:

'*the risk that many markets partecipants are simultaneously affected by severe losses, which then spread through the system*'.

Therefore, it's clear that the academics have opted for relaxing the condition of default propagation to consider the spread of losses. Hence the materialization of systemic risk is in this case clearly identifiable and not subjected to any interpretation [1].
A proliferation of studies have been conducted around this definition. Brownlees and Engle (2017), Tobias and Brunnermeier (2016), Acharya et al. (2017) and Lehar (2005) represent only a fraction of the extensive body of literature on systemic risk and its measurement, based on the aforementioned definition. This concept is widely accepted both in financial literature and among financial regulators, with the latter now considering it as a viable policy tool.
In this work, I focus exclusively on a market-driven measure developed by Tobias and Brunnermeier (2016). This measure utilizes market performance to estimate the market losses of banks and assess their contribution to the systemic risk level of the system.

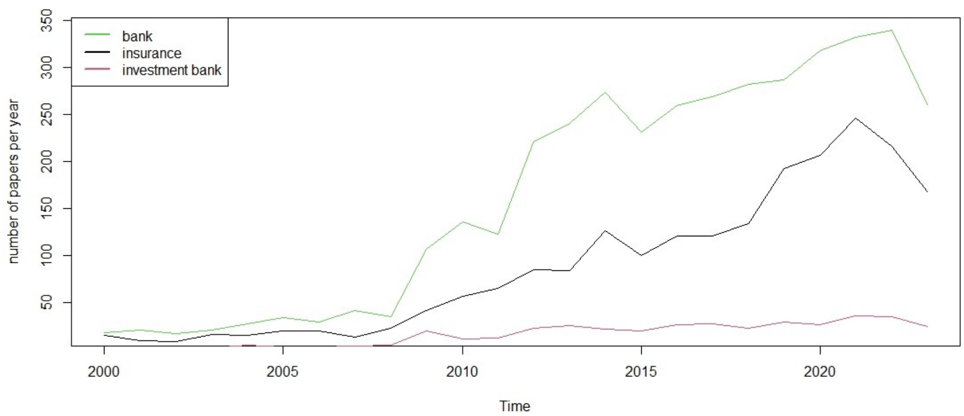
[1] The default in banking could have a moltitude of meanings.

Therefore, significant attention will be given to banks' ability to exert a negative influence on the system during periods of distress. Furthermore, as brilliantly suggested by Morris and Shin (2008) the $CoVaR$ measure would aid in determining the *"systemic impact factor"* of banks in the system, effectively summarizing how each bank could potentially negatively spill over onto others. This approach could assists regulatory bodies in accounting for interconnectedness aspects (Acharya et al. (2010)), consequently, providing a more empirical tool for regulations.
This represents one of the current approaches in systemic risk assessment, prioritizing the assessment of contagion over being contagious. To evaluate spillover directions, other measures, such as those proposed by Diebold and Yılmaz (2014) or Billio et al. (2012) , should be taken into account.
In conclusion, this choice was motivated by two primary objectives. Firstly, it aims to provide regulators with a more targeted and empirical tool, allowing them not only to discern the genuinely influential drivers but also to synthesize this information into a risk-based assessment of the systemic importance of each individual bank. Secondly, it pertains to a modeling decision, as this category of models enables the management and analysis of a multivariate pool of factors, thereby facilitating the identification of significant ones, overcoming the limits of spillover direction analysis which typically considers only one aspect of banks, usually their market performance.

Why banks are often associated to systemic risk?

Beyond the definition, one could also argue about the kind of financial firms that have received the most attention on this topic. In the next figure are displayed the evolution of numbers of papers published related to the banking systemic risk, insurance systemic risk and investments banking systemic risk.

Figure 1: Number of paper published for each category specified



Note: For each series the number of papers that have the following words in the tile have bene retrieved: *'bank systemic risk'*, *insurance systemic risk'*, *'investment bank systemic risk'*.

As you may noticed there is a large predominance of banking systemic risk literature, even though the other two series have approximately followed the same pattern. Indeed,

after the 2008 crisis the number of studies on the topic is skyrocketed (Engle (2018)).
And the reasons for this predominance are stratified and all relate to the important role ricovered in the financial system by the banks, the peculiarities of their business and impactful effect on economics [2] (Jokipii and Monnin (2013)). First and foremost, the liquidity creation function of banks, that finance illiquid assets (mainly mortgage and other long-lasting lending operations) with mostly extremely liquid fundings is of primary concern. This exposes the banks to a shortage of liquidity in case of bank runs[3] (Diamond and Dybvig (1983)), or in less extremely cases to an excessive maturity mismatch (between assets and liabilities) due to a flattening of the yield curve (that could induce also high borrowing cost for banks). Furthermore, banks are exposed to economic downturns that could induce a deterioration of the credit portfolio, making it more illiquid (difficult to securitize and trade externally) and unprofitable as a source of revenue (as the assignment of claims results in a loss on credit exposures). This can sometimes bind banks to dangerous fire sales, which, like a spiral, could amplify the downturn. And for this multiple reasons that the liquidity crisis have been recognized perillous in both idyosincratic level and systemic one, as documented by Brunnermeier and Pedersen (2009). At this purpose the systemic regulation have tried to prevent this inconvenience towards the institutions of liquidity requirements, namely the LCR (liquidity coverage ratio) [4] and the NSFR (Net stable funding ratio)[5] (Basel (2013)). This, even not diclarely systemic risk measures assurges to protect the system by preserving the stability of single institutions avoiding that the worsen of maturity mismatch could destabilize institutions. Some concern have been raised about the real effectivity of this measures, since their proneness to be manipulated (Cetina and Gleason (2015)) or the focus on quantity in place of quality of assets involved, a shortsightedness that not consider extremely toxic but liquid assets (Perotti and Suarez (2002)).
A second motivation for which banks are under consideration of the literature is that the banking system is naturally densely interconnected. The interbank market, while serving as a funding option for banks, also represents a clear contagion channel. This is due to the prevalence of short and long-term interbank agreements between various financial institutions. Consequently, the collapse of one bank or a herding distress could potentially trigger a cascade effect impacting the counterparties in the interbank market clearing (Allen and Gale (2000)). This is the main field on which the regulators are not stil aligned. Indeed, a consideration of the interconnectedeness aspect has been done only among systemically important banks (SIFIs) for which has been structured an imposition of additional prudential capital requirements, ranging from 1% to 3.5% based on risk-weighted assets. These designation is made using a weighted indicator, where size and interconnectideness (of greater banks) properties accounted for more than 40% of the assessment (on Banking Supervision (2013)). And the literature on this topic have always assumed a more systemic potection view then regulation, that is mainly concentrated to avoid bail-outs of giant financial conglomerates. Indeed, Morris and Shin (2008) show that risk-based capital requirements not calibrated to the links structure in the banking system could be inadeguate, leading to an increase of risk. Moreover, a risk-weighted

[2] The literature consistently emphasizes the pivotal role of banks in driving economic growth (Korkmaz (2015)), primarily attributed to their lending activities that support investments, their function in transmitting monetary impulses, and their position as the primary source for countries seeking debt support.

[3] What happened with Silicon Valley bank (SVB) and Sberbank.

[4] Idealized to equip banks of the necessary short-term provisions to meet short-term liquidity needs.

[5] Concretely, it imposes an upper limit on short-term debt.

scheme could hide shortcomings that could endanger the system. Indeed, as raised by Georg (2011) interbank esposures (and financial assets) have a lower ponderation in risk-weighted assets calculation compared to real assets ones (Corporate and family loans and corporate bonds). Therefore there is an incentive in recurring to wholesale funding that exacerbates the interlinks among banks and feed the risk of propagation of a crisis.
The third motivation is that banks tend to assume risk in a correlated manner, making them more susceptible to business cycles, which leads to what is known as the *'leverage cycle'* (Aymanns and Farmer (2015)). Institutions typically increase their investments during favorable economic periods (especially households credits) and reduce their leverage during economic downturns. Consequently, this activates the leverage procyclicality effect, forcing institutions to sell assets in declining markets, thereby leading to losses. Naturally, increasing losses undermine banking stability (Adrian and Shin (2010)), that is what happens during the sub-prime crisis. To face this effect the regulation have imm-posed countercyclical buffers to smooth the leverage cycle, calibrating additional capital surchages to the macroeconomical cycle (more stringent during build-up phases where is taken more risk, and relaxed during downturn period where a flight to quality acts) (on Banking Supervision (2010)). Moreover, with (Committee et al. (2014)) it has introduced the 3% leverage ratio limit, at the scope of making institutions more *'skin in the game'*, reducing the risk-shifting to the market and allowing a better control of risk with capital.

Pitfalls of systemic regulation

Since the 2008 financial crisis, which emphasized the need for a comprehensive regulatory framework to mitigate the *'butterfly effect'* in the banking system, policymakers and regulators have expedited the implementation of more suitable and effective banking regulations. This has led to a significant shift in the regulation approach of banks. Specifically, the regulatory focus has transitioned from a micro-prudential perspective (Basel I and II) to a macro-prudential one (Basel III), reflecting a systemic supervision approach aimed at maintaining the stability of the financial system by regulating various aspects of financial institutions' operations. Furthermore, the crisis has spurred discussions about banking systemic risk, resulting in the establishment of key regulatory bodies such as the Financial Stability Board (FSB) in 2010, tasked with encouraging and eventually harmonizing national legislation related to systemic risk in the financial sector (Helleiner (2010)). To this end, the Dodd-Frank Act in the United States was among the earliest regional legislations adopted, focusing on consumer protection, transaction transparency enhancement, and limits on proprietary trading positions, with a specific emphasis on Systemically Important Financial Institutions (SIFIs) (Congress (2010)). Similarly, the European Parliament responded by establishing the European Systemic Risk Board (ESRB) as part of the EU financial supervisory system reform, with the primary goal of preventing or mitigating systemic risk within the European community (Regulation (EU) No 1092/2010, later revised with Regulation (EU) 2019/2176).
The regulatory provisions mentioned in the previous paragraph, structured by supranational organizations such as the Basel Committee and the Financial Stability Board and adopted by nations and federations, have primarily mitigated the risk of subsequent financial crises, although further measures may still be necessary (Benoit et al. (2017)).

However, certain drawbacks in the current regulations have been highlighted by academics. One key concern revolves around liquidity ratios , which, intended to manage maturity mismatches, could potentially impede banks' lending operations, particularly during times of crisis, leading to a shift toward wholesale operations and more liquid investments, mainly the financial market negotiated ones [6]. This, in turn, could compromise the fundamental role of banks as intermediaries in the financial system, aimed at managing varying maturities between their asset and liability sides. And as if that were not enough, this could enlarge the sensibility of institutions to crisis, since their margins become more volatile and largely dependent by the financial world and less from the economy.
Furthermore this behaviour tighten bank network interconnectideness. Focusing exclusively on larger institutions, perceived as more interconnected, could lead to distortions, exacerbating moral hazard concerns due to reliance on the implicit public *'bail-out'* guarantee. However, this strategy alone may not suffice to contain systemic disruptions. A systemic crisis can emerge not only from the negative spillover effects of major institutions but also from numerous interconnected smaller defaults. (Brunnermeier et al. (2009)).
For this reason a deepen investigation of the underlying mechanism is needed, fostering the debate on the actual systemic risk prevention regulation.

Why Eurozone banking sector?

The analysis focuses on the European banking sector, including Swiss and UK banks. The choice is not arbitrary and is driven by various reasons. The Eurozone not only endured the 2008 crisis but also weathered the sovereign debt crisis, which weakened the European banking system (Roman and Bilan (2012) and Acharya and Steffen (2013)). Furthermore, there are significant structural reasons that make Europe an attractive focus from a systemic perspective.
Firstly, the financial system in the Eurozone is predominantly 'bank-centric,' increasing the likelihood of systemic crises as supported by Langfield and Pagano (2016). A disruption in this system could potentially have significant adverse effects on the real economy. Moreover, the European system accounts for 13 out of 30 Systemically Important Financial Institutions (SIFIs) (Board (2022)), which are the first line of systemic crisis containment.
Additionally, the banking sector is highly concentrated. Calice et al. (2021) support the notion that high concentration can affect bank stability by promoting increased risk-taking behavior and leading to a general rise in interest rates due to the reduced competition (Mishkin (1999a), Uhde and Heimeshoff (2009)). Both of these factors also raise concerns for policymakers and regulators, who might find themselves trapped in the *'too big to fail'* dilemma, thereby intensifying apprehensions during any adverse conjunctural events that could harm banks. These concerns are closely linked to the costs associated with the bail-in and bail-out of such banks, especially considering the challenges associated with swiftly replacing of failing banks in their activities (Committe (2013)).
Finally, in Europe, a significant bank-country nexus exists, particularly in peripheral countries, a characteristic that has been demonstrated as a weak point for bank stability (Liu and Varotto (2021)).

[6] This is one of the main reason of the increase of non-interest margin weight in banks balance-sheets

Thesis structure, purpose and results synthesis

After having deescribed the context and motivation behind my analysis, it becomes necessary to provide a more comprehensive overview of the research objectives. The empirical research project under the thesis aims to address the knowledge gap concerning the primary drivers of systemic risk in the banking sector, investigating both the macroeconomic and firm-specific dimensions in a novel empirical manner. This approach aims to distinguish the significant determinants from the less influential ones.

The thesis begins with a comprehensive analysis of the impact of energy-related variables on the systemic risk profile of banks in the first chapter. From a theoretical perspective, electricity and natural gas prices are expected to influence financial institutions' performances and risk profiles through two distinct trajectories. These are the inflation channel (Jones et al., 2004), wherein a rise in inflation level caused by a jump in commodities prices could lead to credit market frictions and increased distress in existing credit positions; and the GDP channel documented by Brückner and Ciccone (2010) and Kilian and Park (2009) which, depressed by turmoil in energy commodities markets, in turn might negatively affect banking sector as well as the market of financial institution. In clonclusion, this initial assesment provides the first proof of a sensibility of banks to these macrofactors; an output that become highlighting for policy makers during the actiual energy crisis.

The second chapter goes beyond the preceding analysis, exploring all possible influential factors that could affect banks from a systemic perspective. It does not confine the investigation to well-established financial variables found in banking literature, such as volatility levels, stock market performance, yield curve slope, yield spread, and interbank interest rates. These variables have received significant attention, often overshadowing other fundamental drivers. This investigation surpasses traditional banking systemic risk knowledge by expanding the set of potential explanatory macro-factors and allowing the model to identify the most significant ones through a formal data-driven approach, utilizing the framework of Tobias and Brunnermeier (2016), and implementing a variable selection scheme inspired by the algorithm of Belloni and Chernozhukov (2011). The analysis extensively covers the monetary policy level, recognizing the role of banks in transmitting monetary impulses throughout the economy and the implications of policy forces on bank performance and stability. The results shed light on the role of interest rates, providing evidence of the positive impact of long-term interest rates on bank stability [7], supporting the thesis of Samuelson (1945). Additionally, they highlight the regional impact of interbank conditions, significant for banks in weak-economy countries. The currency exchange market will also be considered, prompted by the warning of the systemic risk board that emphasizes the need to monitor foreign currency exposure for cross-border spillover risk BOARD (2011). In this context, the significant role of Euro/$ exchange rate emerges, impacting the European banking system due to its high exposure to dollar-denominated contracts, including lending and derivatives, as well as its central role in Yankee bond issues.

Furthermore, we will consider metrics such as CISS intermediaries and CISS bonds (Hollo et al. (2012)). These metrics offer a comprehensive view of financial distress levels across bond and intermediary sectors (banks, insurance company, investments funds, investment banks and other institutional investors). This choice will help shed light on the presence

[7] Some remarks about this output have been raised in the second chapter.

of cross-market contagions in financial markets, drawing attention to the spread of large financial multibusiness conglomerates that could facilitate the propagation of crises.

Economic conditions constitute the fourth macro area under consideration. Information provided by proxies for GDP (gross domestic product) and inflation levels has been taken into account. To the best of my knowledge, this marks the first empirical investigation of these factors in the context of systemic risk analysis at a high frequency. This approach is well-suited to capture the reaction of banks to changes in these variables. The results appear to support the notion of the detrimental effect of rising inflation expectations and the positive impact of GDP growth.

The last area of interest concerns key commodities such as oil, natural gas, and gold prices. Due to the lack of literature, the specific role of these commodities in the banking system has not been fully defined, especially with regard to the gold price. Surprisingly, this factor emerges as both a bank loss and systemic risk explainer. This is primarily driven by the nature of this commodity, which supplies inflation information (being closely linked to inflation expectations according to Fortune (1987)), monetary policy actions, and currency exchange (as central banks regulate reserves to support currency exchange and set policy operations).

The results obtained in the second chapter opened the doors to new suggestive reflections, given the extremely important role of the gold price in determining the losses of banks and thus the contagion effect within the system. Moreover, the analysis has confirmed the central role of sovereign bond conditions and stressed the stability role of the long-term interest rate. Furthermore, contrary to the literature on the topic, the equity market volatility has been established as a systemic risk-triggering factor, even though it does not exert pressure on the banking system in stable periods. This is closely related to leverage containment, as low volatility periods stimulate the risk-taking behaviors of banks, which could lead to destabilizing effects in the system during turmoils.

The third chapter of the thesis will be dedicated to the analysis of idiosyncratic factors that have the greatest influence on the systemic risk level of financial institutions. The systemic risk measure synthesized in the previous chapter will serve as the reference point for this analysis. Particular attention will be dedicated to the most significant drivers highlighted by systemic risk regulations, with a specific focus on the dichotomy that essentially underpins systemic risk regulation: the importance of size and interconnectedness. To the best of my knowledge, a comprehensive analysis of the banking facets that are most strongly linked to higher systemic impacts of banks has not been provided yet, especially making a differentiation of the periods (distinguishing between crisis periods from stable ones). Also in this case, a model selction approach to enforce the analysis is used. At this purpose the panel lasso regression of Babii et al. (2022) has been employed. The results have depicted a clear situation, in which size per se is not sufficient to justify systemic risk level and that during crisis the interconnectedeness (represented by the interbank ratio of banks) is extremely foundamental. Moreover, the non-interest margin and the amount of non-performing loans is of major concern (especially in banking crisis).

Contribuition to the literature and future research development

My study contributes to the literature in several ways. This work aims to address the gap by providing a comprehensive assessment of the factors determining the systemic risk of banks, fostering cross-fertilization between the literature and financial regulation.
An analysis of existing literature reveals a predominant focus on a limited set of macroeconomic and microeconomic variables, leading to a significant omitted variables bias. In light of these results, an urgent need for a holistic approach has been recognized (Ellis et al. (2022)). The thesis addresses this gap and uncovers some interesting insights that enrich the literature on this topic. Particularly it's shedded light on the role of long-run interest rates Samuelson (1945), inflation Mishkin (1999b), and GDP levels in impacting both banks and fianancial system. It has also identified a novel systemic importance warning factor that explains both bank and systemic losses, closely tied to fluctuations in the price of gold. This latter factor has demonstrated a high level of significance in elucidating systemic turmoils. Furthermore, the study emphasizes the importance of volatility levels and the sovereign yield spread. The former has proven to be a crucial explanatory variable for only extreme events, enhancing the literature that considers it in also stable and normal periods Tobias and Brunnermeier (2016), thereby supporting the regulatory principles under the leverage limit (Basel III). As for the latter, which serves as a clear distress-explanatory variable for both banks and system, its impactful role has often been underestimated, especially in terms of regulations (Altavilla et al. (2017)).
From an idiosyncratic perspective, the research highlights the significance of interconnectedness over the size of institutions as a critical systemic feature, particularly during periods of crisis, contribuiting on the this topic literature (Nils (2018)). These findings underscore the need to reformulate the current systemic regulations, shifting the focus from individual agents only to an orientation towards a more platform-based regulatory framework.
Moreover, even the systemic risk measurement is a prolific research field, a lack of global measure that provide a realistic evaluation of risk is currently unaivalable, as also pointed out by Benoit et al. (2017). As discussed earlier, this research endeavor also aims to offer (an embryonic) tool that incorporates all the relevant factor information, assisting regulation in determining the systemic risk relevance of each bank and facilitating the design of more targeted regulatory solutions.

Where was I born and where am I going.

This thesis represents the culmination of a challenging journey. The first chapter was conceived at the onset of the Russian-Ukraine war and the initial signs of market turmoil in the energy sector. While initially focusing on the Italian case [8], my investigation of the existing literature highlighted the lack of evidence regarding the impact of natural gas on banks. The second chapter naturally followed, as I recognized the opportunity to delve deeper and explore the multitude of factors affecting the banking sector, aiming to

[8] Highlighting the Bank of Italy's perspective on this topic, exemplified by Ignazio Visco's speech, the former Governor of the Bank of Italy, on 'Energy Crisis, Inflation, and Monetary Policy'

identify the most fundamental ones. This idea emerged from an exploration of the banking literature and regulations surrounding systemic risk. Indeed, several papers, such as Benoit et al. (2017), De Bandt and Hartmann (2000) and Ellis et al. (2022) have emphasized the lack of holistic measurements of systemic risk for both banks and systems, which effectively incorporate various market indicators. The third chapter horizontally expands on the previous investigation, driven by the need to assist regulation. Indeed, identifying market factors influencing banking systemic risk is only the first step. A further study concerning the bank-specific characteristics that make individual institutions more prone to becoming a threat to the system could help refining regulatory targeting.

This research path signifies only the first step of a new experience, as the research in this field continues to advance, with further enhancements on the horizon. Indeed, the thesis predominantly focuses on market-driven measures, with potential plans for implementing robustness tests using other hybrid approaches. Moreover, future investigations into market connectivity and its role in driving crises would be the future directory of my research (why not, through a research observatory).

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Chapter 1

How electricity and natural gas prices affect financial systemic risk.

1.1 Introduction

1.1.1 Snapshot of the electricity and natural gas markets' dependence

Over the past three years, geopolitical turmoil stemming from the ongoing Russian invasion of Ukraine and the COVID-19 pandemic has had far-reaching consequences. Notably, these events have not only skyrocketed the price of many commodities in the Eurozone but has also severely affected the volatility in their respective markets (Yating et al., 2022), undermining the real economy and consequently the financial sector (Goodell, 2020). The most pronounced effects have been observed in the European electricity and natural gas markets, primarily due to the energy-importing nature of European countries (Batlle et al., 2022). Furthermore, it is noteworthy that the principal energy partner for European countries is the Russian Federation (Baranowski, 2022).
In this context, Natural gas (NG) plays a pivotal role in the whole European energy sector. This significance arises from the pricing mechanism that intimately ties the final price of electric power to its marginal production cost. The recent conjunctural events had further highlighted the strong interdependence between natural gas and electricity prices in the Eurozone, in consequence of the day-ahead framework governing the European energy markets. Within this market infrastructure, the electricity price is continuously determined by matching the electricity's marginal cost and the energy demand in a marginal price-based market design. Often referred to as the *Merit order* system, this framework rules the electricity price setting by identifying the energy source that establishes the equilibrium price. Research by Zakeri et al. (2022) has demonstrated that in 2019, two third of the time the electricity price has been driven by the natural gas price in the European exchanges, despite natural gas accounting for only 37% of electricity production across European countries (on average among European Countries). This underscores the prevalence of natural gas in this *pay-as-clear* electricity market (ACER, 2021). Furthermore, this study has documented that the dependence on natural gas in energy price settlement tends to amplify when the marginal cost of electricity production increases, settling the electricity equilibrium price even higher, the more is the marginal cost for the electricity production, which is ultimately function of the CO^2 costs and the

price of the natural gas itself (Roeger and Welfens, 2022). As if that were not enough, the price settlement through the merit order clearing has proven to be a flywheel of contagion among commodity markets in time of distress; this being closely tied to the natural gas-centric nature of the electricity (Chuliá et al., 2019). Similarly, the European Union Agency for the Cooperation of Energy Regulators (ACER) in late 2021 indicated that electricity prices in Europe were significantly linked to dynamics in the natural gas market, thereby making them highly dependent on price movements and supply-demand dynamics (ACER, 2021). Consequently, they are heavily influenced by the import of Liquefied Natural Gas (LNG) from North-East Asia and South America, which played a pivotal role in raising commodity prices during and after the pandemic. The pipeline import from Russia has also emerged as a key factor driving the surge in electricity prices (Zakeri et al., 2022).

1.1.2 *'Spill the beans'* on spill-over channels

The scenario described thus far, along with the energy market fundamentals in Europe, constitutes a perilous transmission channel for negative externalities affecting the economy and the financial sector. Thi concern is compounded by the dominant role of the natural gas in shaping energy markets. Consequently, it is natural asking how and to what extent turmoil in the natural gas market and electricity price movements might impact the real economy, and what could be the implications for the financial sector.

In this specific research area, the scientific literature is only recently beginning to emerge. Traces of energy's subordination and spill-overs effects from energy markets to the real economy have been uncovered by Anton (2021), who provides evidence that firms' profitability is significantly affected by natural gas market conditions as a relevant component of energy price. Such evidence is based on data until 2016, thereby excluding the pandemic's macroeconomic downturn and the subsequent energy price surge, intensified by the implications of the Russian invasion of Ukraine. Additionally, Wang et al. (2022) point out how volatility in the natural gas market can be successfully predicted by global indexes of uncertainty and economic conditions. Similarly, Gargano and Timmermann (2014) and Hu et al. (2020) develop econometric models to capture the forecastable component of commodities prices using economic macro-factors. This not only establishes a direct causal relationship between commodity demand and market prices but also bridges the gap between the real economy and the commodity market dynamics. The reverse effect has also been demonstrated by van de Ven and Fouquet (2017) that have brilliantly shown how shocks in energy price impact on GDP, suggesting diversifying production sources enhance economic resilience. Additionally, Rizvi et al. (2022) emphasize how changes in natural gas prices impact short-term equity market returns, albeit without a lasting structural effect.

Regarding the financial sector, from a theoretical perspective, electricity and natural gas prices are expected to impact financial institutions' performances and risk profiles through two distinct trajectories, as demonstrated for other commodity types. The first one is the so-called inflation channel (Jones et al., 2004), wherein a rise in inflation level caused by a jump in commodities prices could lead to credit market frictions and increased distress in existing credit positions, both potentially detrimental to the banking sector (Huybens and Smith, 1999). The second spillover channel, documented by Brückner and Ciccone (2010) and Kilian and Park (2009), is driven by GDP and the employment rate changes, which, depressed by turmoil in energy commodities markets, in turn might negatively

affect banking sector as well as the market of financial institution.
The aforementioned researches suggest investigating the new scenarios in natural gas and electricity markets (in terms of levels and volatility) could worsen the stability of European financial institutions. The impact of surging energy prices on firms' productivity, unemployment rates, GDP, and inflation levels could result in additional stress for European monetary and Financial institutions, proportional to their exposure to energy-sensitive sectors. Above all, Financial institutions might face increased capital requirements to absorb credit exposure losses and mitigate the effects of macroeconomic variable shifts. This impact could be magnified by relatively larger price increases at the country level, thus requiring policy and monetary measures for preserving financial stability and preventing undesirable outcomes.
These premixes introduce the aim of the paper, which seeks to investigate the impact of energy market conditions (specifically electricity and natural gas futures prices) on the systemic risk profile of the financial institutions in the Euro Area. In this way, we aim to assess the systemic perturbation affecting financial intermediaries and the financial sector as a whole, resulting from negative externalities originating in these markets. To achieve this, we employ a modified version of the $CoVaR$ methodology introduced in Tobias and Brunnermeier (2016). This methodology evaluates changes in value at risk within the system, contingent on the stress levels of individual institutions, controlling for both institution-level variables and exogenous factors, such as monetary policy conditions, financial indicators, electricity and natural gas prices. This approach enables us to assess the impact of energy and gas prices on systemic stress conditions of individual financial institutions and the financial sector as a whole.
We develop the proposed methodological strategy using a dataset composed of merged balance sheet and stock price data from publicly listed financial institutions operating within the Euro Area. This dataset provides the endogenous information on which to measure the impact of a pool of exogenous financial, monetary, and credit factors, along with the inclusion of energy market prices. The available sample spans from 2010 to 2021, covering years before the pandemic-induced global economic downturn and the subsequent recovery, coinciding with the surge in natural gas prices that began in the second half of 2021 due to the Russian-Ukraine conflict. We find that our methodology performs well in explaining stress conditions compared to an ECB-originated index (the Composite indicator of System Stress, CISS), displaying some potential for anticipatory capability.
Our study contributes to the literature in several ways. Firstly, we are the first to present an evaluation of the impact of electricity and natural gas on the European financial market using a systemic systemic risk approach. There is a lack of research documenting these relations; indeed, the existing literature mainly focused on perturbances in financial markets induced by the oil markets (Antonakakis et al. (2014), Kang and Ratti (2013), Zhang (2017)). Secondly, our work could serve as a "watershed" for the renewable energy sector, and, simultaneously, it could feed the need for a reformulation of the European electricity price settlement framework. Indeed, it highlights the vulnerability of the European financial sector to extreme movements of commodity markets, prompting the need to disanchor the marginal price settlement by introducing a system with minor fossil fuels dependence to settle the electricity price (Roeger and Welfens, 2022), and to diversify the electricity sources, boosting the renewable energies production (Jain and Shrimali, 2022).
The remainder of the paper is structured as follows. Section 2 describes the methodol-

ogy and the dataset. Section 3 shows and discusses the results. Section 4 presents our conclusions.

1.2 Literary review

In the last decade, a considerable number of scholars and practitioners have been examining new patterns of cross-connectedness among financial markets stemming from globalization, financial liberalization, and trade integration (Caporin et al., 2021). These links have become increasingly intricate and challenging to investigates, necessitating sophisticated techniques to understand the directions and the magnitude of cross-effects among markets. In light of this, a substantial body of literature has dedicated its efforts to study the financial market networks and estimate the aforementioned cross-effects among markets. Foremost among these studies is the groundbreaking research by Engle and Manganelli (2004), who employed the non-linear quantile regression to explore the effects of variables on the tails of selected market variable distributions. This work represents the first attempt at describing tail events using non-linear models. Another notable contribution is from F.X. Diebold et al. (Diebold and Yilmaz (2009), Diebold and Yilmaz (2012), Diebold and Yılmaz (2014)), that developed an intuitive measure of contagion in financial markets based on impulse-response analysis of structural vector autoregressive processes. This measure has been widely used to study the spillover effects from other sectors to financial markets. These methodologies, along with numerous others, have been adopted to estimate various interrelations among markets, especially cross-effects among commodity markets (Mensi et al. (2013), Du and McPhail (2012),Křehlík and Baruník (2017),Lu et al. (2019), Barbaglia et al. (2020),An et al. (2020), Xiao et al. (2020), Yahya et al. (2019)). For istance, Rehman et al. (2018) underscore the central role of the oil market shocks in influencing returns' tail behaviours across all other commodity markets. However, Khalfaoui et al. (2021) find weak significant dependency between energy and non-energy commodity prices using the quantile coherency approach developed by Baruník and Kley (2019). These results are not entirely consistent with the findings of Albulescu et al. (2020), who document asymmetric tail dependence between energy, agriculture, and metal markets. Along the same lines is the work of Du and McPhail (2012) and Umar et al. (2021) that demonstrate how the energy price is an irrefutable determinant in influencing prices both in agricultural markets and in metal markets. Additionally, Rehman and Vo (2021) identify returns integration between energy fuels markets and precious metal commodities.

Regarding the relationship between oil market and natural gas market Hulshof et al. (2016) and Nick and Thoenes (2014) document the poor connectivity between these two commodity markets, contrary to the prevailing sentiment in the literature, influenced by Panagiotidis and Rutledge (2007) and Brown and Yucel (2008), who assert otherwise. However, the literature lacks investigations into this link during turmoil periods, thus yielding non-univocal conclusions.

A substantial body of literature examines the effect of oil prices on stock markets and stock returns, and the spill-over effect of oil markets on the economy (Abbas Rizvi and Itani (2022), Kilian and Park (2009),Basher et al. (2018),Hamdi et al. (2019),Wei et al. (2020), Li et al. (2020)). The last two cited papers concur on the existence of the so-called natural resources curse, wherein natural resources could impede countries' economic growth paths. Antonakakis et al. (2014) explore the relations between oil markets

and country level-risk, finding a bilateral relationship between economic policy uncertainty and oil prices. Similarly, Kang and Ratti (2013) apply the same methodology (structural VAR-impulse response analysis) to stock market returns, reveiling how the oil market significantly influences both countries and stock markets with a time delay. Nazlioglu et al. (2015) investigate volatility co-movements between oil and financial markets, demonstrating a severe risk connectedness between the two. Geng et al. (2021) go further, providing the inverse effects of financial markets' movements on oil markets. On the same wavelength are the findings discovered by Zhang (2017) who demonstrates how oil markets impact mostly regional financial markets but suffer from movements in international financial markets. Kang et al. (2017) arrive at similar results, demonstrating increased spill-overs during crisis episodes, analyzing the period between the 2002 to 2016. Besides, energy markets and stock markets tend to be more connected during financial crisis as proven by Jebabli et al. (2022), who further show that stock markets were net transmitters of volatility to energy markets during the 2008 global financial crisis, while the patterns differed during the Covid-19 crisis, in which commodities had a more significant influence on financial markets than viceversa. This last statement has also been validated by Abuzayed and Al-Fayoumi (2021), who shed light on the structural link between crude oil and stock markets. Moreover, the analysis of the remaining literature reveals that most previous studies have primarily focused on the oil market, paying little attention to the natural gas market and even less on other sources of energy (see e.g., Ewing and Malik (2016), Mensi et al. (2013)).
At the current state of the art, no one has investigated the impact of electricity and natural gas markets on the financial sector, particularly regarding the timing and magnitude of these economic shocks. For this reason, we aim to investigate whether financial institutions are affected by energy downturns in a similar manner to what has already been demonstrated for the impact of rising oil prices.

1.3 Methodology

1.3.1 Model description

This section outlines the methodology used to compute institutions' CoVaR building upon the original formulation introduced in the milestone paper written by Tobias and Brunnermeier (2016). The authors proposed this novel methodology to measure the contribution of individual institutions to the overall systemic risk within the financial sector. This goes beyond simply considering the risk arising from direct interconnections among firms due to contractual linkages, by also evaluating the potential indirect spillover effects of macroeconomic risk factors on the financial landscape. In doing so,the $CoVaR$ measure is initially derived. This measure quantifies the potential losses within the financial system as a result of the financial distress of each institution. Specifically, it involves calculating the Value at Risk (VaR) of the entire financial system conditioned on the VaR of the $j-th$ institution:

$$Pr(X_{system} \leq CoVaR_q^{system} | X_j = VaR_q^j) = q \tag{1.1}$$

Where X_{system}, X_j represent the loss variables of the financial sector and the $j-th$ institution, respectively, and q is the chosen distributional quantile. Pr symbolize the classical probability function.

The marginal contribution of each $j-th$ institution to the global systemic risk is captured by the $\Delta CoVaR$, which is calculated using the following expression:

$$\Delta CoVaR_q^{system|j} = CoVaR_j^{system|X_j=VaR_q^j} - CoVaR_j^{system|X_j=VaR_{50\%}^j} \tag{1.2}$$

It expresses the difference between the potential losses incurred in the financial system due to significant losses of the $j-th$ institution, and the VaR of the system under the scenario of median state of X_j. A larger disparity between these two variables indicates a greater systemic impact resulting from losses in the $j-th$ institution.
The next step in the analysis involves estimating time varying quantities, requiring evaluation of the introduced measures for each data point within the considered analysis period. To address this challenge, we opted to use quantile regression (Koenker, 2005), approaching the parameters estimation through the IRLS (iterated reweighted least of squares), due to its efficiency and precision, particularly for large datasets (Muggeo et al., 2012). Quantile regression not only accommodates non-linear relationships among variables but also accounts for tail events of variables through exogenous macroeconomic and financial state covariates. The flexibility of this approach provides an avenue for enhancing the original model to assess the potential impacts of energy and natural gas prices on financial sector stability. Specifically, it's possible to evaluate Var, $CoVaR$ and $\Delta CoVaR$ over time, while controlling for these new state variables. Concretely, the general formulation of the panel data quantile regression equations, involving the new factors, is displayed in the following:

$$\widehat{VaR_{t,q}^j} = \widehat{\beta_0^j} + \widehat{\boldsymbol{\beta^j}}\boldsymbol{Z_{t-m}} + \widehat{\boldsymbol{\gamma^j}}\boldsymbol{E_{t-j}} \tag{1.3}$$

$$\widehat{CoVaR_{t,q}^{system|j}} = \widehat{\beta_0^{system|j}} + \widehat{\alpha_p^j}VaR_{t,q}^j + \widehat{\boldsymbol{\beta^{system}}}\boldsymbol{Z_{t-m}} + \widehat{\boldsymbol{\gamma^{system}}}\boldsymbol{E_{t-j}} \tag{1.4}$$

$$\Delta \widehat{CoVaR_{t,q}^{system|j}} = \widehat{CoVaR_{t,q}^{system|j}} - \widehat{CoVaR_{t,50\%}^{system|j}} = \widehat{\alpha_p^j}VaR_{t,q}^j - \widehat{\alpha_{50\%}^j}VaR_{t,50\%}^j \tag{1.5}$$

Where:

- Z_{t-m} is the vector of financial and economical state variables lagged by $'m'$ period of time.
- E_{t-j} is the vector of energy and natural gas prices lagged by $'j'$ periods of time.

Unlike to the original model, we have introduced a dependence of the parameter α_q^j on the quantile considered. Therefore, when calculating the $\Delta\widehat{CoVaR}_{t,q}$ (as in equation 1.5), the values $\widehat{VaR}_{t,q}^j$ and $\widehat{VaR}_{t,50\%}^j$ are multiplied by $\widehat{\alpha}_p^j$ and $\widehat{\alpha}_{50\%}^j$, respectively, which were estimated in equation 1.4. This enhancement is consistent with the existing literature in this field. Several authors have cautioned against assuming a priori equality of coefficients across quantiles (Davino et al. (2013), Koenker and Machado (1999)). Regarding the lag of the covariates, this is not predetermined, unlike the approach taken in the paper of Tobias and Brunnermeier (2016), where the independent variables are time-shifted by one period. While we have found support for the one-period lag assumption in the financial variables vector Z_{t-m}, such as in Huang and Uryasev (2018), and Duan et al. (2021), the lag order selection would not be predetermined in this study; instead it will be determined through an appropriate stepwise selection scheme. In contrast to financial covariates, the introduction of covariates lagged by more than one period is well justified in the literature concerning natural resources markets. For example, Qin (2020) demonstrates that the financial sector's response to shocks in oil price and supply experiences a delay of several weeks. This supports the exclusion of contemporaneous effects of the covariates and underscores the importance of identifying the appropriate lag order."

1.3.2 Variables selection, research sample and data construction

We propose the $CoVaR$ analysis using weekly frequency data covering the period from December 31, 2010, to December 31, 2021, for a sample of European financial institutions. This timeframe encompasses years preceding the pandemic-related global economic downturn and the subsequent recovery, which coincides with the rise in natural gas prices starting in the second half of 2021. The selection of the sample size was conditional upon data availability for a sufficient number of institutions. Therefore, we conducted the analysis on the top 45 European financial institutions in terms of size. This choice allows us to directly confirm accounting data from their respective balance sheets and better observe the impacts of fluctuations in commodities markets. Both the selection of weekly frequency data and the sample size align with those used in closely related literature, such as studies by Acharya et al. (2017), and Borri and Di Giorgio (2022), Huang and Uryasev (2018). Regarding the composition of the sample institutions, all of them are listed firms falling within one of the following categories of financial institutions [1]: commercial bank, savings bank, private banking, finance company and investment and trust corporation. For each institution, we collected the Total asset and total equity values at a yearly frequency from the BankFocus database
In the next **Table 1.1** is displayed the financial sample investigated:

Table 1.1: Financial institutions sample

Name	**Country**	**Specialisation**
Bnp Paribas	France	Commercial bank
Societe Generale	France	Commercial bank
Deutsche bank ag	Germany	Commercial bank
Credit Agricole sa	France	Cooperative bank
Intesa Sanpaolo	Italy	Commercial bank
Banco Santander sa	Spain	Commercial bank
Caixabank s.a.	Spain	Commercial bank
Unicredit spa	Italy	Commercial bank
Banco bilbao vizcaya argentaria sa	Spain	Commercial bank
Commerzbank ag	Germany	Commercial bank
Banco de sabadell sa	Spain	Commercial bank
Banca di montepashi di siena	Italy	Commercial bank

[1] These are the specializations provided by BankFocus, Moody's analytics data provider.

Bper banca spa	Italy	Commercial bank
Bankinter sa	Spain	Commercial bank
Erste group bank ag	Austria	Commercial bank
Raiffeisen bank international ag	Austria	Cooperative bank
Mediobanca-banca di credito finanziario spa	Italy	Commercial bank
National bank of greece ag	Greece	Commercial bank
Banco commercial portugues sa	Portugal	Commercial bank
Caisse regionale de credit agricole mutuel de paris et d'ile-de-france sc	France	Commercial bank
Credito emiliano spa	Italy	Cooperative bank
Banca popolare di sondrio spa	Italy	Cooperative bank
Aareal bank ag	Germany	Real estate and mortgage finance inst.
Banca mediolanum spa	Italy	Commercial bank
Caisse regionale de credit agricole mutuel du Languedoc sc	France	Savings bank
Oberbank ag	Austria	Commercial bank
Caisse regionale de credit agricole mutuel atlantique vendee sc	France	Cooperative bank
Caisse regionale de credit agricole mutuel sud rhone alpes sc	France	Cooperative bank
Hellenic bank public company limited	Greece	Commercial bank
Banco di desio e della brianza spa	Italy	Commercial bank
Caisse regionale de credit agricole mutuel de la touraine et du poitou sc	France	Cooperative bank
Van lanschot kempen n.v	Netherlands	Commercial bank
Banca Generali spa	Italy	Commercial bank
Caisse regionale de credit agricole mutuel toulouse 31 sc	France	Cooperative bank
Caisse regionale de credit agricole mutuel loire haute-loire sc	France	Cooperative bank
Bank fur tirol und vorarlberg ag	Austria	Commercial bank
Credit agricole du morbihan	France	Commercial bank
Aktia bank plc	Finland	Commercial bank
Altarea s.a	Finland	Investment and trust corporation
Alpha services and holdings societe anonyme	Greece	Commercial bank
Alandsbanken abp	Finland	Commercial bank
Attica bank spa	Greece	Commercial bank

Viel e cia sa	France	Finance company
Banca profilo spa	Italy	Private bank
Grenke ag	Germany	Finance company
Conafi spa	Italy	Bank holding company

To conduct the analysis described thus far, we have chosen to maintain the construction of the dependent variable used in the original paper. Specifically, we assess the growth rate of total assets for each financial institution (and its variant for the system) as the variable to be evaluated for VaR:"

$$X_{j,t} = \frac{ME_{j,t}LEV_{j,t} - ME_{j,t-1}LEV_{j,t-1}}{ME_{j,t-1}LEV_{j,t-1}} \tag{1.6}$$

Where $ME_{j,t}$ and $LEV_{j,t}$ respectively stand for market equity and leverage ratio of the $j-th$ firm at time t. To perform the analysis at a weekly frequency, the components of this latter ratio have been transformed to conduct the original series to a higher frequency one. Rather than opting for a simple linear interpolation between adjacent years, as suggested instead by the author of the $CoVaR$ approach, we aimed to enhance the accuracy of estimates by extracting information from weekly stock prices using time series disaggregation. This approach uncovers the high-frequency series (HF) by observing the low-frequency one (LF), achieved through regression of LF on variables closely linked to it, but available at a higher frequency. Thus, we construct the HF for $ME_{j,t}$,$LEV_{j,t}$ towards weekly stock prices [2] employing the technique developed by Denton (1971) and refined by Dagum and Cholette (2006). Utilizing stock prices as HF indicators aligns with the conditions recommended by the ECB for time disaggregation techniques, whereby *"candidate high frequency indicators should closely approximate the expected short-term movement of the target variable and show a good correlation with the original target variable"* (Buono et al. (2018)).

The method is organized in two steps. In the first step of our analysis, the annualized series of stock prices, denoted by $\boldsymbol{X_{hf}}$, is regressed on the annual series of balance-sheet data, denoted by $\boldsymbol{X_{lf}}$. The matrix of coefficients is then evaluated using generalized least squares regression (GLS), represented as:"

$$\widehat{\beta}(\Sigma) = \boldsymbol{[X_{hf}^T A^T (A\Sigma A^T) A X_{hf}]^{-1} X_{hf}^T A^T (A\Sigma A^T)^{-1} y_{lf}} \tag{1.7}$$

Where the annualized data have been obtained through the matrix $\boldsymbol{A}$, which is a properly conversion matrix [3], multiplied by $\boldsymbol{y_{lf}}$, which is the low frequency series. In the second step, assuming that the relationship between the yearly series and the annualized one holds for all time horizons, including the weekly timestep, we performed the weekly disaggregation of the series as follows::

$$\boldsymbol{\widehat{y}_{hf} = \widehat{\beta} X_{hf} + D(y_{lf} - \widehat{y}_{hf})} \tag{1.8}$$

[2] All the stock price series have been downloaded from Refinitiv database.

[3] $\boldsymbol{A}$ is the conversion matrix that characterized the "sum" type of temporal disaggregation: $I_{n_l} \bigotimes J_{n/n_l}$. Where n_l and n are respectively the number of annual and weekly observations. The symbol $\bigotimes$ stands for the Kronecker product, meanwhile I_{n_l} and J_{n/n_l} stands for the identity matrix of dimension n_l and the row-vector composed of 1 of dimension n.

Where $\boldsymbol{D}$ is the so-called distribution matrix responsible for distributing the residuals $\boldsymbol{y_{lf}} - \boldsymbol{\widehat{y}_{hf}}$ among the preliminary weekly series. At this purpose, to make this attribution, we employed the method developed by Litterman (1983) which estimates the D matrix by assuming that the low-frequency data is a non-stationary process. This approach aligns with the work of Bontempi et al. (2015).The results of the GLS estimations will be presented in the Appendix section.
Regarding the covariates used in the analysis, the inclusion of financial and economic state variables follows the literature strands in systemic risk measurement (Del Vecchio et al. (2022) and Tobias and Brunnermeier (2016)); the incorporation of chosen commodities prices is a novelty in this research field, to the best of our knowledge. In relation to the macroeconomic, financial and energy factors the following state covariates have been included in the analysis:

- **Change in the slope of European yield curve:** this metric is renowned as a business cycle predictor (Adrian et al. (2010a), Croushore and Marsten (2016)), indeed it has demonstrated that high slopes anticipate periods of economic growth, while low slopes predict economic contractions (Liu and Moench (2016)), making it efficient early-warning predictor. However, instead of adhering to the standard formulation of the variable, which typically is represented by the difference between long-term spot rate (typically at 10-year maturity) and short-term spot rate (typically at 1-year maturity) (a formulation that can vary significantly due to the arbitrary choice of maturities used for the interest rates), we choose to analyze the series of the β_1 coefficient in the Nelson-Siegel-Svensson model (Nelson and Siegel (1987)). The ECB uses the latter model daily to fit the yield curve of the Eurozone, providing the historical series of β_1 coefficient (one of the components of the model) that uniquely represents the slope of the yield curve, as discussed in the ECB working paper of Afonso and Martins (2012) and by Diebold and Li (2006). To ensure more realistic results, our analysis used yield curve estimations involving all issuers within the Eurozone. (**Table 1.3** , 3th row)

- **The weekly VSTOXX EUR**: this variable measures the volatility (historical volatility) observed in the 50 largest stocks in Europe (the components of the EUROSTOXX 50 index). Higher volatility indicates increased uncertainty in the market, leading to an elevated risk of extreme losses. Moreover, volatility can be regarded as the price of risk in the financial market. It reflects not only investors' aversion to risk but also the likelihood of defaults due to rising credit spreads, viewed from a structural perspective (Gonzalez-Hermosillo (2008)). (**Table 1.3**, 4th row)

- **Short-term liquidity spread:** We construct this variable as the difference between EURIBOR rate at three months maturity and the spot interest rate at the same maturity. This difference signals a shortage of liquidity in the market the more is the proximity of the EURIBOR (the most spread interbank rate in Europe) to the spot rate (derived as the weighted average return of bonds issued by European states) (Holló et al. (2012)). (**Table 1.3**, 7th row)

- **Equity market returns:** to represent this variable in the analysis,we chose to use the weekly returns recorded by the EUROSTOXX 50 index, which serves as the primary proxy for the equity market in Europe. (Daly and Vo (2008)). (**Table 1.3**, 8th row)

In relation to the commodities variables, we have identified two variables:

- **Natural gas return**: To represent this state covariates, the intraday-ahead contract with the shortest maturity date traded on the Amsterdam Stock Exchange (Dutch Title Transfer Facility - TTF) was selected. The TTF is recognized as the leading exchange in Europe for energies products (Chuliá et al. (2019)), and it is known for its price affordability, as confirmed by Akcora and Kocaaslan (2023). This choice was driven by the lack of a comprehensive historical series for natural gas spot prices, thus, the spot price was approximated using the nearest future price, following the approach of Lautier and Raynaud (2011). (**Table 1.3**, 2nd row).

- **Electricity spot price return**: Similarly, for the variable of electricity spot price returns, a proxy was used due to the absence of a representative price for all European countries. To the best of our knowledge, the most suitable proxy for the electricity price in the Eurozone is the electricity price component [4] of the harmonized indices of consumer Prices (HICP index), provided by the statistical warehouse of the ECB (**Table 1.3**, 1st row).

Two of the aforementioned time series were originally collected in monthly frequency, thus, to align the analysis with a weekly frequency, these series were interpolated to a weekly frequency using tension-spline interpolation, a well-recognized technique in the literature known for its performance and affordability (Angelini et al. (2003)). We acknowledge that interpolation has limitations, particularly regarding overfitting issues. However, the aim of this paper is not focused on forecasting; rather, it aims to fill the gaps in data with a smooth and realistic approximation.
In **Table 1.3** below are reported detailed information about the dataset construction, the notation used, measurements, the frequency of response variables and covariates' data, as well as the subsequent transformations applied::

Table 1.3: Data description and transformation of variables

Variables	**Abbrev.**	**frequency**	**Original unit**	**Source**	**Transf.**
Banks' stock prices	/	weekly	Euro	Refinitiv	/
Banks accounting data	/	yearly	Euro	BankFocus	Time disaggregation
Electricity spot price return (HICP)-ECB	El.ITY	monthly	Euro/kwh	Eurostat	Spline Int.
Natural gas return-Future at 3months	NAT.GAS	weekly	Euro/MWh	Refinitiv	/
Change in the slope of Euro yield curve	SLOPE	weekly	Pure num.	Refinitiv	/
VSTOXX	VSTOXX	weekly	Pure num.	Refinitiv	/

[4] The electricity price component in HICP index excludes all the sources used to produce electricity. Details on this series could be found on Eurostat HICP components, under the coicop CP0451 code (Classification of individual consumption by purpose).

Euribor at 3 months	EUR	monthly	Percentage	ECB statistical data warehouse	Spline int.
Spot interest rate at 3 months	YLD	weekly	Percentage	ECB statistical data warehouse	/
Change in short-term liquidity spread	EUR.YLD	weekly/der	Percentage	Refinitiv	/
European Equity market returns	EUR.STOXX	weekly	Euro	Refinitiv	/

Notes: The change in short-term liquidity spread has been derived subtracting the spot interest rate to the Euribor rate. 'weekly(der)' stands for weekly derivation, since the series is the difference between a weekly series (YLD) and a interpolated weekly frequency (EUR).

In the Appendix section (**Table 1.11**,**Figure 1.4** and **Figure 1.5**) the numerical and graphical results of the interpolation are also displayed. These results include the mean squared error, the degree of smoothing in the spline, and the smoothing factor used to determine the number of knots in the interpolation procedure (I.J. Shoenberg, 1964).

1.4 Empirical results

1.4.1 State variables statistics

The summary statistics for the covariates at a weekly frequency are presented in the following table (**Table 3**). It emerges forthwith, looking at the relative standard deviation (column Rel. SD) that the variables with the highest degree of time variability are the slope of the yield curve and the change in the EUROSTOXX index. Following closely behind are the weekly changes in natural gas prices.

Table 1.4: Summary statistics of covariates

	mean	**SD**	**Rel.SD**	**min**	**max**	**1% quantile**	**ADF**
EUR.YLD	0,32773	0,00380	6,81467	-0,01293	0,02286	-0,00995	-5.952***
EUR.STOXX.	0,00070	0,01193	16,9442	-0,05258	0,05182	-0,03217	-6.139***
SLOPE	-0,00046	0,02470	53,8907	-0,13251	0,10164	-0,07571 -	6.845***
VSTOXX	21,5747	6,66336	0,30884	11,5767	49,5192	12,5262	-4.001***
EL.ITY	0,00055	0,00380	6,81467	-0,01293	0,02286	-0,00995	-5.952***
NAT.GAS.	0,00311	0,03784	12,1465	-0,11430	0,25144	-0,08624	-4.017***

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. For ADF it's intended the result of the augmented Dickey-Fuller test for stationarity of time series (D.A. Dickey W.A. Fuller, 1979). Rel. SD stands for Relative standard deviation, it's calculated as: $\frac{SD}{|\mu|}$.

The heightened variability in the slope change covariate can be attributed to the reduced persistence of the ECB β_1 factor during the financial crisis, that unfolded over the decade under consideration (Papailias (2022)). Similar conclusions can be drawn about the variability in equity markets. The turbulence triggered initially by the sovereign debt crisis and subsequently by the COVID-19 outbreak and the reverberations from the Russian-Ukraine conflict has kept the markets in a state of turmoil (Yating et al. (2022), Jebabli et al. (2022), Asadi et al. (2022)). Turning to the energy regressors, the summary results point out taht the commodities variables have exhibited a particular tumultuousness in the past decade, whit a dizzying excursion between the mean values and the first percentile of empirical distributions, especially in the case of natural gas. These patterns are primarly driven by the the price hikes that became pronounced at the beginning of 2021 (Mbah and Wasum (2022)).

Upon further examination of the correlations among variables, it is evident from **Table 1.5** that the relationships between state and energy variables are coherent. Notably, the correlations between Eurostoxx50 performance and electricity and natural gas imply a positive co-movement, even though higher energy prices tend to increase volatility in the equity market.

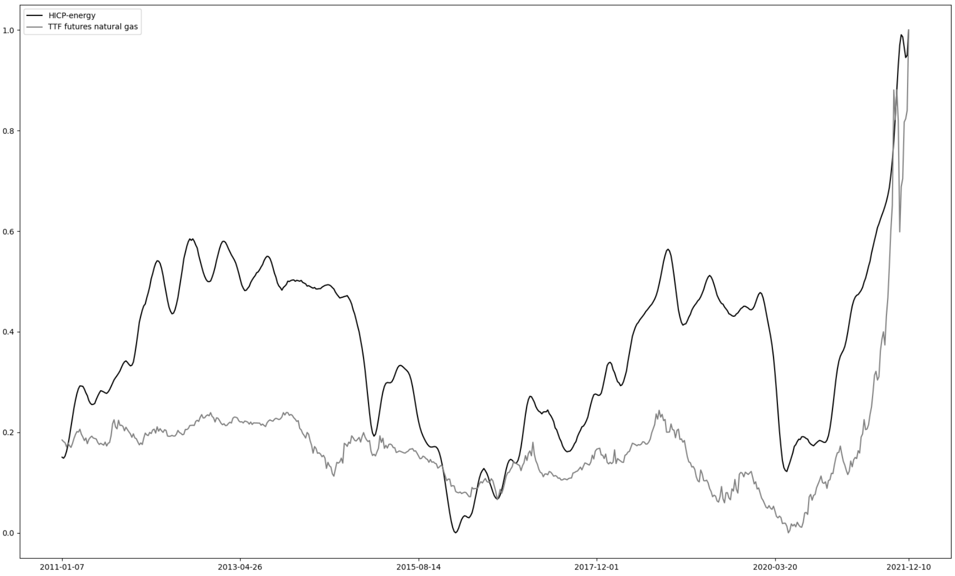
Table 1.5: Pearson correlation matrix

	EUR.YLD	**EUR.STOXX.**	**SLOPE**	**VSTOXX**	**EL.ITY**	**NAT.GAS.**
EUR.YLD	1					
EUR.STOXX.	-0.50979	1				
SLOPE	-0.50101	0.756913	1			
VSTOXX	-0.312351	-0.44956	-0.07214	1		
EL.ITY	-0.14022	0.156124	-0.20991	-0.18514	1	
NAT.GAS.	-0.05583	0.261815	-0.04072	-0.02611	0.693185	1

Notes: The correlations have been evaluated on the weekly price, instead of doing them on the respective weekly changes

These findings are partially aligned with the existing literature on this theme, which acknowledges that turmoil in commodity markets certainly impacts the volatility of the financial market (Asadi et al. (2022)). However, these findings represent a novel perspective from the standpoint of market performances. This stands in contrast to the extensive literature that examines the connections between commodity markets and stock markets (Abbas Rizvi and Itani (2022), Abuzayed and Al-Fayoumi (2021))which typically indicates a negative impact of rising commodities prices on stock markets. Another noteworthy observation is the correlation between electricity and natural gas, which empirically demonstrates the close relationship between the two prices due to the merit order system mentioned earlier. Graphically, **Figure 1.1** below illustrates the substantial price growth (particularly for natural gas) over the past year (the values are normalized for ease of comparison between the series):

Figure 1.1: Summary, prices of energy and natural gas



The commodities shocks observed in 2021 are undoubtedly influenced by the aftermath of the COVID-19 outbreak. Initially, this led to a significant reduction in energy demand and consumption due to disruptions in transportation, flights, and business operations, especially in countries where stringent measures like lockdowns were implemented (Norouzi et al. (2021)).Subsequently, this reduction in demand created a surplus supply situation, partly due to production delays and reduced investments in the energy sectors (Mofijur et al. (2021)), leading definitely to the spike in price levels. Furthermore, by the end of 2021, this demand-supply dynamics, coupled with low energy inventory levels (Kuik et al. (2022)) were exacerbated by the emergence of tensions between Russia and Ukraine, which further pushed up commodity prices.
This interplay of factors can be observed in **Figure 1.1**, where the significant energy price fluctuations prior to 2020 were mostly unrelated to the dynamics of natural gas prices. However, post-2020, the price increases (accompanied by expectations of prolonged scarcity and heightened uncertainty due to political tensions) drove up prices in both markets, suggesting a joint dynamic.

1.4.2 VaR, $CoVaR$ ad $\Delta CoVaR$ estimation results

The results of this section validate the fundamental assumption that drove the motivation behind this research. More precisely, the prices of energy and natural gas commodities stand out as significant factors when evaluating tail events within both individual institutions and the wider financial system. The estimation outcomes are presented in the subsequent **Table 1.6**, which illustrates the statistical findings arising from different combinations of lagged variables. These results have been subjected to winsorization at the 1st and 99th percentile levels, effectively mitigating potential distortions caused by outliers (Anginer et al. (2014)).

Table 1.6: Coefficients' significance in Conditional quantile regressions for different time-lagged covariates

(i)	(1)		(2)		(3)		(4)		(5)		(6)	
	$\widehat{V^j_{1\%,t}}$	$\widehat{CV^{sys\|j}_{1\%,t}}$	$\widehat{V^j_{1\%,t}}$	$\widehat{CV^{sys\|j}_{1\%,t}}$	$\widehat{V^j_{1\%,t}}$	$\widehat{CV^{sys\|j}_{1\%,t}}$	$\widehat{V^j_{1\%,t}}$	$\widehat{CV^{sys\|j}_{1\%,t}}$	$\widehat{V^j_{1\%,t}}$	$\widehat{CV^{sys\|j}_{1\%,t}}$	$\widehat{V^j_{1\%,t}}$	$\widehat{CV^{sys\|j}_{1\%,t}}$
intercept	0.017	0.266	0.002	0.453	0.009	0.263	0.002	0.117	0.019	0.231	0.054	0.430
EUR.STOXX$_{t-1}$	0.171	0.262	0.237	0.147	0.269	0.316	0.134	0.201	/	/	/	/
SLOPE$_{t-1}$	0.133	0.334	0.073	0.327	0.140	0.372	0.123	0.312	/	/	/	/
VSTOXX$_{t-1}$	0.015	0.009	0.006	0.001	0.030	0.005	0.020	0.005	/	/	/	/
EUR.YLD$_{t-1}$	0.037	0.002	0.002	0.005	0.013	0.046	0.035	0.035	/	/	/	/
EUR.STOXX$_{t-2}$	/	/	/	/	/	/	/	/	0.154	0.441	0.226	0.135
SLOPE$_{t-2}$	/	/	/	/	/	/	/	/	0.118	0.244	0.094	0.247
VSTOXX$_{t-2}$	/	/	/	/	/	/	/	/	0.026	0.002	0.024	0.001
EUR.YLD$_{t-2}$	/	/	/	/	/	/	/	/	0.026	0.017	0.014	0.040
EL.ITY$_{t-1}$	0.209	0.000	/	/	/	/	/	/	/	/	/	/
NAT.GAS$_{t-1}$	0.070	0.023	/	/	/	/	/	/	/	/	/	/
EL.ITY$_{t-2}$	/	/	0.197	0.000	/	/	/	/	/	/	/	/
NAT.GAS$_{t-2}$	/	/	0.046	0.005	/	/	/	/	/	/	/	/
EL.ITY$_{t-3}$	/	/	/	/	0.169	0.009	/	/	0.161	0.001	/	/
NAT.GAS$_{t-3}$	/	/	/	/	0.043	0.058	/	/	0.075	0.006	/	/
EL.ITY$_{t-4}$	/	/	/	/	/	/	/	/	/	/	0.208	0.001
NAT.GAS$_{t-4}$	/	/	/	/	/	/	/	/	/	/	0.040	0.022
EL.ITY$_{t-5}$	/	/	/	/	/	/	0.187	0.051	/	/	/	/
NAT.GAS$_{t-5}$	/	/	/	/	/	/	0.095	0.143	/	/	/	/
α_{t-1}	/	0.310	/	0.272	/	0.306	/	0.359	/	/	/	/
α_{t-2}	/	/	/	/	/	/	/	/	/	0.331	/	0.258

Pseudo$-R^2$	0.099	0.322	0.113	0.326	0.095	0.323	0.092	0.293	0.069	0.314	0.077	0.301

Notes: $\widehat{V^j_{1\%,t}}$ and $\widehat{CV^{sys|j}_{1\%,t}}$stand respectively for the estimated VaR of the j-th institution at the 1% and the $CoVaR$ of the system respect to the j-th institution at the 1% level. The alfa covariate represent the coefficient of the VaR in equation (3). The numbers in the first row indicate the models' enumeration.

The p-values for the financial state variables, shifted by one week, appear to be significant across the board, except for the slope variable, which doesn't appear particularly significant in all the models. This can be attributed to the nature of this predictor. As indicated by Rudebusch and Williams (2009) and Liu and Moench (2016), the slope of the yield curve is a stronger predictor of recessions in the medium to long time horizon, while in the short run its relevance is limited. This observation is consistent with our analysis, where the significance level of the slope variable slightly increases when the financial regressors are shifted by two periods. Unsurprisingly, volatility emerges as a determinant factor in explaining losses in the market, showing statistical significance in all presented models (Huang and Uryasev (2018)). Turning to the statistical results for the energy variables, they exhibit a noteworthy level of significance, particularly evident in the results of the first and second models. Notably, the energy covariates appear to be particularly significant in determining both the institutional indicator of stress $\widehat{V}^j_{1\%,t}$ and the systemic measure $\widehat{CV}^{sys|j}_{1\%,t}$ with the CoVar measure displaying an average p-value of approximately 0. This underscores the importance of these regressors in explaining adverse outcomes in the financial market. Even when extending the lag to three and five time periods, as seen in models (3) and (5), the explanatory power of the energy regressors remains substantial. This suggests that energy conditions have a structural impact on financial markets, where movements in natural gas and electricity exert a persistent influence.

To determine the appropriate lag order for the energy and state variables, a decision metric based on the lowest Pseudo$-R^2$ of Koenker and Machado (1999) was adopted, following a similar approach to Pönkä and Zheng (2019). Accordingly, based on this model selection method, model (2), which employs state and energy variables shifted back by one-time lag and two-time lags respectively, best captures the underlying reality. The subsequent table displays the average results of the regression coefficient magnitudes for model (2), as selected through the aforementioned model selection process. Alongside these results, variations of model (2) excluding the energy variables are also presented, evaluated at the 50% quantile. For these analyses, coefficients falling within the 1st and 99th quantiles in the distribution were excluded.

Table 1.7: Average Coefficients' magnitude

	interc.	EURO.ST.	SLOPE	VSTOXX	EUR.YL.	EL.ITY	NAT.GAS	alpha	Pseudo$-R^2$
$\widehat{VaR}^j_{1\%,t}$	-0.005	0.102	0.005	-0.023	-0.009	-0.356	-0.0049	/	11.3%
$\widehat{VaR}^j_{1\%,t}$ we	-0.004	0.173	0.003	-0.003	-0.0005	/	/	/	9.4%
$\widehat{VaR}^j_{50\%,t}$	0.001	0.332	0.001	-0.030	0.0001	0.058	0.002	/	27.2%
$\widehat{VaR}^j_{50\%,t}$ we	0.0012	0.032	0.003	-0.0037	0.0002	/	/	/	24.6%
$\widehat{CoVaR}^{sys\|j}_{1\%,t}$	-0.002	0.140	0.016	-0.010	-0.015	-1.046	-0.094	1.205	32.6%
$\widehat{CoVaR}^{sys\|j}_{1\%,t}$ we	-0.009	0.158	-0.006	-0.040	-0.008	/	/	1.317	18.6%

Notes: $\widehat{VaR}^j_{1\%,t}$, $\widehat{VaR}^j_{1\%,t}$ we, $\widehat{VaR}^j_{50\%,t}$ and $\widehat{VaR}^j_{50\%,t}$ we stand respectively for the estimated VaR of the $j-th$ institution at the 1% level, VaR at the 1% level without energy covariates, VaR at the 50% level and VaR at the 50% level without energy regressors. The last two rows report the $CoVaR$ of the system respect to the j-th institution at the 1% level, with and without the energy regressors. The alfa covariate represent the coefficient of the VaR in equation (3).

The initial findings, presented in **Table 1.6**, align with expectations. Volatility, interbank spread, and energy variables negatively impact the 1% VaR and $CoVaR$, consistent with the original paper by (Tobias and Brunnermeier (2016)). Conversely, the slope of yield curves has a positive effect on VaR due to the profitability enhancement resulting from rising interest rates for involved institutions (Adrian et al. (2010b),Aydemir and Ovenc (2016)). In terms of electricity and natural gas covariates, the coefficients' relative magnitudes indicate that changes in energy-related variables have a more pronounced impact than financial covariates, particularly with respect to electricity prices. Indeed, the average magnitude of the electricity regressor for the systemic measure ($CoVaR$) surpasses other coefficients significantly, underscoring the financial institutional market's vulnerability to electricity price shocks.

It's important to note that the baseline model without energy-related variables closely resembles the energy-augmented model in terms of the common components. However, the models (with and without energy variables) display notable differences in terms of fit to the data. The energy-augmented model, especially for $CoVaR$ estimation, appears better suited to accurately describe data variability (as indicated by $Pseudo-R^2$). This suggests that the reduced model, similar to the original one in terms of covariate selection, falls short in explaining financial market losses accurately when they stem from non-financial markets, such as turmoil in commodities markets.

Turning to the significance of the regressors, **Table 1.8** reports the average significance levels across banks from two perspectives. The first row presents the average significance levels of regressors (quantile regression p-values) for the top 10 banks in terms of total assets within the sample. The second row considers the bottom 10 banks per dimension.

Table 1.8: cross-sectional average p-value

	interc.	EURO.ST.	SLOPE	VSTOXX	EUR.YL.	EL.ITY	NAT.GAS
$\widehat{VaR}^{j}_{1\%,t}$ (%) top 10	0.0003	0.253	0.116	0.001	0.002	0.251	0.012
$\widehat{VaR}^{j}_{1\%,t}$ (%) last 10	0.059	0.192	0.102	0.002	0.007	0.178	0.006

Notes: $\widehat{VaR}^{j}_{1\%,t}$ (%) top 10, $\widehat{VaR}^{j}_{1\%,t}$ (%) last 10 stand respectively for the estimated VaR of the j-th institution at the 1% level of the top 10 institutions for total assets and the VaR at the same quantile level for the 10 last banks for total assets in the sample.

It's evident that smaller institutions are more vulnerable compared to larger ones, as the causal relationship between losses and energy market behavior is more robust for them. This market dynamic is further substantiated by the average coefficients obtained from the quantile regression analysis on the same two groups, as discussed in the previous table. Specifically, **Table 1.9** displays the average coefficients for the top 10% and bottom 10% of institutions based on their size.

Table 1.9: cross-sectional average coefficients

	interc.	EURO.ST.	SLOPE	VSTOXX	EUR.YL.	EL.ITY	NAT.GAS
$\widehat{VaR}^{j}_{1\%,t}$ (%) top 10	-0.0071156	0.011	0.006	-0.027	-0.092	-0.234	-0.003
$\widehat{VaR}^{j}_{1\%,t}$ (%) last 10	-0.010677	0.009	0.032	-0. 019	-0.010	-0.373	-0.008

Notes: $\widehat{VaR}^{j}_{1\%,t}$ (%) top 10, $\widehat{VaR}^{j}_{1\%,t}$ (%) last 10 stand respectively for the estimated VaR of the j-th institution at the 1% level of the top 10 institutions for total assets and the VaR at the same quantile level for the 10 last banks for total assets in the sample.

It is worth noting that the bottom 10% of banks in the sample appear to be more responsive to changes in energy prices, as well as to interbank spread, which represents a cost of financing. On the other hand, larger institutions exhibit lower sensitivity to energy-related price changes; this is not surprising, given the higher level of diversification achievable with larger portfolios. However, despite their reduced sensitivity to energy prices, larger institutions are more affected by the VSTOXX, as observed in well-established findings in the literature (see e.g. Laeven et al. (2016) and Varotto and Zhao (2018) for discussions on size as a factor influencing a bank's VaR).
Digging deeper into the analysis, we have also examined how the financial system responds to the combined circumstances of the recent events such as the Russia-Ukraine war, the ongoing effects of COVID-19, and the turmoil in energy markets. The predicted

outputs of the quantile regressions discussed thus far are presented in the following **Table 1.10**. The values are computed by calculating the mean and standard deviation over the sample period for each institution and then averaging these values across all institutions. Similarly, the 1% and 99% extremes of the value distribution have been excluded in this case as well.

Table 1.10: cross-sectional average coefficients

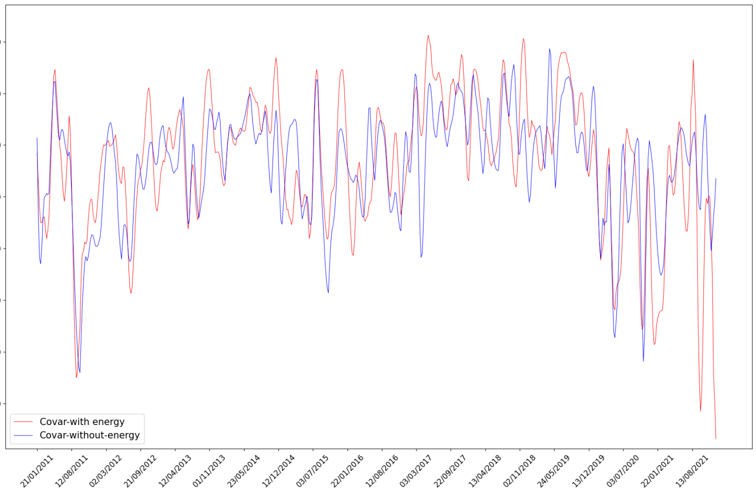
	Mean	SD
$X_{j,t}$ (%)	0.05	0.89
$\widehat{VaR}^{j}_{1\%,t}$ (%)	-0.99	0.60
$\widehat{VaR}^{j}_{1\%,t}$ (%) 2021	-1.35	0.47
$\Delta\widehat{CoVaR}^{j}_{1\%,t}$ (%)	-1.76	0.13
$\Delta\widehat{CoVaR}^{j}_{1\%,t}$ (%) 2021	-2.42	0.88

Notes: $\widehat{VaR}^{j}_{1\%,t}$ (%) 2021, $\Delta\widehat{CoVaR}^{j}_{1\%,t}$ (%) 2021 stand respectively for the estimated VaR of the j-th institution in 2021 and the CoVaR at the same quantile level for the 2021.

The obtained results reveal a distinct pattern. Over the past year, the financial markets have exhibited increased risk compared to the average risk observed during the considered sample period. This holds true both from the perspective of individual institutions, which have shown a higher estimated $\widehat{VaR}^{j}_{1\%,t}$ on average, and in terms of the average contribution to systemic risk from individual institutions. Specifically, the average systemic risk contribution has consistently risen in 2021 when compared to the average across the entire sample period (as indicated in the last two rows of **Table 9**). The variability of the results does not appear to follow a single direction, indeed for the systemic measure ($\Delta\widehat{CoVaR}^{j}_{1\%,t}$) apart from the previously discussed increase in systemic contribution, the variability across the sample is almost seven times greater than that observed throughout the entire sample period. Conversely, the estimations of $\widehat{VaR}^{j}_{1\%,t}$ exhibit greater stability when focusing solely on the 2021 period. This contrasted effect is attributed to the coefficient ($\widehat{\alpha}^{j}_{q}$) and the increase in $\widehat{VaR}^{j}_{1\%,t}$ during 2021, both of which have amplified the oscillations.
To further illustrate the results for ($\widehat{CoVaR}^{system}_{1\%,t}$), **Figure 1.2** presents the plot of $\widehat{CoVaR}^{system}_{1\%,t}$ with energy regressors (red line) and without energy regressors (blue line). This evaluation is based on the summation of $\widehat{CoVaR}^{system|j}_{1\%,t}$ for all $j-th$ institutions, across each sample period.
The plot reveals notable trends in $\widehat{CoVaR}^{system}_{1\%,t}$ obtained from the energy-augmented model, exhibiting prominent peaks starting from the latter part of 2019. Those between 2019 and 2021 are undeniably influenced by the financial state variable, evident from the considerable overlap of the two $CoVar$ series. Conversely, it is evident that the shocks experienced in 2021 are predominantly attributed to the disruptions in energy markets. This observation underscores how the financial system has been impacted by the swift

escalation of energy commodities prices during this period. Overall, the inclusion of energy regressors introduces greater variability to $\widehat{CoVaR}^{system}_{1\%,t}$ compared to the estimation conducted without energy covariates.

Figure 1.2: cross-sectional sum time varying CoVaR plot

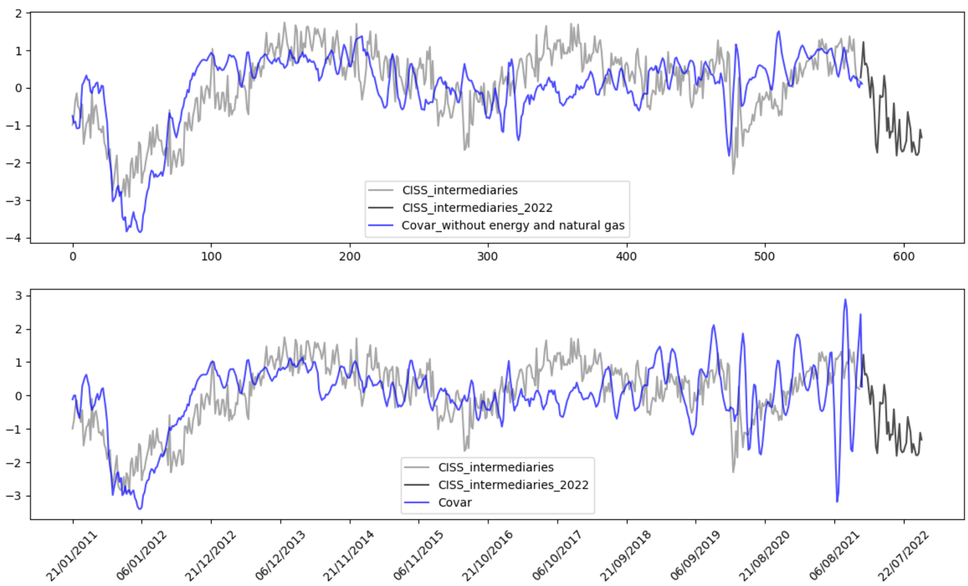


1.5 Robustness check

To illustrate our findings, we present a comparison in **Figure 1.3** between the performance of $\Delta CoVaR$ (with and without energy-related variables) and the ECB-originated composite indicator of systemic stress (CISS) for monetary and financial institutions, specifically focusing on the subindex that pertains to financial intermediaries' systemic stress. The CISS, developed by Holló et al. (2012), under the auspices of the ECB, has garnered recognition as a preeminent composite indicator of systemic stress in literature, due to its enhanced predictive capability during periods of financial instability (see Bekaert and Hoerova (2014)).The CISS amalgamates data from a specific set of micro stress indicators across various market segments, encompassing equity market, bond market, money market, foreign exchange, derivatives, bank sector, insurance sector, other financial institutions, payment systems area, settlement system infrastructures, and clearing systems.

This comparison is intended to highlight the influence of electricity and natural gas prices (and consequently, inflation) on the financial market, as the CISS series does not explicitly account for these effects. To ensure comparability between the two series, both have been normalized. Additionally, the historical CISS series has been multiplied by minus one, considering that, unlike the $CoVar$ measure, higher values of the CISS indicator represent peaks of systemic stress.

Figure 1.3: cross-sectional sum time varying CoVaR plot



Specifically, the $\Delta CoVaR$ without energy variables adequately captures the dynamics of the CISS, except for the period between 2016 and 2018. On the other hand, the $\Delta CoVaR$ with energy variables closely mirrors the CISS dynamics up until 2017. However, starting from 2017, the $\Delta CoVaR$ with energy variables exhibits significant volatility that leads to pronounced peaks in 2021, primarily driven by the surge in inflation resulting from energy-related factors. This period of extreme volatility appears to foreshadow the subsequent increase in stress observed in the CISS series from the latter part of 2021 onwards. **Figure 1.3** offers some evidence of a slight yet discernible improvement in the performance of $\Delta CoVaR$-energy compared to the specification without energy prices. Particularly noteworthy is the behavior during 2020, when energy prices experienced an unprecedented surge over the last two decades. In this case, the $\Delta CoVaR$-energy specification aligns more closely with the CISS than the non-energy specification. These deductions prompt a reconsideration of systemic stress indicators and measures that predominantly rely on financial databases. Neglecting fundamental factors such as inflation levels, as discussed by Jones et al. (2004) and Huybens and Smith (1999), might undermine the comprehensiveness of such indicators in capturing all aspects of potential stress within the financial system.

1.6 Concluding remarks

In this paper, we estimate the impact of energy-related variables on the financial systemic risk profile of major institutions in Europe. To achieve this, we have employed the $CoVaR$ methodology developed by Tobias and Brunnermeier (2016). This approach enables us to account for institution-level variables, as well as other financial and macroeconomic factors that might influence banks' stability and profitability. We leverage the strength of this methodology to explore the potential repercussions of surging energy prices on the financial institutions' market.

Our analysis is specifically focused on assessing the influence of electricity and natural gas prices on the stability of major private financial institutions headquartered in the Euro Area, as well as on the overall stability of the financial system. We investigate the period from 2011 to 2021. Our findings reveal that energy-related variables impact the VaR and $CoVaR$ to a degree comparable to the effects of other commonly studied variables, such as interbank spreads and market volatility. Additionally, our results highlight that smaller institutions are more vulnerable than larger, well-structured ones to shocks from energy markets (**Table 1.9**).

Digging deeper into the analysis and focusing on the results from 2021, it becomes evident that financial market losses became more substantial on average compared to the entire sample period (2011 to 2021). Furthermore, the increase in extreme losses during this period led to a rise in the average systemic risk contribution of individual institutions (**Table 1.9**). Moreover, our research demonstrates that the $\Delta CoVaR$ serves as a valuable measure of systemic stress conditions when compared to the CISS index created by the ECB. Notably, the $\Delta CoVaR$ developed in this study, using data up to 2021, anticipates the stress observed in the CISS index in 2022.

The policy implications of our analysis are straightforward. As indicated by our findings, financial stability is compromised by energy market conditions. Therefore, regulatory bodies should prioritize ensuring that financial institutions are as resilient as possible to energy price volatility. Supervisory institutions should implement effective strategies to monitor financial institutions' exposure to energy-related risks. Additionally, a revision of the electricity price formation mechanism is of paramount importance, including a reevaluation of the role of natural gas prices. The latter has been a primary driver of electricity price shocks in 2021 and beyond, thus significantly contributing to the financial vulnerabilities in the Eurozone.

In the future, further improvements to the model could include the utilization of higher frequency data and the involvement of a greater number of institutions. Additionally, a more comprehensive analysis is necessary, introducing inflation proxies to better discern the role of energy commodities from the impact of inflation on the banking sector. Moreover, it would be valuable to analyze these variables within a broader multivariate framework, potentially structuring a variable selection scheme to isolate the most influential effects. Furthermore, to ensure a more reliable analysis, this analysis should be conducted in a less manipulated environment, perhaps using stock market data directly. These aspects remain open for future research.

In conclusion, while there are many aspects that warrant further investigation, our study underscores that the causes of losses in the financial institutional sector are multifaceted. Relying solely on financial factors for explanation falls short. This realization should encourage the incorporation of additional auxiliary covariates, ranging from macroeconomic variables (such as unemployment rates or GDP growth) to commodities factors (such as changes in oil prices or agriculture commodity prices).

1.7 Appendix

Table 1.11: GLS regression results

	Total asset	Total equity
Bnp Paribas	$7.415e^{+05***}$ $(5.2e^{+04})$	$2.431e^{+05***}$ $(1.4e^{+03})$
	R^2 =0.949	R^2 =0.983
Societe Generale	$9.872e^{+05***}$ $(9.17e^{+04})$	$3.677e^{+05***}$ (2219.762)
	R^2 =0.913	R^2 =0.965
Deutsche bank AG	$1.368ee^{+05***}$ $(1.36e^{+04})$	$2.929e^{+05***}$ (2754.545)
	R^2 =0.901	R^2 =0.919
Credit Agricole SA	$1.339e^{+05***}$ $(1.77e^{+05})$	$3.416e^{+05***}$ $(1.02e^{+04})$
	R^2 =0.837	R^2 =0.531
Intesa Sanpaolo	$6.612e^{+06***}$ $(7.76e^{+04})$	$1.152e^{+05***}$ (5106.740)
	R^2 =0.866	R^2 =0.979
Banco Santander sa	$2.33e^{+06***}$ $(4.68e^{+05})$	$5.595e^{+05***}$ $(7.2e^{+04})$
	R^2 =0.683	R^2 =0.858
Caixabank s.a.	$2.245e^{+06***}$ $(4.36e^{+05})$	$2.754e^{+05***}$ $(4.4e^{+04})$
	R^2 =0.699	R^2 =0.797
Unicredit spa	$3.178e^{+05***}$ $(7.94e^{+04})$	$1.605e^{+05***}$ $(1.7e^{+04})$
	R^2 =0.577	R^2 =0.898
Banco bilbao vizcaya argentaria sa	1.6080^{**} (0.151)	$3.974e^{+04***}$ $(1.0e^{+04})$
	R^2 =0.910	R^2 =0.608
Commerzbank ag	$6.597e^{**}$ $(1.01e^{+05})$	$0.1380e^{+04***}$ (0.008)
	R^2 =0.759	R^2 =0.965
Banco de sabadell sa	$0.3049e^{*}$ (0.481)	$2.229e^{+04***}$ (6391.91)
	R^2 =0.40	R^2 =0.549
Bper banca spa	$2.771e^{04**}$ (2.148)	0.297^{*} (0.174)
	R^2 =0.689	R^2 =0.272
Bankinter sa	0.1956^{**} (0.070)	1037.1046 (3158.101)

	R^2 =0.385	R^2 =0.023
Erste group bank ag	$5.159e^{***}$ (8128.72)	0.0127^{***} (0.003)
	R^2 =0.781	R^2 =0.710
Raiffeisen bank international ag	$8.883e^{**}$ (5939.753)	6796.0754^{***} (1237.470)
	R^2 =0.953	R^2 =0.751
Mediobanca-banca di credito finanziario spa	$1.546e^{05**}$ ($3.1e^{+04}$)	9981.9887^{***} (1032.091)
	R^2 =0.713	R^2 =0.903
National bank of greece ag	32.0366 (32.190)	−6.3305 (14.373)
	R^2 =0.090	R^2 =0.012
Banco commercial portugues SA	32.0366 (32.190)	−6.3305 (14.373)
	R^2 =0.090	R^2 =0.012
Caisse regionale de credit agricole mutuel de paris et d'ile-de-france sc	$1.209e^{05**}$ (3.16^{04})	$1.215e^{05**}$ (2.18^{04})
	R^2 =0.554	R^2 =0.552
Credito emiliano spa	$1.209e^{05**}$ (3.16^{04})	$1.215e^{05**}$ (2.18^{04})
	R^2 =0.554	R^2 =0.552
Banca popolare di sondrio spa	0.1593^{**} (0.038)	3654.7883^{*} (3735.105)
	R^2 =0.602	R^2 =0.402
Aareal bank AG	$9.53e^{04**}$ (8558.342)	8022.0040^{**} (78.774)
	R^2 =0.723	R^2 =0.96
Banca mediolanum spa	7994.2910^{***} (825.681)	0.0102^{**} (0.0002)
	R^2 =0.694	R^2 =0.854
Caisse regionale de credit agricole mutuel du Languedoc sc	3609.7987^{***} (432.856)	1660.6621^{**} (337.572)
	R^2 =0.863	R^2 =0.708
Oberbank ag	2193.264^{***} (250.510)	970.0858^{**} (61.231)
	R^2 =0.873	R^2 =0.958
Caisse regionale de credit agricole mutuel atlantique vendee sc	5429.73^{***} (637.164)	7659.78^{**} (500.557)
	R^2 =0.867	R^2 =0.959
Caisse regionale de credit agricole mutuel sud rhone alpes sc	$1.077e^{05***}$ ($1.18e^{04}$)	382.696^{**} (32.992)
	R^2 =0.883	R^2 =0.924

Hellenic bank public company limited	Greece	Commercial bank
Banco di desio e della brianza SPA	$2670.615e^{***}$ (380.764)	502.416^{**} (49.067)
	R^2 =0.814	R^2 =0.913
Caisse regionale de credit agricole mutuel de la touraine et du poitou sc	0.0152^{***} (0.003)	211.65^{**} (16.7328)
	R^2 =0.644	R^2 =0.941
Van lanschot kempen n.v	9889.91^{***} (933.616)	8907.11^{**} (543.418)
	R^2 =0.910	R^2 =0.961
Banca Generali spa	0.0027^{***} (0.00002)	409.155^{**} (38.719)
	R^2 =0.839	R^2 =0.918
Caisse regionale de credit agricole mutuel toulouse 31 sc	2829.745^{***} (368.741)	40.0015^{**} (0.001)
	R^2 =0.840	R^2 =0.828
Caisse regionale de credit agricole mutuel loire haute-loire sc	0.0097^{***} (0.0001)	689.23^{**} (48.088)
	R^2 =0.891	R^2 =0.949
Bank fur tirol und vorarlberg ag	0.0028^{***} (0.001)	0.0003^{**} ($3.62e^{***}$)
	R^2 =0.719	R^2 =0.848
Credit agricole du morbihan	$2.04e^{04***}$ (2430.7)	366.43^{**} (32.071)
	R^2 =0.863	R^2 =0.929
Aktia bank plc	$1272.115e^{***}$ (48.494)	0.0003^{**} ($4.38e^{05**}$)
	R^2 =0.984	R^2 =0.929
Altarea s.a	6820.4331 (7119.14)	784.77^{**} (136.66)
	R^2 =0.084	R^2 =0.744
Alpha services and holdings societe anonyme	5295.663^{**} (703.55)	463.40^{***} (9.974)
	R^2 =0.835	R^2 =0.995
Alandsbanken abp	1953.2434 (1230.674)	-325.3020 (965.150)
	R^2 =0.052	R^2 =0.110
Attica bank spa	$1.134e^{04***}$ (1502.85)	110.78^{**} (30.690)
	R^2 =0.836	R^2 =0.566
Viel e cia sa	$1.623e^{05***}$ ($1.43e^{04}$)	-8.9293 (10.977)
	R^2 =0.921	R^2 =0.06

Banca profilo spa	1957.88* (832.859)	$1.257e^{04}$** (1635.93)
	R^2 =0.356	R^2 =0.841
Grenke ag	175.4814** (63.95)	54.5132* (33300)
	R^2 =0.43	R^2 =0.21
Conafi spa	$2.04e^{04}$** ($1.056e^{02}$)	1797.09*** (472.243)
	R^2 =0.737	R^2 =0.551

Notes: $\widehat{VaR^j_{1\%,t}}$ (%) 2021, $\Delta \widehat{CoVaR^j_{1\%,t}}$ (%) 2021 stand respectively for the estimated VaR of the j-th institution in 2021 and the CoVaR at the same quantile level for the 2021.

Table 1.12: MSE error of tension spline interpolation

	MSE	k	s
ELI.ITY	0.0198	2	0.05
EUR.YLD	0.0347	5	0.02

Notes: MSE stands for Mean squared error, meanwhile k represents the degree of the smoothing spline and s represents the smoothing factor used to choose the number of knots

Figure 1.4: Graph of interpolated series of electricity price

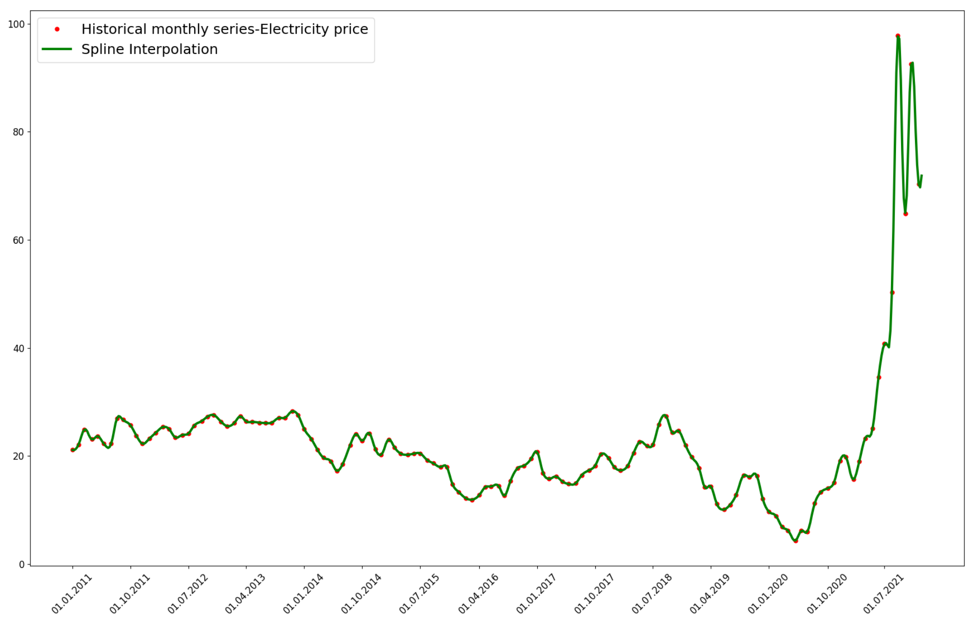
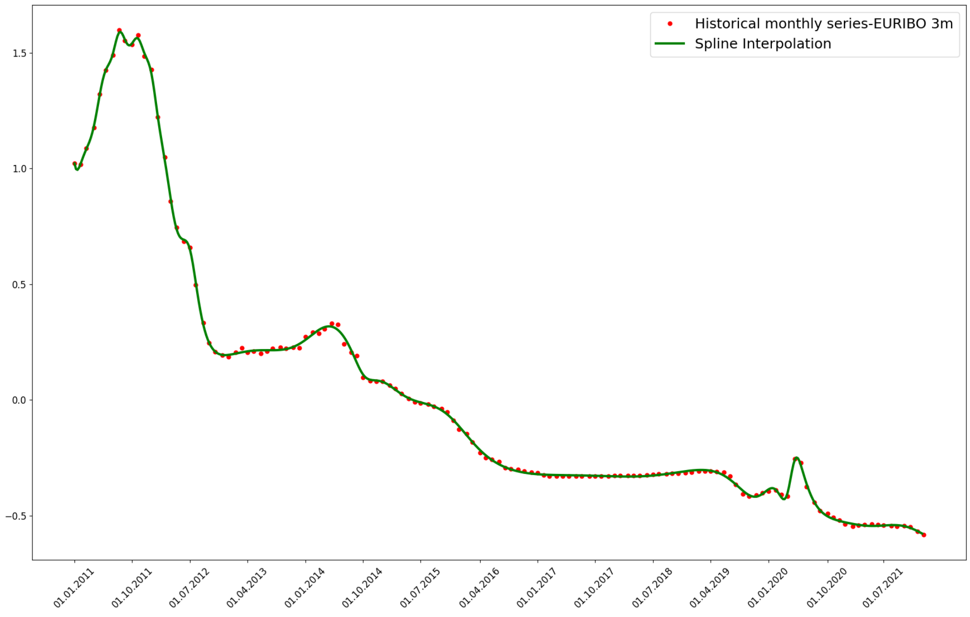


Figure 1.5: Graph of interpolated series of the Euribor at 3 months



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Chapter 2

"Let the merket judge": unveiling the banking systemic risk impactful macro-drivers

2.1 Introduction and motivation

Systemic risk in the banking sector has become a subject of interest since the outbreak of the 2008 crisis, attracting several scholars and regulators with the intention of unraveling the dynamics of these extreme phenomena. But the recent push of this research stream set down on a series of research milestones, which in retrospect have not been considered. One of the foundamental drivers investigated in the systemic risk context is the liquidity risk. Bhattacharya and Gale (1987) was the pioneer in raising the liquidity problem as the main determinant of systemic risk, focusing on maturity mismatch excess, giving the born to a profound doctrine on the theme that have documented new insights. Highlighting is the work of Brunnermeier (2009) which emphasizes the role of eocnomical downturns and the *'originate-to-distribute'* orientation of banks in affecting liquidity in interbank markets during the great crisis (2008), since the drop in value of assets could affect deterioration of collaterals values that worsen the wholesale funding, exacerbating credit crunch and triggering a liquidity spiral. Even, according to Diamond and Rajan (2005), a single bank default could induce a systemic perturbation due to a reduction of liquidity pool. [1]

But systemic events could also be exacerbated by the risk-taking behaviours of banks, that tends to take on excessive amount of risks in stable periods, creating procyclical perillous effects. Bernanke and Gertler (1989) and Holmstrom and Tirole (1997) are only two of the main exponents in this field.

The latter two represent only the mostly significant dynamics from which systemic crises could arise. However, other relevant systemic mechanisms have been extensively explored, such as the risk-sharing that emerges from contractual interlinks (Allen and Gale (2000)) highlighting the crucial role of network interconnection. This latter, increasing complexity, could foster opacity of some operations that can lead to distress (Haldane and May (2011)). Furthermore, in development are the theories on market freezes that

[1] This could be dependent on the loss of confidence of depositors (Diamond and Dybvig (1983)), leading to potential withdrawals, and the loss of confidence in the interbank market due to an increase in counterparty risk (Flannery (1996)).

could immobilize bank operativity (Acharya et al. (2011)).
These dynamics all originate and are activated by macrodrivers, whose effects could be amplified or smoothened by bank-specific characteristics that regulate institutions' susceptibility to common risk factors (this topic will be addressed in the next chapter). The strand of literature that study the origins is tireleslly making great strides. Tobias and Brunnermeier (2016) have tried to synthetize a measure of systemic risk that involves market determinants (as the stock and bond market conditions) with factors direct expressions of monetary policy (such as interbank interest rates and sovereign yield spread). Batten et al. (2014) investigates the volatility impact on SIFIs banks. Duca and Peltonen (2013) and Hollo et al. (2012) build upon a financial indicator stress mainly focusing on financial markets information. Bitar (2021) documented how a large foreign operativity of banks could expose banks to severe undervaluation of assets; at similar conclusions arrives Ranciere et al. (2010) who highlight that the high banks' currency mismatch [2] could both trigger and amplify systemic downturns. These studies attempting to address this gap by investigating real macro determinants often narrow their focus to individual variables or a limited set of these, without considering the multidimensionality that underpins this phenomenon.
Therefore, this research aims to contribute to the existing literature providing a comprehensive analysis that encompasses various sources of systemic risk, exploiting the complete set of already documented mechanism (and discovering new insights). In doing so, drawing support from numerous dynamic investigations, two goals can be achieved: 1) Disentangling the actual impactful drivers and 2) Understanding and disentagling the co-dynamics of these drivers and how their interactions act on the banking system. This effort would contribute to support regulation by highlighting the scale of priorities on which to target regulatory solutions, and laying the groundwork for a more comprehensive risk measure that encompasses the multitude of sources of systemic risk.
In doing so, It's proposed a new improvement of the framework presented in Tobias and Brunnermeier (2016) , allowing to discern effective impactful determinants in a comprehensive data-driven manner. This is achieved by leveraging the power of a specific LASSO (least absolute shrinkage and selection operator) adjustment of the original quantile regression scheme proposed by the authors
The secondary objective of this paper is perfectly connected to the latter methodological choice. Indeed, a robustness check of this new approach with the widely used $CoVaR$ measure will be performed, highlighting its limitations, and emphasizing the advantages of the proposed analysis in better capturing systemic drivers and calculating risk contributions of European banks.
The remainder of the paper is structured as follows: Section 2.2 describes the developed methodology. Section 2.3 details the construction of the dataset, with a specific focus on the rationale behind the inclusion of variables. Section 2.4 presents and discusses the results. Section 2.5 offers a robustness check, considering the original $CoVaR$ algorithm. Finally, Section 2.6 is dedicated to conclusions and comments.

2.2 Literary review

The literature that investigates the determinants of systemic risk is fragmented, with most of it focused on a single-factor approach, as anticipated in the previous paragraph and

[2] banks' foreign currency denominated unhedged liabilities divided by total bank assets

detailed in the next **subsection 2.4.2**. This section is dedicated to provide an overview of the current strands addressing the disentanglement of factors in banking systemic risk from a different perspective. A comprehensive literary review for each individual factor will be conducted in the following pages; therefore, literature investigating singular factors in systemic risk will not be included in this section, as a more in-depth analysis will be carried out in the subsequent pages.

At this state of the art, two differentiated approaches can be distinguished: one that investigates the interconnections among banks, isolating only the decisive ones, and the other that, contrarily, investigates the common factors. The works belonging to the first category include Hautsch et al. (2015), Xu et al. (2019), Billio et al. (2012), Barigozzi and Brownlees (2019) and Demirer et al. (2018). All of them consider only the loss spillovers among banks as risk factors, attempting to isolate the relevant connection topology. Therefore, these works mainly focus on internal banking sector factors, instead of investigating external agents. The first two papers try to include state-contingent factors along with interconnection elements; however, in all cases, they yield insignificant results and the systemic factors are discarded by the selection models. This behavior can be easily attributed to the large co-movement of financial firms and the restricted variability of some state variables [3].

On the other hand, there is a dearth of studies focusing on industry-external factors, hindering the disentanglement of the main external influences. The frequently mentioned work by Tobias and Brunnermeier (2016), along with studies adopting similar approaches, stands out as the first to demonstrate the derivation of a systemic risk measure based on macro-factors, utilizing a qualitative selection of determinants. Petrella et al. (2019) extends the study by including currency exchange rates, while Hollo et al. (2012) attempts to aggregate various market indicators to produce a synthetic measure of systemic stress. However, the work of Giglio et al. (2016) is closest to the present research effort, as the authors propose dimension reduction estimators among different systemic risk measures in the literature, demonstrating their validity in predicting future shocks. However, to the best of our knowledge, no studies have proposed a clear formalization of any selection process for macro drivers. This work aims to address this gap in the literature, providing a replicable approach for isolating the effective drivers.

[3] Generally, examinations of interconnections are based on stock price variations, which are normally more volatile than macroeconomic/state variables, such as interest rate levels.

2.3 Methodology explanation

The methodology employed for conducting the proposed investigation is founded on an enhanced LASSO modification of the $CoVaR$ algorithm developed by Tobias and Brunnermeier (2016). The latter aims to assess the individual institution's contribution to the overall systemic financial risk using conditional quantile regression [4] (Koenker and Bassett Jr, 1978).

For each specific institution i it's firstly estimated the $VaR^i_{t,q}$ of the market value of equity returns X^i_t at the predetermined confidence levele $q \in (0, 1)$, tipically defined following this equality:

$$Pr(X^i_t \leq VaR^i_{t,q}) = q \tag{2.1}$$

Where Pr denotes the probability. Next, the firm's contribution to overall systemic risk is evaluated using $CoVaR$, which represents the VaR of the financial system returns conditioned on the distress situation of each single institution (so, in case of losses equal to the VaR of the returns of that insitution at that time) :

$$Pr(X^{system}_t \leq CoVaR^{system}_{t,q} | X^i_t = VaR^i_{t,q}) = q \tag{2.2}$$

These estimations are conducted using a dynamic factor model (Stock and Watson, 2002), an approach that seeks to justify or explain time variation of determined quantities with common covariates (also called state variables):

$$X^i_t = \beta^i_0 + Z_{t-m}\beta^i + \varepsilon^i_t \tag{2.3}$$

$$X^{system}_t = \beta^{system|i}_0 + Z_{t-m}\beta^{system|i} + \gamma^{system|i} X^i_t + \varepsilon^{system|i}_t \tag{2.4}$$

Where Z_{t-m} denotes the m-lagged state variables vector. In literature, the common components vector is lagged by one period, as suggested in Chao (2015), but in this work a lag selection procedure has been employed (**subsection 2.3.1**), thus no assumptions have been imposed.

These linear equation are estimated by the means of conditional quantile regression:

$$\widehat{VaR^i_{t,q}} = \widehat{\beta^i_0} + Z_{t-m}\widehat{\beta^i} \tag{2.5}$$

$$\widehat{CoVaR^{system|i}_{t,q}} = \widehat{\beta^{system|i}_0} + \widehat{\gamma^{system|i}} VaR^i_{t,q} + Z_{t-m}\widehat{\beta^{system|i}} \tag{2.6}$$

where the coefficient are standardly evaluated minimizing the classical quantile loss function (Koenker, 2005):

$$\widehat{\beta^i_q} = \arg\min_{\beta^i_q} \frac{1}{T} \sum_{t=1}^{T} \rho_q(X^i_t - Y_t\beta^i_q) \tag{2.7}$$

Where ρ_q is the check function, $\widehat{\beta^i_q}$ is the vector of estimated coefficients and:

$$\begin{cases} \begin{cases} X^i_t = X^i_t; \\ Y_t\beta^i_q = \beta^j_0 + Z_{t-m}\beta^j \end{cases} & \text{if } VaR \\ \\ \begin{cases} X^i_t = X^{system}_t \\ Y_t\beta^i_q = \beta^{system|i}_0 + Z_{t-m}\beta^{system|i} + \gamma^{system|i} X^i_t \end{cases} & \text{if } CoVaR \end{cases} \tag{2.8}$$

[4] A model that incorporates the conditioning on specific values (or intervals of values) of the predictors into the quantile linear equation.

To address the main objective of the paper, It's proposed an enhancement of the analysis by incorporating one of the most effective shrinking selection schemes in the quantile regression framework, specifically the one proposed by Belloni and Chernozhukov (2011). This method has been widely employed for handling large datasets and has shown remarkable results, even with financial panel data, as documented by Hautsch et al. (2015) and Xu et al. (2019). However, to the best of our knowledge, this is the first instance of its application in model selection within dynamic factor models area, attaining the $CoVaR$ framework.

The dimensional reduction algorithm proposed by the authors assumes that the true data-generating model is highly sparse. Given s the number of nonnull coefficients, the following statement holds:

$$s \leq \frac{n}{\log(n \vee k)} \tag{2.9}$$

where k is the number of covariates and n the number of time observations. It's evident that this assumption aligns well with cases involving panel data with numerous regressors, accounting also for the situations where $n < k$.

The lasso scheme proposed is based on on a two-step approach. In the first step, a specific lasso add-on is considered, utilizing a weighted penalty factor that modifies the original minimization problem as follows:

$$\widehat{\beta}^i_{q,pen} = \arg\min_{\beta^i_q} \frac{1}{T} \sum_{t=1}^{T} \rho_q(X^i_t - Y_t \beta^i_q) + \lambda \frac{\sqrt{q(1-q)}}{T} \sum_{j=1}^{k} \widehat{\sigma}_j |\beta^i_{j,q}| \tag{2.10}$$

Where λ is a tuning parameter that regulates the magnitude of the penalty, σ_j is the estimator of standard deviation of i-th variable and the subsrict 'pen' stands for 'penalized', indicating the estimator obtained throught the lasso shrinkage proposed.

After completing that step, the quantile regression equation is then evaluated, involving only the restricted set of non-null coefficients from the aforementioned lasso equation.

$$\widehat{\beta}^i_q = \arg \min_{\beta^i_{q,\Omega_{pen}}} \frac{1}{T} \sum_{t=1}^{T} \rho_q(X^i_t - Y_t \beta^i_q) \tag{2.11}$$

where:

$$\Omega_{pen} = \{|\widehat{\beta}^i_{j,q,pen}| > 0, \forall j = 1...k\} \tag{2.12}$$

This two step allows to investigates also the significance of regressors involving a bootstrap procedure, as proposed by He and Hu (2002). For what concern the data, they have been standardized to reconduct the variance to the unit, in order to meet the assumptions of one of the two design cases (design 1) developed by the authors (pag. 89 of the original paper). This transformation also prevents a feature with significantly higher variance (determined by the variable's scale) from dominating the objective function, which could otherwise hinder the estimator's ability to correctly learn from other features as expected.

One of the primary drawbacks of model selection through lasso regularization involves the choice of the tuning parameter, which is mostly determined via cross cross-validation algorithms. However, according to Homrighausen and McDonald (2014), who show the first demonstration of risk consistency of tuning hyperparameters in LASSO using these approaches, the results could be highly dependent by this step. The significant contribution of Belloni and Chernozhukov (2011) lies in addressing this concern by introducing a procedure for tuning the hyperparameter in a completely data-driven manner, thereby avoiding the bias introduced by calibration approaches. Indeed, the latter is defined on the following variable:

$$\Lambda = \sup_{q \in U} \max_{1 \leq j \leq k} \sum_{t=1}^{T} \left| \frac{y_{j,t}(q - 1_{q_t \leq q})}{\widehat{\sigma}_j \sqrt{q(1-q)}} \right| \tag{2.13}$$

Where $y_{j,t}$ represents the $j-th$ variable at a time t and $\{q_t, t = 1...T\}$ are i.i.d uniform $(0, 1)$ random variables, indipendent from the regressors.
Then, the hyperparameter is set considering the subsequent:

$$\lambda = c \cdot Q(\Lambda, 1 - a|Y) \tag{2.14}$$

Where $c > 1$ is a constant, generally fixed to 2, and $Q(., 1 - a|.)$ represents the 1-α quantile of Λ conditioned to the dataset of covariates. The quantile suggested also by Bickel et al. (2009) is the 90%, so with a α of 10%. In order to estimate λ tha authors suggest proceeding via simulation. This involves generating Λ multiple times and then calculating the $1 - \alpha$ quantile of the simulations.
Under the setting proposed, it has been demonstrated the oracle property (Zou, 2006) of the lasso method , that in formal terms implies:

$$Pr\left(\sup_{q \in U} \parallel \widehat{\beta}_{q,pen} - \beta_q \parallel \geq \epsilon_\varepsilon \right) \leq \frac{\varepsilon}{\exp^{\psi \log(n \vee k)} k_s} \sqrt{\frac{s \log n \vee k}{n}} \tag{2.15}$$

where sup $\parallel . \parallel$ denotes the supremum norm, s is the bound of the number of non-zero components of the true model, ψ is a constant and $k_s > 0$ derived from the restricted eigenvalue condition, expressed in Candes and Tao (2007). Therefore, under boundness of s, it's straightforward implied:

$$Pr\left(\sup_{q \in U} \parallel \widehat{\beta}_{q,pen} - \beta_q \parallel \geq \epsilon_\varepsilon \right) \longrightarrow_{n \to \infty} 0 \tag{2.16}$$

Thus, the estimates of the lasso regression proposed are stochastically bounded by the number s of nonnull components contained in the true model. Moreover, equally highlighting is the results on the consistency of the selector, for which it's true the following results:

$$Pr\left(\sup_{q \in U} \parallel \widehat{\beta}_{q,pen} \parallel_0 \geq \epsilon_\varepsilon \right) \leq \varepsilon s \tag{2.17}$$

Thanks to the latter, it's clear how the probability of wrongly including null coefficient is quite negligible. These results demonstrates how well performing is the algorithm described that meets the desidered properties for a right model selection scheme.

2.3.1 Lag selection

As anticipated in the previous paragraph, the lag order of state variables is not pre-determined, but it's selected using the the Adalasso procedure developed by Wu and Liu (2009), modified with the lag penalty proposed by Konzen and Ziegelmann (2016). Formally, the lag selection is based on the following equation:

$$\widehat{\beta}^{i}_{q,lag} = \arg\min_{\beta^i_q} \frac{1}{T}\sum_{t=1}^{T} \rho_q(X^i_t - Y_{t,lag}\beta^i_{q,lag}) + \lambda \sum_{j=1}^{k} w_j|\beta^i_{j,q,lag}| \tag{2.18}$$

where $Y_{t,lag}$ is the set of covariates, augmented by the lagged series of each one. $w_j = (|\widehat{\beta}^{i,ridge}_{j,q}|e^{-gl})^{-1}$ represents the temporal weights applied to each regressors, where l and g are the lag order and the lag penalty respectively, meanwhile $\widehat{\beta}^{i,ridge}_{j,q}$ represent the pre-estimated coeffficient of the quantile ridge regression:

$$\widehat{\beta}^{i,ridge}_{q} = \arg\min_{\beta^i_q} \frac{1}{T}\sum_{t=1}^{T} \rho_q(X^i_t - Y_{t,lag}\beta^i_{q,lag}) + \lambda \sum_{j=1}^{k} (\beta^i_{j,q,lag})^2 \tag{2.19}$$

Contrarely to what was done in the paper of Konzen and Ziegelmann (2016), where all covariates with their lagged version were only penalized, in this paper It's performed a lag exclusion. This means that for each variable,only the lagged version exhibiting the greatest average magnitude (across all banks) of its coefficient is chosen. The selected unpenalized covariates will form the set of covariates in the algorithm described in the previous paragraph.
Furthermore, to optimize the penalizing parameter lag, g, a comparison of mean square errors (MSE) was conducted to identify the optimal parameter level corresponding to the lowest MSE. Specifically, a k-fold cross-validation was performed solely on the market returns to determine the optimal g parameter, assumed to be the same across all market components.

2.4 Data

This section is entirely dedicated to describe the dataset composition, with particular dedication to the set of state covariates involved in both the VaR and $CoVaR$ analysis.

2.4.1 Sample selection and dependent variable formation

The analysis considered a time sample period that spans from January 1, 2016, to December 31, 2022, covering the *pre-crisis period* (from 2016 to 2020) and subsequently capturing the effect of COVID-19 outbreak and the onset of the Russian-Ukraine war (from 2020 to the end of 2022).
As for the bank sample, accounting and stock data were collected for 76 listed banks spread across the entire Europe, including the UK and Switzerland. The list of the banks considered is provided in the following table:

(*Insert Table 2.12 here*)

As you may observe, the sample is highly representative considering that the cumulative total assets of the sample at the end of 2022 account for nearly 65% of the entire banking system in Europe, including the UK and Switzerland. Furthermore, nearly all countries are represented. Notably, the most advanced banking sectors, those of France, UK, Germany, italy, Spain and Switzerland constitute more than the 50% of the sample.
Moving on, the dependent variable chosen, the market value of equity X_t^i, is the weekly stock return (contrarely to what was done in chapter 1), preferring not introducing complexity deriving from variable transformations. Moreover, the analysis assumes Efficient market hypothesis (EMH) (Fama (1970)) which theorizes that the stock prices discount all the public and private information, therefore also the balance sheet resultants. To construct the system equity return, it has summed the weighted stock returns of the banks in the sample, where the weights have been estimated dividing the weekly temporal disaggregation of quarterly total assets of each banks on the sum of the disaggregations for all the banks.

2.4.2 State covariates

As previously mentioned, the purpose of this paper is to identify the main drivers that significantly influence the systemic risk profile of financial institutions. To achieve this objective, the set of regressors has been expanded compared to the original set reported in Tobias and Brunnermeier (2016), which considers the volatility level, the stock market performance, the sole of the yield curve, the housing stock market performance, the credit spread (expressed by the differential in yield of high rating bonds and the investment grade bonds) and the liquidity spread (exspressed by the 3-months spread between interbank rate and a bond risk-free rate).
The implementation has been carried out through five main directives, aligning with the factors that are considered in the literature impactful determinants regarding the financial sector. For each of these areas, representative indicators have been collected and will

be employed as state covariates in the analysis described above.
Before delving into the discussion of each of the predictors in the field, one of the innovative choices of this paper is now anticipated. The cross-continental effects between Europe, including UK and Switzerland, and US banking market have been taken into account. Indeed, building upon findings from Cerutti et al. (2014) and Rey (2015), it is established that the VIX (the volatility of US equity market) significantly influences the reduction of cross-border bank flows between these two continents. Similar results have been reported by Li and Zinna (2014) who highlight a non-accidental co-behaviour between the credit risks of UK and US banks, implying how the two sytems are higly interconnetted and mutually influential. Choudhry and Jayasekera (2014) proof the influence of US banking stock market (along with UK and Germany) on the performance of south-mediterranean banking sectors, unvealing how in crisis periods the contagion rise significantly. The two systems are integrated also for currency reasons. Pursuant the investigation of Societe Generale of 2012 [5], European institutions are at the forefront of issuing Yankee bonds [6] worldwide. Indeed, as pointed out by Rixtel et al. (2015) the amount of US dollar-denominated bonds issued (especially the long-term ones) by the European banks steadily increased in the first decade of 21st century, with sporadic declines in conjunction with the global crisis of 2008 and the euro area sovereign debt crisis of 2011. This trend can be attribuited to the high liquidity of dollar-denominated derivatives market, increasing the likelihood of banks obtaining hedging positions while also benefiting from the covered interest parity in exchange markets.
Given the aforementioned reasons, it is justified to consider the conditions of the US money, currency exchange, and equity markets. The latter, along with all the covariates used, will be thoroughly described and justified in the subsequent parts of this paragraph.

Monetary policy

The first area of expansion whitin the covariates set gathers all the pertinent monetary policy leading indicators. To begin, Jung (2023) has demonstrated how the moovements in OIS rate [7] (Overnight-index-swap rate) capture monetary policy actions by reflecting the investor reactions to monetary surprises and changes in central banks decisions. To this end Altavilla et al. (2019), investigating the OIS curve response to ECB comunications, have found how changes in short horizon swap rates are largely influenced by release window contents in ECB conference, suggesting the market swiftly adjusts these metrics in response to preliminary monetary information. Moreover, Lloyd (2021) underscore the importance of the OIS rate level in interpreting future market expectations of short-term interest rates. This interpretation aligns with the conclusions of Michaud and Upper (2008) who emphasize the predictive role of OIS along with its informative nature regarding the average credit risk premium in the market. Another pivotal barometer of Europe's money market stability is the EURIBOR (Euro Inter-Bank Offered Rate) [8], which drives the fund raising and the liquidity within the Euro interbank market [9]. This

[5] https://www.reuters.com/article/europeanbanks-dollars-idUKL1N0I81M720131018

[6] U.S. dollar denominated debt securities that are issued by non-US players.

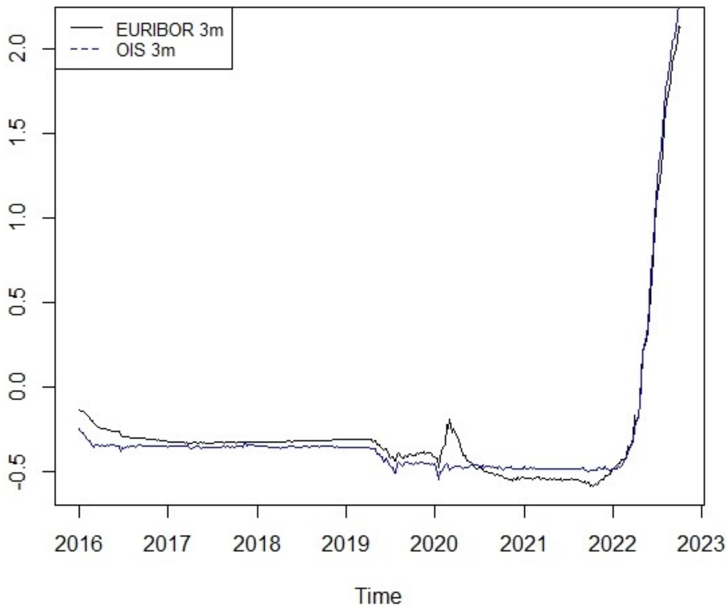
[7] It's the rate of the fixed leg of a an interest rate swap contract, where the floating leg is calculated on the EONIA rate (later explained).

[8] The benchmark rate of interest applied to lending operations among banks.

[9] The choice of EURIBOR over the LIBOR (London Interbank Offered Rate) is motivated by several factors. Firstly, EURIBOR is calculated based on a broader range of insitutions, which mitigates extreme values and reduces manipulability (Gyntelberg and Wooldridge (2008), Vaughan and Finch (2017)).

is a monetary key-driver, it influences the profitability of financial institutions,thereby conditioning the risks taken by banks and their susceptibility to systemic crises (Bikker and Vervliet, 2018).
While the last two indicators described offer slightly distinct insights, they exhibit a high degree of cointegration, as depicted in the following figure:

Figure 2.1: Euribor 3m vs OIS 3m



To mitigate the estimation bias which could arise from the strong temporal relationship between these two variables (see Pedroni (2019)), it has been decided to incorporate in the analysis the OIS-EURIBOR spread, considering the 3 months tenor[10]. The EURIBOR-OIS spread, particularly at this maturity, has been extensively studied in the literature (e.g. Nobili (2009),Schwarz (2019),Taylor and Williams (2009),Taboga (2014)). Its significance extends beyond its recognized role as a synthetic measure of both credit and liquidity risk within the interbank market [11], encompassing market risk-neutral expectations. For the cross border effect, the US TED spread has been used. This is the mark-up between the 3-month Libor rate and the 3-month T-bill. This variable is used as a measure for the level of financial turmoil in the interbank market. Brunnermeier and Pedersen (2009) raise the validity of the TED spread for gauging the severity of the liquidity shortage in interbank sector, moreover Melvin and Taylor (2009) assert that

Additionally, unlike LIBOR, EURIBOR is quoted exclusively in Euros, limiting the presence of different currencies in the analysis. Thi currency uniformity allows for a clearer separation of currency effects from money market fluctuations. Thirdly, as also documented by Filipović and Trolle (2013), EURIBOR holds recognized benchmark status within the Eurozone interbank market, also compared to the EUR LIBOR.

[10]This particular maturity is widely recognized as the benchmark for non-overnight interest rate contracts (e.g. Filipović and Trolle (2013),Cheng et al. (2010)) making it a suitable proxy for measuring strains in the interbank market Santis and Stein (2016). This variable aligns with quarterly balance sheet logic, potentially accounting for accounts' window-dressing or mortgage rate adjustments.

[11]The first one is related to the default of interbank borrowers, meanwhile the second is related to the high illiquidity if interbank deposits.

the contrast between unsecured interbank loans rate (as the Libor) and the risk-free rate (provided by the T-bill yield) provides a measure also of credit risk in interbank market. Another significant money market indicator to consider is the slope of the yield curve, which was originally proposed as part of the covariate set by Tobias and Brunnermeier (2016). The slope is recognized as a business cycle predictor, particularly for impending recessions (Liu and Moench (2016),Croushore and Marsten (2016)). In the context of banks stability, Alessandri and Nelson (2015),Albertazzi and Marchetti (2010) and Adrian and Shin (2008) highlight its substantial impact. Flattening of the yield curve has a notable repercussion on bank margins, compressing fixed income profits and increasing the likelihood of losses. It also tightens credit conditions, potentially precipitating recession or dampening expansion. Conversely, a steeper yield curve, while beneficial for bank profitability by elevating long-term yields, prompts substantial investments in illiquid assets. This exposes the financial system to liquidity shortages in the event of abrupt interest rate changes (Bhattacharya and Fulghieri, 1994). Therefore in both the cases, one procyclical (the flatter one) and the other countercycical (the steeper one), the slope of the yield curve could supplies outstanding insights for assessing the systemic risk level in the financial market. Both cases, procyclical (flatter yield curve) and countercyclical (steeper yield curve), suggest that the slope of the yield curve offers valuable insights for assessing systemic risk in the financial market. From the measurement standpoint, instead of representing the slope as the difference between the 10-year and 3-month bond yields, as commonly done in the literature, I have chosen to implement the analysis using the β_1 factor of the Nelson and Siegel (1987) model. This factor is standardly employed by the ECB to daily fit the yield curve in the Eurozone[12], and punctually provided by the FED for the US treasury bond yield curve [13]. Diebold and Li (2006) discuss how this factor serves as good proxy for the slope in comparison to the 10year-3month spread, which has been found to be barely representative of monetary transmission and a misleading predictor in some instances (Howell (2018)).
The analysis includes the overnight rates for both the Europe and U.S. markets: the EONIA rate (Euro OverNight Index Average) and the FFER (Federal fund effective rate), respectively. These rates reflect the interest rates at which financial institutions conduct overnight operations, mainly REPO ones (repurchase agreement operations), and mirror the economy's interest rate level. These are marginally influenced by central bank official interest rates via corridor systems, making them a direct expression of central authority decisions. As higlighted by Ampudia and Van den Heuvel (2018) the interest rate levels has severely affected credit institution margins in the stagflation period between 2008-2018, due to their impact on fixed-income and derivatives instruments and overall economic conditions. This phenomenon pushed institutions to seek higher-yield investments (*reach-for-yield*) (Bubeck et al., 2020) and to increase leverage, thus increasing the risk-taking (particularly for less capitalized banks). This increased riskiness, triggered by the market's demand for higher returns and influenced by herding behavior, has been identified as a response to the market price of risk, as noted by (Kabundi and De Simone, 2020). Unfortunately, as of 2021, the European Central Bank (ECB) has introduced a new overnight benchmark known as STR (Euro Short-Term Rate) to replace

[12]It's important to clarify that the yield to maturity curve, modeled with the Nelson-Siegel-Svensson model differs from the interest rate curve, although they often overlap in practice

[13]https://www.federalreserve.gov/data/nominal-yield-curve.htm

the EONIA[14]. Consequently, this transition has led to a disruption in the data series. To address this challenge, the STR series has been adjusted to match the scale of the previous EONIA data.

The last (but not the least) monteary policy indicator is the EURIRS rate with 10 year maturity (Euro interest rate swap)[15]. The EURIRS rate serves as the reference rate for fixed-rate mortgages in Europe [16], and therefore is the pivotal rate for long-run interest rate operations (both lending and derivatives contracts). Following Samuelson (1945) and recently Borio et al. (2017) an increase in long-term interest rates (more often connected also to a steepening of the yield curve) produce higher interest margin due to the *'retail deposits endownement effect'* in the liability side always augmented by the positive effect induced by the existing floating rate lending stock. This have a stabilizing impact for intermediaries Saksonova (2014). On the other hand, as demonstrated by Bakoush et al. (2020), tensions on OTC (Over the Counter markets) interest rates derivatives, due to abrupt change of interest rates levels, could trigger a systemic liquidity shortage in the interbank market. This scenario, as documented by Nier et al. (2007), might amplify the likelihood of a systemic breakdown. Another relevant reason to include long-horizon IRS is directly related to the CoCo (Contingent Convertible) bond[17] market. This type of instrument has became popular among large and significant banks (Fajardo and Mendes (2020)) and is a prominent public bail-in option (dos Santos Mendes et al. (2022)). The main characteristics is that are practically perpetual and therefore required long-term hedging swap contracts. Thus a surge in the fixed leg of interest rate swaps might signal an increse of CoCo bond returns, implying a rise in the stability risk of the financial intermediaries. The choice of the 10-year tenor is also linked to this reason, as the ECB (long-horizon interest rate) sets the long-term interest rate for longstanding contracts at a fixed 10-year maturity

Macroeconomics indicators

The next spillover channel considers macroeconomic foundamentals. Historically, these factors have not been included in high frequency analysis due to the inavailability of statioary time series. To address this issue, this study proposes to include two high-frequency market-based proxies for GDP (gross domestic product) and HICP (Harmonised Index of Consumer Prices). Specifically, for GDP, the European and US GDP-trackers have been used[18]. The empirical literature has shown significant interest in this theme, especially regarding the size of capital buffers and their relationship with business cycles. Jokipii and Milne (2008) found evidence of counter-cyclicality in capital buffer consistency, especially for large banks. Also Ayuso et al. (2004) arrived at similar conclusion, stimating that

[14]For further references see:https://www.ecb.europa.eu/stats/financial_markets_and_interest_rates/euro_short-term_rate/html/index.en.html

[15]The rate considered is the the one payed by the fixed leg of the interest rate swap contract. This latter rate, according to the ECB (https://www.ecb.europa.eu/pub/financial-stability/fsr/html/ecb.fsr202211~6383d08c21.en.html) is the most actively traded derivative in the Euro area.

[16]The reason for including this variable lies in its ability to offer long-term insights into the future cost of borrowing money, in contrast to the EURIBOR rate that is the interbank benchmark rate for short-horizon operations.

[17]It's a hybrid loss-absorption debt instrument issued by credit institutes which embed the option, exercisable by the bank, to convert debt into equity, typically in order to deal with under-capitalisation periods.

[18]The GDP tracker is developed and published by the OECD (Organisation for Economic Co-operation and Development https://www.oecd.org/economy/weekly-tracker-of-gdp-growth/).

the capital buffers of Spanish banks could be reduced by up to 17% with a 1% increase in regional GDP. Additionally, the German banking sector has demonstrated how capital buffers behave counter-cyclically, with low-capitalized banks reducing capital buffers for various reasons both in booms and busts [19]. In contrast, well-capitalized banks exhibit a long-term perspective by maintaining capital buffers and risk-weighted assets during economic booms. However, during downturns, they expand capital buffers by raising capital and lowering risk-weighted assets. This shifting of buffers has been demonstrated to contribute to instability in the financial system, as it could undermine the effective loss-absorbing capacity of institutions, as suggested by Bui et al. (2017), thus potentially triggering a financial (and economic) systemic crisis (Arnold et al., 2012).
For the second macroeconomic proxy, the study employs the inflation-linked swap rate [20]. Furthermore, for this proxy, spatial averages of the 1-year and 5-year maturity swap rates are utilized. This choice aims to capture short- and long-term expectations of future inflation levels. Indeed, following Miccoli and Neri (2019) the fixed leg rate reflects investors' expected rate of inflation over the contract's time horizon. Several papers have investigated the inflation channel's impact on bank stability. Mishkin (1999) and Bernanke and Gertler (1995) demonstrate how sharp increases in inflation level are dominant factors in deteriorating institutions stability, often due to augmented *adverse selection* [21] tendencies or the deterioration of firms' balance sheets, both of which impact credit risk. Moreover, de Mendonça and da Silva (2018) found a significant impact of inflation levels on systemic risk contribution of the Brazilian banking market. Similarly, García and Rambaud (2023) show evidence of inflation having a greater impact compared to that of official interest observations.

Equity and bonds markets

The other main area considered is that of the financial stock market, for which I have collected five main sentinel covariates. The primary ubiquitous one is the volatility level in the stock market, expressed by the VSTOXX index [22] for Europe and the VIX index [23] for the USA financial market[24]. A significant body of the financial stability literature has already explored the significance of the volatility of the stock markets in conditioning the soundness of financial institutions . Mieg (2022) hypothesize that market volatility acts as a risk amplifier for price risk within the banking sector, rendering less stable institutions particularly vulnerable. Batten et al. (2022), use quantile regressions to demonstrate that substantial negative impacts on GSIBs' stock performance [25] arise principally from lower quartile jumps in the VIX. On the same wavelength are also the findings of Mensi et al. (2019) who show that increased volatility levels in equity markets heighten credit risk for

[19] This decrease is jointly driven by capital and riskweighted assets, because it appears that they are not fully capable to prompty adapt the capital to the level of risk.

[20] Idelly negotiates for hedging from inflation level oscillation, the contract forsees fixed rate payments in return for inflation-adjusted (HICP excluding tobacco) rate payments.

[21] With this term is intended the irrational behaviour of funneling resources towards riskier obligors.

[22] Volatility of the STOXX 500 index (`https://qontigo.com/index/v2tx/`)

[23] (`https://www.cboe.com/tradable_products/vix/`)

[24] To be more precise, it is widely acknowledged in the literature that the VIX has become the leading measure of risk volatility worldwide worldwide Bardgett et al. (2019)

[25] Where GSIB stands for Global Systemically Important Banks, according to the bank of international settlmente nomenclature.

credit institutions.
In addition to the volatility measure, It has included the weekly returns of the EUROSTOXX 50 [26] and the S&P500[27].
For the bond markets, to represent the sovereign yield spread, often called credit spread (as in Tobias and Brunnermeier (2016)), it has introduced the spread between the yields of non-AAA-rated country bonds and the AAA-rated country bonds whitin the Europe, both sourced from the ECB datawarehouse. This spread has been a fundamental driver of the sovereign debt crisis, serving as the link between countries' debts and the banking sector, a connection that could prove highly detrimental in the event of downturns Liu and Varotto (2021). Additionally, as highlighted by Hardy and Zhu (2023), banks act as the primary dealers of sovereign bonds in financial markets, thereby exposing themselves to countries stock devaluations.

Financial stress indicators

Beyond the market variables, two other market-based indicators that synthesize stress conditions in the bond market and the market of financial intermediaries have been included. These indicators are components of the CISS (Composite Indicator of Systemic Stress) indicator developed by (Hollo et al., 2012), and are provided daily by the [28]. Specifically, the CISS includes the CISS-bond for the bond market and the CISS-intermediaries for the market of financial intermediaries, which encompasses entities such as banks, mutual funds, investment banks, insurance companies, and more.

Currencies exchange rates

One less explored ares in banking stability is the impact of fluctuations in foreign currency exchange rates on banks. Studies such as those by Kasman et al. (2011), and earlier works by e Grammatikos et al. (1986) and Chamberlain et al. (1997), have demonstrated that banks are indeed exposed to the swings ins exchange rates.The European Central Bank (ECB) has also addressed this issue, as highlighted in the "RECOMMENDATION OF THE EUROPEAN SYSTEMIC RISK BOARD of 21 September 2011 on lending in foreign currencies (ESRB/2011/1) (2011/C 342/01)" warning banks about excessive foreign lending activities and stating that::

> *"Excessive foreign currency lending may produce significant systemic risks for those Member States and may create conditions for negative cross-border spillover effects".*

To capture this significant effect, the decision was made to include the exchange rates with the US dollar (as it is the world's reserve currency and widely used for loans globally, as stated by (Eren and Malamud, 2022)), along with the British pound sterling (which rank as the fourth most traded currencies, according to the Triennial Central Bank Survey on OTC foreign exchange turnover in April 2022 by the Monetary and Economic Department, 2022).
To provide more detail, it has decided to not include also the £/$ changes, relying on the findings discovered by Ivanova and Ausloos (2002), which substain that £ and € react in a similar manner to the $ value changes.

[26] `https://qontigo.com/index/SX5E/`
[27] `https://www.spglobal.com/spdji/en/indices/equity/sp-500/#overview`
[28] `https://sdw.ecb.europa.eu/browseExplanation.do?node=9689686`

Commodities

Limited attention has been given to understanding the extent and nature of the impact of price fluctuations in commodities markets on bank losses and their propagation throughout the financial sector. One of the pioneering efforts to shed light on this issue is attributed to Qin (2020), who compellingly demonstrates that shocks in both price and supply of oil have an enduring effect on the stability of credit institutions. Tverberg (2012) has argued that countries reliant on oil imports experience credit crunches following contractions in oil supply. While analogous findings are expected to apply to natural gas prices and supply (NG), equivalent insights from financial literature are yet to be found. To represent both of these variables, 3-month future contracts are employed. This choice arises from the lack of comprehensive spot prices, leading us to approximate the spot prices using the nearest future prices, following a similar approximation strategy as employed by Lautier and Raynaud (2012).

Even for the gold price, there is a lack of literature, despite the fact that it deserves significant attention. Gold ranks as the third most liquid asset in the market (Gopalakrishnan and Mohapatra (2018)). Research by Elbadri and Bektaş (2022) demonstrate that the gold price affects the bank stability (represented by the z-score) both in the short and long run. Moreover, as higlighted by Cai et al. (2001), low financial asset prices, coupled with low nominal interest rates, attract investors who perceive gold as a safe haven, stimulating demand and consequently driving up its price. This trend has been evident since 2021 when the price of gold surged abruptly, breaking the $2,000.00 per ounce mark following the SVB bank and Credit Suisse crises [29]. Therefore, an increase of gold price might signal impending distress in financial and credit markets.

In the following table are summarized the covariates used, the source and the transformations applied.

Table 2.1: Data description and transformation of variables

Variables	Abbrev.	frequency	Original unit	Source	Transf.
Natural gas-Future 3m	GAS	weekly	Euro/MWh	Refinitiv	first.diff.
Oil-Future 3m	OIL	weekly	Euro	Refinitiv	first.diff.
Gold-Euro spot	GOLD	weekly	Euro	Refinitiv	first.diff.
Slope Euro yield curve	SLOPE	weekly	Pure num.	ECB statistical data warehouse	first.diff.
Slope US yield curve	US.SLOPE	weekly	Pure num.	ECB statistical data warehouse	first.diff.
VSTOXX	VSTOXX	weekly	Pure num.	Refinitiv	/
VIX	VIX	weekly	Pure num.	Refinitiv	/
Euribor-OIS 3m spread	EUR	weekly	Percentage	ECB statistical data warehouse	first.diff.
EURIRS 10y	EURIRS	weekly	Percentage	Refinitiv	first.diff.
AAA-nonAAA spread	CREDIT	weekly	Percentage	ECB statistical data warehouse	first.diff.
EONIA/STR	EONIA	weekly	Percentage	ECB statistical data warehouse	first.diff.
Federal fund eff.rate	EFFR	weekly	Percentage	FED	first.diff.
TED spread	TED	weekly	Percentage	FED	first.diff.
EUROSTOXX 50	EUR.STOXX	weekly	Euro	Refinitiv	log return
S&P500	S&P	weekly	Euro	Refinitiv	log return
Real estate market	REAL.EST.	weekly	Euro	Refinitiv	log return
Euro-dollar exchange	€/$	weekly	Euro	Refinitiv	first.diff.

[29] https://www.wsj.com/articles/banking-worries-fuel-gold-price-rally-66d0fc6d

Euro-Yen exchange	€/¥	weekly	Pure num.	Refinitiv	first.diff.
Euro-sterling exchange	€/£	weekly	Pure num.	Refinitiv	first.diff
CISS bond	BOND	weekly	Pure num.	ECB statistical data warehouse	first.diff.
CISS intermediaries	INTERM.	weekly	Pure num.	ECB statistical data warehouse	first.diff.
EU GDP tracker	EU.GDP.	weekly	Pure num.	OECD	first.diff.
US GDP tracker	US.GDP.	weekly	Pure num.	OECD	first.diff.
EU Inflation linked swap 1y	EU.HICP1	weekly	Pure num.	Refinitiv	first.diff.
EU Inflation linked swap 5y	EU.HICP2	weekly	Pure num.	Refinitiv	first.diff.
US Inflation linked swap 1y	US.HICP1	weekly	Pure num.	Refinitiv	first.diff.
US Inflation linked swap 5y	US.HICP2	weekly	Pure num.	Refinitiv	first.diff.

Notes: 'first.diff.' stands for first difference transformation. The AAA-non AAA spread, as described in the text is the difference between AAA bond yield and non-AAA bonds yield of Euro countries.

2.4.3 Summary statistics

The following **Table 2.2** provide the summary statistics of the covariates involved along with the dependent variable considered. All the variables have been summarize after being transformed according to **Table 2.1**:

Table 2.2: Summary statistics of covariates

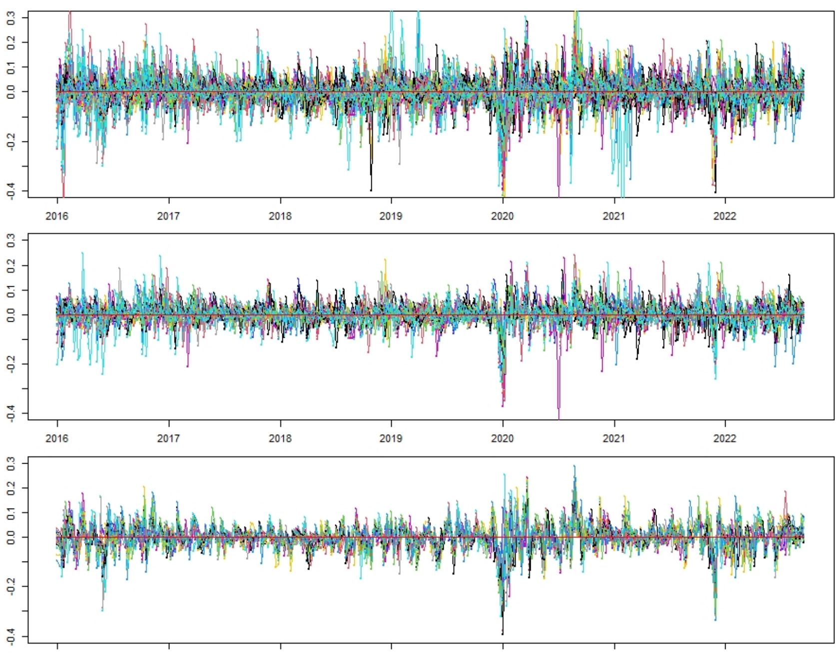
	mean	**SD**	**Rel.SD**	**min**	**max**	**1% quantile**	**ADF**
$X_{j,t}$	-2.22^{-05}	0.0486	2179.81	-0.876	0.511	-0.1525	$8.429e^{-07}$
$X_{j,t}$ CP	-0.0001	0.0567	567	-0.876	0.396	-0.1446	$6.521e^{-08}$
$X_{j,t}$ SP	3.91^{-05}	0.0401	1027.48	-0.5232	0.5113	-0.1211	$4.360e^{-08}$
$X_{j,t}$ top 20	-0.0002	0.0510	182.441	-0.3941	0.2891	-0.15084	$2.708e^{-16}$
$X_{j,t}$ top 20 CP	0.0036	0.0552	263.898	-0.3941	0.2891	-0.1478	$3.961e^{-9}$
$X_{j,t}$ top 20 SP	-0.0008	0.0415	49.6919	-0.2992	0.2052	-0.1114	$6.746e^{-11}$
$X_{j,t}$ last 20	0.0108	0.0357	33.023	-0.4832	0.2399	-0.1056	$1.222e^{-13}$
$X_{j,t}$ last 20 CP	0.0006	0.0437	66.09	-0.4832	0.2399	-0.1290	$7.012e^{-10}$
$X_{j,t}$ last 20 SP	0.0013	0.0302	22.054	-0.2106	0.22314	-0.0833	$9.202e^{-08}$
NAT.GAS	1.67e-01	13.7579	82.389	-139.52	113.05	-38.180	$3.717e^{-33}$
OIL	1.24e-01	3.1324	25.251	-16.980	15.070	-8.6064	$8.309e^{-09}$
GOLD	1.99	24.408	12.239	-106.165	126.50	-79.153	$6.784e^{-07}$
SLOPE	-1.87e-03	0.0690	36.835	-0.5375	0.5004	-0.2203	$9.043e^{-29}$
US.SLOPE	-4.66e-03	0.0543	11.648	-0.1600	0.2440	-0.1459	0.01618
VSTOXX	2.07e+01	8.2342	0.3967	10.689	74.332	11.107	0.005223
VIX	1.88e+01	7.9811	0.4249	9.1400	66.040	9.4776	0.083513
EUR	8.87e-04	0.0174	19.641	-0.1076	0.0940	-0.0606	$2.215e^{-06}$
EURIRS	6.01e-03	0.0843	14.025	-0.28200	0.3410	-0.2181	0.01282
CREDIT	2.86e-03	0.0768	26.841	-0.2361	0.3435	-0.1774	0.000599
EONIA	2.53e-03	0.0352	13.934	-0.3298	0.4568	-0.0220	$1.439e^{-28}$
EFFR	6.81e-03	0.1539	22.581	-1.5960	1.417	-0.3480	0.000436
EUR.STOXX	1.44	92.9288	64.473	-646.05	334.09	-250.10	$5.719e^{-33}$
S&P	5.41	80.8139	14.949	-406.10	301.17	-238.73	$2.731e^{-33}$
Real.Est.	-1.68e-01	5.0675	30.179	-43.135	17.408	-15.1807	$2.294e^{-17}$

€/$	-4.27e-05	0.0116	271.56	-0.0412	0.0447	-0.0297	$1.000e^{-04}$
€/¥	2.66e-02	1.4913	56.089	-4.7303	4.6250	-3.8564	$3.302e^{-33}$
€/£	4.09e-04	0.0093	22.780	-0.0329	0.0396	-0.01865	$3.762e^{-33}$
BOND	1.14e-04	0.0136	120.11	-0.0431	0.0458	-0.0295	$4.528e^{-21}$
INTERM.	1.96e-04	0.0225	115.02	-0.1041	0.0665	-0.0547	$4.603e^{-27}$
EU.GDP.	2.55e-02	0.7334	28.761	-8.6939	2.6116	-1.473	$3.087e^{-11}$
US.GDP.	3.46e-02	0.7809	22.592	-7.4563	3.0291	-1.974	$3.812e^{-33}$
EU.HICP1	1.13e-02	0.2376	21.048	-2.1125	0.9450	-0.8887	$6.131e^{-07}$
EU.HICP2	5.21e-03	0.0857	16.453	-0.4800	0.3000	-0.2755	$6.78e^{-13}$
US.HICP1	3.89e-03	0.1812	46.569	-0.9900	0.7895	-0.4933	$2.639e^{-08}$
US.HICP2	2.58e-03	0.0877	33.953	-0.5200	0.4500	-0.2363	$6.131e^{-07}$

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. For ADF it's intended the result of the augmented Dickey-Fuller test for stationarity of time series (Dickey and Fuller, 1979). Rel. SD stands for Relative standard deviation, it's calculated as: $\frac{SD}{|\mu|}$. $X_{j,t}$ symbolize the dependent variable used, meanwhile CP and SP stands respectively for crisis period and stangflation period.

As emerged from the above **Table 2.2** the weekly equity returns (first row) exhibit approximately a 0 mean with significant excursion from the minimum to maximum values throughout the sample period. This behaviour is primarily driven by the crisis period observations (second row), which, on average across the sample, show larger departures from the mean value (which is slightly lower than zero), as it's seen in the returns plot at the following figure (**Figure 2.2**) where the noticeable risk shift from 2020 onwards is recognizable.

Figure 2.2: Percentage returns plot



Notes: The returns of all the banks in the sample (first on top), the returns of the last twenty banks for total assets (in the middle) and the returns of the forst 20 banks (in the bottom).

It's also interesting to note the different behaviours of the last and top 20 banks (ordered according to the list in **Table 2.12**). The top 20 banks exhibit high variability on average, as evidenced by the relative standard deviation, compared to the stable period. Same pattern is followed by the last 20 banks for dimension. Generally, the top 20 banks exhibit higher variability, possibly due to the active trading of their stocks by financial investors.

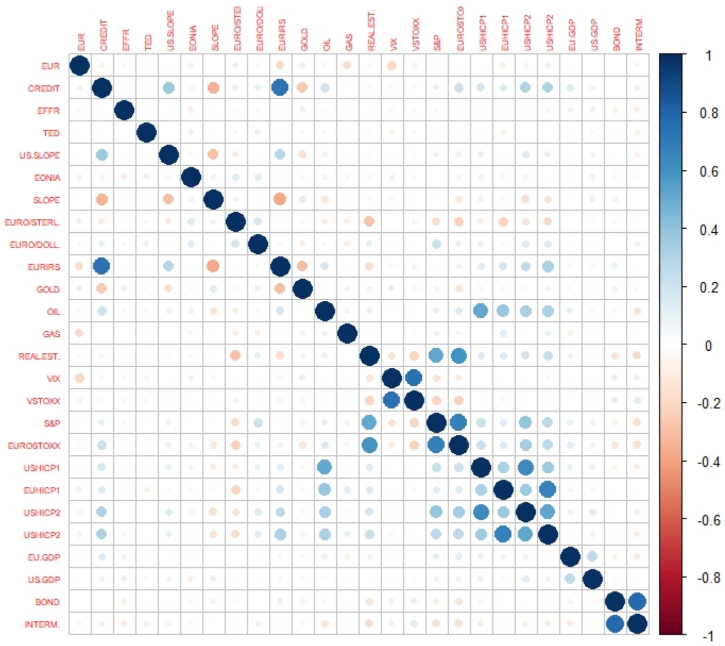
The covariates show high dispersions, above all the commodities ones, that have been aboundately shaken since 2020 (Goodell (2020), Yating et al. (2022)), and the financial stress indicators (CISS bond and CISS intermediaries) that traces the panic occurs with the outbreak of COVID-19 first (Elnahass et al. (2021),Shabir et al. (2023)) and then with the Russian-Ukraine war (as highlighted also from the European systemic risk board European stability board). Concerning the stationarity, all the series exhibit this property, including the VSTOXX and VIX series which are borderline cases. However, supported by the existing literature on this topic, the decision has been made to keep the covariates in their original levels.

For what concern the normality, looking at the **Figure 2.22** that reports the Box plots of the covariates, it emerges how most of all are from the normality standard, exhibit asymmetry (as in the case of VSTOXX and VIX) and kurtosis. This is largely provoked by the outlier formation caused by the eventful period considered.

(*Insert Figure 2.22 here*)

Seeing at the correlation plot in the following figure (**Figure 2.3**) most of the variables exhibit weak linear relationships. However, the EURIRS and the sovereign bond spread are significantly negatively correlated [30], and the VIX-VSTOXX pair confirms strong interlinkages between the US and EU markets.

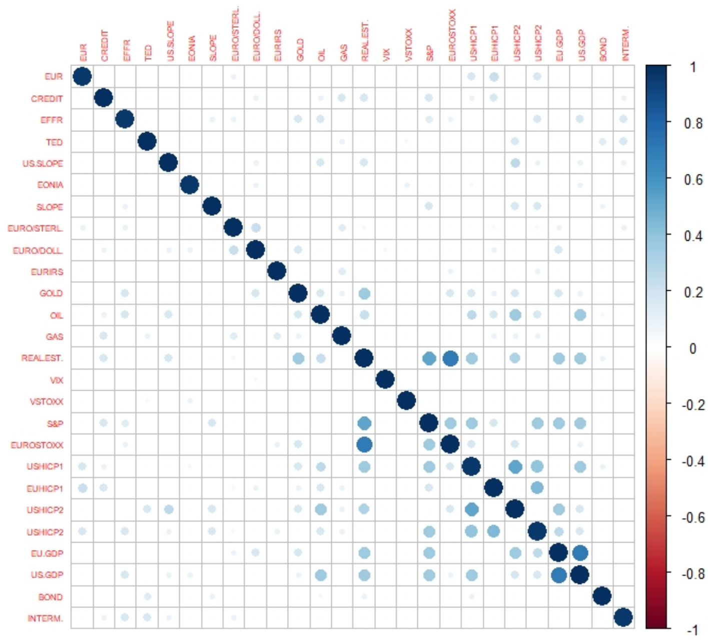
Figure 2.3: Correlation plot



[30]This would be dependent by the

As explained in the variable description section, changes in the sovereign yield spread reflect the perceived alterations in a country's creditworthiness. However, as highlighted by De Santis and Stein (2015), sovereign yields also serve as benchmark reference rates for determining key interest rates, such as the ones for households and corporations lending (hence, including also the EURIRS). Therefore, the correlation between policy rate moovements and sovereign yield fluctuations is of extremely importance for ensuring an effective transmission mechanism of the monetary impulse. Thus, it is reasonable to expect that an increase in interest rates could impact the credit risk of countries, potentially leading to a widening of yield spreads. Not surprising is also the high correlation of the two declinations of CISS (the bond and intermediaries markets), considering the high nexus between financial institutions and bond markets. With regard to commodities, only the oil price exhibits a simulatneous correlation with inflation levels. However, this does not exclude possible delayed relationships [31].
Further valuable insights are presented in the subsequent **Figure 2.4**, displaying the tail dependence matrix. This matrix was constructed using the lower tail dependence coefficient, as described in **section 2.7**. The coefficient serves as a measure of extremal dependence, assessing the strength of dependence in the far tails of the bivariate distributions. Evaluating this measure can provide justification for the results, as highly tail-dependent variables may influence the selection process due to redundancy in tail information. According to this measure, variables appear to be largely independent during extreme negative events. Exceptions are the links of US GDP and EU GDP, which undoubtedly demonstrate the interlinkages also between the two real economies (not only the financial connection), and the EUROSTOXX and the REAL estate that exhibit a non-negligible tail dependence, indicating that the real estate sector follows the trajectory of the stock market during distress periods [32].

Figure 2.4: Tail dependence coefficient plot

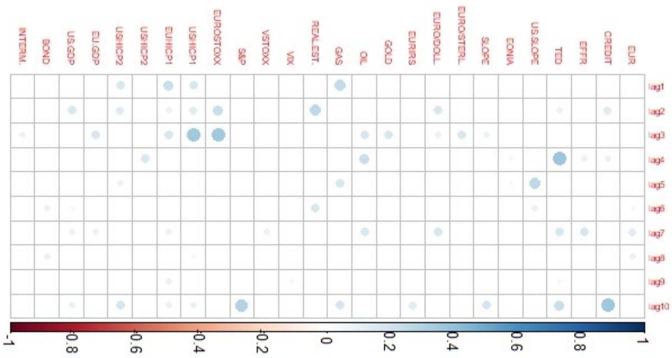


[31] It's likely the effects of GAS and GOLD have a lagged impact on inflation expectations. For this, further investigotions are needed.

[32] The co-movements in mean of these two variables has been already demonstrated in Okunev et al. (2000) and Chang et al. (2014)

Moreover, upon observing the first vertical stripe of the figure, the monetary policy drivers, along with the currency market conditions, appear to have weak tail-relationships with financial markets. This might be attributed to time-delayed cause-effect relationships between the two groups or, less likely, a clear tail-interdependence.
In **Figure 2.5**, the results of the tail coefficient between each variable and its lagged version are presented. It is apparent that there is weak auto-dependence in the left tail for all the variables. This lack of tail memory could contribute to stabilizing the estimations and prevent biases from arising.

Figure 2.5: Auto-Tail dependence coefficient plot



2.5 Results

2.5.1 WladAlasso output

As highlighted in the previous paragraph tha analysis starts from a lag selection preliminary investigation for all the quantile involved, so the 5% and the 50% .
The lag-penalty constant has been set considering the one that produces the lower MSE with a cross-validation analysis on the market returns.
In the following **Figure 2.6** and **Figure 2.7** have been displayed the lag selection computed with the WladAlasso scheme proposed, considering the average coefficients values extracted from the lasso regressions for lag-selection. The results have been obtained considering the g parameter of Equation 2.18 obtained via k-fold cross-validation on the banking market returns, as explained in the **subsection 2.3.1**.

Figure 2.6: Average coeffiecient magnitude at 5% quantile

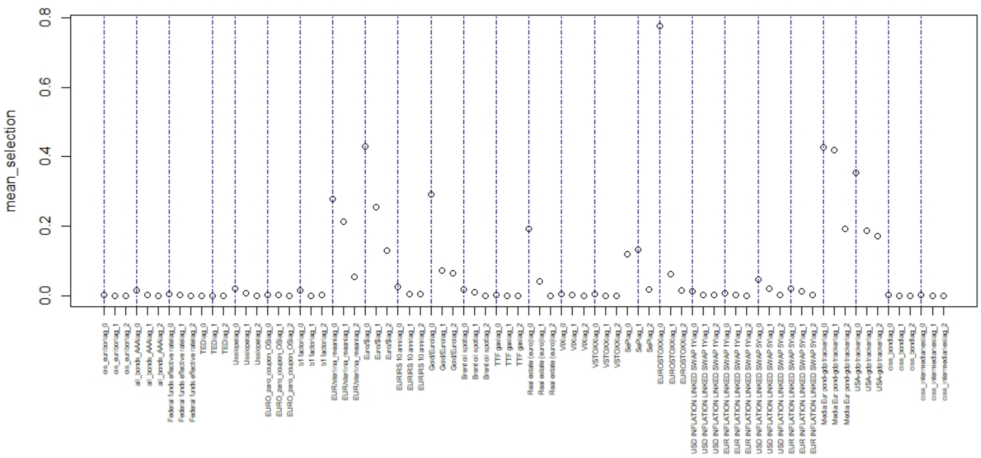
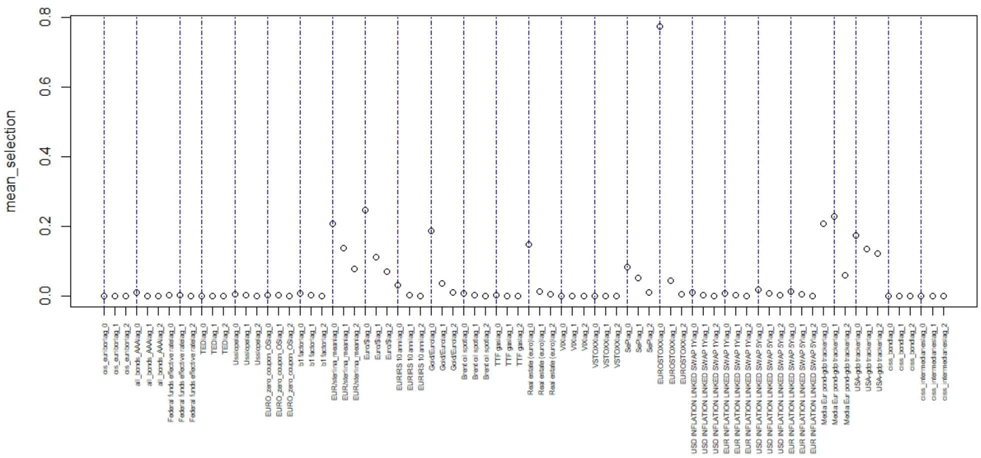


Figure 2.7: Average coeffiecient magnitude at 50% quantile



As anticipated above, the contemporaneous effects of variables are much more important than those exhibited by lagged values, except for the TED spread and the S&P 500 returns in the 5% quantile, and the EFFR and EU-GDP for 50% that have a one period lagged effect. This could have a two-fold explanation. The first one is technical and can be attributed to the variable transformations. Differentiating the variables eliminates the temporal memory and time trend. The second explanation is that in a fast information environment, news continuously updates prices (assumed that the efficient market hypothesis holds [33]), consequently reducing the time it takes for new information to be

[33]Looking at Sewell (2012), Malkiel (1989) assuming EMH is not unrealistic, especially in pre and post crisis periods (Anagnostidis et al. (2016)). In crisis period the mean reverting behaviour of stocks, so the estrangement from the EMH, is mainly due to the hearding behaviour, therefore an unpredictable phenomenon (Horta et al. (2014)).

reflected in prices.
Moreover, as displayed in the previous figures, the EUROSTOXX50 shows the greatest average coefficient magnitude in both the quantile selected, along with the currency exchange rates and the European GDP. It's not surprising to observe the magnitude of the volatility covariates, given their dimension (they have not been differentiated, contrary to the others).
The lag selection results are compliant with the covariates time structure proposed in Petrella et al. (2019) and Bernal et al. (2014), who studied the equations with contemporary state variables.

2.5.2 Results of VaR and $CoVaR$ with the lasso adjustment

In this section, the results of the variable selection scheme documented in **section 2.3** with covariates lagged according to the results obtained in the previous section have been reported. In detail, the two tables below (**Table 2.3** and **Table 2.4**) show the main quantiles of the distributions of the p-values estimated for the LASSO approach that modifies the original $CoVaR$ algorithm at 5% and 50% quantiles, regarding the VaR estimation. In the **Appendix of results estimation** it's provided the complete estimation panel for the VaR regressions.

Table 2.3: P-value quantiles at 5%

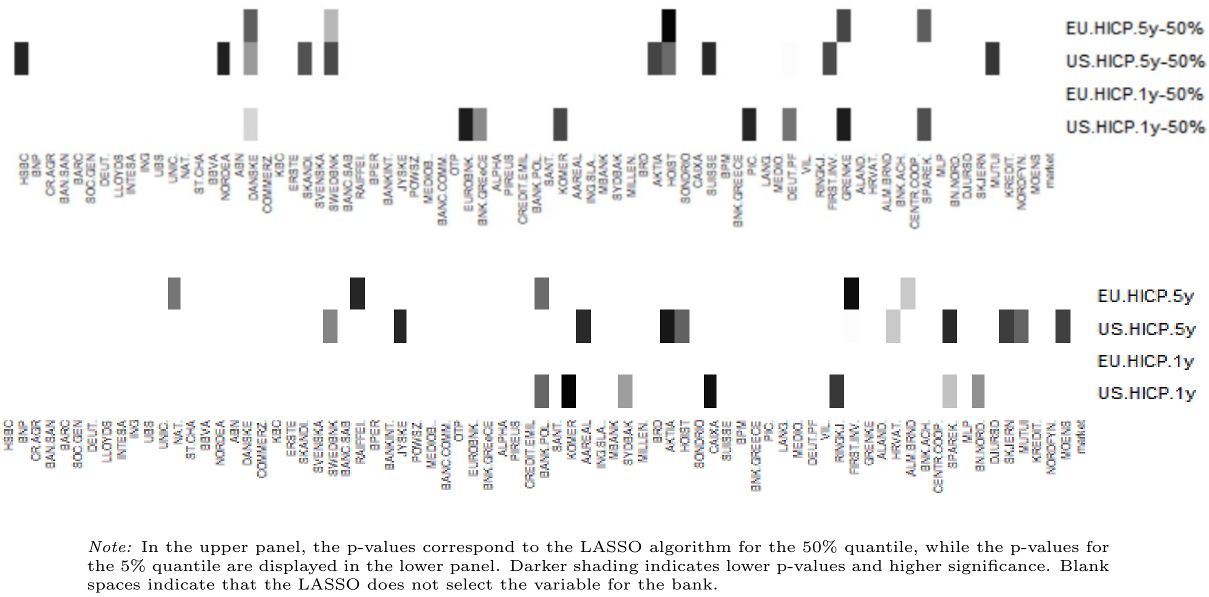
	Quantiles				
	0%	25%	50%	75%	100%
(Intercept)	0.0000	0.0000	0.0000	0.0000	0.0000
EUR-OIS	0.0000	0.0004	0.0751	0.0853	0.0960
CREDIT	0.0002	0.0103	0.0986	0.1957	0.5835
EFFR	0.0009	0.2792	0.5575	0.7087	0.8600
TED	0.0975	0.1446	0.2466	0.4578	0.7416
US.SLOPE	0.0929	0.0929	0.0929	0.0929	0.0929
EONIA	0.0840	0.2306	0.3772	0.5237	0.6703
SLOPE	0.0222	0.0466	0.0580	0.3929	0.7027
EUR/£	0.0152	0.0283	0.0414	0.0437	0.0460
EUR/$	0.0000	0.0140	0.0513	0.3153	0.9847
EURIRS	0.0000	0.0032	0.0134	0.0962	0.2950
GOLD	0.0000	0.0077	0.0645	0.1098	0.2817
OIL	0.0265	0.0509	0.0965	0.1756	0.8186
GAS	0.0422	0.2144	0.5243	0.6133	0.6553
Real.Est.	0.0036	0.0938	0.2551	0.4906	0.8809
VIX	/	/	/	/	/
VSTOXX	0.0000	0.0020	0.0284	0.1226	0.8249
S&P	0.0000	0.1105	0.2880	0.7440	0.9051
EURO.XX	0.0000	0.0000	0.0023	0.0491	0.8272
US.HICP.1y	0.0221	0.1561	0.4181	0.6136	0.7749
EU.HICP.1y	/	/	/	/	/
US.HICP.5y	0.0004	0.0387	0.0915	0.2068	0.5055
EU.HICP.5y	0.0038	0.1190	0.4220	0.4675	0.8455
EU.GDP	0.0004	0.1381	0.3274	0.6373	0.9965
US.GDP	0.0135	0.0939	0.4375	0.7156	0.7735
BOND	0.0111	0.0728	0.1605	0.2161	0.8714
INTERM.	0.0031	0.1052	0.1406	0.3347	0.8513

Table 2.4: P-value quantiles at 50%

	Quantiles				
	0%	25%	50%	75%	100%
(Intercept)	0.0006	0.2874	0.5146	0.7910	0.9943
EUR-OIS	0.0152	0.0158	0.0165	0.0171	0.0178
CREDIT	0.0000	0.0044	0.2538	0.4266	0.9934
EFFR	/	/	/	/	/
TED	0.0025	0.0045	0.0341	0.0800	0.0876
US.SLOPE	0.0291	0.0586	0.0880	0.0898	0.0916
EONIA	/	/	/	/	/
SLOPE	0.1334	0.1334	0.1334	0.1334	0.1334
EUR/£	0.0000	0.0047	0.0050	0.0860	0.0923
Euro/$	0.0000	0.0026	0.0112	0.0648	0.1669
EURIRS	0.0001	0.0096	0.0344	0.0890	0.3004
GOLD	0.0000	0.0023	0.0155	0.0494	0.1321
OIL	0.0061	0.0166	0.0530	0.1066	0.2956
GAS	/	/	/	/	/
Real.Est	0.0000	0.0209	0.0745	0.2440	0.4745
VIX	/	/	/	/	/
VSTOXX	0.0004	0.0181	0.0687	0.1026	0.1926
S&P	0.0027	0.1618	0.2936	0.4556	0.8784
EURO.XX	0.0000	0.0000	0.0000	0.0001	0.4422
US.HICP.1y	0.0002	0.0101	0.0728	0.1408	0.2853
EU.HICP.1y	/	/	/	/	/
US.HICP.5y	0.0001	0.0482	0.1247	0.1907	0.6682
EU.HICP.5y	0.0095	0.2445	0.3359	0.3388	0.6422
EU.GDP	0.0001	0.0026	0.0546	0.1775	0.2236
USA.GDP	0.0211	0.0298	0.0386	0.0473	0.0560
BOND	0.0015	0.0069	0.0122	0.0176	0.0230
INTERM	0.0218	0.0420	0.0838	0.2171	0.5304

As is evident from the previous tables, the factors influencing banking losses are diverse and varied. Volatility and stock market returns have established themselves as significant distress factors, showing great significance across nearly the entire sample. Moreover, looking at the the tables in the **Appendix of results estimation**, they are the omnipresent covariates chosen by the shrinkage approach (LASSO). Surprisingly, the VIX has never been chosen, indicating how the information provided by the VSTOXX supplies the sufficient volatility information, given also the high correlation of the series, as displayed in **Figure 2.3**. Also in theory, evidence of this relation are provided, as in Benedetto et al. (2021) and Baele (2005) that document an high information flow from the two volatility indexes, especially in crisis periods. This enforces even more the theory of strong interconnectedeness between the US and EU financial markets also regarding the banking sector (Niţoi and Pochea (2022)).
The inflation expectations for the Europe at one year do not appear to be a major concern, unlike the US inflation expectations, which seem to be the leading inflation parameter for the European countries (plus US and Switzerland) as well (in both the **Figure 2.4** and **Figure 2.3** these variables appears largely correlated). Furthermore, the theory supporting the detrimental impact of inflation on banks (Mishkin (1999) and Bernanke and Gertler (1995)) has been fully demonstrated, since a vertiginous positive change in future inflation levels (what is happened from the 2020 onwards) leads to a worsening of the VaR of banks. Another curious funding regards the distribuition of inflation significance. Indeed, looking at the following **Figure 2.8**, that shows the heatmap of the LASSO selection for the inflation covariates, the distribuition is unbalanced towards smaller banks (especially for the 5% quantile).

Figure 2.8: Inflation heatmap for VaR at 50% (upper panel) and 5% (bottom panel)

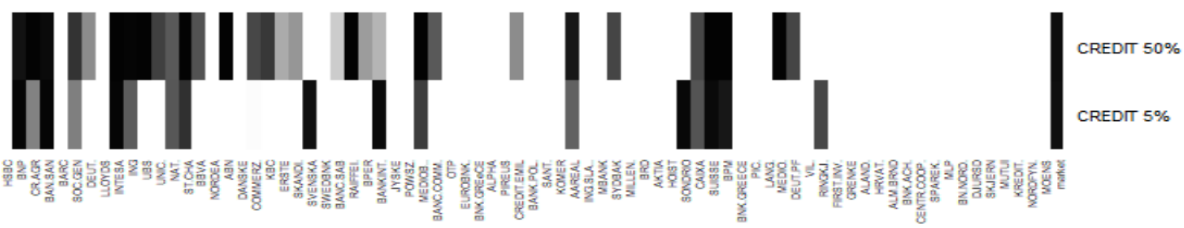


Note: In the upper panel, the p-values correspond to the LASSO algorithm for the 50% quantile, while the p-values for the 5% quantile are displayed in the lower panel. Darker shading indicates lower p-values and higher significance. Blank spaces indicate that the LASSO does not select the variable for the bank.

One possible explanation for this outcome can be attributed to the business orientation of banks. Smaller ones tend to rely more on lending compared to larger ones (Walter (2009)), which have a more diversified business, both from the asset and the liability side. Inflation generally leads to an increase in loans losses (debtors struggle to service debts) and is linked to a contraction in the credit market, which offsets earnings from subsequent

interest rate increases. This business specificity also conduces to a greater aggressivity in short-term interbank liabilities to fund themselves in crisis periods, that with a raise of interest rate shrinks even more the interest margin. Moreover it's likely that smaller banks have a limited capability of managing maturity mismatch and duration gap that with the raise of interest rate, consequent to the surge of inflation, combined with a credit restrictions could induce a liquidity contraction.
All in all, the information on banks losses provided by the previous variabels is quite sparse. One of the main explanations for this scarce role of inflation expectations is determined by the Gold price, which, as indicated in the **Table 2.3** and the tables in the Appendix, is one of the most significant regressors. Nonetheless, there is a severe lack of literature regarding this variable, particularly for what concerns the banking sector and after the gold standard sunset (Economics (2011)). Fortune (1987) documented a substitution effect between gold and inflation expectations, particularly among investors with fixed-income investments. As inflation levels rise, investors with fixed nominal returns shift towards gold, increasing its demand and consequently its price (given its inelastic supply). Aye et al. (2017) provide proofs of cointegration between gold price and consumer price index in UK, meanwhile Batten et al. (2014) and Levin et al. (2006) echo this sentiment, supporting the notion of gold's hedging role against inflation within the realm of the interest rate channel, recognizing the role of gold as a peculiar monetary asset. Indeed, this latter has been used exhtensively by central banks to protect the purchasing power in high inflation time segments and subtracting themselves to the '*fear of floating*' of equity instruments and currencies (Aizenman and Inoue (2013)). Moreover, as proven by Erb and Harvey (2013) the gold price and the monetary interest rates tend to be highly negative correlated, impliying a strict interdipendence between the two. In light of this, it's natural concluding that the Gold price supplies inflation insights that de facto substituites the inflation expecation information provided by the inflation linked swaps (that formally encompasses the inflation expectations of the financial players) and include supporting evidence of the impactfulness of interest rates. This results affirm the key role of gold in explaining banking results, since it encompasses a complete multifacet macroeconomic warming indicator.
The next variable to pay attention to is assuredly the difference between the average yield of AAA bonds and the average yield of all the bonds in Europe, which, as anticipated in the variable description section, serves as a proxy for credit risk. As highlighted in the results appendix, the lasso selects this variable in 19 out of 77 banks (including the market returns) for the 5% quantile and 32 out of 77 for the 50% quantile, demonstrating its high influence in explaining losses and normal returns. Furthermore, some evidence of the distribution of this variable can be seen in the following **Figure 2.9**:

Figure 2.9: Credit heatmap for VaR at 5% and 50%



Note: Darker shading indicates lower p-values and higher significance. Blank spaces indicate that the LASSO does not select the variable for the bank.

As you may have noticed, there is a significant concentration among larger banks in both the 5% and 50% quantiles, whereas among smaller banks, the credit proxy does not seem to have as much influence. This could be largely due to the fact that less structured banks do not have significant exposures (as a ratio of total assets) in sovereign bonds, owing to their traditional business model. Furthermore, as documented by Liu and Varotto (2021) who investigated the level of sovereign bond holdings by banks during the subprime crisis, surprisingly, although smaller banks resorted to substantial debt holdings during the crisis, the level of government bond holdings can contribute positively to loan growth and bank soundeness. However, a significant involvement in the sovereign bond market could strengthen the sovereign-bank nexus and cause instability in banks during periods of government and economic distress. This explains why larger banks often experience a greater sensibility to change in yield spreads, particularly in countries on the periphery and those facing economic challenges, such as Italy and Spain. In such cases, banks often serve as the *'lender of last resort for countries'*, and they may be subject to moral suasion from governments. This pressure on bank ownership can lead to a substantial influx of public debt toward domestic larger banks (Becker and Ivashina (2018)).
The primary interest lies in understanding why a positive change in bond spread amplifies banking losses. It appears that an increase in bond yields is linked to both banking losses and overall banking market performance, as found in the study of Borri and Di Giorgio (2022). This correlation could be primarily attributed to the renegotiation losses or market-to-market adjustments associated with holding bonds in the balance sheets [34]. Additionally, higher sovereign risk diminishes the value of collateral in the interbank market, compelling banks to make costly margin adjustments that can deplete resources and erode capital (Panetta et al. (2011)). Furthermore, a deterioration in a country's sovereign creditworthiness can reduce the funding benefits that banks typically derive from government guarantees, as noted by (Izumi (2020)).
Another complementary variable to the bond yield is the EURIBOR-OIS spread, which serves as an indicator of distress in the interbank market. The results are intriguing, as they indicate a specific regional impact. Specifically, the losses of only certain banks from Italy (Intesa, Unicredit, Mediobanca, and BPM), Greece (Eurobank Ergasias, National Bank of Greece, and Alpha Bank), and the UK (Lloyds and Natwest) are well explained by this essential driver. Conversely, it appears that this variable has little to no impact on median returns, clearly indicating its role as an explanatory factor in extreme scenarios. This results are explained by the credit risk part of this spread. Indeed, the mentioned banks belongs to countries hit by the crisis more then the others. The UK banks have suffered from the Brexit event, that have most likely made, along with the depreciation of pounds, more expensive the access to international wholesale funding. Differently, for italian and greek institutions, the sovereign issue do not allow to have favourable condition on wholesale funding. Moreover, italian are prevantly borrowers, following the borrower prototype outlined by Affinito (2012). Similarly, also the greek banks are net borrowers in interbank market since their recent renewed access to the interbank market with the Pandemic Emergency Purchase Programme introduced to face COVID-19 crisis, and the need of funding for recovering from the Non-performing Loans (NPLs) wave heritated by the sovereign crisis (Mylonas and Magginas (2017)).
Skipping to the overnight interbank conditions, according to **Table 2.3** and the output shown in the Appendix, the EONIA rate and the EFFR do not seem to be significant in

[34]Citing De Marco (2019), the banks usually inscribed sovereign bonds in the banking book, with the intention of holding till maturity, therefore are exposed to marked-to-market more.

explaining losses for banks. This may be due to the analyzed period partially covering the NIRP (negative interest rate period), which has been proven to be detrimental for banks (Ampudia and Van den Heuvel (2018)). On the contrary the positive changes observed with the restricting policy of US and BCE have boosted the interest margin in the short-run, for the non-quick passive interest rates adjustments. Therefore, the impact of this variable may not be fully assessed in a short-horizon high-frequency analysis, requiring a time-delayed investigation.
In contrast, the results for the long-term interest rate (EURIRS rate) indicate a response by banks (and the system) to rate changes. It reveals a notable positive effect when this rate increases in both the 5% and 50% quantiles. A higher value in this rate explain a reduction of bank losses and increases the median returns. This suggests that a higher long-term interest rate induces an enhancement of the interest margin, compensating for the devaluations on existing fixed-income assets, as mentioned earlier and compliant with the existing literature on the topic that lies on the work of Samuelson (1945). Therefore the market perceives that European banks benefit from higher returns not discounting the general financial instability consequent to the subsequent credit restriction or the general augmented cost for hedging (as also underscored by the ECB report Financial stability). However, readers should be aware of the regional validity and the type of business of the banks involved, given that European banks tend to have floating rate mortgages and rely particularly on deposits, whose price is often unresponsive to interest rate fluctuations [35].
On the contrary the roles of CISS intermediaries and CISS bond are clear and irrefutable. Both contribute to explain the losses in banking market, meanwhile exert a reduced role in the median value of returns. Therefore, naturally, the banks suffer from turmoil in financial institution markets, and show vulnerability to bond market downturns.
Differntly from what stated in the Tobias and Brunnermeier (2016), the slope of the yield curve for both US and UK have no explanatory meaning, even though for those sporadic cases, the significance is high. This could be dependent by the inclusion of both the short-term rates (EONIA, EURIBOR and EFFR) and the long ones (EURIRS) that could supplement the information on yield curve.
For what concern the energy commodities returns the significance is low for the natural gas and higher for oil in both 5% and 50% quantile regression (**Table 2.3** and **Table 2.4**). In the following heatmap there are the institutions that have shown sensibility to these variables (**Figure 2.10**):

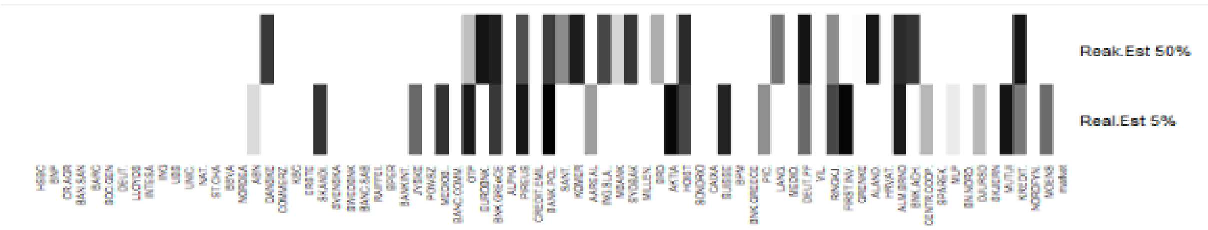
Figure 2.10: Oil and Gas for VaR at 5% and 50%

Note: Darker shading indicates lower p-values and higher significance. Blank spaces indicate that the LASSO does not select the variable for the bank.

[35] Therefore further analysis that will involve the next future periods are necessary to understand also the long-term effect.

Although a discernible pattern is not readily identifiable, there appears to be a clear predominance of oil in predicting banking losses, whereas gas does not seem to exert any effect in the 50% quantile regression. This finding seemingly contradicts the hypothesis proposed in the previous chapter, although this outcome could be detrmined by the structured algorithm. As discussed in the conclusions of the previous chapter, a comprehensive variable filtration process was necessary to ensure a more nuanced representation of the phenomenon. The selection scheme prioritized factors deemed more representative of banking and systemic risk performance. Furthermore, since natural gas and oil prices play a role in determining inflation [36], their impacts were effectively captured through the inclusion of inflation-linked variables, such as the inflation-linked swap and the gold price. The new findings pertain to the signs of impacts, indicating that a rise in oil prices appears to foster institutional stability, thereby reducing losses. Conversely, the gas price seems to have a negative impact on bank losses. This effect could potentially be influenced by omitted conjunctural factors not represented in the analysis, including variables related to limitations on gas importations due to the Ukraine-Russian war.
A different role is covered by the Real Estate returns, which show a significant explanatory impact in both left-tail and median bank returns (**Table 2.4**), displaying size-dependent variability. Indeed, following Deng et al. (2019) in the past years the share devoted to real estate loans increases notably, due to the growth of constructions driven by housing prices, inducing banks to be more dependent from this market, consequently *'somatizing'* downturn periods. Moreover, it seems that the influence of real estate market exercises the greater effects on smaller banks, since looking at the following table **Figure 2.11**, for the first 8 banks the algorithm excludes this variable.

Figure 2.11: Real estate heatmap for VaR at 5% and 50%



Note: Darker shading indicates lower p-values and higher significance. Blank spaces indicate that the LASSO does not select the variable for the bank.

The study also underscores the significance of currency exchange, particularly focusing on the Euro/$ exchange rate. Excluding HSBC, the coefficient for both the 5% and 50% quantiles demonstrates a positive trend, indicating that a devaluation of the Euro against the dollar has adverse effects on banks. This finding supports the idea that European banks have considerable exposure to dollar-denominated credit and bonds, rendering them vulnerable and impacting overall bank stability(Kasman et al. (2011)). Conversely, the Euro/£variable exhibits a negative influence on the losses of English banks, including Natwest and Lloyds. This reflects the impact of the devaluation on their balance sheets due to their higher exposure to Euro-denominated assets. Shifting the focus to Euro headquartered banks, with the exception of Unicredit bank, the results suggest the absence of the *'Brexit effect'* on European banks. This finding is likely

[36]They are at the base of electricity production which is one of the HICP component

attributed to their proactive liquidation or reduction of pound-denominated assets before the Brexit referendum (Carvalho and Schmitz (2022)).
In conclusion, some remarks on the significance level is mandatory. As you can see from the results in the **Appendix of results estimation**, the significance of the selected regressors for smaller banks is generally weeker then the one shown by bigger banks. This is mainly due to the fact that larger banks are more exposed to market-wide events and so to systemic relevance factors, as documented by Baele et al. (2007). In other words, it's likely that the level of risk diversification of large banks might riduce the idyiosincratic risk but make the financial instutions more vulnerable to large swings in different type of macro-factors.

2.5.3 Market and systemic risk

After identifying the determinants affecting individual banks, the next step involves market analysis, which serves as the foundation for establishing the $CoVar$ and estimating the systemic contributions of banks. The results of the post-penalized regression for market returns are presented in the following table **Table 2.5**:

Table 2.5: Post penalized quantile regression market

	market at 5%	market at 50%
(Intercept)	-0.0275^{***}	-0.0017°
	(0.0023)	(0.0012)
CREDIT	-0.0515^{**}	-0.0360^{*}
	(0.0213)	(0.0188)
TED	/	-0.0119^{*}
	/	(0.0068)
EURIRS	/	0.0449°
	/	(0.0311)
GOLD	-0.2235°	-0.3646^{***}
	(0.1380)	(0.0851)
VSTOXX	-0.0324^{***}	/
	(0.0097)	/
EURO.XX	0.8311^{***}	0.9998^{***}
	(0.1492)	(0.0582)
EU.GDP	/	0.3732^{**}
	/	(0.1891)
INTERM.	-0.0127°	/
	(0.0072)	/
Num. obs.	363	363
Pseudo-R^2	0.59	0.49

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

It emerges that the set of variables affecting the market returns varies across different quantiles of the returns distribution, and amazingly all the involved coefficients are statistically significant (even someone poorly). The first notable observation is the distinct impact of volatility, which influences the banking market in the tail but not in the 50% quantile, indicating it as a pure tail-significant variable and consequently a source of systemic perturbation Mieg (2022). Indeed, a raise of price oscillations induce a volatility of market-dependent fraction of the portfolio of banks and furthermore destabilize the non-interest margin (Brunnermeier et al. (2020) and Lehar (2005)). But the factor that

renders volatility systemic is the correlation of activities, as banks tend to adopt similar investment practices in the financial market. Therefore, an escalation in uncertainty could readily propagate among banks, engendering an uncontrolled impact on their balance sheets. Moreover, the so-called *'volatility paradox'*, studied by Brunnermeier and Sannikov (2014), suggests that the risks for the financial sector grow during low-volatility periods and manifest in crisis scenarios when volatility increases, exerting significant pressure on institutions. Stable periods create a risk appetite and increase the leverage of institutions (and short-termism), leading to an incapability of managing the risks taken, resulting in liquidity contractions in extreme cases.
The other full tail-factors is the CISS intermediaries. This variable that captures the distress situations of all the financial intermediaries markets provide a relevant information for the system. This suggest that a systemic turbolence that involves every type of financial institutions is reverbered on the banking system. This support the cross-financial markets spillovers literature (Adams et al. (2014)), especially insurance companies, that are significant investors in financial markets, as they typically invest premiums from policyholders, thereby contributing to the instability of financial markets. Furthermore, they are closely connected to banks through high levels of ownership links, leading to the emergence of giant financial conglomerates (`https://www.ecb.europa.eu/pub/pdf/fsr/art/ecb.fsrart200912en_05.pdf`). This reinforces the connections between these two types of financial institutions, creating an important contagion channel. Similar deductions are also valids for institutional investors, such like investment funds and investment banks.
On the contrary, the EURIRS, the TED spread, and the changes in European GDP seem to condition the median state of banks, rather than constituting drivers of systemic risk alarms (since they appear as regressors in the median quantile and not in the 5%). Regarding the latter variable, as well as for individual bank results, an increase in consumption and production stimulates the credit market from the asset side, as well as the consistency of customer deposits, boosting profitability. Similar impacts hold true for the long-term interest rate (EURIRS), which exhibits an indisputable positive effect for the system, as also highlighted and documented by Samuelson (1945). Indeed, the stabilizing role of this element is mainly due to the growth of bank returns. However, similar to the results from the previous paragraph, these results have to be contextualized, and including the period following the current financial crisis might help in defining the definitive role of this variable. As for the TED spread, it is a globally recognized interbank spread measure, indicating that the interbank channel, not limited to a specific region, plays a stabilizing role in the banking sector, particularly when it decreases, more than the regional interbank conditions (EONIA and EURIBOR-OIS spread) [37].
There are also impactful determinants across all the quantiles of return distributions: movements in the price of gold, changes in credit spreads, and Euro Stoxx returns. This is significant as these variables represent two different financial conditions, namely the status of sovereign bonds and stock markets, while the third incorporates combined financial and macroeconomic information. The first two elements affect the asset side of the balance sheet of banks, while the third one is connected to the price level and interest rate, as well as the monetary policy actions and currency exchange rates, all of which have the power to influence both sides of the balance sheets.
The sovereign yield spread has been proven to be a harbinger of systemic crises, as

[37] In this case banks have more wholesale funding options, even if the currency risk has to be taken into account.

demonstrated during the sovereign crisis of 2011, which brought Greek banks to their knees and severely affected Italian and Spanish banks, and also undermining the entire system De Marco (2019) . Nevertheless, it is a condition that is highly prevalent in the operations of banks, given the significant nexus with domestic countries of European banks. Similarly, the Euro Stoxx performance, representing the stock market condition, serves as a barometer of the lending capacity of banks in normal times, as the demand for deposits and investment diversification is also linked to financial market conditions Lin (2020). On the other hand the asset price collapses threaten banking sector because of the generalized decline in the value of collaterals, and might lead to a *'flight to liquidity'* that could trigger a lending squeeze, immobilizing the banking structure (Radde (2015)). The gold price, as documented in the previous paragraph, is a multifaceted variable. It's ascertained it's role of *'safe haven'* during crisis, that elevates it as one of the first early warming indicators, also for the banking system. But this is the first finding, to the best of my knowledge, that documents such a clear relathionsip with the systemic stress of banking sector. This relathionship has disparate origins.
To further validate the approach and establish a foundation for understanding the contribution of banks to systemic risk, the following table summarizes the p-value distributions of quantile regressions for the 5% and 50% levels (**Table 2.6** and **Table 2.7**) in relation to the $CoVaR$ analysis for the bank sample. The equation was estimated using the set of regressors selected by the algorithm for market returns. In other words, only the variables deemed significant in explaining both the tail and median market performance were included. Therefore, the primary distinction from the original model by Tobias and Brunnermeier (2016) lies in the consideration of different variables for market returns as well.
The full estimation output is in the appendix section.

Table 2.6: P-value $CoVaR$ at 5%

	Quantiles				
	0%	25%	50%	75%	100%
(Intercept)	0.0000	0.0000	0.0000	0.0000	0.0000
CREDIT	0.0013	0.0132	0.0272	0.0971	0.8733
GOLD	0.0005	0.0495	0.1311	0.3508	0.9010
VSTOXX	0.0000	0.0004	0.0023	0.0078	0.0650
EURO.XX	0.0000	0.0000	0.0000	0.0000	0.0010
INTERM.	0.0011	0.1022	0.1679	0.3714	0.9951
VAR	0.0000	0.0000	0.0140	0.2161	0.9692

Table 2.7: P-value $CoVaR$ at 50%

	Quantiles				
	0%	25%	50%	75%	100%
(Intercept)	0.0150	0.1613	0.2725	0.4043	0.7565
CREDIT	0.0069	0.0197	0.0413	0.0767	0.4703
TED	0.0003	0.0232	0.0489	0.0850	0.7686
EURIRS	0.0169	0.1273	0.1692	0.3119	0.9637
GOLD	0.0000	0.0000	0.0001	0.0010	0.2488
EURO.XX	0.0000	0.0000	0.0000	0.0000	0.0000
EU.GDP	0.0136	0.0683	0.1325	0.3312	0.8460
VAR	0.0000	0.0000	0.0005	0.0482	0.9765

Note: Darker shading indicates lower p-values and higher significance, **Equation 2.6**.

As you may noticed the estimations confirms the significance of the approach followed, since quite for all the banks the distribution of p-values demonstrates higher significance in 50% of the sample and in most of the cases also for the 75% of the sample.

2.6 Robustness Check: comparison with the original $CoVaR$ approach

To validate the approach in identifying the most influential factors in the banking sector, the results are displayed in comparison with the ones obtained using the set of lagged covariates proposed by Tobias and Brunnermeier (2016). At this purpose in the following **Table 2.8**, **Table 2.9**, **Table 2.10** and **Table 2.11** are shown the quantile of the distributions of the p-value estimated applying the original model, both for the VaR and $CoVaR$ quantities. To see at the complete set of estimate, the **Appendix of results estimation** provide all the quantile regression results also for this original appproach.

Table 2.8: P-value VaR at 5% with T.B.

	Quantiles				
	0%	25%	50%	75%	100%
(Intercept)	0.0000	0.0000	0.0000	0.0000	0.0000
CREDIT	0.0653	0.3311	0.5735	0.7856	0.9832
SLOPE	0.0052	0.1429	0.3442	0.6296	0.9801
VSTOXX	0.0000	0.0038	0.0168	0.1340	0.9669
EURO.XX	0.0049	0.1552	0.3707	0.5393	0.9822
Real.Est	0.0128	0.2195	0.4060	0.7429	0.9649
EUR-OIS	0.0003	0.0885	0.2814	0.6117	0.9960

Table 2.9: P-value VaR at 50% with T.B.

	Quantiles				
	0%	25%	50%	75%	100%
(Intercept)	0.0110	0.2389	0.4001	0.7091	0.9770
CREDIT	0.0171	0.2325	0.4287	0.6933	0.9974
SLOPE	0.0037	0.3097	0.5132	0.8255	0.9981
VSTOXX	0.0066	0.2373	0.4139	0.6438	0.9958
EUROSTOXX	0.0277	0.3546	0.5940	0.8051	0.9959
Real.Est	0.0158	0.3843	0.5975	0.7781	0.9988
EUR-OIS	0.0308	0.1947	0.3583	0.8064	0.9830

Table 2.10: P-val $CoVaR$ at 5% with T.B.

	Quantiles				
	0%	25%	50%	75%	100%
(Intercept)	0.0000	0.0000	0.0000	0.0000	0.0000
CREDIT	0.0168	0.2999	0.5893	0.7953	0.9981
SLOPE	0.0190	0.1494	0.3498	0.6127	0.9399
VSTOXX	0.0000	0.0005	0.0038	0.0130	0.8173
EUROSTOXX	0.0038	0.1321	0.2381	0.6201	0.9714
Real.Est	0.0094	0.1146	0.3960	0.7143	0.9860
EUR-OIS	0.0001	0.0170	0.1102	0.2814	0.9678
Var	0.0000	0.0000	0.0000	0.0056	0.6760

Table 2.11: P-val $CoVaR$ at 50% with T.B.

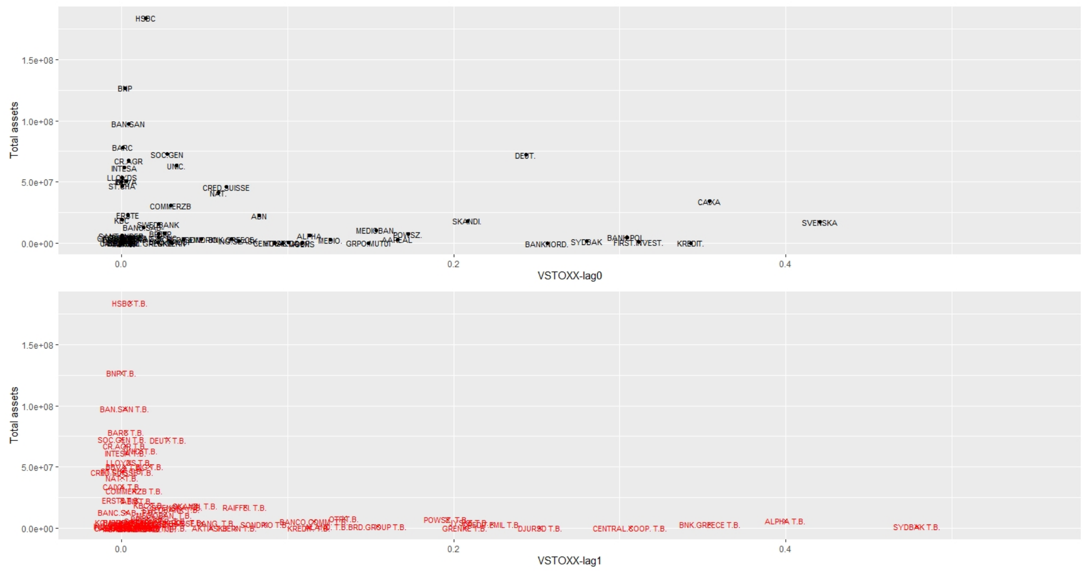
	Quantiles				
	0%	25%	50%	75%	100%
(Intercept)	0.0669	0.4968	0.7173	0.8639	0.9921
CREDIT	0.0083	0.3610	0.5523	0.7853	0.9946
SLOPE	0.0558	0.3460	0.5056	0.6698	0.9893
VSTOXX	0.0010	0.1734	0.3284	0.5421	0.9375
EUROSTOXX	0.0296	0.3204	0.5337	0.8053	0.9844
Real.Est	0.0568	0.2968	0.5222	0.7486	0.9799
EUR-OIS	0.0133	0.0772	0.2393	0.5885	0.9476
Var	0.0000	0.0000	0.0000	0.0001	0.4085

Note: VAR represents the value at risk of each single institution, according to the equation **Equation 2.6**

The results, confronted with **Table 2.3**, **Table 2.4**, **Table 2.6** and **Table 2.7** from the previous section, are self-explanatory. Indeed, the significance levels of the two approaches differ substantially. Indeed, as you may noticed especially for the 50% both for the VaR and $CoVaR$ the regressors are basically not significant, which is an ulterior proof of the goodness of the approach proposed from two aspects. The contemporaneous effects finding has been confirmed, supporting the works of Petrella et al. (2019) and Bernal et al. (2014). Hence, despite the potential forecasting benefits of incorporating lagging regressors, empirical evidence does not support this notion, particularly concerning explanations for median returns. This finding further reinforces the theory of efficient markets in banking sector stocks, as prices appear to promptly reflect innovations. Additionally, the variable selection approach adopted in addressing this issue has proven to be advantageous, since the high significance registered by the regressors selected, affirming

the conclusions drawn by Bayer (2018), who underlines the efficacy of LASSO approach in VaR-based analysis, especially in crisis periods.
Mooving to the regressors analysis, the previous paragraph has highlighted the role of volatility as exclusively a tail-explanatory factor and for VaR and for $CoVaR$. Therefore, including them as regressors in the 50% quantile regression could introduce significant distortions. On the other hand, for the 5% quantile, this factor *'monopolizes'* the statistical significance of the models (**Table 2.8** and **Table 2.10**), being absolutely significant, unlike the other regressors, which, except for the EUR-OIS, are largely statistically negligible.
Furthermore, in comparing the significance levels between the Lasso approach and the original model, restricted to the banks recognized by the model to be impacted by volatility, the results provide clear evidence. The significance comparison is also conducted visually, with the banks arranged in a sorted manner based on their size, represented by the total asset value. This process will be carried out for all the examined variables.
In the following **Figure 2.12** are displayed the volatility results:

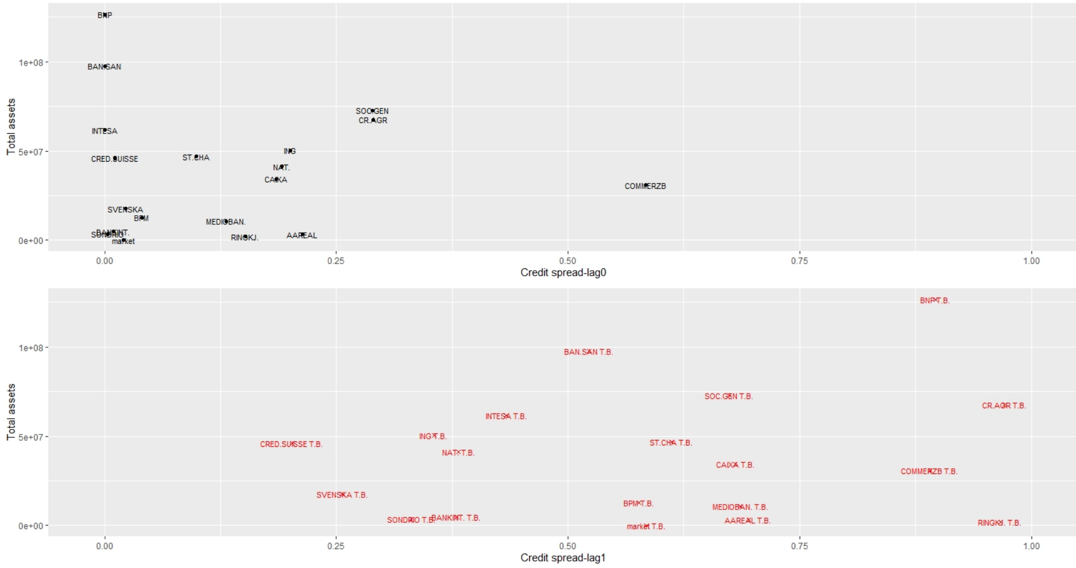
Figure 2.12: Vstoxx-value confront



Note: In the upper panel, the p-value corresponds to the LASSO algorithm, while in the lower panel, it represents the p-value of the original algorithm. In this latter case, each bank is indicated with the T.B. mark, representing the initials of the authors of the native algorithm.

The volatility level appears to have a slightly more pronounced significance when using the original model, although the differences are not particularly notable. Several factors might contribute to this observation. Firstly, the VSTOXX variable has been included in the model at a level (not differentiated), this could have influenced these results due to the persistence of memory in the series. Additionally, the *'leverage effect'* might have caused a time-lagged impact, where increased volatility preceded distress. Looking at the distibution of the significance levels, the impact is distinct, as volatility has a stronger influence on larger banks while diminishing in significance for smaller ones, which are typically less leveraged (Dávila and Walther (2020)).
The other variable in the original factor model is the sovereign yield spread. In the next **Figure 2.13** are displayed the results, in line with the previous VSTOXX analysis, concerning this variable.

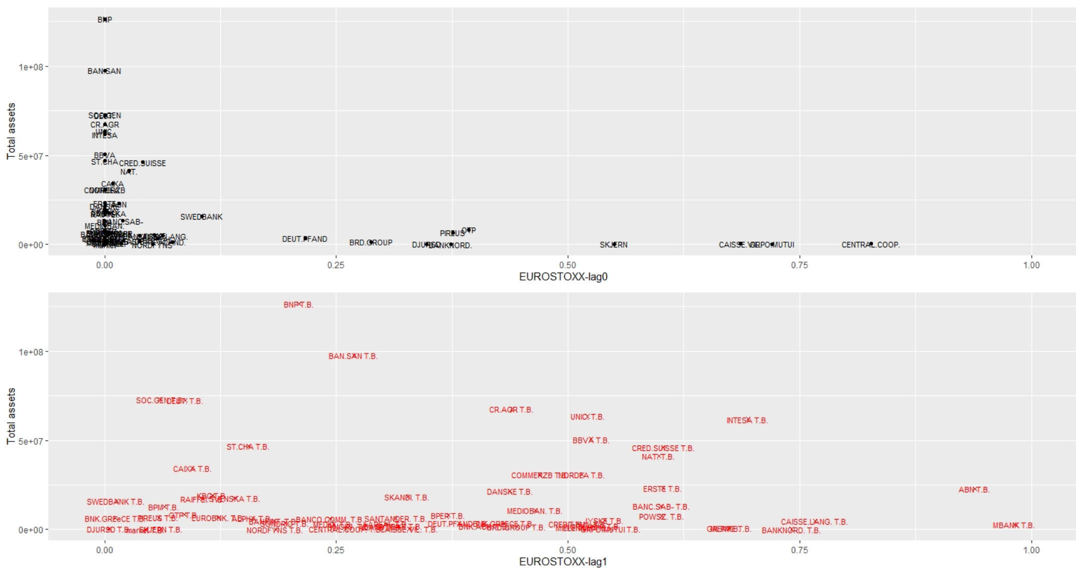
Figure 2.13: Credit-value confront



Note: In the upper panel, the p-value corresponds to the LASSO algorithm, while in the lower panel, it represents the p-value of the original algorithm. In this latter case, each bank is indicated with the T.B. mark, representing the initials of the authors of the native algorithm.

It is evident that the contemporary shock in this variable is more significant compared to the lagged one. This clearly indicates how innovations immediately impact both banks and the banking system, given the high sovereign investments of the European (plus UK and Swiss) banks. In this case, it reveals the limitation of the original model, which was structured to analyze the global banking sector, mainly dominated by US banks. The latter are not as dependent on country debts as much as the European banking sector (Hardy and Zhu (2023)), which is notably more susceptible to sovereign bond oscillations. The next **Figure 2.14** shows another highlighting result, regarding the stock market fluctuations (EUROSTOXX returns):

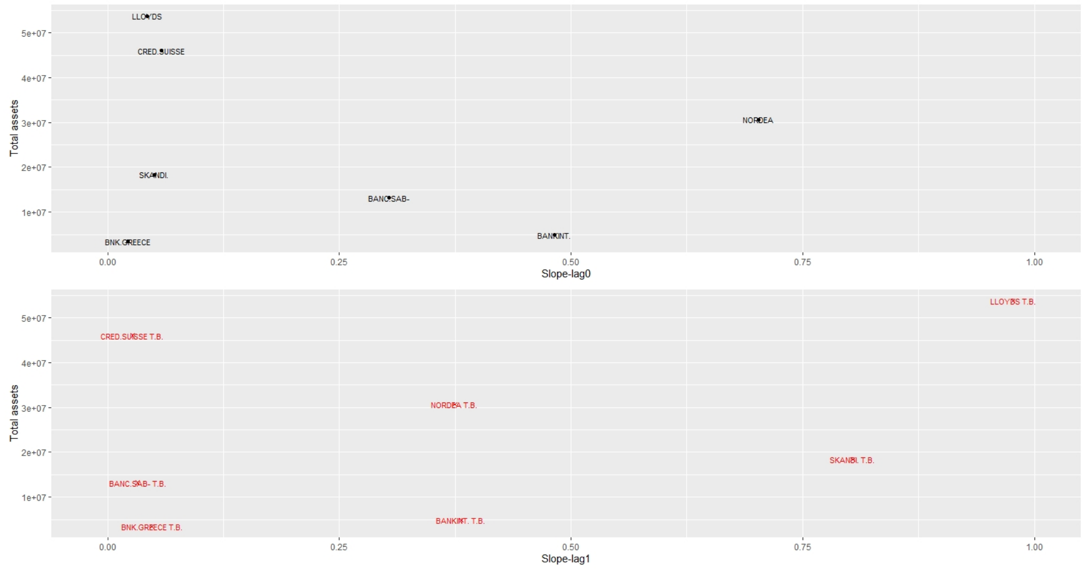
Figure 2.14: Eurostoxx-value confront



Note: In the upper panel, the p-value corresponds to the LASSO algorithm, while in the lower panel, it represents the p-value of the original algorithm. In this latter case, each bank is indicated with the T.B. mark, representing the initials of the authors of the native algorithm.

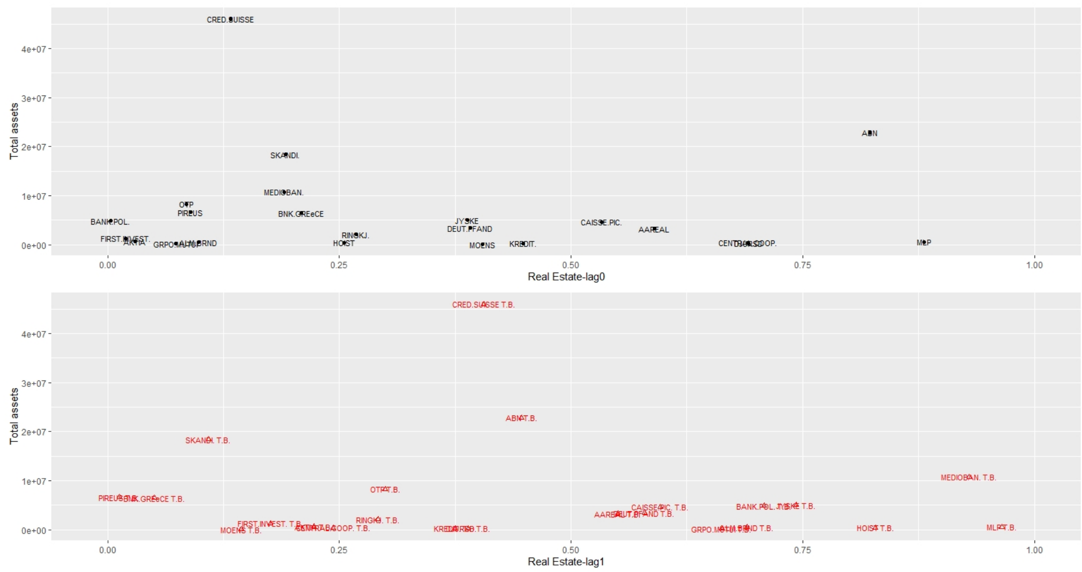
As it's visible also in this case, the contemporaneous effect greatly prevails on the lagged ones, conforting even more the goodness of the approach followed.
In the next **Figure 2.15**, **Figure 2.17** and **Figure 2.17** are shown the results for the other three variables that compose the variables set used in Tobias and Brunnermeier (2016) analysis, considering, also in this case, all the banks which have been impacted by the variables according to the LASSO approach.

Figure 2.15: Slope-value confront



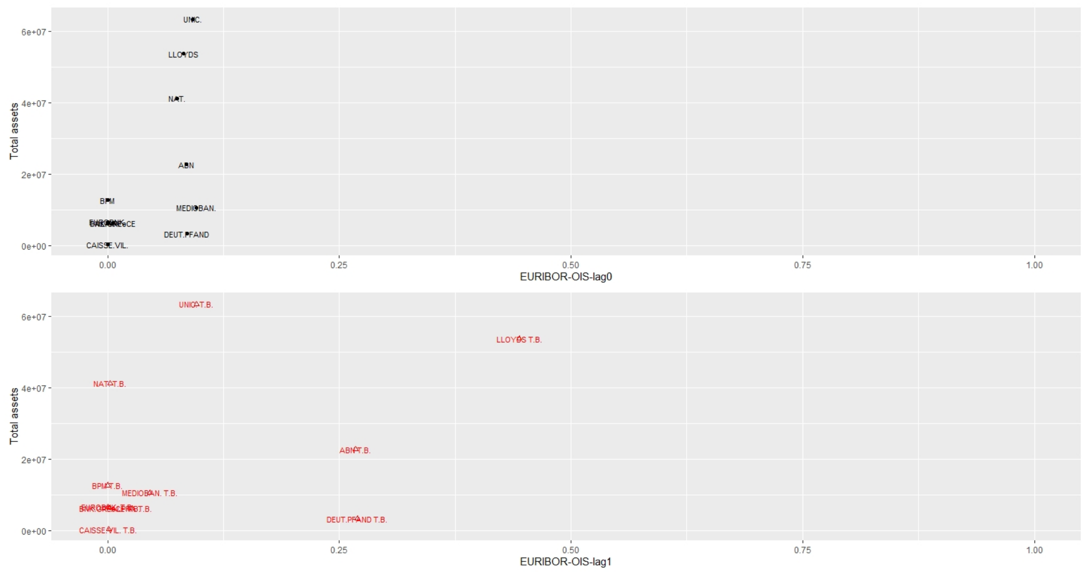
Note: In the upper panel, the p-value corresponds to the LASSO algorithm, while in the lower panel, it represents the p-value of the original algorithm. In this latter case, each bank is indicated with the T.B. mark, representing the initials of the authors of the native algorithm.

Figure 2.16: Real estate p-value confront



Note: In the upper panel, the p-value corresponds to the LASSO algorithm, while in the lower panel, it represents the p-value of the original algorithm. In this latter case, each bank is indicated with the T.B. mark, representing the initials of the authors of the native algorithm.

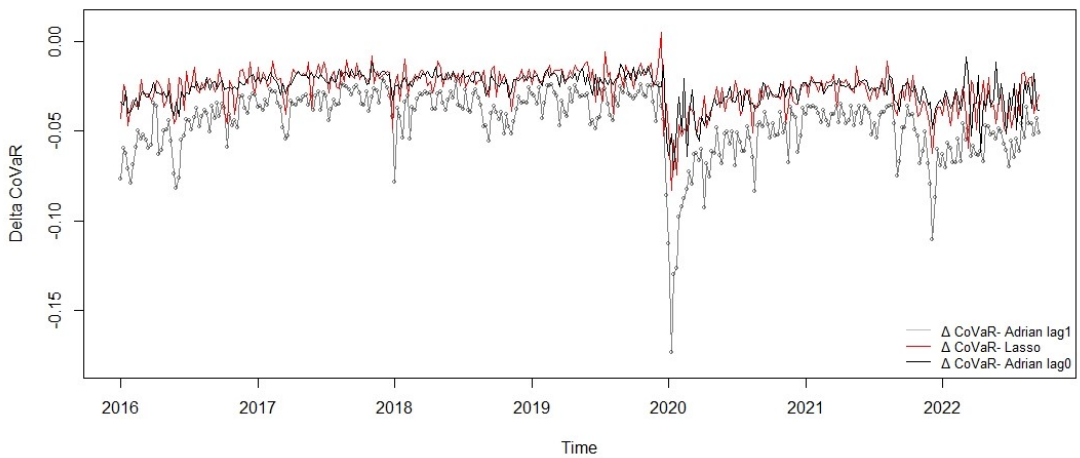
Figure 2.17: EURIBOR-OIS p-value confront



Note: In the upper panel, the p-value corresponds to the LASSO algorithm, while in the lower panel, it represents the p-value of the original algorithm. In this latter case, each bank is indicated with the T.B. mark, representing the initials of the authors of the native algorithm.

The results from these three plots are consistent with the previous findings. Specifically, in terms of the EURIBOR-OIS spread and the SLOPE variables, the shrinking approach produces more significant results, particularly for the former, which exhibits significance across all selected banks. However, different conclusions arise when examining the results for the Real-estate sector. In both models, the sector displays poor significance, despite being prominently selected by the algorithm in the banking sample, particularly for smaller banks (as highlighted in the preceding paragraphs). Further investigation is necessary for this variable, potentially influenced by EUROSTOXX returns (given the high dynamic relationship between the two markets Al Refai et al. (2021), demonstrated also by the **Figure 2.3**) or possible state-dependent variations. Indeed, the literature recognizes that the relationship between banks, stock markets, and the real estate sector is stronger during crisis periods Bessler et al. (2015)), therefore a period separation could induce a regime-shifting bias of the estimates. To conclude the paragraph, the average $\Delta CoVaR$ across the sample of banks (**Figure 2.18**) is calculated using the original model with a one-period lag and no lag of variables, along with the LASSO modification.

Figure 2.18: Average Delta Covar



The figure displays significant overlaps between the series calculated using the original model without lag and the LASSO modification. However, the $\Delta CoVaR$ computed with the original model appears to be mean-shifted, occasionally amplifying oscillations. This observation may be attributed to the poor 50% regression results in the original model, as seen in the **Appendix of results estimation**, that do not fit the median returns at all. This deduction becomes evident when examining the Pseudo-R^2 of the quantile regressions, calculated according to the method devised by Koenker and Machado (1999), that are also shown in the output tables in the **Appendix of results estimation**. To better understand the improvement in model selection, the following figures display the R^2 results for all the involved regressions, highlighting the differences between the new and original approaches.

Figure 2.19: R^2 fo VaR

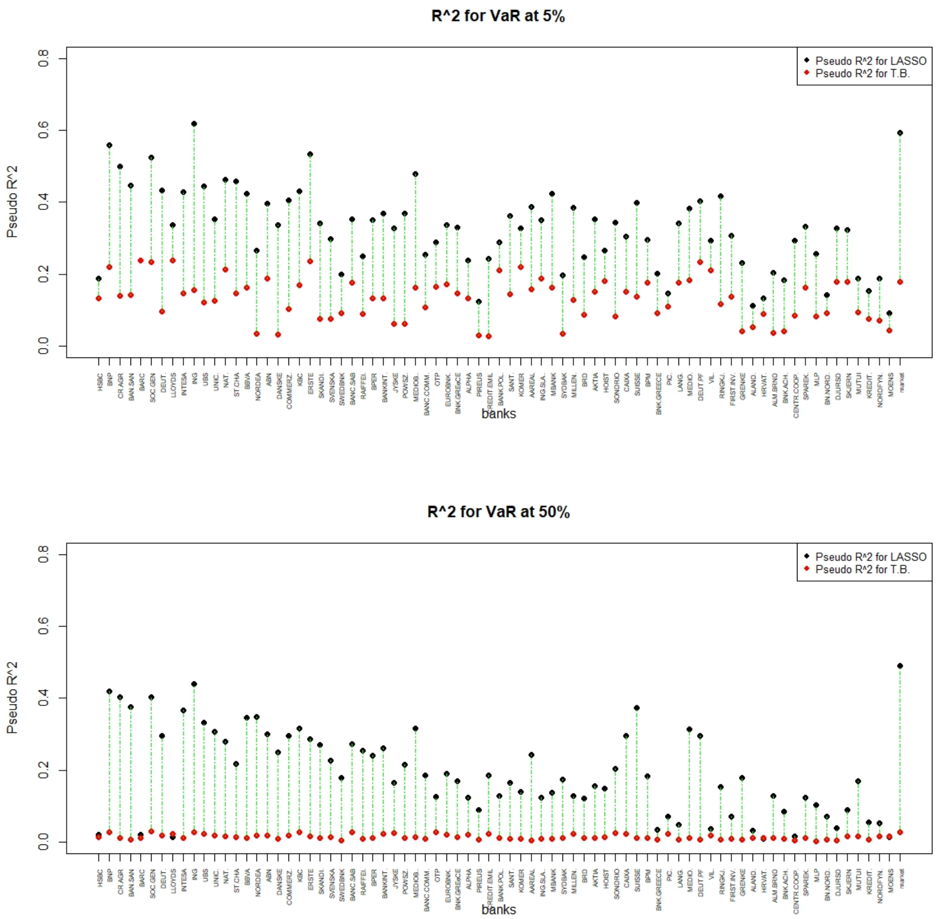
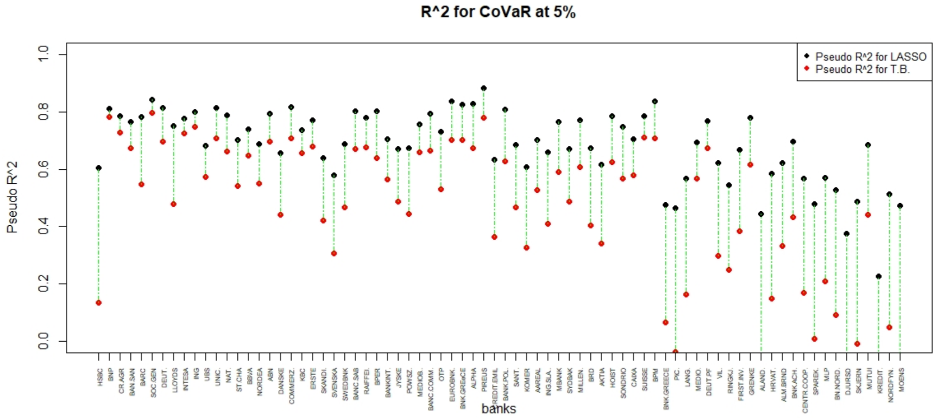
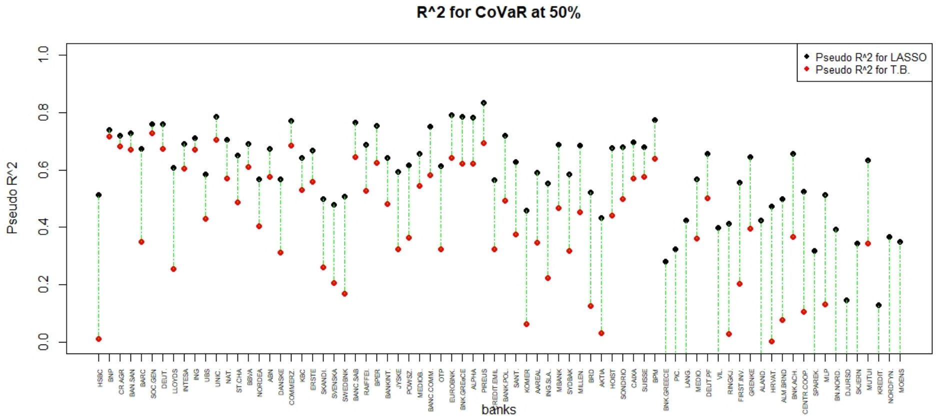


Figure 2.20: R^2 fo $CoVaR$

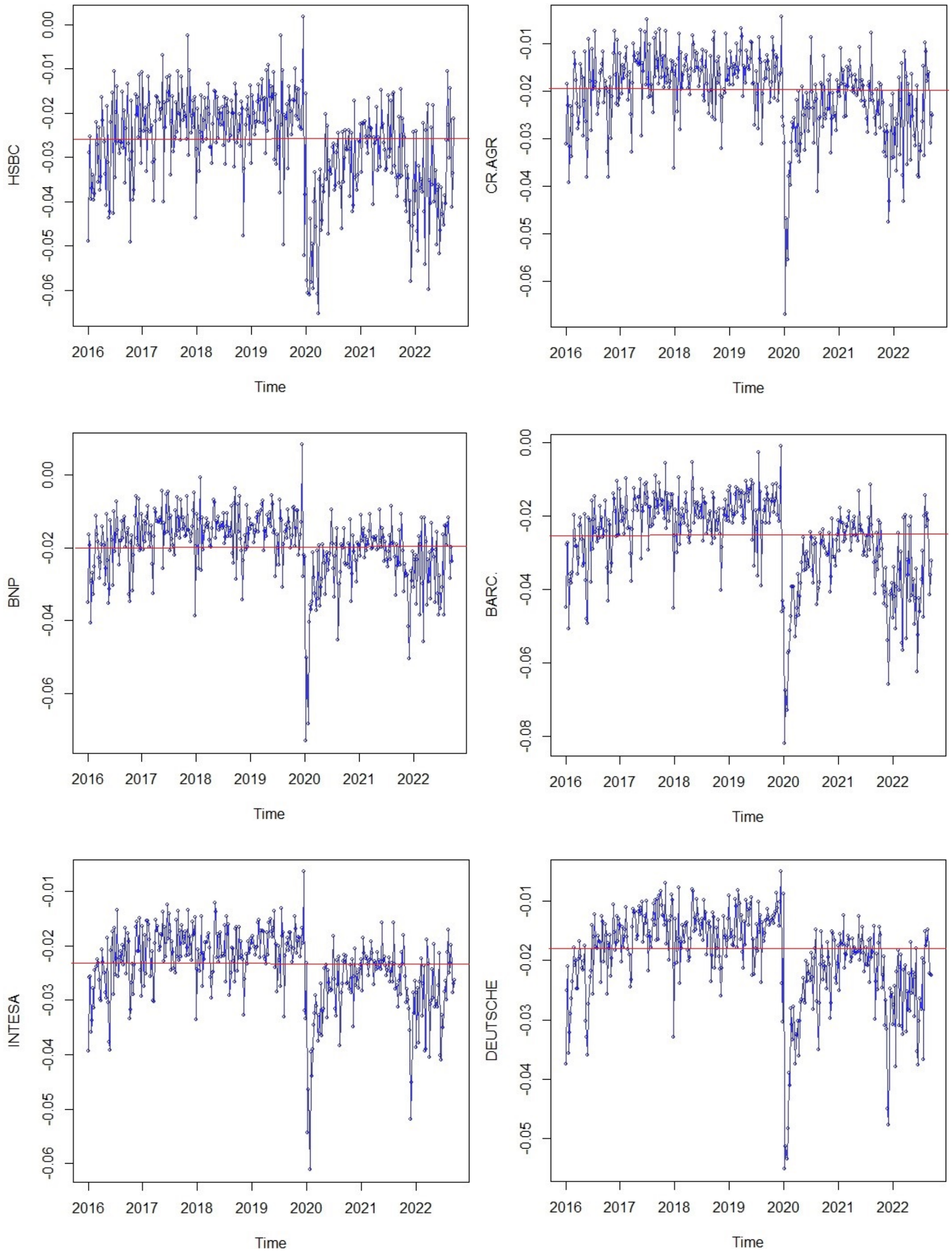




2.6.1 Systemic risk during Covid-19 plus Russian-Ukraine war turmoils

In the present paragraph will be commented the results about the behaviour of systemic contribuition in all the samle considered. Precisely, in the next **Figure 2.21** is plot the $\Delta CoVaR$ for the first six banks for total assets in the sample.

Figure 2.21: $\Delta CoVaR$ for the first 6 bigger banks



As you may have noticed, there is a clear and similar pattern in all, resembling the one in **Figure 2.18**. There is a significant spike at the beginning of 2020, coinciding with the lockdown announcements, and a less pronounced general increase in risk contribution at the start of 2022, following the outbreak of the Russian-Ukraine war.Moreover, a more persistent level of contribution is recognizable in the second crisis event, while during the COVID-19 crisis, after the surge, the level of risk contribution abruptly declined. This latter could have been dependent by the tempestive official presentation of the ECB's pandemic emergency purchase programme (PEPP)[38] and is perfectly in line with the results of Borri and Di Giorgio (2022). No real countermeasures from the ECB have been implemented for the Russian-Ukraine war; on the contrary, there have been maximum and frequent interest rate hikes that failed to address the turmoil in financial markets. Moreover, sanctions imposed to Russia have exerted great systemic impact

[38]https://www.ecb.europa.eu/mopo/implement/pepp/html/index.en.html

also for the sanctioning parties as highlighted by Qureshi et al. (2022). The other main notably aspect regards the apparent regime switching in the behaviour of the $\Delta CoVaR$ series. Indeed, after the COVID-19 outbreak a shift in the regime level of contribuiton is visible, marked qualitatively by the horizontal red lines. This clearly implies that the last systemic events have raised the warnings level perceived by the market, made the systemic globally more unstable.

2.7 Conclusion and comments

The paper proposes a comprehensive approach to disentangle the significant determinants, building on an LASSO technique that improves the original model developed by Tobias and Brunnermeier (2016). The results offer valuable insights for a better understanding of the origins of crisis events in the banking sector. The role of volatility and market uncertainty, along with the sovereign yield as a fundamental driver, remains central to banking instabilities, even after the sovereign crisis of 2011. Additionally, new warning factors have been discovered, including the significant role of Gold price oscillations in determining both banks and system stability. Gold's status as a *'safe haven'* for financial players and monetary policy makers underscores its importance as an essential barometer of the state of the economy, providing anticipatory information also for the bank stability. This study could also prove useful for banking regulations. It highlights the significance of interconnectedness within and across financial intermediary markets, emphasizing the need to pay attention not only to the banking sector but also to other segments of the financial market. Furthermore, the role of volatility reinforces the importance of leveraging constraints provided by the Basel III accords. Attention must be focused on the connection between banks and countries through the sovereign bonds channel. According to Altavilla et al. (2017), this element could act as a catalyst for systemic turmoil, particularly due to excessive reliance, especially for less capitalized banks, on these instruments. This raises the necessity of reconsidering prudential regulations, as country exposures are still currently regarded as *'risk-free'*, and there are no concentration limits on their holdings on Banking Supervision (2017).
In conclusion, it has been demonstrated that there has been a structural change in the systemic risk (**Figure 2.21** and **Figure 2.18**) of banks, rendering them more prone to threatening the system. Regulators need to pay careful attention to this element, as the effects resulting from higher margins, due to an increase in interest rates, may soon prove insufficient to offset the materialization of this risk.
Future improvements of this model will involve expanding the sample dataset to ensure a more uniform representation of all European countries. Additionally, the construction of a policy tool based on these findings will be provided, considering the work of Del Vecchio et al. (2022), which enhances the $CoVaR$ analysis to align more closely with regulatory guidelines in this field.

Mathematical appendix

The tail dependence is an extreme value theory (EVT) concept (McNeil et al., 2015) that has been widely used to study the multivariate relationships in the extreme tails of the distributions of the involved variables, both empirically and theoretically. Bivariate tail dependence is expressed by the following two expressions:

$$\lambda_u = \lim_{q \to 0^+} Pr(X_2 > F_2^{\leftarrow}(q) | X_1 > F_1^{\leftarrow}(q)) \tag{2.20}$$

$$\lambda_l = \lim_{q \to 1^-} Pr(X_2 \leq F_2^{\leftarrow}(q) | X_1 \leq F_1^{\leftarrow}(q)) \tag{2.21}$$

Where λ_u and λ_l represent the upper and lower tail coefficients, respectively, while $F_{\cdot}^{\leftarrow}(q)$ represents the inverse of the cumulative distribution function. With regards to Figure 2.4 the shown quantity have been estimated using the empirical bivariate copula (Deheuvels, 1979), which is defined as the discrete function C_n given by:

$$C_n\left(\frac{i}{n}, \frac{j}{n}\right) = \frac{\#\left\{x_1, x_2 | x_1 \leq x_1^{(i)} \cup x_2 \leq x_2^{(j)}\right\}}{n} \tag{2.22}$$

Where $x_{\cdot}^{(i)}$ is the order statistics (the ith smallest value) of the sample and # provides the cardinality of the subsequent set. In this way it's straightforward:

$$\lambda_l = \frac{C_n\left(q, q\right)}{q}; \lambda_u = \frac{C_n\left(1-q, 1-q\right)}{1-q} \tag{2.23}$$

List and figure appendix

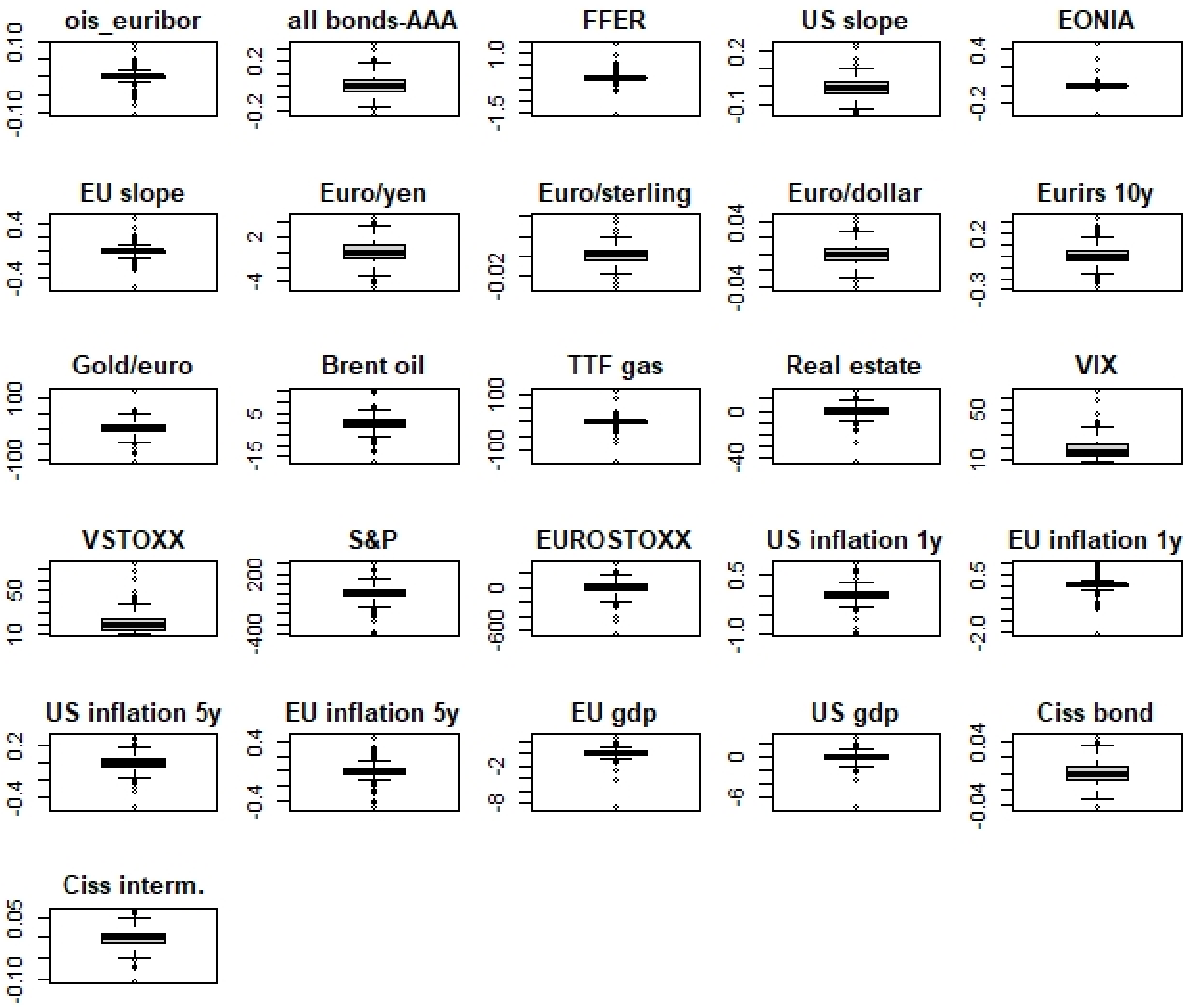
Table 2.12: Financial institutions sample

Name	Abbreviation	Country	Specialisation
HSBC holdings PLC	HSBC	UK	Commercial bank
Bnp Paribas	BNP	France	Commercial bank
Credit Agricole SA	CR.ACGR	France	Cooperative bank
Banco Santander SA	BAN.SAN	Spain	Commercial bank
Barclays PLC	BARC	UK	Commercial bank
Societe Generale	SOC.GEN	France	Commercial bank
Deutsche bank ag	DEUT	Germany	Commercial bank
Lloyds banking group PLC	LLOYDS	UK	Commercial bank
Intesa Sanpaolo	INTESA	Italy	Commercial bank
ING groep NV	ING	Netherlands	Commercial bank
UBS group AG	UBS	Switzerland	Commercial bank
Unicredit spa	UNIC	Italy	Commercial bank
Natwest group PLC	NAT	UK	Commercial bank
Standard Chartered PLC	ST.CHA	UK	Commercial bank
Banco bilbao vizcaya argentaria sa	BBVA	Spain	Commercial bank

Nordea bank ABP	NORDEA	Finland	Commercial bank
ABN Amro bank NV	ABN	Netherlands	Commercial bank
Danske bank AS	DANSKE	Finland	Commercial bank
Commerzbank AG	CBK.DE	Germany	Commercial bank
KBC groep NV	KBC	Belgium	Commercial bank
ERSTE groep bank AG	ERSTE	Austria	Commercial bank
Skandinaviska enskilda banken AB	SKANDI	Sweden	Commercial bank
Swedbank AB	SWED.	Sweden	Commercial bank
Banco de sabadell sa	BANC.SAB	Spain	Commercial bank
Raiffeisen bank international ag	RAIF	Austria	Cooperative bank
Bper banca SPA	BPER	Italy	Commercial bank
Bankinter SA	BANKINT	Spain	Commercial bank
Jyske bank AS	JYSKE	Denmark	Commercial bank
Powszechna kasa oszczednosci bank polski SA	POWSZ	Poland	Commercial bank
Mediobanca SPA	MEDIOB	Italy	Commercial bank
Banco commercial portugues SA	COMM.P	Portugal	Commercial bank
OTP bank PLC	OTP	Hungary	Commercial bank
Eurobank ergasias SA	EUR.BNK	Greece	Commercial bank
National bank of greece SA	BNK.GRE	Greece	Commercial bank
Piraeus financial holdings SA	PIREUS	Greece	Commercial bank
Alpha SA	ALPHA	Greece	Commercial bank
Credito emiliano spa	CRED.MI	Italy	Cooperative bank
Bank polska kasa optieki SA	BNK.POL	poland	commercial bank
Santander bank polska	SAN	Poland	commercial bank
Komercni	KOMER	Czech	commercial bank
Aareal bank ag	AAREAL	Germany	Real.Est and mortgage inst.
Ing Bank Slaski S.A. p capital group	ING.SLA	Poland	Commercial bank
Mbank SA	MBANK	Poland	Commercial bank
Sydbank	SYDBNK	Sweden	Commercial bank
Bank millenium	MILLEN	Poland	Commercial bank
BRD groupe societe generale SA	BRD	Romania	Cooperative bank
Aktia bank plc	AKTIA	Finland	Commercial bank
Hoist bank PLC	HOIST	Serbia	Commercial bank
Banca popolare di sondrio SPA	SONDRIO	Italy	Commercial bank
Caixa bank S.A.	CAIXA	Spain	Commercial bank
Credit suisse group ag	SUISSE	Switzerland	Commercial bank
Banco bpm SA	BPM	Italy	Commercial bank
Bank of greece	BNK.GREECE	Greece	Commercial bank
CRCAM brie picardie SC	PC	France	Cooperative bank
CRCAM du languedoc SC	LANG	France	Cooperative bank
Banca mediolanum	MEDIO	Italy	Coommercial bank
Deutsche pfandriefbank AG	DEYT.PF	Germany	Coommercial bank

CRCAM de l'ille et vilaine SA	VIL.	France	Cooperative bank
Ringkjobing landbobank aktieselskab	RINGKJ	Denmark	Commercial bank
First Investment bank AD	FIRST.INV	Finland	Commercial bank
Grenke AG	GRENKE	Deutshland	Cooperative bank
Alandsbanken abp	ALAND	Finland	Commercial bank
Hrvatska postanska bank DD	HRVAT.	Hungary	Commercial bank
Alm. Brand A.S	ALM.BRD	Denmark	Commercial bank
Bank ochrony SrodowiskaRODOWISKA SA-BOS SA	BNK.ACH	Poland	Cooperative bank
Central Cooperative bank AD	CENTR.COOP	Bulgary	Cooperative bank
Sparekassen Sjalland-Fyn A/S	SPAREk	denmark	Commercial bank
MLP.SE	MLP	Denmark	Commercial bank
Banknordik P/F	BN.NORD.	Denmark	Commercial bank
Djurslands Bank A/S	DJURSD	Denmark	Commercial bank
Skjern bank A/S	SKJERN	Denmark	Commercial bank
Gruppo mutuionline SPA	MUTUI	Italy	Private bank
kreditbanken A/S	KREDIT	Denmark	Commercial bank
Nordfyns bank A/S	NORDFYN	Denmark	Commercial bank
Moens bank A/S	MOENS	Denmark	Commercial bank

Figure 2.22: Covariates box plots



Appendix of Results estimation

For the table in this section, the initials T.B. stands for Tobias and Brunnermeier. Therefore, the output according to the original model are market with these initals. The other results, not marked, reported with the words 'Post-penalized' refer to the LASSO algorithm

Table 2.13: Post penalized quantile regression for VaR at 5%

	HSBC	BNP	CR.AGR	BAN.SAN	BARC	SOC.GEN	DEUT.	LLOYDS	INTESA	ING	UBS	UNIC.	NAT.	ST.CHA	BBVA	NORDEA	ABN	DANSKE	CBK.DE	KBC
(Inte.)	-0.0505^{***}	-0.0427^{***}	-0.0437^{***}	-0.0454^{***}	-0.0699^{***}	-0.0541^{***}	-0.0669^{***}	-0.0594^{***}	-0.0515^{***}	-0.0376^{***}	-0.0406^{***}	-0.0749^{***}	-0.0529^{***}	-0.0485^{***}	-0.0565^{***}	-0.0529^{***}	-0.0549^{***}	-0.0533^{***}	-0.0729^{***}	-0.0452^{***}
	(0.0039)	(0.0032)	(0.0048)	(0.0045)	(0.0089)	(0.0052)	(0.0041)	(0.0060)	(0.0059)	(0.0027)	(0.0040)	(0.0064)	(0.0067)	(0.0028)	(0.0042)	(0.0075)	(0.0057)	(0.0037)	(0.0064)	(0.0035)
EUR-OIS								-0.0115°	-0.0102^{*}			-0.0108^{*}	-0.0074°				-0.0090^{*}			
								(0.0070)	(0.0047)			(0.0065)	(0.0048)				(0.0049)			
CRE		-0.0856^{***}	-0.0417	-0.1175^{***}		-0.0591			-0.1273^{***}	-0.0447°			-0.0662°	-0.0368^{*}					-0.0367	
		(0.0248)	(0.0359)	(0.0372)		(0.0575)			(0.0370)	(0.0346)			(0.0447)	(0.0219)					(0.0726)	
EFFR	0.1055^{***}							0.0118												
	(0.0190)							(0.0665)												
TED		-0.0271^{*}					-0.0199													
		(0.0158)					(0.0194)													
US.SLOPE																		0.0553^{*}		
																		(0.0326)		
EONIA																				
SLOPE								0.1361^{**}								0.0202				
								(0.0627)								(0.0630)				
EUR/£								-0.9890^{**}				-1.2490^{**}	-1.4734^{**}							
								(0.5033)				(0.5659)	(0.7110)							
EURO/$	-0.0077									0.2801					0.3677					
	(0.3947)									(0.2605)					(0.3963)					
EURIRS										0.0728^{*}				0.1038^{***}					0.1340^{*}	0.1534^{***}
										(0.0419)				(0.0370)					(0.0750)	(0.0471)
GOLD	-0.3744^{*}		-0.8772^{***}		-0.6875^{*}	-0.5039^{*}	-0.6264^{**}	-0.9469^{***}		-0.7671^{***}		-1.0426^{**}	-0.4106°						-0.6212^{***}	
	(0.2075)		(0.3178)		(0.3941)	(0.3050)	(0.3003)	(0.2359)		(0.1951)		(0.4401)	(0.3036)						(0.2344)	
OIL		0.0964^{*}											0.1861^{**}	0.0622^{*}						
		(0.0583)											(0.0830)	(0.0372)						
GAS							-0.0364													
							(0.0297)													
Real.est.																	0.0774			
																	(0.3513)			
VIX																				

	HSBC	BNP	CR.AGR	BAN.SAN	BARC	SOC.GEN	DEUT.	LLOYDS	INTESA	ING	UBS	UNIC.	NAT.	ST.CHA	BBVA	NORDEA	ABN	DANSKE	CBK.DE.	KBC
VSTOXX	-0.0424^{***}	-0.0309^{***}	-0.0328^{***}	-0.0317^{***}	-0.0990^{***}	-0.0457^{***}	-0.0189°	-0.0859^{***}	-0.0503^{***}	-0.0452^{***}		-0.0419^{**}	-0.0317^{*}	-0.0373^{***}	-0.0413^{***}		-0.0436^{*}		-0.0377^{*}	-0.0529^{***}
	(0.0157)	(0.0104)	(0.0116)	(0.0101)	(0.0247)	(0.0175)	(0.0137)	(0.0212)	(0.0164)	(0.0094)		(0.0201)	(0.0164)	(0.0083)	(0.0154)		(0.0250)		(0.0193)	(0.0142)
S&P							0.1175													
							(0.2396)													
EURO.XX		1.4531^{***}	1.2132^{***}	0.9334^{***}		1.5277^{***}	1.4435^{***}		1.5396^{***}	1.1636^{***}	1.1507^{***}	1.4209^{***}	0.6178^{**}	0.6352^{***}	0.8966^{***}	0.9706^{***}	0.8807^{***}	0.6960^{***}	1.1074^{***}	0.9914^{***}
		(0.1703)	(0.1752)	(0.1862)		(0.2406)	(0.2664)		(0.2439)	(0.1368)	(0.1094)	(0.2996)	(0.2742)	(0.0858)	(0.2581)	(0.1613)	(0.3178)	(0.1057)	(0.2032)	(0.1356)
US.H.1y																				
EU.H.1y																				
US.H.5y																				
EU.H.5y													0.0802							
													(0.1167)							
EU.GDP		0.5276	0.6958	-0.0897						0.7217^{*}						0.9605°	0.3321	1.3878^{***}		
		(0.5252)	(0.6697)	(0.6330)						(0.4351)						(0.7356)	(0.7420)	(0.4670)		
BOND																				
INTERM.		-0.0256°				-0.0299	-0.0563^{***}			-0.0212°								-0.0170		
		(0.0189)				(0.0274)	(0.0174)			(0.0145)								(0.0196)		
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.19	0.56	0.5	0.45	0.24	0.53	0.43	0.34	0.43	0.62	0.44	0.35	0.46	0.46	0.42	0.27	0.4	0.34	0.41	0.43

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.14: Post penalized quantile regression for VaR at 5% (cont)

	ERSTE	SKANDI.	SVENSKA	SWED.	BANC.SAB	RAIF.	BPER	BANKINT.	JYSKE	POWSZ.	MEDIOB..	COMM.P	OTP	EUR.BNK.	BNK.GRE.	ALPHA	PIREUS	CRED.EMI.	BNK.POL.	SANT.
(Intercept)	-0.0465^{***}	-0.0385^{***}	-0.0395^{***}	-0.0459^{***}	-0.0705^{***}	-0.0678^{***}	-0.0821^{***}	-0.0450^{***}	-0.0508^{***}	-0.0492^{***}	-0.0514^{***}	-0.0875^{***}	-0.0610^{***}	-0.1024^{***}	-0.0978^{***}	-0.0921^{***}	-0.1604^{***}	-0.0485^{***}	-0.0942^{***}	-0.0548^{***}
	(0.0035)	(0.0042)	(0.0034)	(0.0068)	(0.0058)	(0.0097)	(0.0065)	(0.0033)	(0.0038)	(0.0040)	(0.0048)	(0.0079)	(0.0081)	(0.0082)	(0.0074)	(0.0072)	(0.0203)	(0.0040)	(0.0096)	(0.0033)
EUR-OIS											-0.0091^{*}			-0.0363^{***}	-0.0179^{**}	-0.0275^{***}				
											(0.0045)			(0.0067)	(0.0073)	(0.0066)				
CRE			-0.0740^{**}					-0.0993^{***}			-0.0775^{*}									
			(0.0289)					(0.0354)			(0.0380)									
EFFR				0.0304																
				(0.0631)																
TED					-0.0221°															

	ERSTE	SKANDI.	SVENSKA	SWED.	BANC.SAB	RAIF.	BPER	BANKINT.	JYSKE	POWSZ.	MEDIOB..	COMM.P	OTP	EUR.BNK.	BNK.GRE.	ALPHA	PIREUS	CRED.EMI.	BNK.POL.	SANT.
					(0.0161)															
US.SLOPE																				
EONIA										−0.0236										
										(0.0611)										
SLOPE		0.0732**			0.0767			0.0310												
		(0.0335)			(0.0811)			(0.0461)												
EUR/£																				
EURO/$	0.4441				0.9647**					1.0090***										
	(0.3738)				(0.4407)					(0.3645)										
EURIRS							0.2803***							0.0832				0.0906**		
							(0.0452)							(0.0784)				(0.0412)		
GOLD	−0.4840*						−0.9227***					−0.6415°		−1.5673***	−0.5381*					
	(0.2673)						(0.3380)					(0.4300)		(0.5506)	(0.2832)					
OIL	0.1086°		0.0224								0.1522°									
	(0.0708)		(0.0890)								(0.1148)									
GAS	−0.0210				−0.0810°				−0.0098	−0.0208										
	(0.0328)				(0.0594)				(0.0226)	(0.0469)										
Real.Est.		0.2046°							0.1877		0.3158		0.6036*		0.5081°		1.5320°		1.4460***	
		(0.1544)							(0.2123)		(0.2517)		(0.3390)		(0.3428)		(0.9861)		(0.4637)	
VIX																				
VSTOXX	−0.0373***	−0.0147°	−0.0093	−0.0292**	−0.0384***	−0.0085	−0.0443**	−0.0423***	−0.0312***	−0.0225°	−0.0213°	−0.0059	−0.0556**			−0.0535*		−0.0339**	−0.0432	−0.0558***
	(0.0131)	(0.0095)	(0.0117)	(0.0137)	(0.0135)	(0.0215)	(0.0173)	(0.0136)	(0.0104)	(0.0154)	(0.0147)	(0.0175)	(0.0256)			(0.0238)		(0.0148)	(0.0361)	(0.0140)
S&P									−0.0367											
									(0.2961)											
EURO.XX	0.9039***	0.5614***	0.6210***	0.4071°	0.7552***	1.5039***	1.0645***	0.4239**	0.5234**	0.6379***	1.0386***	0.9075***	0.4426	1.3792***	1.0470***	0.8027***	0.6725	0.7572***		0.4632***
	(0.1544)	(0.1622)	(0.1862)	(0.2900)	(0.2899)	(0.3640)	(0.2821)	(0.2026)	(0.2603)	(0.1563)	(0.2880)	(0.3052)	(0.5150)	(0.2810)	(0.3513)	(0.2391)	(0.7696)	(0.1769)		(0.1718)
US.H.1y																			0.1205	
																			(0.1368)	
EU.H.1y																				
US.H.5y				0.1235					−0.2018**											
				(0.1215)					(0.0972)											
EU.H.5y						−0.2208°													0.1998	
						(0.1599)													(0.2661)	
EU.GDP	0.9673*		−0.0075							0.6769	0.3501									
	(0.5680)		(0.5411)							(0.6219)	(0.7373)									
US.GDP		0.1965						0.2088												0.9399*
		(0.2563)						(0.5708)												(0.5095)
BOND															−0.0465°					

	ERSTE	SKANDI.	SVENSKA	SWED.	BANC.SAB	RAIF.	BPER	BANKINT.	JYSKE	POWSZ.	MEDIOB..	COMM.P	OTP	EUR.BNK.	BNK.GRE.	ALPHA	PIREUS	CRED.EMI.	BNK.POL.	SANT.
															(0.0338)					
INTERM.					-0.0327°							-0.1044^{***}		-0.0400						
					(0.0245)							(0.0364)		(0.0330)						
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.53	0.34	0.3	0.2	0.35	0.25	0.35	0.37	0.33	0.37	0.48	0.25	0.29	0.34	0.33	0.24	0.12	0.24	0.29	0.36

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.15: Post penalized quantile regression for VaR at 5% (cont)

	KOMER	AAREAL	ING.SLA..	MBANK	SYDBAK	MILLEN.	BRD	AKTIA	HOIST	SONDRIO	CAIXA	SUISSE	BPM	BNK.GREECE	PIC.	LANG.	MEDIO.	DEUT.PF	VIL.
(Intercept)	-0.0433^{***}	-0.0462^{***}	-0.0464^{***}	-0.0706^{***}	-0.0505^{***}	-0.0697^{***}	-0.0554^{***}	-0.0384^{***}	-0.0741^{***}	-0.0652^{***}	-0.0560^{***}	-0.0485^{***}	-0.0991^{***}	-0.0353^{***}	-0.0412^{***}	-0.0418^{***}	-0.0410^{***}	-0.0555^{***}	-0.0503^{***}
	(0.0028)	(0.0048)	(0.0059)	(0.0043)	(0.0050)	(0.0050)	(0.0062)	(0.0032)	(0.0083)	(0.0051)	(0.0046)	(0.0071)	(0.0078)	(0.0036)	(0.0045)	(0.0028)	(0.0056)	(0.0056)	(0.0042)
EUR-OIS													-0.0272^{***}					-0.0074^{*}	0.0179^{***}
													(0.0057)					(0.0036)	(0.0051)
CRE		-0.0455								-0.1105^{***}	-0.0535°	-0.1577^{***}	-0.1425^{**}						
		(0.0372)								(0.0338)	(0.0364)	(0.0582)	(0.0690)						
EFFR																			
TED						-0.0121										-0.0159			
						(0.0284)										(0.0142)			
US.SLOPE																			
EONIA			-0.1197^{*}																
			(0.0658)																
SLOPE												0.1020^{*}		0.0821^{**}					
												(0.0566)		(0.0356)					
Eur/£																			
EURO/$	0.1864		1.0671^{**}	1.8824^{***}		2.1573^{***}													
	(0.3186)		(0.4901)	(0.2906)		(0.3877)													
EURIRS																			
GOLD	-0.3049^{**}												-0.6758°		0.5181°		-0.4697^{*}		
	(0.1720)												(0.4847)		(0.3287)		(0.2463)		
OIL		0.1834^{**}	0.1184°																
		(0.0821)	(0.0765)																
GAS																			

	KOMER	AAREAL	ING.SLA..	MBANK	SYDBAK	MILLEN.	BRD	AKTIA	HOIST	SONDRIO	CAIXA	SUISSE	BPM	BNK.GREECE	PIC.	LANG.	MEDIO.	DEUT.PF	VIL.
REAL.EST.		0.1889						0.3174^{**}	0.4318			0.4260°			0.1022			0.2091	
		(0.3230)						(0.1409)	(0.4742)			(0.3274)			(0.1678)			(0.2512)	
VIX																			
VSTOXX	-0.0573^{***}	-0.0328°	-0.0268^{**}	-0.0985^{***}	-0.0179	-0.0928^{***}	-0.0346^{**}	-0.0164^{*}	-0.0549^{*}	-0.0350^{**}	-0.0148	-0.0408^{*}		-0.0167^{**}	-0.0352^{**}	-0.0367^{***}	-0.0324^{*}	-0.0705^{***}	-0.0601^{***}
	(0.0091)	(0.0226)	(0.0136)	(0.0162)	(0.0157)	(0.0172)	(0.0148)	(0.0086)	(0.0243)	(0.0164)	(0.0164)	(0.0222)		(0.0084)	(0.0139)	(0.0099)	(0.0157)	(0.0219)	(0.0131)
S&P							0.7525°	0.2601°										0.6471^{**}	
							(0.4620)	(0.1781)										(0.2796)	
EURO.XX		0.5435^{*}	0.5028^{**}	0.8838^{***}	0.5600^{**}	0.6919^{***}	0.3233			0.8841^{***}	0.6984^{**}	1.0199^{**}	1.7856^{***}	0.4578^{***}		0.3042^{*}	1.0921^{***}	0.3744	0.0765
		(0.3041)	(0.1973)	(0.1716)	(0.2638)	(0.1758)	(0.2882)			(0.2140)	(0.2726)	(0.4643)	(0.2510)	(0.1069)		(0.1600)	(0.1748)	(0.3159)	(0.2037)
US.HICP.1y	-0.1038^{**}				-0.0289						-0.1122^{*}								
	(0.0441)				(0.0581)						(0.0648)								
EU.HICP.1y																			
US.HICP.5y		-0.3262^{**}						-0.2216^{***}	-0.3456°										
		(0.1626)						(0.0750)	(0.2428)										
EU.HICP.5y																			
EU.GDP					0.1175			0.2381		1.0043°						0.5392°	1.1650^{*}		1.0177^{*}
					(0.7463)			(0.5072)		(0.7225)						(0.3873)	(0.6670)		(0.5826)
US.GDP									0.4275										
									(1.1815)										
BOND				-0.0361^{***}						-0.0316°									
				(0.0121)						(0.0215)									
INTERM.											-0.0395°	0.0052							
											(0.0243)	(0.0301)							
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.33	0.39	0.35	0.42	0.2	0.38	0.25	0.35	0.27	0.34	0.3	0.4	0.3	0.2	0.15	0.34	0.38	0.4	0.29

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.16: Post penalized quantile regression for VaR at 5% (cont)

	RINGKJ.	FIRST.INV.	GRENKE	ALAND.	HRVAT.	ALM.BRND	BNK.ACH.	CENTR.COOP.	SPAREK.	MLP	BN.NORD.	DJURSD	SKJERN	MUTUI	KREDIT.	NORDFYN.	MOENS	market
(Intercept)	-0.0323^{***}	-0.0582^{***}	-0.0683^{***}	-0.0406^{***}	-0.0538^{***}	-0.0493^{***}	-0.0781^{***}	-0.0480^{***}	-0.0314^{***}	-0.0424^{***}	-0.0353^{***}	-0.0289^{***}	-0.0334^{***}	-0.0628^{***}	-0.0266^{***}	-0.0384^{***}	-0.0398^{***}	-0.0275^{***}
	(0.0026)	(0.0049)	(0.0063)	(0.0029)	(0.0053)	(0.0046)	(0.0066)	(0.0028)	(0.0034)	(0.0041)	(0.0052)	(0.0022)	(0.0030)	(0.0059)	(0.0023)	(0.0039)	(0.0050)	(0.0021)
EUR-OIS																		

	RINGKJ.	FIRST.INV.	GRENKE	ALAND.	HRVAT.	ALM.BRND	BNK.ACH.	CENTR.COOP.	SPAREK.	MLP	BN.NORD.	DJURSD	SKJERN	MUTUI	KREDIT.	NORDFYN.	MOENS	market
CRE	−0.0447*																	−0.0515**
	(0.0265)																	(0.0215)
EFFR																		
TED			−0.0812*			−0.0072												
			(0.0451)			(0.0211)												
US.SLOPE																		
EONIA																		
SLOPE																		
EUR/£																		
EURO/$								0.6884***										
								(0.2624)										
EURIRS																		
GOLD																		−0.2235°
																		(0.1380)
OIL					0.1067**						0.0130							
					(0.0529)						(0.0643)							
GAS				−0.0143					−0.0509**									
				(0.0212)					(0.0252)									
REAL.EST.	0.1552	0.5312**				0.3472*		0.0613		−0.0507		0.0521		0.6273*	0.1019		0.1519	
	(0.1363)	(0.2253)				(0.1980)		(0.1394)		(0.3442)		(0.1184)		(0.3642)	(0.1377)		(0.2009)	
VIX																		
VSTOXX	−0.0239***	−0.0120	−0.0529**	−0.0017				−0.0156*	−0.0222**	−0.0342***	−0.0130	−0.0267***	−0.0224**	−0.0287°	−0.0101		−0.0213*	−0.0324***
	(0.0066)	(0.0131)	(0.0243)	(0.0073)				(0.0084)	(0.0088)	(0.0114)	(0.0128)	(0.0063)	(0.0100)	(0.0209)	(0.0102)		(0.0122)	(0.0095)
S&P		0.1660				0.3236°			0.4427***	0.0502	−0.0370	0.2340°	0.1448			0.2141°	0.0458	
		(0.2654)				(0.2054)			(0.0806)	(0.2544)	(0.2352)	(0.1647)	(0.1498)			(0.1422)	(0.1892)	
EURO.XX	0.4150***		0.9150***	0.3304*			0.8960***	0.0235		0.6719**	0.2375	0.1063	0.0811	0.1218		0.2998**		0.8311***
	(0.1228)		(0.2576)	(0.1807)			(0.2049)	(0.1023)		(0.2645)	(0.2862)	(0.1209)	(0.1301)	(0.3403)		(0.1382)		(0.1463)
US.HICP.1y	−0.0386								−0.0140		−0.0568							
	(0.0309)								(0.0539)		(0.0935)							
EU.HICP.1y																		
US.HICP.5y		−0.0930			−0.1071				−0.2099**				−0.1747**	−0.2079°			−0.1803*	
		(0.1454)			(0.1356)				(0.0981)				(0.0853)	(0.1569)			(0.1051)	
EU.HICP.5y		−0.2246**				0.0127												

	RINGKJ.	FIRST.INV.	GRENKE	ALAND.	HRVAT.	ALM.BRND	BNK.ACH.	CENTR.COOP.	SPAREK.	MLP	BN.NORD.	DJURSD	SKJERN	MUTUI	KREDIT.	NORDFYN.	MOENS	market
		(0.0893)				(0.0650)												
EU.GDP	-0.3128		-0.1140	0.0019	1.6006^{**}	0.4365	0.6764	1.6529^{***}			0.0680	-0.2113				0.4095		
	(0.3363)		(0.9432)	(0.4368)	(0.7700)	(0.8343)	(0.9235)	(0.4269)			(0.6957)	(0.3662)				(0.4661)		
US.GDP		1.3183^{**}				0.1500									0.4998°			
		(0.5904)				(0.6155)									(0.3136)			
BOND	-0.0185^{*}							-0.0032										
	(0.0100)							(0.0202)										
INTERM.								-0.0149					-0.0399^{***}					-0.0127°
								(0.0272)					(0.0153)					(0.075)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.42	0.31	0.23	0.11	0.13	0.2	0.18	0.29	0.33	0.26	0.14	0.33	0.32	0.19	0.15	0.19	0.09	0.59

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.17: Post penalized quantile regression for VaR at 50%

	HSBC	BNP	CR.AGR	BAN.SAN	BARC	SOC.GEN	DEUT.	LLOYDS	INTESA	ING	UBS	UNIC.	NAT.	ST.CHA	BBVA	NORDEA	ABN	DANSKE	COMMERZ.	KBC
(Intercept)	0.0030^{*}	0.0007	-0.0005	-0.0014	0.0009	-0.0003	-0.0023	-0.0005	-0.0012	-0.0029^{*}	-0.0014	-0.0001	-0.0016	-0.0024	-0.0026°	0.0009	0.0006	-0.0010	-0.0010	0.0001
	(0.0016)	(0.0019)	(0.0018)	(0.0016)	(0.0024)	(0.0023)	(0.0027)	(0.0021)	(0.0014)	(0.0016)	(0.0018)	(0.0027)	(0.0020)	(0.0020)	(0.0018)	(0.0013)	(0.0020)	(0.0016)	(0.0023)	(0.0018)
EUR-OIS																				
CRE		-0.0462^{*}	-0.0553^{***}	-0.0431^{*}		-0.0364°	-0.0158		-0.0671^{***}	-0.0505^{**}	-0.0529^{***}	-0.0385	-0.0357	-0.0799^{***}	-0.0233		-0.0618^{***}		-0.0383	-0.0286
		(0.0263)	(0.0198)	(0.0248)		(0.0229)	(0.0370)		(0.0158)	(0.0206)	(0.0186)	(0.0384)	(0.0443)	(0.0232)	(0.0271)		(0.0202)		(0.0452)	(0.0288)
EFFR																				
TED			-0.0279^{***}							-0.0198^{**}		-0.0185°				-0.0172^{***}				
			(0.0098)							(0.0079)		(0.0121)				(0.0060)				
US.SLOPE							0.0967^{*}													
							(0.0546)													
EONIA																				
SLOPE															0.0314°					
															(0.0216)					
EUR/£				-0.4373^{***}	-0.8756^{***}			-0.5163^{***}					-1.4995^{***}	-0.4053^{*}					-0.4738^{*}	
				(0.1415)	(0.2188)			(0.1783)					(0.3130)	(0.2256)					(0.2568)	
EURO/$									0.3403^{*}								0.3480°		0.8399^{***}	
									(0.1748)								(0.2308)		(0.2328)	
EURIRS		0.0599^{*}	0.0580^{**}	0.0655^{**}		0.1246^{***}	0.1402^{***}			0.0435^{*}		0.1198^{**}	0.0551		0.0473	0.0599^{***}		0.0660^{**}	0.2337^{***}	0.0891^{**}

	HSBC	BNP	CR.AGR	BAN.SAN	BARC	SOC.GEN	DEUT.	LLOYDS	INTESA	ING	UBS	UNIC.	NAT.	ST.CHA	BBVA	NORDEA	ABN	DANSKE	COMMERZ.	KBC
		(0.0357)	(0.0292)	(0.0326)		(0.0422)	(0.0440)			(0.0254)		(0.0602)	(0.0532)		(0.0430)	(0.0149)		(0.0306)	(0.0750)	(0.0381)
GOLD	-0.2697^{*}	-0.4505^{**}	-0.2744^{**}	-0.2658^{*}		-0.5003^{***}	-0.3725^{**}		-0.2244^{*}	-0.4177^{***}		-0.6413^{***}			-0.3217^{**}	-0.1908^{**}	-0.4097^{**}	-0.2941^{**}		-0.3604^{**}
	(0.1464)	(0.1971)	(0.1285)	(0.1459)		(0.1729)	(0.1518)		(0.1219)	(0.1355)		(0.1643)			(0.1559)	(0.0952)	(0.1617)	(0.1286)		(0.1569)
OIL										0.0653^{**}										
										(0.0279)										
GAS																				
REAL.EST.																		0.2124^{*}		
																		(0.1235)		
VIX																				
VSTOXX																				
S&P																				
EURO.XX		1.3143^{***}	1.2951^{***}	1.2817^{***}		1.4215^{***}	1.5344^{***}		1.1333^{***}	1.2791^{***}	1.0799^{***}	1.5220^{***}	0.8768^{***}	0.9809^{***}	1.3684^{***}	0.8919^{***}	1.2049^{***}	0.5711^{***}	1.3468^{***}	1.0130^{***}
		(0.0887)	(0.0878)	(0.1185)		(0.1081)	(0.1345)		(0.0749)	(0.0813)	(0.0797)	(0.1343)	(0.1492)	(0.1094)	(0.0882)	(0.0584)	(0.0970)	(0.0974)	(0.1440)	(0.1165)
US.HICP.5y	-0.1194^{***}															-0.1273^{***}		0.0771		
	(0.0452)															(0.0309)		(0.0805)		
EU.HICP.5y																		−0.0523		
																		(0.0590)		
US.HICP.1y																		−0.0416		
																		(0.0419)		
EU.HICP.1y																				
EU.GDP										0.4433°										
										(0.3056)										
US.GDP																		0.6777^{*}		
																		(0.3671)		
BOND																				
INTERM.																				
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.02	0.42	0.4	0.38	0.02	0.4	0.3	0.01	0.37	0.44	0.33	0.31	0.28	0.22	0.35	0.35	0.3	0.25	0.3	0.32

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.18: Post penalized quantile regression for VaR at 50 (cont)

	ERSTE	SKANDI.	SVENSKA	SWEDBNK	BANC.SAB	RAIFFEI.	BPER	BANKINT.	JYSKE	POWSZ.	MEDIOB..	BANC.COMM.	OTP	EUROBNK.	BNK.GREeCE	ALPHA	PIREUS	CREDIT.EMIL	BANK.POL.	SANT.
(Intercept)	-0.0002	0.0004	-0.0026^{*}	0.0010	-0.0016	0.0026	-0.0017	0.0005	0.0035^{**}	-0.0014	0.0012	-0.0036	0.0005	0.0020	0.0000	-0.0066°	-0.0125^{**}	0.0001	0.0007	-0.0009
	(0.0020)	(0.0014)	(0.0014)	(0.0012)	(0.0026)	(0.0024)	(0.0028)	(0.0019)	(0.0017)	(0.0021)	(0.0017)	(0.0031)	(0.0022)	(0.0038)	(0.0044)	(0.0045)	(0.0058)	(0.0016)	(0.0032)	(0.0023)
EUR-OIS																				
CRE	-0.0068	-0.0051			0.0004	-0.0794^{***}	-0.0128	-0.0050			-0.0701^{***}	-0.0257						-0.0115		
	(0.0329)	(0.0148)			(0.0427)	(0.0250)	(0.0449)	(0.0263)			(0.0219)	(0.0324)						(0.0258)		
EFFR																				
TED																				
US.SLOPE			0.0401^{*}																0.1099^{**}	
			(0.0215)																(0.0506)	
EONIA																				
SLOPE																				
EURIRS	0.0758°	0.0450^{**}	0.0549^{***}	0.0406^{*}	0.1785^{***}		0.0966^{*}	0.1354^{***}				0.0879^{**}						0.0696^{*}		
	(0.0505)	(0.0205)	(0.0191)	(0.0228)	(0.0579)		(0.0503)	(0.0420)				(0.0432)						(0.0365)		
EUR/£					-0.6266^{**}															
					(0.2504)															
EURO/&					0.9165^{***}					0.9840^{***}		0.7810^{**}	0.7128^{***}						0.6599^{**}	1.1043^{***}
					(0.3131)					(0.2105)		(0.3879)	(0.2739)						(0.3238)	(0.3378)
GOLD	-0.4880^{***}				-0.6440^{***}		-0.5795^{***}	-0.2412°	-0.3269^{**}					-0.7786^{***}				-0.3084^{*}		
	(0.1183)				(0.2329)		(0.1366)	(0.1747)	(0.1396)					(0.2617)				(0.1701)		
OIL						0.0587									0.1569^{*}	0.2166^{***}				
						(0.0609)									(0.0944)	(0.0809)				
GAS																				
REAL.EST.													0.1814	0.6488^{***}	0.6077^{**}		0.3971°		0.3598^{*}	0.1861
													(0.1928)	(0.2189)	(0.2436)		(0.2696)		(0.1986)	(0.1526)
VIX																				
VSTOXX										-0.0099			-0.0169°							
										(0.0080)			(0.0114)							
S&P										0.0214									0.1306	
										(0.1503)									(0.3219)	
EURO.XX	1.0895^{***}	0.8329^{***}	0.7537^{***}	0.6837^{***}	1.1857^{***}	1.0209^{***}	1.2149^{***}	0.9484^{***}	0.8686^{***}	0.8628^{***}	1.2034^{***}	1.1207^{***}	0.4696^{***}	0.7719^{***}	1.0020^{***}	1.3995^{***}	1.0514^{***}	0.7670^{***}	0.5063^{**}	0.7492^{***}
	(0.0879)	(0.0526)	(0.0682)	(0.0744)	(0.1857)	(0.1231)	(0.1213)	(0.0998)	(0.1114)	(0.1603)	(0.1482)	(0.1496)	(0.1713)	(0.2171)	(0.2104)	(0.2349)	(0.3175)	(0.1108)	(0.2436)	(0.1375)
US.HICP.5y		-0.0619°		-0.0649°																

	ERSTE	SKANDI.	SVENSKA	SWEDBNK	BANC.SAB	RAIFFEI.	BPER	BANKINT.	JYSKE	POWSZ.	MEDIOB..	BANC.COMM.	OTP	EUROBNK.	BNK.GREeCE	ALPHA	PIREUS	CREDIT.EMIL	BANK.POL.	SANT.
		(0.0433)		(0.0437)																
EU.HICP.5y				−0.0190																
				(0.0425)																
US.HICP.1y														-0.1669^{***}	−0.0912					
														(0.0411)	(0.0722)					
EU.HICP.1y																				
EU.GDP																				
US.GDP																				
BOND																				
INTERM.												−0.0234		-0.0480^{**}	−0.0123		-0.0540^{**}			
												(0.0224)		(0.0208)	(0.0185)		(0.0268)			
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.29	0.27	0.23	0.18	0.27	0.25	0.24	0.26	0.16	0.22	0.32	0.19	0.12	0.19	0.17	0.12	0.09	0.19	0.13	0.17

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.19: Post penalized quantile regression for VaR at 50 (cont)

	KOMER	AAREAL	ING.SLA..	MBANK	SYDBAK	MILLEN.	BRD	AKTIA	HOIST	SONDRIO	CAIXA	SUISSE	BPM	BNK.GREECE	PIC.	LANG.	MEDIO.	DEUT.PF	VIL.
(Intercept)	−0.0019	−0.0009	−0.0010	−0.0026	0.0001	−0.0005	0.0010	0.0006	−0.0008	−0.0007	−0.0021	-0.0052^{***}	0.0000	0.0010	−0.0008	-0.0021°	0.0008	−0.0015	0.0003
	(0.0018)	(0.0014)	(0.0018)	(0.0023)	(0.0017)	(0.0028)	(0.0018)	(0.0015)	(0.0030)	(0.0024)	(0.0021)	(0.0016)	(0.0040)	(0.0014)	(0.0011)	(0.0015)	(0.0013)	(0.0019)	(0.0015)
EUR-OIS																			0.0038^{**}
																			(0.0016)
CRE		-0.0351°			−0.0226						−0.0275	-0.0732^{***}	-0.1251^{***}				-0.0409^{***}	−0.0260	
		(0.0222)			(0.0243)						(0.0275)	(0.0160)	(0.0356)				(0.0152)	(0.0295)	
EFFR																			
TED												-0.0146^{*}							
												(0.0077)							
US.SLOPE																			
EONIA																			
SLOPE																			

	KOMER	AAREAL	ING.SLA..	MBANK	SYDBAK	MILLEN.	BRD	AKTIA	HOIST	SONDRIO	CAIXA	SUISSE	BPM	BNK.GREECE	PIC.	LANG.	MEDIO.	DEUT.PF	VIL.
EUR/£																			
EURO/$			0.6227^{**}	1.1126^{***}		0.9483^{***}	0.4645^{**}										0.5742^{***}		
			(0.2990)	(0.3180)		(0.3150)	(0.1951)										(0.1795)		
EURIRS		0.0797^{**}			0.0728°					0.0905^{***}	0.1295^{***}							0.0934^{**}	
		(0.0347)			(0.0487)					(0.0319)	(0.0327)							(0.0432)	
GOLD											-0.3808^{***}		-0.6340^{**}						
											(0.1245)		(0.3094)						
OIL		0.0912^{**}										0.0524°							
		(0.0373)										(0.0355)							
GAS																			
REAL.EST.	0.2395^{**}		0.2206^{*}	0.1570	0.2777^{*}		0.0842		0.4659^{**}							0.0979		0.4467^{***}	
	(0.0961)		(0.1303)	(0.1840)	(0.1629)		(0.1095)		(0.2285)							(0.0865)		(0.1709)	
VIX																			
VSTOXX				-0.0208^{**}			-0.0186^{***}								-0.0121^{***}				
				(0.0096)			(0.0056)								(0.0044)				
S&P	0.1108						0.1245	0.1075							0.1161	0.1829			0.1015
	(0.1003)						(0.1477)	(0.1108)							(0.0914)	(0.1491)			(0.0954)
EURO.XX	0.3467^{***}	0.8978^{***}	0.4638^{***}	0.7106^{***}	0.5675^{***}	0.9017^{***}	0.3861^{***}	0.4336^{***}	0.5027^{***}	1.1343^{***}	1.1096^{***}	1.2059^{***}	1.1158^{***}	0.2158^{***}	0.1352°	0.1196	0.9653^{***}	0.8627^{***}	0.1576°
	(0.1172)	(0.0676)	(0.1457)	(0.1540)	(0.1507)	(0.1773)	(0.1454)	(0.0878)	(0.1892)	(0.0995)	(0.0970)	(0.0610)	(0.1781)	(0.0556)	(0.0931)	(0.1206)	(0.0446)	(0.1386)	(0.1168)
US.HICP.5y								-0.0766°	-0.1169			-0.1077^{*}						0.0345	
								(0.0508)	(0.0962)			(0.0575)						(0.0747)	
EU.HICP.5y									-0.1360^{**}										
									(0.0574)										
US.HICP.1y	-0.0575^{*}														-0.0649^{**}			-0.0698^{*}	
	(0.0312)														(0.0268)			(0.0418)	
EU.HICP.1y																			
EU.GDP								1.0336^{***}											
								(0.3360)											
US.GDP									1.1006^{**}										
									(0.5048)										
BOND																			
INTERM.																			
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.14	0.24	0.12	0.14	0.17	0.13	0.12	0.16	0.15	0.2	0.29	0.37	0.18	0.03	0.07	0.05	0.31	0.3	0.4

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.20: Post penalized quantile regression for VaR at 50 (cont)

	RINGKJ.	FIRST.INV.	GRENKE	ALAND.	HRVAT.	ALM.BRND	BNK.ACH.	CENTR.COOP.	SPAREK.	MLP	BN.NORD.	DJURSD	SKJERN	MUTUI	KREDIT.	NORDFYN.	MOENS	market
(Intercept)	0.0027^{**}	-0.0002	-0.0025°	-0.0004	-0.0001	0.0002	-0.0056^{**}	-0.0025^{*}	0.0002	0.0016	-0.0007	0.0003	-0.0007	0.0016	0.0009	-0.0001	0.0009	-0.0017°
	(0.0013)	(0.0021)	(0.0019)	(0.0019)	(0.0012)	(0.0016)	(0.0025)	(0.0015)	(0.0011)	(0.0017)	(0.0011)	(0.0010)	(0.0011)	(0.0023)	(0.0013)	(0.0013)	(0.0013)	(0.0012)
EUR-OIS									-0.0037^{**}									
									(0.0015)									
CRE																		-0.0360^{*}
																		(0.0210)
EFFR																		
TED																		-0.0119^{*}
																		(0.0069)
US.SLOPE																		
EONIA																		
SLOPE																		
EURO/$							0.4592°							0.7462^{***}	0.2076^{*}			
							(0.2885)							(0.2733)	(0.1258)			
EURO/£							0.4592°							0.7462^{***}	0.2076^{*}			
							(0.2885)							(0.2733)	(0.1258)			
EURIRS																		0.0449°
																		(0.0307)
GOLD																		-0.3646^{***}
																		(0.0861)
OIL																		
GAS																		
REAL.EST.	0.1324		0.1004	0.2379^{***}		0.2352^{**}	0.3302^{**}								0.2242^{***}			
	(0.1107)		(0.1440)	(0.0775)		(0.1186)	(0.1643)								(0.0478)			
VSTOXX				-0.0094^{*}					-0.0058°									
				(0.0055)					(0.0036)									
S&P		0.3408^{**}	0.1624			0.2062°	0.1014		0.2267^{**}	0.1448^{*}		0.0598	0.2827^{***}					
		(0.1695)	(0.1493)			(0.1287)	(0.2228)		(0.0881)			(0.0984)	(0.1054)				(0.0858)	
EURO.XX	0.5022^{***}	0.1485	0.6946^{***}			0.3058^{*}	0.3629°	0.2133^{***}	0.1195°		0.3018^{***}	0.2086^{**}	0.0701	0.7615^{***}		0.2011^{***}		0.9998^{***}

	RINGKJ.	FIRST.INV.	GRENKE	ALAND.	HRVAT.	ALM.BRND	BNK.ACH.	CENTR.COOP.	SPAREK.	MLP	BN.NORD.	DJURSD	SKJERN	MUTUI	KREDIT.	NORDFYN.	MOENS	market
	(0.0902)	(0.1228)	(0.1314)			(0.1658)	(0.2353)	(0.0681)	(0.0796)		(0.0599)	(0.0852)	(0.0948)	(0.1063)		(0.0483)		(0.0538)
US.HICP.5y		−0.0939°												−0.1089*				
		(0.0638)												(0.0660)				
EU.HICP.5y			−0.0466	−0.0630**					−0.0353									
			(0.0414)	(0.0269)					(0.0352)									
US.HICP.1y			−0.1034***						−0.0519**									
			(0.0286)						(0.0263)									
EU.HICP.5y																		
I EU.GDP													0.3746			0.7753***		0.3732**
													(0.3462)			(0.2087)		(0.1840)
BOND						−0.0148**					−0.0162***							
						(0.0058)					(0.0046)							
INTERM.			−0.0219**										−0.0082°					
			(0.0104)										(0.0053)					
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.15	0.07	0.18	0.03	0.01	0.13	0.08	0.01	0.12	0.1	0.07	0.04	0.09	0.17	0.05	0.05	0.01	0.49

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.21: T-B quantile regression for VaR at 5%

	HSBC	BNP	CR.AGR	BAN.SAN	BARC	SOC.GEN	DEUT.	LLOYDS	INTESA	ING
(Intercept)	−0.0498***	−0.0657***	−0.0723***	−0.0721***	−0.0731***	−0.0828***	−0.0946***	−0.0637***	−0.0717***	−0.0702***
	(0.0038)	(0.0074)	(0.0073)	(0.0072)	(0.0057)	(0.0071)	(0.0087)	(0.0079)	(0.0072)	(0.0092)
CREDIT	−0.0546	0.0066	0.0015	0.0283	−0.0944°	0.0193	−0.0404	−0.1438*	0.0389	0.0514
	(0.0515)	(0.0503)	(0.0354)	(0.0499)	(0.0600)	(0.0490)	(0.0543)	(0.0738)	(0.0485)	(0.0534)
SLOPE	0.0111	0.1017	0.1021	0.1906**	0.0419	0.0320	0.1398	0.0025	0.2179**	0.2153*
	(0.0536)	(0.0849)	(0.1062)	(0.0875)	(0.0996)	(0.0890)	(0.1269)	(0.0890)	(0.0897)	(0.1189)
VSTOXX	−0.0690***	−0.0664***	−0.0914***	−0.0764***	−0.0928***	−0.0879***	−0.0702**	−0.0874***	−0.0713***	−0.0920**
	(0.0244)	(0.0160)	(0.0301)	(0.0219)	(0.0289)	(0.0181)	(0.0312)	(0.0287)	(0.0220)	(0.0364)
EURO.XX	−0.2923	0.4649	0.4019	0.4695	−0.0482	0.7156**	0.7227°	−0.3021	0.1553	0.6845°
	(0.2994)	(0.4057)	(0.4959)	(0.4358)	(0.4921)	(0.3520)	(0.4715)	(0.4497)	(0.3984)	(0.4649)
Real.est.	0.0957	−0.3520	−0.3663	−0.5799°	0.6806*	−0.6769**	−0.0974	0.6732°	0.1291	−0.4765°
	(0.3400)	(0.3466)	(0.3599)	(0.3720)	(0.3759)	(0.3150)	(0.3526)	(0.4824)	(0.3515)	(0.3267)
EUR-OIS	−0.0142***	−0.0112*	−0.0098	−0.0153**	−0.0170**	−0.0106	−0.0218*	−0.0068	−0.0134*	−0.0182**
	(0.0055)	(0.0067)	(0.0078)	(0.0076)	(0.0072)	(0.0087)	(0.0112)	(0.0082)	(0.0081)	(0.0093)

	UBS	UNIC.	NAT.	ST.CHA	BBVA	NORDEA	ABN	DANSKE	COM.	KBC
(Intercept)	−0.0573***	−0.0884***	−0.0688***	−0.0690***	−0.0712***	−0.0593***	−0.0721***	−0.0655***	−0.0994***	−0.0670***
	(0.0059)	(0.0096)	(0.0086)	(0.0072)	(0.0087)	(0.0122)	(0.0077)	(0.0079)	(0.0075)	(0.0074)
CREDIT	0.0628*	0.0280	−0.0556	0.0234	0.0786°	−0.0038	0.0192	−0.0149	0.0093	0.0668°
	(0.0370)	(0.0621)	(0.0595)	(0.0463)	(0.0507)	(0.0482)	(0.0461)	(0.0626)	(0.0708)	(0.0439)
SLOPE	0.0876	0.2022°	0.0737	0.1959***	0.1522**	0.0861	0.1354°	0.0167	0.1565°	0.1690***
	(0.0856)	(0.1306)	(0.0917)	(0.0729)	(0.0735)	(0.0971)	(0.1049)	(0.1163)	(0.1141)	(0.0612)
VSTOXX	−0.0730***	−0.0800***	−0.0970***	−0.0565***	−0.0636***	−0.0436	−0.1013***	−0.0295	−0.0811**	−0.0578**
	(0.0249)	(0.0299)	(0.0281)	(0.0162)	(0.0216)	(0.0403)	(0.0385)	(0.0349)	(0.0334)	(0.0267)
EURO.XX	0.6259**	0.2967	−0.2419	0.5163°	0.3056	0.3198	−0.0346	0.3577	0.3300	0.5501°
	(0.2658)	(0.3999)	(0.4565)	(0.3207)	(0.4841)	(0.4775)	(0.4558)	(0.4222)	(0.4562)	(0.3455)
Real.est.	−0.2767	−0.0562	−0.0655	−0.4170	−0.2717	−0.3455	−0.2837	−0.0740	−0.1543	−0.4978*
	(0.2586)	(0.4537)	(0.3568)	(0.3313)	(0.4067)	(0.3721)	(0.3571)	(0.4695)	(0.3629)	(0.2678)
EUR-OIS	−0.0174***	−0.0165**	−0.0197***	−0.0114°	−0.0098	−0.0107	−0.0129	0.0048	−0.0211**	0.0058
	(0.0052)	(0.0079)	(0.0062)	(0.0073)	(0.0100)	(0.0093)	(0.0117)	(0.0098)	(0.0100)	(0.0080)

	HSBC	BNP	CR.AGR	BAN.SAN	BARC	SOC.GEN	DEUT.	LLOYDS	INTESA	ING	UBS	UNIC.	NAT.	ST.CHA	BBVA	NORDEA	ABN	DANSKE	COMMERZ.	KBC
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.13	0.22	0.14	0.14	0.24	0.23	0.1	0.24	0.15	0.16	0.12	0.12	0.21	0.15	0.16	0.03	0.19	0.03	0.1	0.17

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.22: T-B quantile regression for VaR at 5% (cont)

	ERSTE	SKANDI.	SVENSKA	SWED.	BANC.SAB	RAIF.	BPER	BANKINT.	JYSKE	POWSZ.	MEDIOB..	COMM.P	OTP	EUR.BNK.	BNK.GRE.	ALPHA	PIREUS	CRED.EMI.	BNK.POL.	SANT.
(Intercept)	−0.0684***	−0.0543***	−0.0491***	−0.0527***	−0.0890***	−0.0718***	−0.0908***	−0.0628***	−0.0603***	−0.0713***	−0.0663***	−0.0993***	−0.0677***	−0.1128***	−0.1180***	−0.1142***	−0.2053***	−0.0612***	−0.1039***	−0.0722***
	(0.0066)	(0.0060)	(0.0046)	(0.0080)	(0.0104)	(0.0151)	(0.0089)	(0.0069)	(0.0080)	(0.0092)	(0.0087)	(0.0102)	(0.0099)	(0.0135)	(0.0129)	(0.0100)	(0.0356)	(0.0057)	(0.0115)	(0.0065)
CREDIT	0.0284	0.0322	0.0391	0.0517	−0.0703	0.0832°	−0.0271	−0.0412	−0.0652°	0.0137	0.0244	−0.0417	−0.0068	−0.0494	−0.0762	0.0528	0.0393	−0.0066	0.0080	0.0373
	(0.0521)	(0.0453)	(0.0341)	(0.0585)	(0.0809)	(0.0573)	(0.0786)	(0.0508)	(0.0482)	(0.0448)	(0.0567)	(0.0709)	(0.0590)	(0.0727)	(0.0775)	(0.1044)	(0.1860)	(0.0362)	(0.0707)	(0.0434)
SLOPE	−0.0950°	−0.0258	0.0155	0.0419	0.1712**	0.1032	0.0442	0.0903	0.0022	0.1000	0.1126	0.1122	0.1109°	0.0604	0.0186	0.0916	0.1483	0.0223	0.0936	0.1321°
	(0.0722)	(0.0993)	(0.0836)	(0.0949)	(0.0801)	(0.0947)	(0.0926)	(0.0928)	(0.0910)	(0.0999)	(0.1252)	(0.1056)	(0.0743)	(0.1595)	(0.1668)	(0.1425)	(0.1943)	(0.0721)	(0.0988)	(0.0921)
VSTOXX	−0.0978***	−0.0594*	−0.0440*	−0.0438**	−0.0762***	−0.0514°	−0.0651**	−0.0525***	−0.0310°	−0.0570	−0.0723**	−0.0492°	−0.0463°	−0.0932*	−0.0635°	−0.0315	−0.0596	−0.0245	−0.0904**	−0.0446**
	(0.0203)	(0.0312)	(0.0226)	(0.0213)	(0.0261)	(0.0322)	(0.0283)	(0.0175)	(0.0220)	(0.0460)	(0.0321)	(0.0371)	(0.0291)	(0.0491)	(0.0471)	(0.0433)	(0.0728)	(0.0216)	(0.0440)	(0.0217)
EURO.XX	0.2010	0.2820	0.3648°	0.8081**	0.2607	0.9486*	0.5183	0.4547	0.2461	0.2223	0.3038	0.6423	0.5808°	1.0970*	1.8789**	1.0661°	2.3800*	0.2149	0.7901	0.3513
	(0.3791)	(0.2925)	(0.2803)	(0.3201)	(0.4986)	(0.5398)	(0.5312)	(0.3656)	(0.4078)	(0.3801)	(0.4584)	(0.5658)	(0.4407)	(0.6640)	(0.8185)	(0.6892)	(1.2907)	(0.3171)	(0.7234)	(0.3605)
Real. Est.	−0.0279	−0.4079°	−0.2952*	−0.3751	−0.3395	−0.5847°	−0.5188	−0.5775*	0.1191	−0.0768	0.0365	−0.4340	−0.3389	−0.6115	−1.5329*	−0.3487	−2.7638**	−0.1005	−0.2167	−0.1955
	(0.3659)	(0.2714)	(0.1782)	(0.3146)	(0.4306)	(0.3713)	(0.4227)	(0.3484)	(0.3649)	(0.3956)	(0.4782)	(0.5372)	(0.3353)	(0.5343)	(0.7820)	(0.7673)	(1.2419)	(0.3600)	(0.5864)	(0.2850)
EUR-OIS	0.0030	−0.0075	−0.0077*	−0.0132**	−0.0063	−0.0057	−0.0097	0.0039	−0.0052	0.0093	−0.0186**	−0.0026	0.0080	−0.0418***	−0.0395***	−0.0240**	0.0213	−0.0043	0.0146	0.0000
	(0.0084)	(0.0065)	(0.0044)	(0.0065)	(0.0094)	(0.0132)	(0.0093)	(0.0062)	(0.0096)	(0.0104)	(0.0091)	(0.0111)	(0.0095)	(0.0111)	(0.0130)	(0.0110)	(0.0337)	(0.0059)	(0.0150)	(0.0068)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.24	0.07	0.07	0.09	0.18	0.09	0.13	0.13	0.06	0.06	0.16	0.11	0.16	0.17	0.15	0.13	0.03	0.03	0.21	0.14

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.23: T-B quantile regression for VaR at 5% (cont)

	KOMER	AAREAL	ING.SLA..	MBANK	SYDBAK	MILLEN.	BRD	AKTIA	HOIST	SONDRIO	CAIXA	SUISSE	BPM	BNK.GREECE	PIC.	LANG.	MEDIO.	DEUT.PF	VIL.
(Intercept)	−0.0534***	−0.0659***	−0.0627***	−0.0866***	−0.0605***	−0.0852***	−0.0567***	−0.0530***	−0.0747***	−0.0827***	−0.0706***	−0.0904***	−0.1096***	−0.0396***	−0.0406***	−0.0441***	−0.0590***	−0.0670***	−0.0508***
	(0.0048)	(0.0059)	(0.0067)	(0.0090)	(0.0059)	(0.0102)	(0.0073)	(0.0067)	(0.0093)	(0.0077)	(0.0046)	(0.0107)	(0.0091)	(0.0046)	(0.0046)	(0.0057)	(0.0072)	(0.0087)	(0.0051)
CREDIT	−0.0285	−0.0251	−0.0287	−0.0019	0.0094	−0.0012	−0.0150	0.0284	−0.0229	−0.0586	0.0164	−0.0958	0.0487	0.0342	−0.0296	−0.0077	0.0560°	0.0074	0.0095

	KOMER	AAREAL	ING.SLA..	MBANK	SYDBAK	MILLEN.	BRD	AKTIA	HOIST	SONDRIO	CAIXA	SUISSE	BPM	BNK.GREECE	PIC.	LANG.	MEDIO.	DEUT.PF	VIL.
	(0.0452)	(0.0585)	(0.0619)	(0.0589)	(0.0540)	(0.0527)	(0.0461)	(0.0370)	(0.0713)	(0.0643)	(0.0430)	(0.0782)	(0.0893)	(0.0351)	(0.0315)	(0.0378)	(0.0404)	(0.0632)	(0.0350)
SLOPE	0.0871*	0.0543	0.1407*	0.1280°	0.0467	0.1408	0.0662	0.0750	0.0542	0.0846	0.1124°	0.2020**	0.0556	0.1036*	0.0484	0.0570	0.1164*	0.1183°	0.0776
	(0.0527)	(0.1157)	(0.0825)	(0.0841)	(0.0874)	(0.1417)	(0.0970)	(0.0626)	(0.0894)	(0.1204)	(0.0688)	(0.0896)	(0.1262)	(0.0545)	(0.0534)	(0.0510)	(0.0616)	(0.0818)	(0.0816)
VSTOXX	−0.0691***	−0.0743***	−0.0631***	−0.1104***	−0.0200	−0.1517***	−0.0393°	−0.0458**	−0.0934***	−0.0711*	−0.0617***	−0.1235***	−0.0502°	−0.0147	−0.0367**	−0.0442*	−0.0571***	−0.0801***	−0.0887***
	(0.0154)	(0.0274)	(0.0176)	(0.0401)	(0.0275)	(0.0528)	(0.0278)	(0.0232)	(0.0303)	(0.0397)	(0.0153)	(0.0294)	(0.0374)	(0.0140)	(0.0143)	(0.0228)	(0.0183)	(0.0282)	(0.0266)
EURO.XX	−0.0640	0.3582	0.2245	0.0105	0.4033	−0.3021	−0.2841	0.3068	−0.1973	0.5304°	0.3582°	−0.2952	1.2021**	0.2219	−0.1922	−0.0825	0.3365	0.4693	0.2340
	(0.2187)	(0.2949)	(0.3866)	(0.4432)	(0.3926)	(0.5179)	(0.3929)	(0.3164)	(0.4236)	(0.3937)	(0.2274)	(0.6047)	(0.5963)	(0.2686)	(0.2223)	(0.2863)	(0.3136)	(0.5069)	(0.2282)
REAL. EST.	0.0568	−0.1622	−0.2153	−0.2311	−0.1018	−0.1760	0.4538°	−0.4112	−0.0902	−0.1012	−0.3350°	0.4532	−0.4030	0.1086	0.1554	0.0765	−0.1197	−0.2464	−0.2578
	(0.2167)	(0.2912)	(0.3891)	(0.4344)	(0.3611)	(0.5132)	(0.3270)	(0.3312)	(0.4023)	(0.4297)	(0.2499)	(0.5345)	(0.4395)	(0.2427)	(0.2663)	(0.2493)	(0.3223)	(0.4107)	(0.2687)
EUR-OIS	0.0010	−0.0152**	0.0155**	0.0088	−0.0100°	−0.0047	−0.0014	0.0022	−0.0129°	−0.0092	−0.0060	0.0050	−0.0335***	−0.0024	−0.0016	0.0128**	−0.0040	−0.0071	0.0157***
	(0.0060)	(0.0070)	(0.0060)	(0.0113)	(0.0072)	(0.0113)	(0.0053)	(0.0068)	(0.0088)	(0.0078)	(0.0054)	(0.0108)	(0.0081)	(0.0051)	(0.0046)	(0.0061)	(0.0078)	(0.0069)	(0.0055)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.22	0.16	0.19	0.16	0.03	0.13	0.09	0.15	0.18	0.08	0.15	0.14	0.18	0.09	0.11	0.18	0.18	0.23	0.21

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.24: T-B quantile regression for VaR at 5% (cont)

	RINGKJ.	FIRST.INV.	GRENKE	ALAND.	HRVAT.	ALM.BRND	BNK.ACH.	CENTR.COOP.	SPAREK.	MLP	BN.NORD.	DJURSD	SKJERN	MUTUI	KREDIT.	NORDFYN.	MOENS	market
(Intercept)	−0.0436***	−0.0665***	−0.0828***	−0.0464***	−0.0572***	−0.0641***	−0.0908***	−0.0561***	−0.0340***	−0.0541***	−0.0415***	−0.0279***	−0.0366***	−0.0763***	−0.0292***	−0.0404***	−0.0434***	−0.0496***
	(0.0050)	(0.0076)	(0.0130)	(0.0035)	(0.0051)	(0.0083)	(0.0112)	(0.0049)	(0.0044)	(0.0050)	(0.0040)	(0.0040)	(0.0051)	(0.0069)	(0.0028)	(0.0056)	(0.0047)	(0.0042)
CREDIT	0.0018	0.0395	−0.0298	−0.0280	−0.0535	−0.0101	0.0047	−0.0568°	−0.0184	−0.0196	−0.0549°	−0.0054	0.0061	−0.0347	−0.0230	0.0429°	−0.0380	0.0134
	(0.0416)	(0.0553)	(0.0714)	(0.0354)	(0.0478)	(0.0417)	(0.0701)	(0.0431)	(0.0357)	(0.0361)	(0.0389)	(0.0272)	(0.0432)	(0.0438)	(0.0238)	(0.0301)	(0.0446)	(0.0247)
SLOPE	0.0021	0.0831°	0.0369	0.0565°	0.0617	0.1339	0.1414	0.0457	0.0093	0.0502	0.0701°	0.0379	0.0055	0.0480	0.0607	0.0171	0.0766	0.0959°
	(0.0804)	(0.0630)	(0.1240)	(0.0413)	(0.0793)	(0.1049)	(0.1271)	(0.0778)	(0.0485)	(0.0671)	(0.0451)	(0.0488)	(0.0511)	(0.0720)	(0.0511)	(0.0630)	(0.0658)	(0.0588)
VSTOXX	−0.0504**	−0.0902***	−0.0758°	−0.0193*	−0.0161	0.0012	−0.0271	−0.0214	−0.0433***	−0.0297**	−0.0370**	−0.0159	−0.0197*	−0.0570**	−0.0229°	−0.0022	−0.0490***	−0.0700***
	(0.0211)	(0.0303)	(0.0570)	(0.0114)	(0.0247)	(0.0294)	(0.0345)	(0.0221)	(0.0140)	(0.0116)	(0.0156)	(0.0130)	(0.0105)	(0.0241)	(0.0145)	(0.0181)	(0.0178)	(0.0180)
EURO.XX	0.3368	0.1578	−0.3066	0.1787	0.2123	0.5574°	0.4397	0.3167	0.1127	0.1284	0.0741	0.3647**	0.4087**	−0.2330	0.2151°	0.2949	0.0361	0.5012**
	(0.2887)	(0.3980)	(0.6612)	(0.1671)	(0.3663)	(0.3634)	(0.4538)	(0.2722)	(0.2279)	(0.2733)	(0.2072)	(0.1448)	(0.2023)	(0.3698)	(0.1415)	(0.2417)	(0.2817)	(0.2420)
REAL. EST.	−0.3184	−0.5903°	−0.1340	−0.1460	0.2926	−0.1550	0.0789	−0.2998	0.3599°	0.0129	0.0582	−0.1068	0.1759	0.1627	−0.1403	−0.0303	−0.3182°	−0.3913**
	(0.2914)	(0.3793)	(0.5571)	(0.1352)	(0.3374)	(0.3654)	(0.4518)	(0.2625)	(0.2414)	(0.2815)	(0.1960)	(0.1230)	(0.1555)	(0.3500)	(0.1618)	(0.2129)	(0.2254)	(0.1839)
EUR-OIS	−0.0021	0.0026	0.0145	0.0020	−0.0172***	0.0044	0.0112	−0.0030	−0.0013	0.0057	−0.0016	−0.0015	−0.0001	0.0051	−0.0049	−0.0006	−0.0004	−0.0087*
	(0.0058)	(0.0069)	(0.0150)	(0.0035)	(0.0054)	(0.0083)	(0.0090)	(0.0061)	(0.0063)	(0.0047)	(0.0044)	(0.0028)	(0.0054)	(0.0083)	(0.0040)	(0.0070)	(0.0053)	(0.0047)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.12	0.14	0.04	0.05	0.09	0.03	0.04	0.08	0.16	0.08	0.09	0.18	0.18	0.09	0.08	0.07	0.04	0.18

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.25: T-B quantile regression for VaR at 50%

	HSBC	BNP	CR.AGR	BAN.SAN	BARC	SOC.GEN	DEUT.	LLOYDS	INTESA	ING	UBS	UNIC.	NAT.	ST.CHA	BBVA	NORDEA	ABN	DANSKE	COMMERZ.	KBC
(Intercept)	0.0033*	0.0026	0.0024	0.0004	0.0022	0.0040°	−0.0030	0.0014	0.0050**	−0.0003	0.0007	0.0010	0.0017	0.0006	0.0011	0.0031	0.0038°	0.0015	0.0036	0.0037*
	(0.0018)	(0.0023)	(0.0021)	(0.0028)	(0.0026)	(0.0029)	(0.0028)	(0.0024)	(0.0025)	(0.0024)	(0.0019)	(0.0041)	(0.0029)	(0.0024)	(0.0025)	(0.0025)	(0.0029)	(0.0025)	(0.0038)	(0.0021)
CREDIT	−0.0167	−0.0206	−0.0329	−0.0286	−0.0302	−0.0420	−0.0151	−0.0045	−0.0415°	−0.0313	−0.0148	−0.0106	−0.0226	−0.0075	−0.0311	−0.0115	−0.0030	0.0067	−0.0126	0.0162
	(0.0188)	(0.0270)	(0.0269)	(0.0269)	(0.0310)	(0.0350)	(0.0262)	(0.0191)	(0.0259)	(0.0261)	(0.0224)	(0.0393)	(0.0269)	(0.0202)	(0.0315)	(0.0217)	(0.0290)	(0.0212)	(0.0362)	(0.0235)
SLOPE	0.0349	0.0599°	0.0310	0.0227	0.0400	0.1122**	0.0307	0.0030	0.0487	0.0417	0.0296	0.0342	0.0255	0.0063	0.0086	0.0317	0.0874°	0.0402	0.1541**	0.0651°
	(0.0361)	(0.0425)	(0.0361)	(0.0356)	(0.0605)	(0.0533)	(0.0529)	(0.0404)	(0.0380)	(0.0406)	(0.0494)	(0.0514)	(0.0555)	(0.0310)	(0.0436)	(0.0506)	(0.0622)	(0.0480)	(0.0752)	(0.0444)
VSTOXX	0.0138**	0.0246*	0.0072	0.0118	0.0127	0.0247°	0.0134	0.0155°	0.0068	0.0186°	0.0173°	0.0018	0.0114	0.0164*	0.0012	0.0101	0.0212°	0.0073	0.0063	0.0087
	(0.0062)	(0.0132)	(0.0101)	(0.0138)	(0.0154)	(0.0168)	(0.0146)	(0.0119)	(0.0136)	(0.0139)	(0.0116)	(0.0177)	(0.0119)	(0.0099)	(0.0140)	(0.0095)	(0.0137)	(0.0089)	(0.0157)	(0.0096)
EURO.XX	−0.0551	−0.0028	0.0008	−0.0516	−0.1274	−0.3244°	0.0739	−0.1880°	−0.1528	0.1609	0.0333	−0.2460	−0.0574	−0.1359	−0.0323	0.0594	−0.0012	0.0282	−0.1907	−0.2635°
	(0.1190)	(0.1668)	(0.1540)	(0.1990)	(0.1822)	(0.2078)	(0.2389)	(0.1343)	(0.1414)	(0.1867)	(0.1634)	(0.2429)	(0.1812)	(0.1712)	(0.1769)	(0.1211)	(0.1767)	(0.1239)	(0.1879)	(0.1795)
REAL. EST.	0.1077	0.0546	0.0773	0.0602	0.2254	0.2487	−0.1570	0.2308°	0.2330°	0.0379	−0.0069	0.0479	0.1067	0.1762	−0.1530	−0.0563	0.1973	−0.0490	0.1051	0.0800
	(0.1177)	(0.1951)	(0.1799)	(0.2058)	(0.1947)	(0.2351)	(0.2063)	(0.1537)	(0.1763)	(0.1956)	(0.1635)	(0.2649)	(0.2683)	(0.1889)	(0.2067)	(0.1455)	(0.2050)	(0.1276)	(0.2612)	(0.1429)
EUR-OIS	−0.0043**	−0.0036	−0.0011	0.0005	−0.0030	−0.0059°	−0.0050	−0.0054*	−0.0034	−0.0047°	0.0002	−0.0069°	−0.0066*	−0.0035	−0.0035	−0.0036	−0.0043	−0.0039°	−0.0067°	−0.0056**
	(0.0020)	(0.0035)	(0.0026)	(0.0035)	(0.0032)	(0.0041)	(0.0040)	(0.0031)	(0.0031)	(0.0036)	(0.0031)	(0.0046)	(0.0037)	(0.0032)	(0.0039)	(0.0033)	(0.0041)	(0.0029)	(0.0047)	(0.0024)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.01	0.03	0.01	0.01	0.01	0.03	0.02	0.02	0.01	0.03	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.01	0.02	0.03

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.26: T-B quantile regression for VaR at 50% (cont)

	ERSTE	SKANDI.	SVENSKA	SWEDBNK	BANC.SAB	RAIFFEI.	BPER	BANKINT.	JYSKE	POWSZ.	MEDIOB..	BANC.COMM.	OTP	EUROBNK.	BNK.GREeCE	ALPHA	PIREUS	CREDIT.EMIL	BANK.POL.	SANT.
(Intercept)	0.0037°	0.0032**	−0.0004	0.0021	0.0013	0.0034	−0.0011	0.0034	−0.0002	0.0024	0.0030	−0.0015	0.0055**	0.0022	0.0079°	−0.0011	−0.0080	0.0006	−0.0001	0.0029
	(0.0024)	(0.0015)	(0.0016)	(0.0017)	(0.0034)	(0.0030)	(0.0036)	(0.0029)	(0.0023)	(0.0027)	(0.0026)	(0.0034)	(0.0025)	(0.0044)	(0.0049)	(0.0041)	(0.0065)	(0.0022)	(0.0040)	(0.0029)
CREDIT	0.0108	−0.0046	0.0135	−0.0038	−0.0441	−0.0381	−0.0430	−0.0456*	−0.0398**	−0.0131	−0.0068	−0.0394	−0.0164	−0.0684	−0.0739°	−0.0728°	−0.0332	−0.0352°	0.0115	−0.0107
	(0.0313)	(0.0145)	(0.0167)	(0.0160)	(0.0387)	(0.0337)	(0.0347)	(0.0271)	(0.0199)	(0.0232)	(0.0277)	(0.0328)	(0.0256)	(0.0539)	(0.0538)	(0.0472)	(0.0641)	(0.0221)	(0.0400)	(0.0253)
SLOPE	0.0637	0.0358	0.0089	0.0035	0.0459	0.0367	0.0051	0.0700*	0.0022	0.0275	0.0444	0.0330	0.1284**	0.1605*	−0.0917	0.0014	0.0647	0.0044	0.0543	0.0266
	(0.0508)	(0.0352)	(0.0284)	(0.0307)	(0.0653)	(0.0586)	(0.0507)	(0.0372)	(0.0347)	(0.0420)	(0.0561)	(0.0557)	(0.0503)	(0.0831)	(0.0747)	(0.0528)	(0.0861)	(0.0291)	(0.0644)	(0.0307)
VSTOXX	0.0036	0.0114*	0.0116°	0.0067	0.0069	0.0092	0.0120	0.0112	0.0092	−0.0048	0.0141	0.0070	−0.0040	0.0055	0.0129	−0.0033	−0.0105	0.0128*	0.0154	−0.0087
	(0.0136)	(0.0069)	(0.0071)	(0.0085)	(0.0185)	(0.0130)	(0.0166)	(0.0119)	(0.0084)	(0.0095)	(0.0141)	(0.0167)	(0.0120)	(0.0279)	(0.0241)	(0.0213)	(0.0277)	(0.0075)	(0.0155)	(0.0170)
EURO.XX	−0.1633	−0.0341	0.1040	0.0249	−0.1560	−0.0375	0.1563	−0.0995	−0.0345	−0.1146	0.0678	0.0359	−0.3411*	0.2470	0.0631	0.2231	0.0473	0.0196	0.2381	−0.1242
	(0.1570)	(0.1039)	(0.0848)	(0.0976)	(0.2708)	(0.2570)	(0.2395)	(0.1692)	(0.1498)	(0.1725)	(0.1743)	(0.2294)	(0.1866)	(0.3119)	(0.2980)	(0.3137)	(0.4371)	(0.1352)	(0.2058)	(0.2092)
REAL. EST.	0.1578	0.0782	−0.0518	0.0197	0.0558	0.1044	−0.0848	0.1558	0.3310**	0.0425	−0.1213	0.1051	0.3246*	0.1220	−0.0117	0.1528	0.1432	0.0664	−0.0518	0.0231
	(0.2303)	(0.0934)	(0.1089)	(0.1003)	(0.2672)	(0.2452)	(0.2621)	(0.1908)	(0.1289)	(0.1757)	(0.1534)	(0.2367)	(0.1897)	(0.3163)	(0.3185)	(0.2275)	(0.4068)	(0.0969)	(0.2093)	(0.1637)
EUR-OIS	−0.0070**	0.0010	−0.0008	0.0002	−0.0105**	−0.0007	−0.0062	−0.0036	−0.0015	−0.0036	0.0007	−0.0030	−0.0001	−0.0079°	−0.0056	−0.0094°	−0.0049	−0.0039*	−0.0029	−0.0020

	ERSTE	SKANDI.	SVENSKA	SWEDBNK	BANC.SAB	RAIFFEI.	BPER	BANKINT.	JYSKE	POWSZ.	MEDIOB..	BANC.COMM.	OTP	EUROBNK.	BNK.GREeCE	ALPHA	PIREUS	CREDIT.EMIL	BANK.POL.	SANT.
	(0.0031)	(0.0021)	(0.0024)	(0.0025)	(0.0043)	(0.0034)	(0.0050)	(0.0038)	(0.0027)	(0.0031)	(0.0033)	(0.0046)	(0.0031)	(0.0060)	(0.0056)	(0.0066)	(0.0066)	(0.0021)	(0.0045)	(0.0032)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.01	0.01	0.01	0	0.03	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.03	0.02	0.01	0.02	0.01	0.02	0.01	0.01

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.27: T-B quantile regression for VaR at 50% (cont)

	KOMER	AAREAL	ING.SLA..	MBANK	SYDBAK	MILLEN.	BRD	AKTIA	HOIST	SONDRIO	CAIXA	SUISSE	BPM	BNK.GREECE	PIC.	LANG.	MEDIO.	DEUT.PF	VIL.
(Intercept)	−0.0005	0.0010	0.0026	0.0012	0.0037°	0.0029	0.0056***	0.0016	0.0017	0.0019	0.0017	−0.0034	0.0029	0.0011	−0.0010	−0.0002	0.0037°	0.0004	0.0014
	(0.0018)	(0.0020)	(0.0027)	(0.0031)	(0.0026)	(0.0041)	(0.0020)	(0.0015)	(0.0025)	(0.0027)	(0.0027)	(0.0030)	(0.0038)	(0.0014)	(0.0016)	(0.0017)	(0.0024)	(0.0030)	(0.0016)
CREDIT	−0.0142	−0.0016	−0.0211	−0.0190	−0.0340	−0.0633**	−0.0202	−0.0191°	−0.0427°	−0.0325	−0.0365	−0.0244	−0.0016	−0.0172	−0.0291**	0.0086	0.0106	−0.0167	−0.0027
	(0.0259)	(0.0192)	(0.0217)	(0.0282)	(0.0282)	(0.0316)	(0.0256)	(0.0141)	(0.0286)	(0.0276)	(0.0324)	(0.0291)	(0.0382)	(0.0150)	(0.0124)	(0.0136)	(0.0211)	(0.0294)	(0.0157)
SLOPE	0.0225	0.0022	0.0100	0.0413	0.0045	0.0819*	−0.0037	0.0238	0.0313	0.0324	0.0912*	0.0588	0.0027	0.0022	0.0060	0.0037	0.0507	0.0014	0.0063
	(0.0321)	(0.0297)	(0.0340)	(0.0524)	(0.0416)	(0.0473)	(0.0496)	(0.0222)	(0.0651)	(0.0470)	(0.0467)	(0.0666)	(0.0608)	(0.0150)	(0.0247)	(0.0228)	(0.0421)	(0.0513)	(0.0272)
VSTOXX	0.0029	0.0059	0.0046	−0.0057	0.0069	−0.0032	−0.0032	0.0062	0.0076	0.0272***	0.0140	−0.0040	0.0109	0.0000	−0.0103**	−0.0056	0.0181	−0.0147	−0.0049
	(0.0061)	(0.0119)	(0.0086)	(0.0087)	(0.0088)	(0.0106)	(0.0106)	(0.0054)	(0.0096)	(0.0095)	(0.0122)	(0.0133)	(0.0152)	(0.0049)	(0.0048)	(0.0077)	(0.0157)	(0.0146)	(0.0069)
EURO.XX	−0.1283	−0.1728°	−0.2109*	−0.1752	−0.0188	−0.4055**	−0.0383	−0.0451	−0.2788°	−0.1611	−0.1756	−0.0875	0.0886	−0.0341	−0.0338	0.0762	0.0345	0.1353	−0.0537
	(0.1094)	(0.1319)	(0.1270)	(0.1573)	(0.1579)	(0.1939)	(0.1389)	(0.0936)	(0.1712)	(0.2382)	(0.1653)	(0.1831)	(0.2419)	(0.0789)	(0.0843)	(0.1162)	(0.1472)	(0.2420)	(0.0920)
REAL. EST.	0.1212	0.1379	0.2018°	0.0902	0.0759	0.3647°	0.2257°	0.0671	0.1250	0.2655	0.2081	0.1207	0.0756	0.0564	0.0682	−0.0190	−0.0048	−0.2040	0.1652°
	(0.1082)	(0.1358)	(0.1506)	(0.1651)	(0.1439)	(0.2340)	(0.1669)	(0.1032)	(0.2082)	(0.2282)	(0.1692)	(0.1767)	(0.2932)	(0.0763)	(0.0929)	(0.0973)	(0.1760)	(0.2032)	(0.1241)
EUR-OIS	−0.0002	0.0022	−0.0015	−0.0025	−0.0003	−0.0036	−0.0002	−0.0002	0.0004	−0.0084**	−0.0040	0.0015	−0.0079*	−0.0003	0.0022	−0.0006	0.0006	0.0006	0.0018
	(0.0024)	(0.0026)	(0.0036)	(0.0034)	(0.0028)	(0.0043)	(0.0027)	(0.0017)	(0.0035)	(0.0038)	(0.0035)	(0.0041)	(0.0045)	(0.0010)	(0.0022)	(0.0018)	(0.0032)	(0.0039)	(0.0023)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.01	0	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.03	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.28: T-B quantile regression for VaR at 50% (cont)

	RINGKJ.	FIRST.INV.	GRENKE	ALAND.	HRVAT.	ALM.BRND	BNK.ACH.	CENTR.COOP.	SPAREK.	MLP	BN.NORD.	DJURSD	SKJERN	MUTUI	KREDIT.	NORDFYN.	MOENS	market
(Intercept)	0.0032**	0.0010	0.0005	0.0016	−0.0006	0.0008	−0.0062*	−0.0018	0.0017	−0.0003	0.0007	0.0012	0.0008	0.0059**	0.0004	−0.0003	0.0027*	0.0019

	RINGKJ.	FIRST.INV.	GRENKE	ALAND.	HRVAT.	ALM.BRND	BNK.ACH.	CENTR.COOP.	SPAREK.	MLP	BN.NORD.	DJURSD	SKJERN	MUTUI	KREDIT.	NORDFYN.	MOENS	market
	(0.0016)	(0.0016)	(0.0025)	(0.0018)	(0.0017)	(0.0016)	(0.0033)	(0.0022)	(0.0015)	(0.0022)	(0.0017)	(0.0011)	(0.0012)	(0.0027)	(0.0013)	(0.0015)	(0.0016)	(0.0017)
CREDIT	0.0012	−0.0089	−0.0082	−0.0151	−0.0347***	−0.0179	−0.0159	−0.0001	0.0014	0.0013	−0.0198°	−0.0159°	−0.0121	−0.0129	0.0007	−0.0119	−0.0164	−0.0096
	(0.0172)	(0.0142)	(0.0268)	(0.0181)	(0.0133)	(0.0184)	(0.0238)	(0.0187)	(0.0162)	(0.0178)	(0.0137)	(0.0101)	(0.0123)	(0.0316)	(0.0095)	(0.0101)	(0.0149)	(0.0183)
SLOPE	0.0119	0.0219	0.0239	0.0088	0.0173	0.0057	0.0178	0.0050	−0.0137	0.0083	0.0030	0.0197	−0.0001	0.0301	0.0220°	0.0240	0.0101	0.0270
	(0.0248)	(0.0331)	(0.0503)	(0.0226)	(0.0207)	(0.0310)	(0.0437)	(0.0321)	(0.0237)	(0.0300)	(0.0342)	(0.0240)	(0.0276)	(0.0566)	(0.0141)	(0.0202)	(0.0187)	(0.0361)
VSTOXX	0.0095°	0.0120*	−0.0020	−0.0032	0.0028	0.0070	0.0160°	−0.0097°	0.0045	0.0010	0.0052	0.0016	0.0021	0.0173°	0.0026	0.0033	0.0087**	0.0125
	(0.0072)	(0.0065)	(0.0085)	(0.0050)	(0.0064)	(0.0061)	(0.0114)	(0.0068)	(0.0050)	(0.0085)	(0.0064)	(0.0043)	(0.0069)	(0.0119)	(0.0047)	(0.0046)	(0.0041)	(0.0104)
EURO.XX	0.0877	−0.0748	−0.0639	−0.0273	0.0363	0.0202	0.0491	−0.0042	0.0801	0.0063	−0.0474	0.0765°	0.0759	−0.0127	0.0087	0.2125**	0.0737	−0.0322
	(0.1066)	(0.1074)	(0.1647)	(0.1159)	(0.0822)	(0.0888)	(0.1403)	(0.1235)	(0.0889)	(0.1177)	(0.0966)	(0.0555)	(0.0782)	(0.1962)	(0.0919)	(0.0964)	(0.0584)	(0.1285)
REAL. EST.	−0.0120	0.1400°	0.2138°	−0.0002	0.0374	0.0692	0.0766	−0.0225	0.0489	0.0650	0.1306	−0.0150	0.0719	0.0329	0.0503	−0.0375	−0.0056	0.0674
	(0.1123)	(0.1089)	(0.1612)	(0.1345)	(0.0870)	(0.0827)	(0.1487)	(0.1322)	(0.0894)	(0.1517)	(0.1241)	(0.0679)	(0.0936)	(0.1826)	(0.0848)	(0.0741)	(0.0672)	(0.1448)
EUR-OIS	−0.0010	−0.0023	0.0021	−0.0029*	−0.0013	0.0028°	0.0035	0.0002	−0.0021	0.0005	−0.0002	0.0002	−0.0003	−0.0037	0.0010	0.0018°	−0.0002	−0.0049**
	(0.0023)	(0.0020)	(0.0028)	(0.0016)	(0.0015)	(0.0020)	(0.0036)	(0.0019)	(0.0017)	(0.0028)	(0.0021)	(0.0012)	(0.0017)	(0.0030)	(0.0014)	(0.0014)	(0.0018)	(0.0024)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0	0.01	0	0.01	0	0.02	0.02	0.01	0.01	0.02	0.03

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.29: Post-penalized $CoVaR$ at 5%

	HSBC	BNP	CR.AGR	BAN.SAN	BARC	SOC.GEN	DEUT.	LLOYDS	INTESA	ING	UBS	UNIC.	NAT.	ST.CHA	BBVA	NORDEA	ABN	DANSKE	COMMERZ.	KBC
(Intercept)	−0.0264***	−0.0184***	−0.0201***	−0.0208***	−0.0248***	−0.0190***	−0.0188***	−0.0256***	−0.0225***	−0.0197***	−0.0256***	−0.0202***	−0.0246***	−0.0258***	−0.0227***	−0.0244***	−0.0225***	−0.0260***	−0.0205***	−0.0225***
	(0.0015)	(0.0013)	(0.0017)	(0.0019)	(0.0016)	(0.0011)	(0.0017)	(0.0016)	(0.0018)	(0.0014)	(0.0020)	(0.0018)	(0.0021)	(0.0017)	(0.0023)	(0.0019)	(0.0016)	(0.0021)	(0.0017)	(0.0017)
CREDIT	−0.0500***	−0.0129	−0.0149	−0.0341**	−0.0425**	−0.0136	−0.0303**	−0.0374**	−0.0224°	−0.0021	−0.0393**	−0.0392***	−0.0439***	−0.0184	−0.0274°	−0.0453**	−0.0329***	−0.0259°	−0.0238*	−0.0347**
	(0.0188)	(0.0132)	(0.0179)	(0.0133)	(0.0173)	(0.0117)	(0.0119)	(0.0183)	(0.0140)	(0.0121)	(0.0169)	(0.0134)	(0.0151)	(0.0198)	(0.0201)	(0.0212)	(0.0124)	(0.0195)	(0.0131)	(0.0139)
GOLD	−0.1314	−0.1860*	−0.2868***	−0.2658**	−0.3230**	−0.2105***	−0.3357***	−0.1372	−0.2469**	−0.2521*	−0.2097°	−0.2354**	−0.1610	−0.3509**	−0.0571	−0.2813*	−0.2424*	−0.1740	−0.3633***	−0.3254***
	(0.1092)	(0.0952)	(0.1023)	(0.1178)	(0.1626)	(0.0707)	(0.0972)	(0.1313)	(0.1139)	(0.1381)	(0.1594)	(0.1006)	(0.1496)	(0.1665)	(0.1829)	(0.1654)	(0.1309)	(0.1700)	(0.0976)	(0.0876)
VSTOXX	−0.0228***	−0.0180***	−0.0165**	−0.0172***	−0.0276***	−0.0168***	−0.0183***	−0.0223***	−0.0145***	−0.0214***	−0.0182***	−0.0239***	−0.0217***	−0.0243***	−0.0220**	−0.0232***	−0.0237***	−0.0192**	−0.0150***	−0.0163**
	(0.0057)	(0.0046)	(0.0073)	(0.0061)	(0.0061)	(0.0049)	(0.0047)	(0.0068)	(0.0055)	(0.0044)	(0.0059)	(0.0075)	(0.0053)	(0.0060)	(0.0090)	(0.0073)	(0.0065)	(0.0092)	(0.0043)	(0.0078)
EURO.XX	0.8424***	0.3396***	0.5057***	0.5251***	0.8908***	0.3955***	0.5240***	0.8981***	0.4446***	0.4157***	0.5722***	0.6126***	0.8483***	0.7703***	0.6511***	0.6539***	0.6375***	0.8251***	0.6374***	0.5613***
	(0.0906)	(0.0956)	(0.1422)	(0.1431)	(0.0818)	(0.0885)	(0.0658)	(0.0984)	(0.0890)	(0.1272)	(0.1221)	(0.0898)	(0.0809)	(0.1418)	(0.1418)	(0.0868)	(0.0728)	(0.1446)	(0.0959)	(0.0960)
INTERM.	−0.0274***	−0.0114°	−0.0108	−0.0164*	−0.0146°	0.0043	−0.0063	−0.0172**	−0.0091	−0.0060	−0.0131	−0.0048	−0.0118°	−0.0290***	−0.0137	−0.0240**	−0.0118	−0.0118	−0.0029	−0.0066
	(0.0083)	(0.0072)	(0.0091)	(0.0086)	(0.0096)	(0.0070)	(0.0093)	(0.0083)	(0.0103)	(0.0075)	(0.0107)	(0.0082)	(0.0090)	(0.0097)	(0.0114)	(0.0109)	(0.0106)	(0.0122)	(0.0085)	(0.0091)
VaR	0.2152***	0.4596***	0.3821***	0.3182***	0.1313***	0.3999***	0.2801***	0.1417***	0.4219***	0.4657***	0.3016***	0.2118***	0.2056***	0.2304***	0.3169***	0.3287***	0.2297***	0.1609**	0.2600***	0.3444***
	(0.0421)	(0.0508)	(0.0584)	(0.0644)	(0.0295)	(0.0481)	(0.0255)	(0.0335)	(0.0530)	(0.0569)	(0.0629)	(0.0367)	(0.0400)	(0.0638)	(0.0640)	(0.0644)	(0.0513)	(0.0630)	(0.0422)	(0.0578)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.6	0.81	0.79	0.76	0.78	0.84	0.81	0.75	0.78	0.8	0.68	0.82	0.79	0.7	0.74	0.69	0.79	0.66	0.82	0.74

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.30: Post-penalized $CoVaR$ at 5% (cont)

	ERSTE	SKANDI.	SVENSKA	SWEDBNK	BANC.SAB	RAIFFEI.	BPER	BANKINT.	JYSKE	POWSZ.	MEDIOB..	BANC.COMM.	OTP	EUROBNK.	BNK.GREeCE	ALPHA	PIREUS	CREDIT.EMIL	BANK.POL.
(Intercept)	−0.0241***	−0.0283***	−0.0262***	−0.0276***	−0.0234***	−0.0256***	−0.0222***	−0.0232***	−0.0264***	−0.0266***	−0.0232***	−0.0250***	−0.0269***	−0.0287***	−0.0288***	−0.0275***	−0.0277***	−0.0243***	−0.0265***
	(0.0019)	(0.0021)	(0.0024)	(0.0023)	(0.0017)	(0.0023)	(0.0012)	(0.0018)	(0.0021)	(0.0021)	(0.0021)	(0.0023)	(0.0023)	(0.0022)	(0.0024)	(0.0018)	(0.0020)	(0.0019)	(0.0025)
CREDIT	−0.0287°	−0.0393°	−0.0258°	−0.0504**	−0.0521***	−0.0307°	−0.0447***	−0.0305*	−0.0374*	−0.0438*	−0.0255°	−0.0689***	−0.0599***	−0.0494**	−0.0503**	−0.0442**	−0.0401*	−0.0418*	−0.0418*
	(0.0191)	(0.0244)	(0.0169)	(0.0206)	(0.0165)	(0.0215)	(0.0169)	(0.0158)	(0.0203)	(0.0243)	(0.0177)	(0.0247)	(0.0225)	(0.0236)	(0.0223)	(0.0186)	(0.0231)	(0.0232)	(0.0237)
GOLD	−0.1070	−0.3478*	−0.3110*	−0.4010**	−0.2244**	−0.3195*	−0.2627**	−0.2333°	−0.2382°	−0.3936*	−0.3582**	−0.1909°	−0.2940°	−0.0292	−0.1501	−0.1496	−0.0723	−0.3912***	−0.1998
	(0.1215)	(0.2048)	(0.1869)	(0.1848)	(0.0953)	(0.1908)	(0.1058)	(0.1442)	(0.1667)	(0.2085)	(0.1775)	(0.1345)	(0.1981)	(0.2092)	(0.2081)	(0.1584)	(0.1896)	(0.1316)	(0.2106)
VSTOXX	−0.0168***	−0.0290***	−0.0201**	−0.0310***	−0.0205***	−0.0302***	−0.0194***	−0.0229***	−0.0290***	−0.0259**	−0.0249***	−0.0223***	−0.0277***	−0.0312***	−0.0304***	−0.0238***	−0.0256***	−0.0210***	−0.0280***
	(0.0054)	(0.0091)	(0.0086)	(0.0111)	(0.0072)	(0.0088)	(0.0051)	(0.0063)	(0.0077)	(0.0110)	(0.0069)	(0.0084)	(0.0105)	(0.0100)	(0.0094)	(0.0077)	(0.0081)	(0.0063)	(0.0092)
EURO.XX	0.4660***	0.7614***	0.7295***	0.7282***	0.6790***	0.6539***	0.6741***	0.6506***	0.7101***	0.8198***	0.5877***	0.6991***	0.7541***	0.8679***	0.9087***	0.8387***	0.8600***	0.7967***	0.8539***
	(0.1213)	(0.1405)	(0.1340)	(0.1494)	(0.1075)	(0.1277)	(0.0763)	(0.1376)	(0.1733)	(0.1424)	(0.1240)	(0.1458)	(0.1352)	(0.1559)	(0.1547)	(0.1359)	(0.1282)	(0.1146)	(0.1429)
INTERM.	−0.0178*	−0.0277**	−0.0337***	−0.0175°	−0.0170*	−0.0237*	−0.0006	−0.0165**	−0.0168°	−0.0139	−0.0048	0.0062	−0.0081	−0.0144	−0.0160	−0.0166°	−0.0173°	−0.0010	−0.0145
	(0.0091)	(0.0137)	(0.0121)	(0.0123)	(0.0094)	(0.0127)	(0.0083)	(0.0076)	(0.0127)	(0.0123)	(0.0091)	(0.0107)	(0.0119)	(0.0144)	(0.0139)	(0.0115)	(0.0133)	(0.0121)	(0.0147)
VaR	0.3697***	0.1258	0.2037**	0.1084	0.1795***	0.1864***	0.2278***	0.2891***	0.1514**	0.0683	0.2587***	0.2045***	0.0801	0.0527°	0.0457	0.0899***	0.0521**	0.2550***	0.0196
	(0.0487)	(0.1000)	(0.0898)	(0.0917)	(0.0346)	(0.0538)	(0.0253)	(0.0583)	(0.0611)	(0.0553)	(0.0648)	(0.0513)	(0.0646)	(0.0407)	(0.0375)	(0.0301)	(0.0226)	(0.0575)	(0.0288)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.77	0.64	0.58	0.69	0.8	0.78	0.8	0.7	0.67	0.67	0.76	0.79	0.73	0.84	0.82	0.83	0.88	0.63	0.81

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.31: Post-penalized $CoVaR$ at 5% (cont)

	SANT.	KOMER	AAREAL	ING.SLA..	MBANK	SYDBAK	MILLEN.	BRD	AKTIA	HOIST	SONDRIO	CAIXA	SUISSE	BPM	BNK.GREECE	PIC.	LANG.	MEDIO.	DEUT.PF
(Intercept)	−0.0265***	−0.0263***	−0.0285***	−0.0274***	−0.0281***	−0.0271***	−0.0275***	−0.0276***	−0.0281***	−0.0273***	−0.0244***	−0.0231***	−0.0212***	−0.0229***	−0.0276***	−0.0269***	−0.0259***	−0.0247***	−0.0260***
	(0.0025)	(0.0025)	(0.0022)	(0.0021)	(0.0020)	(0.0023)	(0.0021)	(0.0023)	(0.0021)	(0.0027)	(0.0018)	(0.0021)	(0.0022)	(0.0015)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0019)
CREDIT	−0.0418*	−0.0445**	−0.0182	−0.0551**	−0.0613***	−0.0218	−0.0458**	−0.0516**	−0.0513**	−0.0556***	−0.0219	−0.0361**	−0.0247	−0.0423**	−0.0373*	−0.0485**	−0.0418**	−0.0445**	−0.0494***
	(0.0237)	(0.0224)	(0.0214)	(0.0214)	(0.0217)	(0.0227)	(0.0193)	(0.0228)	(0.0217)	(0.0198)	(0.0257)	(0.0156)	(0.0216)	(0.0200)	(0.0225)	(0.0211)	(0.0191)	(0.0204)	(0.0171)
GOLD	−0.1998	−0.3441*	−0.0799	−0.1847	−0.1836	−0.3383*	−0.2804°	−0.2061	−0.0810	−0.1481	−0.4378***	−0.1129	−0.3186*	−0.2712**	−0.2802°	−0.1734	−0.1935	−0.3792*	−0.1753
	(0.2106)	(0.2010)	(0.2089)	(0.2055)	(0.2043)	(0.1760)	(0.2108)	(0.2013)	(0.1965)	(0.1902)	(0.1326)	(0.1262)	(0.1670)	(0.1166)	(0.1939)	(0.1733)	(0.1794)	(0.2014)	(0.1368)
VSTOXX	−0.0280***	−0.0271***	−0.0224***	−0.0272**	−0.0287***	−0.0203**	−0.0194*	−0.0327***	−0.0340***	−0.0314***	−0.0180***	−0.0181**	−0.0232***	−0.0212***	−0.0216**	−0.0201**	−0.0223**	−0.0198**	−0.0182**
	(0.0092)	(0.0089)	(0.0078)	(0.0112)	(0.0101)	(0.0083)	(0.0105)	(0.0103)	(0.0089)	(0.0097)	(0.0061)	(0.0080)	(0.0060)	(0.0062)	(0.0104)	(0.0088)	(0.0087)	(0.0089)	(0.0083)
EURO.XX	0.8539***	0.8111***	0.7760***	0.8886***	0.8656***	0.8599***	0.8494***	0.8308***	0.8179***	0.7255***	0.8035***	0.7103***	0.6029***	0.8249***	1.0475***	0.8550***	0.8507***	0.8255***	0.7694***

	SANT.	KOMER	AAREAL	ING.SLA..	MBANK	SYDBAK	MILLEN.	BRD	AKTIA	HOIST	SONDRIO	CAIXA	SUISSE	BPM	BNK.GREECE	PIC.	LANG.	MEDIO.	DEUT.PF
	(0.1429)	(0.1552)	(0.1361)	(0.1471)	(0.1514)	(0.1669)	(0.1418)	(0.1413)	(0.1634)	(0.1518)	(0.1227)	(0.1374)	(0.1068)	(0.1454)	(0.1680)	(0.1295)	(0.1301)	(0.1432)	(0.1388)
INTERM.	-0.0145	-0.0106	-0.0352^{**}	-0.0106	-0.0084	-0.0144	-0.0158	-0.0130	-0.0173°	-0.0191°	-0.0124	-0.0001	-0.0130°	-0.0026	-0.0119	-0.0238^{**}	-0.0187°	-0.0099	-0.0187^{*}
	(0.0147)	(0.0128)	(0.0137)	(0.0113)	(0.0127)	(0.0113)	(0.0133)	(0.0132)	(0.0132)	(0.0121)	(0.0099)	(0.0117)	(0.0093)	(0.0065)	(0.0113)	(0.0109)	(0.0124)	(0.0107)	(0.0099)
VaR	0.0196	0.0801	0.1949^{***}	0.0884^{*}	0.0367	0.1655^{**}	0.0704°	-0.0028	0.0329	0.0510	0.1800^{***}	0.2592^{***}	0.2867^{***}	0.1504^{***}	0.1133°	0.1838^{**}	0.1950^{**}	0.1560^{**}	0.2077^{***}
	(0.0288)	(0.0841)	(0.0710)	(0.0516)	(0.0401)	(0.0827)	(0.0450)	(0.0675)	(0.0856)	(0.0578)	(0.0310)	(0.0719)	(0.0567)	(0.0253)	(0.0798)	(0.0767)	(0.0825)	(0.0722)	(0.0583)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.68	0.61	0.7	0.66	0.77	0.67	0.77	0.67	0.62	0.79	0.75	0.71	0.79	0.84	0.47	0.46	0.57	0.69	0.77

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.32: Post-penalized $CoVaR$ at 5% (cont)

	VIL.	RINGKJ.	FIRST.INV.	GRENKE	ALAND.	HRVAT.	ALM.BRND	BNK.ACH.	CENTR.COOP.	SPAREK.	MLP	BN.NORD.	DJURSD	SKJERN	MUTUI	KREDIT.	NORDFYN.	MOENS
(Intercept)	-0.0259^{***}	-0.0282^{***}	-0.0279^{***}	-0.0265^{***}	-0.0285^{***}	-0.0269^{***}	-0.0277^{***}	-0.0281^{***}	-0.0274^{***}	-0.0282^{***}	-0.0275^{***}	-0.0273^{***}	-0.0291^{***}	-0.0287^{***}	-0.0284^{***}	-0.0282^{***}	-0.0283^{***}	-0.0256^{***}
	(0.0022)	(0.0022)	(0.0024)	(0.0018)	(0.0022)	(0.0020)	(0.0022)	(0.0026)	(0.0021)	(0.0021)	(0.0020)	(0.0019)	(0.0024)	(0.0022)	(0.0022)	(0.0020)	(0.0024)	(0.0024)
CREDIT	-0.0431^{**}	-0.0211	-0.0510^{**}	-0.0450^{*}	-0.0531^{**}	-0.0341°	-0.0531^{**}	-0.0508^{**}	-0.0520^{**}	-0.0508^{**}	-0.0463^{**}	-0.0487^{**}	-0.0496^{**}	-0.0478^{**}	-0.0564^{**}	-0.0572^{**}	-0.0497^{**}	-0.0470^{*}
	(0.0172)	(0.0240)	(0.0227)	(0.0229)	(0.0217)	(0.0214)	(0.0247)	(0.0229)	(0.0220)	(0.0224)	(0.0188)	(0.0231)	(0.0226)	(0.0201)	(0.0234)	(0.0252)	(0.0214)	(0.0247)
GOLD	-0.1791°	-0.3620^{*}	-0.2846°	-0.1483	-0.1139	-0.1451	-0.2002	-0.1751	-0.2235	-0.1338	-0.0674	-0.1657	-0.1746	-0.1497	-0.3451^{*}	-0.2752°	-0.1272	-0.3500^{**}
	(0.1314)	(0.1934)	(0.1800)	(0.1753)	(0.1940)	(0.1915)	(0.1944)	(0.2058)	(0.2134)	(0.2227)	(0.1854)	(0.2012)	(0.1902)	(0.1807)	(0.2016)	(0.1812)	(0.1883)	(0.1568)
VSTOXX	-0.0217^{***}	-0.0239^{**}	-0.0339^{***}	-0.0193^{**}	-0.0233^{***}	-0.0236^{***}	-0.0307^{***}	-0.0344^{***}	-0.0320^{***}	-0.0334^{***}	-0.0227^{***}	-0.0305^{***}	-0.0345^{***}	-0.0291^{***}	-0.0333^{***}	-0.0344^{***}	-0.0332^{***}	-0.0199^{**}
	(0.0081)	(0.0092)	(0.0095)	(0.0089)	(0.0086)	(0.0079)	(0.0096)	(0.0098)	(0.0096)	(0.0094)	(0.0084)	(0.0085)	(0.0089)	(0.0088)	(0.0092)	(0.0090)	(0.0106)	(0.0101)
EURO.XX	0.8567^{***}	0.9146^{***}	0.8027^{***}	0.8362^{***}	0.9305^{***}	0.9220^{***}	0.8221^{***}	0.8266^{***}	0.8255^{***}	0.8353^{***}	0.8881^{***}	0.8551^{***}	0.8916^{***}	0.9288^{***}	0.7603^{***}	0.7874^{***}	0.8477^{***}	1.0246^{***}
	(0.1345)	(0.1593)	(0.1510)	(0.1289)	(0.1274)	(0.1225)	(0.1520)	(0.1531)	(0.1514)	(0.1461)	(0.1505)	(0.1398)	(0.1380)	(0.1408)	(0.1791)	(0.1501)	(0.1575)	(0.1522)
INTERM.	-0.0144°	-0.0111	-0.0122	-0.0123	-0.0180°	-0.0274^{**}	-0.0104	-0.0167	-0.0120	-0.0164	-0.0242^{**}	-0.0160°	-0.0188°	-0.0195°	-0.0184°	-0.0253^{**}	-0.0173	-0.0108
	(0.0100)	(0.0120)	(0.0132)	(0.0128)	(0.0125)	(0.0126)	(0.0122)	(0.0140)	(0.0128)	(0.0131)	(0.0119)	(0.0119)	(0.0130)	(0.0127)	(0.0119)	(0.0121)	(0.0135)	(0.0123)
VaR	0.1635^{**}	0.2215^{**}	0.0319	0.1066^{**}	0.1136^{*}	0.1232^{**}	0.0376	0.0071	-0.0053	0.0118	0.1037°	-0.0631	-0.0730	0.0974^{*}	0.0363	-0.1441°	0.0059	-0.1386^{*}
	(0.0656)	(0.1057)	(0.0773)	(0.0461)	(0.0618)	(0.0566)	(0.0610)	(0.0421)	(0.0601)	(0.0627)	(0.0792)	(0.0801)	(0.1506)	(0.0520)	(0.0503)	(0.0933)	(0.0678)	(0.0759)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.62	0.54	0.67	0.78	0.44	0.58	0.62	0.7	0.57	0.48	0.57	0.53	0.38	0.49	0.68	0.23	0.51	0.47

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.33: Post-penalized $CoVaR$ at 50%

	HSBC	BNP	CR.AGR	BAN.SAN	BARC	SOC.GEN	DEUT.	LLOYDS	INTESA	ING	UBS	UNIC.	NAT.	ST.CHA	BBVA	NORDEA	ABN	DANSKE	COMMERZ.	KBC
(Intercept)	−0.0024**	−0.0008	−0.0014*	−0.0007	−0.0007	−0.0011°	−0.0018**	−0.0007	−0.0003	−0.0010	−0.0007	−0.0008	−0.0007	−0.0008	−0.0010	−0.0004	−0.0013°	−0.0009	−0.0008	−0.0017**
	(0.0010)	(0.0008)	(0.0009)	(0.0008)	(0.0011)	(0.0008)	(0.0009)	(0.0012)	(0.0008)	(0.0008)	(0.0011)	(0.0008)	(0.0010)	(0.0010)	(0.0010)	(0.0012)	(0.0010)	(0.0011)	(0.0007)	(0.0008)
CREDIT	−0.0401***	−0.0168	−0.0101	−0.0244°	−0.0328*	−0.0247**	−0.0305*	−0.0406**	−0.0114	−0.0279*	−0.0330*	−0.0093	−0.0410***	−0.0283*	−0.0205	−0.0474***	−0.0237°	−0.0474**	−0.0346**	−0.0290**
	(0.0150)	(0.0147)	(0.0157)	(0.0155)	(0.0173)	(0.0112)	(0.0172)	(0.0178)	(0.0134)	(0.0151)	(0.0191)	(0.0114)	(0.0131)	(0.0161)	(0.0210)	(0.0172)	(0.0163)	(0.0199)	(0.0149)	(0.0138)
TED	−0.0167***	−0.0053	−0.0047	−0.0099***	−0.0172**	−0.0027	−0.0051	−0.0141*	−0.0076**	−0.0053	−0.0149***	−0.0069°	−0.0110*	−0.0091°	−0.0063	−0.0121*	−0.0095**	−0.0118**	−0.0016	−0.0048
	(0.0058)	(0.0049)	(0.0037)	(0.0036)	(0.0072)	(0.0046)	(0.0055)	(0.0075)	(0.0038)	(0.0044)	(0.0054)	(0.0052)	(0.0058)	(0.0062)	(0.0058)	(0.0067)	(0.0048)	(0.0056)	(0.0055)	(0.0040)
EURIRS	0.0373°	0.0206	0.0242	0.0196	0.0480**	−0.0009	0.0163	0.0400°	0.0359**	0.0152	0.0272	0.0221°	0.0108	0.0155	0.0328	0.0086	0.0334°	0.0262	−0.0123	0.0098
	(0.0243)	(0.0182)	(0.0189)	(0.0229)	(0.0244)	(0.0207)	(0.0240)	(0.0246)	(0.0155)	(0.0228)	(0.0268)	(0.0152)	(0.0214)	(0.0242)	(0.0289)	(0.0284)	(0.0228)	(0.0328)	(0.0224)	(0.0206)
GOLD	−0.2381***	−0.1334**	−0.1630**	−0.1508**	−0.3040***	−0.1364*	−0.1595**	−0.3018***	−0.1868***	−0.1680***	−0.2514***	−0.1462*	−0.2839***	−0.3353***	−0.2029***	−0.2843***	−0.2762***	−0.2910***	−0.1995***	−0.1916***
	(0.0757)	(0.0554)	(0.0666)	(0.0635)	(0.0735)	(0.0787)	(0.0692)	(0.0754)	(0.0542)	(0.0486)	(0.0775)	(0.0759)	(0.0911)	(0.0744)	(0.0577)	(0.0960)	(0.0694)	(0.0775)	(0.0537)	(0.0553)
EURO.XX	1.0155***	0.3547***	0.4849***	0.4730***	0.9744***	0.4456***	0.6442***	0.9534***	0.5477***	0.4823***	0.7113***	0.5982***	0.7099***	0.7212***	0.6331***	0.7710***	0.7144***	0.8550***	0.6326***	0.6280***
	(0.0495)	(0.0815)	(0.0670)	(0.0685)	(0.0517)	(0.0637)	(0.0689)	(0.0569)	(0.0513)	(0.0767)	(0.0699)	(0.0550)	(0.0586)	(0.0753)	(0.0626)	(0.0863)	(0.0767)	(0.0670)	(0.0437)	(0.0603)
EU.GDP	0.3292*	−0.1166	−0.0483	0.1116	0.1458	0.2488	0.2570°	0.2462°	0.0559	−0.1411	0.2886*	0.2867*	0.3538*	0.3925**	0.1312	0.1335	0.0680	0.2076°	0.2693°	0.0771
	(0.1807)	(0.2784)	(0.1604)	(0.1393)	(0.2176)	(0.2442)	(0.1830)	(0.1897)	(0.1528)	(0.2068)	(0.1561)	(0.1545)	(0.2108)	(0.1859)	(0.1520)	(0.2119)	(0.2372)	(0.1615)	(0.1649)	(0.2069)
VaR	0.2181***	0.4954***	0.4239***	0.3765***	0.1246***	0.3684***	0.2522***	0.1139***	0.3859***	0.3790***	0.2681***	0.2875***	0.2227***	0.2321***	0.3075***	0.1882***	0.2419***	0.1383***	0.2467***	0.3534***
	(0.0379)	(0.0516)	(0.0523)	(0.0394)	(0.0262)	(0.0394)	(0.0301)	(0.0299)	(0.0260)	(0.0421)	(0.0480)	(0.0249)	(0.0254)	(0.0390)	(0.0357)	(0.0465)	(0.0482)	(0.0314)	(0.0228)	(0.0414)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.51	0.74	0.72	0.73	0.67	0.76	0.76	0.61	0.69	0.71	0.58	0.79	0.7	0.65	0.69	0.57	0.67	0.57	0.77	0.64

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.34: Post-penalized $CoVaR$ at 50% (cont)

	ERSTE	SKANDI.	SVENSKA	SWEDBNK	BANC.SAB	RAIFFEI.	BPER	BANKINT.	JYSKE	POWSZ.	MEDIOB..	BANC.COMM.	OTP	EUROBNK.	BNK.GREeCE	ALPHA	PIREUS	CREDIT.EMIL	BANK.POL.
(Intercept)	−0.0016*	−0.0011	−0.0006	−0.0010	−0.0007	−0.0012	−0.0012	−0.0019*	−0.0015°	−0.0018°	−0.0020*	−0.0014*	−0.0012	−0.0015°	−0.0011	−0.0011	−0.0014°	−0.0006	−0.0008
	(0.0010)	(0.0013)	(0.0012)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0011)	(0.0010)	(0.0012)	(0.0011)	(0.0008)	(0.0013)	(0.0010)	(0.0010)	(0.0011)	(0.0010)	(0.0011)	(0.0013)
CREDIT	−0.0363***	−0.0496**	−0.0432*	−0.0474**	−0.0345**	−0.0275°	−0.0351***	−0.0337*	−0.0349*	−0.0383**	−0.0179	−0.0332**	−0.0408*	−0.0395*	−0.0462**	−0.0442**	−0.0370*	−0.0303*	−0.0444**
	(0.0122)	(0.0235)	(0.0246)	(0.0191)	(0.0157)	(0.0174)	(0.0125)	(0.0195)	(0.0211)	(0.0176)	(0.0172)	(0.0163)	(0.0220)	(0.0211)	(0.0215)	(0.0223)	(0.0209)	(0.0165)	(0.0191)
TED	−0.0157**	−0.0121°	−0.0146*	−0.0159**	−0.0083***	−0.0047	−0.0148***	−0.0076°	−0.0184***	−0.0130**	−0.0073	−0.0133***	−0.0118°	−0.0131*	−0.0157**	−0.0158**	−0.0121*	−0.0097°	−0.0165**
	(0.0065)	(0.0075)	(0.0078)	(0.0069)	(0.0028)	(0.0068)	(0.0035)	(0.0047)	(0.0044)	(0.0063)	(0.0066)	(0.0044)	(0.0080)	(0.0075)	(0.0078)	(0.0073)	(0.0072)	(0.0061)	(0.0071)
EURIRS	0.0198	0.0295	0.0229	0.0283	0.0059	0.0457*	0.0197	0.0180	0.0497°	0.0431°	0.0520**	0.0295	0.0482°	0.0485°	0.0396	0.0427	0.0450°	0.0372°	0.0429°
	(0.0190)	(0.0347)	(0.0368)	(0.0308)	(0.0226)	(0.0251)	(0.0190)	(0.0285)	(0.0321)	(0.0272)	(0.0255)	(0.0248)	(0.0305)	(0.0311)	(0.0315)	(0.0343)	(0.0323)	(0.0246)	(0.0296)
GOLD	−0.1782**	−0.3399***	−0.3473***	−0.3231***	−0.2394***	−0.2732***	−0.1910***	−0.2404***	−0.2522***	−0.2956***	−0.2787***	−0.2842***	−0.3084***	−0.3426***	−0.3256***	−0.3181***	−0.3636***	−0.2223***	−0.3211***
	(0.0766)	(0.0878)	(0.0724)	(0.0853)	(0.0644)	(0.0701)	(0.0607)	(0.0797)	(0.0720)	(0.0855)	(0.0818)	(0.0685)	(0.0918)	(0.0855)	(0.0834)	(0.0784)	(0.0802)	(0.0755)	(0.0873)
EURO.XX	0.7260***	0.8844***	0.8753***	0.9329***	0.7740***	0.8212***	0.7653***	0.7771***	0.8581***	0.8915***	0.7297***	0.8663***	0.9338***	0.9530***	0.9185***	0.9210***	0.9699***	0.7863***	0.9767***

	ERSTE	SKANDI.	SVENSKA	SWEDBNK	BANC.SAB	RAIFFEI.	BPER	BANKINT.	JYSKE	POWSZ.	MEDIOB..	BANC.COMM.	OTP	EUROBNK.	BNK.GREeCE	ALPHA	PIREUS	CREDIT.EMIL	BANK.POL.
	(0.0780)	(0.0852)	(0.0804)	(0.0663)	(0.0549)	(0.0595)	(0.0442)	(0.0691)	(0.0499)	(0.0555)	(0.0679)	(0.0500)	(0.0610)	(0.0603)	(0.0576)	(0.0720)	(0.0576)	(0.0676)	(0.0647)
Eu.GDP	0.1063	0.2547°	0.2577°	0.3045°	0.1059	0.3726**	0.3427***	0.0397	0.2480°	0.2282°	0.1394	0.1927	0.3187*	0.3852*	0.3296*	0.2094	0.3467*	0.4129*	0.1589
	(0.2467)	(0.1642)	(0.1822)	(0.1970)	(0.2045)	(0.1747)	(0.1303)	(0.2157)	(0.1566)	(0.1720)	(0.2100)	(0.1553)	(0.1624)	(0.2053)	(0.1684)	(0.1773)	(0.1928)	(0.2233)	(0.2110)
VaR	0.2656***	0.1182*	0.1607***	0.0653**	0.1867***	0.1476***	0.1737***	0.2662***	0.1735***	0.1021***	0.2156***	0.1349***	0.0652**	0.0306**	0.0355***	0.0513***	0.0225***	0.2564***	0.0497**
	(0.0437)	(0.0617)	(0.0562)	(0.0296)	(0.0187)	(0.0236)	(0.0174)	(0.0425)	(0.0317)	(0.0266)	(0.0341)	(0.0217)	(0.0281)	(0.0143)	(0.0128)	(0.0151)	(0.0081)	(0.0485)	(0.0205)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.67	0.5	0.48	0.51	0.76	0.69	0.75	0.64	0.59	0.62	0.66	0.75	0.61	0.79	0.78	0.78	0.83	0.57	0.72

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.35: Post-penalized $CoVaR$ at 50% (cont)

	SANT.	KOMER	AAREAL	ING.SLA..	MBANK	SYDBAK	MILLEN.	BRD	AKTIA	HOIST	SONDRIO	CAIXA	SUISSE	BPM	BNK.GREECE	PIC.	LANG.	MEDIO.	DEUT.PF
(Intercept)	−0.0014°	−0.0011	−0.0006	−0.0016°	−0.0016°	−0.0016°	−0.0009	−0.0012	−0.0012	−0.0009	−0.0013°	−0.0015°	−0.0009	−0.0014°	−0.0018°	−0.0014	−0.0011	−0.0005	−0.0009
	(0.0010)	(0.0011)	(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0011)	(0.0012)	(0.0011)	(0.0009)	(0.0011)	(0.0010)	(0.0009)	(0.0011)	(0.0012)	(0.0011)	(0.0013)	(0.0011)
CREDIT	−0.0410**	−0.0457***	−0.0486**	−0.0429**	−0.0374*	−0.0379*	−0.0459**	−0.0441**	−0.0372**	−0.0425***	−0.0299*	−0.0326**	−0.0245*	−0.0281*	−0.0348*	−0.0448**	−0.0463***	−0.0233	−0.0435***
	(0.0187)	(0.0175)	(0.0224)	(0.0191)	(0.0200)	(0.0193)	(0.0199)	(0.0196)	(0.0184)	(0.0152)	(0.0162)	(0.0154)	(0.0145)	(0.0162)	(0.0197)	(0.0188)	(0.0158)	(0.0186)	(0.0165)
TED	−0.0108*	−0.0160**	−0.0191***	−0.0119°	−0.0124*	−0.0112**	−0.0143**	−0.0133*	−0.0128*	−0.0165**	−0.0136***	−0.0026	−0.0134**	−0.0117***	−0.0112°	−0.0158**	−0.0133**	−0.0158**	−0.0158**
	(0.0057)	(0.0069)	(0.0069)	(0.0075)	(0.0065)	(0.0053)	(0.0063)	(0.0068)	(0.0069)	(0.0072)	(0.0048)	(0.0051)	(0.0065)	(0.0044)	(0.0075)	(0.0074)	(0.0060)	(0.0069)	(0.0063)
EURIRS	0.0406°	0.0390°	0.0214	0.0367°	0.0478°	0.0382°	0.0351	0.0459°	0.0441°	0.0371°	0.0382°	0.0124	0.0377*	0.0299°	0.0471°	0.0429°	0.0438*	0.0542**	0.0306
	(0.0288)	(0.0260)	(0.0345)	(0.0282)	(0.0306)	(0.0294)	(0.0331)	(0.0302)	(0.0285)	(0.0254)	(0.0244)	(0.0240)	(0.0208)	(0.0220)	(0.0301)	(0.0279)	(0.0253)	(0.0270)	(0.0262)
GOLD	−0.3365***	−0.2843***	−0.3244***	−0.3845***	−0.3217***	−0.2948***	−0.3380***	−0.3704***	−0.3625***	−0.3213***	−0.2532***	−0.1134	−0.2337***	−0.2431***	−0.3728***	−0.3669***	−0.3630***	−0.3429***	−0.3113***
	(0.0800)	(0.0906)	(0.0783)	(0.0780)	(0.0796)	(0.0766)	(0.0915)	(0.0936)	(0.0829)	(0.0785)	(0.0674)	(0.1039)	(0.0632)	(0.0650)	(0.0891)	(0.0835)	(0.0732)	(0.0851)	(0.0740)
EURO.XX	0.9049***	0.9348***	0.8787***	0.9258***	0.8946***	0.8701***	0.8885***	0.9698***	0.9856***	0.9708***	0.8130***	0.7425***	0.7516***	0.8051***	0.9672***	0.9642***	0.9485***	0.8602***	0.8204***
	(0.0555)	(0.0592)	(0.0726)	(0.0640)	(0.0632)	(0.0560)	(0.0649)	(0.0559)	(0.0592)	(0.0561)	(0.0561)	(0.0682)	(0.0759)	(0.0462)	(0.0596)	(0.0513)	(0.0617)	(0.0696)	(0.0660)
EU.GDP	0.2670°	0.2200	0.2918°	0.3649*	0.2766*	0.2326	0.3252°	0.3652*	0.1997	0.1812	0.1170	0.2209	0.2341°	0.4047***	0.3789*	0.3665*	0.1941	0.1444	0.1892
	(0.1972)	(0.1780)	(0.2269)	(0.1930)	(0.1677)	(0.1831)	(0.2268)	(0.1878)	(0.1825)	(0.1852)	(0.1609)	(0.1892)	(0.1469)	(0.1522)	(0.2143)	(0.1864)	(0.1751)	(0.2553)	(0.2117)
VaR	0.0903***	0.0880**	0.1069***	0.0858**	0.0725**	0.1629***	0.0578**	0.0419	0.0755**	0.0499***	0.1780***	0.2621***	0.1989***	0.1453***	0.0817°	0.0574°	0.1032**	0.1520***	0.1561***
	(0.0254)	(0.0403)	(0.0313)	(0.0381)	(0.0282)	(0.0343)	(0.0234)	(0.0427)	(0.0336)	(0.0189)	(0.0348)	(0.0346)	(0.0407)	(0.0186)	(0.0501)	(0.0393)	(0.0420)	(0.0553)	(0.0416)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.63	0.46	0.59	0.55	0.69	0.58	0.69	0.52	0.43	0.68	0.68	0.7	0.68	0.77	0.28	0.32	0.42	0.57	0.66

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.36: Post-penalized $CoVaR$ at 50% (cont)

	VIL.	RINGKJ.	FIRST.INV.	GRENKE	ALAND.	HRVAT.	ALM.BRND	BNK.ACH.	CENTR.COOP.	SPAREK.	MLP	BN.NORD.	DJURSD	SKJERN	MUTUI	KREDIT.	NORDFYN.	MOENS
(Intercept)	−0.0013	−0.0012	−0.0019*	−0.0015°	−0.0014	−0.0017°	−0.0015	−0.0007	−0.0012	−0.0012	−0.0018°	−0.0014	−0.0014	−0.0020°	−0.0012	−0.0017°	−0.0014	−0.0013
	(0.0013)	(0.0011)	(0.0011)	(0.0010)	(0.0011)	(0.0012)	(0.0012)	(0.0013)	(0.0012)	(0.0010)	(0.0012)	(0.0013)	(0.0011)	(0.0013)	(0.0011)	(0.0011)	(0.0011)	(0.0012)
CREDIT	−0.0410**	−0.0468***	−0.0414**	−0.0364**	−0.0416**	−0.0359*	−0.0375**	−0.0507**	−0.0471**	−0.0409**	−0.0364*	−0.0394*	−0.0409**	−0.0370**	−0.0394**	−0.0356*	−0.0439**	−0.0408**
	(0.0203)	(0.0173)	(0.0189)	(0.0172)	(0.0199)	(0.0209)	(0.0172)	(0.0213)	(0.0194)	(0.0194)	(0.0187)	(0.0218)	(0.0195)	(0.0183)	(0.0188)	(0.0197)	(0.0192)	(0.0198)
TED	−0.0144**	−0.0153**	−0.0151**	−0.0129*	−0.0131*	−0.0118*	−0.0138**	−0.0165**	−0.0183***	−0.0171**	−0.0124*	−0.0133*	−0.0132*	−0.0124*	−0.0146**	−0.0117*	−0.0132**	−0.0139**
	(0.0069)	(0.0060)	(0.0062)	(0.0070)	(0.0069)	(0.0065)	(0.0066)	(0.0064)	(0.0070)	(0.0066)	(0.0071)	(0.0072)	(0.0069)	(0.0070)	(0.0066)	(0.0069)	(0.0066)	(0.0065)
EURIRS	0.0401	0.0344	0.0407°	0.0442°	0.0399°	0.0452°	0.0464*	0.0384	0.0313	0.0498°	0.0477°	0.0464°	0.0417	0.0476*	0.0402°	0.0452°	0.0346	0.0398
	(0.0321)	(0.0286)	(0.0299)	(0.0289)	(0.0308)	(0.0319)	(0.0269)	(0.0325)	(0.0304)	(0.0310)	(0.0304)	(0.0330)	(0.0326)	(0.0285)	(0.0271)	(0.0302)	(0.0289)	(0.0325)
GOLD	−0.3701***	−0.3024***	−0.3095***	−0.3528***	−0.3268***	−0.3677***	−0.3603***	−0.3523***	−0.3748***	−0.3584***	−0.3652***	−0.3698***	−0.3503***	−0.3410***	−0.3445***	−0.3677***	−0.3001***	−0.3510***
	(0.0815)	(0.0778)	(0.0863)	(0.0849)	(0.0773)	(0.0828)	(0.0915)	(0.0808)	(0.0859)	(0.0776)	(0.0906)	(0.0889)	(0.0914)	(0.0988)	(0.0778)	(0.0801)	(0.0867)	(0.0827)
EURO.XX	0.9806***	0.8725***	0.9374***	1.0242***	0.9794***	0.9980***	0.9958***	0.9566***	0.9730***	0.9614***	0.9988***	0.9786***	0.9860***	1.0088***	0.9488***	0.9991***	0.9712***	0.9730***
	(0.0638)	(0.0726)	(0.0543)	(0.0610)	(0.0558)	(0.0643)	(0.0607)	(0.0666)	(0.0554)	(0.0637)	(0.0531)	(0.0596)	(0.0563)	(0.0626)	(0.0584)	(0.0625)	(0.0544)	(0.0668)
EU.GDP	0.3179°	0.3158*	0.2573°	0.3619*	0.3291*	0.3783*	0.2969°	0.2155°	0.2892°	0.3503*	0.3683**	0.3387*	0.3373*	0.3111°	0.3582**	0.3816**	0.3010**	0.3700*
	(0.2009)	(0.1660)	(0.1674)	(0.1998)	(0.1773)	(0.2051)	(0.1968)	(0.1661)	(0.1936)	(0.1888)	(0.1759)	(0.1797)	(0.1831)	(0.2034)	(0.1724)	(0.1772)	(0.1342)	(0.1899)
VaR	0.0329	0.1148**	0.0732***	−0.0141	0.0430°	0.0009	0.0316	0.0610**	0.0300	0.0796°	0.0091	0.0648°	0.0315	0.0274	0.0409°	−0.0032	0.0497°	0.0377
	(0.0416)	(0.0536)	(0.0243)	(0.0326)	(0.0279)	(0.0298)	(0.0389)	(0.0266)	(0.0272)	(0.0540)	(0.0327)	(0.0398)	(0.0653)	(0.0372)	(0.0271)	(0.0519)	(0.0352)	(0.0380)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.4	0.41	0.56	0.64	0.42	0.47	0.5	0.66	0.52	0.32	0.51	0.39	0.15	0.34	0.63	0.13	0.37	0.35

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.37: T-B $CoVaR$ at 5%

	HSBC	BNP	CR.AGR	BAN.SAN	BARC	SOC.GEN	DEUT.	LLOYDS	INTESA	ING	UBS	UNIC.	NAT.	ST.CHA	BBVA	NORDEA	ABN	DANSKE	COMMERZ.	KBC
(Intercept)	−0.0470***	−0.0213***	−0.0237***	−0.0239***	−0.0490***	−0.0238***	−0.0341***	−0.0480***	−0.0276***	−0.0223***	−0.0311***	−0.0282***	−0.0385***	−0.0360***	−0.0335***	−0.0370***	−0.0340***	−0.0393***	−0.0305***	−0.0305***
	(0.0050)	(0.0017)	(0.0027)	(0.0032)	(0.0041)	(0.0021)	(0.0035)	(0.0045)	(0.0023)	(0.0024)	(0.0031)	(0.0035)	(0.0045)	(0.0031)	(0.0041)	(0.0029)	(0.0032)	(0.0028)	(0.0029)	(0.0024)
CREDIT	0.0284°	−0.0069	−0.0299°	−0.0281°	0.0188	−0.0158	−0.0097	0.0243	−0.0128	−0.0210	−0.0161	−0.0188	0.0571*	−0.0034	−0.0093	0.0021	−0.0310	−0.0282°	−0.0181	−0.0611***
	(0.0217)	(0.0151)	(0.0223)	(0.0199)	(0.0266)	(0.0164)	(0.0267)	(0.0243)	(0.0146)	(0.0207)	(0.0365)	(0.0322)	(0.0290)	(0.0319)	(0.0264)	(0.0305)	(0.0275)	(0.0211)	(0.0220)	(0.0230)
SLOPE	0.0743	0.0379°	0.0226	0.0378	0.1073*	0.0140	0.0170	0.1185**	0.0076	0.0044	0.0060	0.0064	0.0078	0.0037	0.0075	0.0322	0.0337	0.0462	0.0454	0.0727*
	(0.0702)	(0.0288)	(0.0353)	(0.0309)	(0.0554)	(0.0242)	(0.0377)	(0.0505)	(0.0281)	(0.0246)	(0.0390)	(0.0384)	(0.0445)	(0.0513)	(0.0336)	(0.0421)	(0.0358)	(0.0404)	(0.0365)	(0.0395)
VSTOXX	−0.0553***	−0.0219***	−0.0021	−0.0241**	−0.0577***	−0.0147*	−0.0265***	−0.0628***	−0.0024	−0.0187**	−0.0298***	−0.0228°	−0.0244**	−0.0477***	−0.0309**	−0.0241**	−0.0308***	−0.0457***	−0.0328***	−0.0190**
	(0.0173)	(0.0054)	(0.0092)	(0.0102)	(0.0126)	(0.0080)	(0.0101)	(0.0157)	(0.0058)	(0.0078)	(0.0094)	(0.0140)	(0.0112)	(0.0163)	(0.0131)	(0.0095)	(0.0097)	(0.0141)	(0.0104)	(0.0089)
EURO.XX	0.4408*	0.0403	−0.0215	−0.1338	0.3313°	0.0555	0.1008	0.3541°	0.1460	−0.0244	0.0706	0.0706	0.2604°	−0.0634	0.1345	−0.0397	−0.0282	−0.0630	−0.2238°	−0.0700
	(0.2645)	(0.0898)	(0.1160)	(0.1487)	(0.2052)	(0.1136)	(0.1544)	(0.2723)	(0.1415)	(0.1093)	(0.1790)	(0.2063)	(0.1960)	(0.2066)	(0.1349)	(0.2139)	(0.1691)	(0.1886)	(0.1385)	(0.1338)
Real.Est	−0.3279*	−0.0613	0.2036°	0.1935°	−0.3937**	−0.0273	−0.1639	−0.3270°	−0.0081	0.0209	−0.0136	−0.0173	−0.3520*	0.0994	−0.0081	0.2473°	0.0178	0.0633	0.1445	0.1382

	HSBC	BNP	CR.AGR	BAN.SAN	BARC	SOC.GEN	DEUT.	LLOYDS	INTESA	ING	UBS	UNIC.	NAT.	ST.CHA	BBVA	NORDEA	ABN	DANSKE	COMMERZ.	KBC
	(0.1988)	(0.1119)	(0.1236)	(0.1396)	(0.1873)	(0.1209)	(0.1920)	(0.2250)	(0.1307)	(0.1167)	(0.1341)	(0.1751)	(0.1850)	(0.1501)	(0.1172)	(0.1826)	(0.1663)	(0.1603)	(0.1848)	(0.1309)
EUR-OIS	−0.0087**	−0.0052***	−0.0031	−0.0010	−0.0050	−0.0028°	−0.0019	−0.0061°	−0.0046**	−0.0023	−0.0061°	−0.0003	0.0013	−0.0110**	0.0044	−0.0018	−0.0003	−0.0092**	−0.0047°	−0.0010
	(0.0044)	(0.0017)	(0.0026)	(0.0034)	(0.0047)	(0.0021)	(0.0033)	(0.0045)	(0.0019)	(0.0026)	(0.0046)	(0.0034)	(0.0045)	(0.0044)	(0.0057)	(0.0031)	(0.0035)	(0.0044)	(0.0030)	(0.0025)
VaR	0.2182*	0.7254***	0.6324***	0.5771***	0.2605**	0.6027***	0.5179***	0.1955**	0.6950***	0.6030***	0.6892***	0.4170***	0.6449***	0.5167***	0.6419***	0.7720***	0.6268***	0.4013***	0.4387***	0.6889***
	(0.1262)	(0.0432)	(0.0598)	(0.0645)	(0.1038)	(0.0478)	(0.0488)	(0.0938)	(0.0521)	(0.0595)	(0.0824)	(0.0648)	(0.0868)	(0.0920)	(0.0596)	(0.0736)	(0.0715)	(0.1151)	(0.0551)	(0.0432)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.13	0.78	0.73	0.67	0.55	0.8	0.7	0.48	0.72	0.75	0.57	0.71	0.66	0.54	0.65	0.55	0.7	0.44	0.71	0.66

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.38: T-B $CoVaR$ at 5% (cont)

	ERSTE	SKANDI.	SVENSKA	SWEDBNK	BANC.SAB	RAIFFEI.	BPER	BANKINT.	JYSKE	POWSZ.	MEDIOB..	BANC.COMM.	OTP	EUROBNK.	BNK.GREeCE	ALPHA	PIREUS	CREDIT.EMIL	BANK.POL.
(Intercept)	−0.0301***	−0.0442***	−0.0377***	−0.0437***	−0.0357***	−0.0341***	−0.0368***	−0.0339***	−0.0468***	−0.0433***	−0.0320***	−0.0388***	−0.0409***	−0.0473***	−0.0495***	−0.0469***	−0.0482***	−0.0362***	−0.0454***
	(0.0035)	(0.0040)	(0.0033)	(0.0039)	(0.0034)	(0.0026)	(0.0041)	(0.0033)	(0.0040)	(0.0041)	(0.0023)	(0.0034)	(0.0035)	(0.0048)	(0.0045)	(0.0044)	(0.0037)	(0.0037)	(0.0038)
CREDIT	−0.0240	−0.0422	−0.0406*	−0.0221	0.0074	−0.0372°	−0.0108	−0.0292	0.0162	0.0080	−0.0131	−0.0066	−0.0307°	−0.0243	0.0111	0.0101	0.0081	0.0024	−0.0066
	(0.0195)	(0.0342)	(0.0243)	(0.0257)	(0.0324)	(0.0227)	(0.0292)	(0.0265)	(0.0314)	(0.0258)	(0.0271)	(0.0237)	(0.0213)	(0.0288)	(0.0275)	(0.0229)	(0.0234)	(0.0246)	(0.0241)
SLOPE	0.0167	0.0964**	0.0631°	0.0829*	0.0290	0.0113	0.0259	0.0089	0.0556	0.0102	0.0310	0.0592°	0.0101	−0.0110	0.0454	0.0761°	−0.0818*	0.1047*	0.0615
	(0.0509)	(0.0454)	(0.0473)	(0.0480)	(0.0407)	(0.0458)	(0.0511)	(0.0291)	(0.0452)	(0.0644)	(0.0288)	(0.0403)	(0.0640)	(0.0579)	(0.0517)	(0.0545)	(0.0477)	(0.0615)	(0.0654)
VSTOXX	−0.0054	−0.0441**	−0.0437***	−0.0511***	−0.0361***	−0.0142	−0.0208°	−0.0282***	−0.0489***	−0.0381**	−0.0239***	−0.0289***	−0.0441***	−0.0464**	−0.0304**	−0.0520***	−0.0612***	−0.0424***	−0.0567***
	(0.0083)	(0.0179)	(0.0150)	(0.0148)	(0.0125)	(0.0116)	(0.0144)	(0.0095)	(0.0109)	(0.0157)	(0.0090)	(0.0102)	(0.0163)	(0.0182)	(0.0148)	(0.0188)	(0.0168)	(0.0162)	(0.0169)
EURO.XX	0.0887	0.3601°	−0.1171	0.1481	0.3253*	0.1358	−0.0940	0.1370	0.4604**	0.3396°	−0.2367°	0.2387°	0.0549	0.3418°	0.3506°	0.5196**	0.6033**	0.0444	0.1400
	(0.1609)	(0.2312)	(0.2032)	(0.2559)	(0.1707)	(0.2061)	(0.2119)	(0.1936)	(0.2038)	(0.2352)	(0.1657)	(0.1816)	(0.2296)	(0.2474)	(0.2263)	(0.2183)	(0.2515)	(0.2108)	(0.2252)
Real.Est	0.0094	−0.0781	0.2304°	−0.0027	−0.2200	−0.0441	0.1472	−0.1412	−0.4439**	−0.1027	0.2152*	−0.3132**	−0.0870	−0.2827°	−0.1068	−0.4068**	−0.4629**	0.0089	−0.1023
	(0.1575)	(0.1514)	(0.1768)	(0.1648)	(0.1853)	(0.1541)	(0.1774)	(0.1814)	(0.1806)	(0.2489)	(0.1226)	(0.1557)	(0.1714)	(0.1821)	(0.1750)	(0.1727)	(0.1881)	(0.1775)	(0.1790)
EUR-OIS	−0.0038°	−0.0073°	−0.0082*	−0.0083*	−0.0047	−0.0124***	0.0016	−0.0002	−0.0002	−0.0122***	−0.0059*	−0.0043	−0.0109**	−0.0086°	−0.0043	−0.0074°	−0.0110**	−0.0037	−0.0069°
	(0.0029)	(0.0051)	(0.0049)	(0.0044)	(0.0043)	(0.0032)	(0.0062)	(0.0030)	(0.0040)	(0.0041)	(0.0031)	(0.0046)	(0.0045)	(0.0056)	(0.0055)	(0.0051)	(0.0045)	(0.0043)	(0.0045)
VaR	0.6018***	0.4638***	0.6807***	0.4163***	0.3574***	0.4793***	0.4301***	0.6726***	0.5044***	0.3563***	0.6025***	0.4150***	0.3060***	0.1441**	0.2391***	0.1617**	0.1105**	0.5477***	0.1334**
	(0.0649)	(0.1381)	(0.0991)	(0.1526)	(0.0521)	(0.0838)	(0.0533)	(0.0724)	(0.0760)	(0.0981)	(0.0940)	(0.0563)	(0.0893)	(0.0598)	(0.0590)	(0.0684)	(0.0462)	(0.0915)	(0.0590)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.68	0.42	0.31	0.47	0.67	0.68	0.64	0.57	0.49	0.44	0.66	0.67	0.53	0.7	0.7	0.67	0.78	0.36	0.63

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.39: T-B $CoVaR$ at 5% (cont)

	SANT.	KOMER	AAREAL	ING.SLA..	MBANK	SYDBAK	MILLEN.	BRD	AKTIA	HOIST	SONDRIO	CAIXA	SUISSE	BPM	BNK.GREECE	PIC.	LANG.	MEDIO.	DEUT.PF
(Intercept)	−0.0454***	−0.0458***	−0.0414***	−0.0443***	−0.0418***	−0.0381***	−0.0413***	−0.0460***	−0.0438***	−0.0406***	−0.0368***	−0.0378***	−0.0296***	−0.0347***	−0.0499***	−0.0452***	−0.0477***	−0.0380***	−0.0373***
	(0.0038)	(0.0041)	(0.0037)	(0.0044)	(0.0050)	(0.0024)	(0.0040)	(0.0046)	(0.0035)	(0.0034)	(0.0046)	(0.0029)	(0.0030)	(0.0041)	(0.0032)	(0.0034)	(0.0040)	(0.0032)	(0.0030)
CREDIT	−0.0066	0.0035	−0.0194	−0.0183	0.0063	−0.0199	−0.0449°	0.0025	−0.0040	−0.0193	−0.0086	−0.0252	0.0231	−0.0029	0.0052	−0.0118	−0.0175	−0.0110	−0.0172
	(0.0241)	(0.0207)	(0.0267)	(0.0274)	(0.0269)	(0.0214)	(0.0278)	(0.0348)	(0.0278)	(0.0246)	(0.0311)	(0.0221)	(0.0284)	(0.0198)	(0.0244)	(0.0248)	(0.0341)	(0.0209)	(0.0230)
SLOPE	0.0615	0.0444	0.0597°	0.0519	0.0210	0.0182	0.0601	0.0508	0.0045	0.0375	0.0535	0.0197	0.0210	0.1004**	0.0359	0.0570°	0.0378	0.0788**	0.0479
	(0.0654)	(0.0552)	(0.0366)	(0.0671)	(0.0567)	(0.0393)	(0.0528)	(0.0617)	(0.0502)	(0.0500)	(0.0468)	(0.0373)	(0.0399)	(0.0399)	(0.0490)	(0.0438)	(0.0516)	(0.0363)	(0.0424)
VSTOXX	−0.0567***	−0.0314***	−0.0538***	−0.0390**	−0.0387***	−0.0343***	−0.0337***	−0.0541***	−0.0438***	−0.0349***	−0.0188°	−0.0347***	−0.0272***	−0.0373**	−0.0460***	−0.0578***	−0.0484***	−0.0089	−0.0197**
	(0.0169)	(0.0106)	(0.0113)	(0.0164)	(0.0136)	(0.0092)	(0.0126)	(0.0166)	(0.0166)	(0.0126)	(0.0119)	(0.0123)	(0.0068)	(0.0148)	(0.0157)	(0.0160)	(0.0185)	(0.0086)	(0.0078)
EURO.XX	0.1400	0.4196°	0.3301*	0.0103	0.3809	0.1057	0.0093	0.4928**	0.2431	0.2135°	−0.3518°	−0.1165	0.0821	0.0975	0.5087***	0.1647	0.1762	−0.1482	−0.0304
	(0.2252)	(0.2851)	(0.1922)	(0.2661)	(0.3087)	(0.1688)	(0.2612)	(0.2335)	(0.2096)	(0.1648)	(0.2474)	(0.1458)	(0.1658)	(0.2051)	(0.1648)	(0.2298)	(0.2548)	(0.1777)	(0.1460)
Real.Est	−0.1023	−0.3017°	−0.1473	−0.0056	−0.3089°	−0.0549	−0.1394	−0.3837**	−0.0296	−0.0108	0.1641	0.2593*	−0.0093	−0.0054	−0.3699**	−0.1070	−0.1203	0.3645**	0.0749
	(0.1790)	(0.2118)	(0.1812)	(0.1796)	(0.2376)	(0.1212)	(0.1817)	(0.1785)	(0.2029)	(0.1364)	(0.2024)	(0.1569)	(0.1290)	(0.2105)	(0.1468)	(0.1682)	(0.2307)	(0.1710)	(0.1529)
EUR-OIS	−0.0069°	−0.0093**	0.0002	−0.0145***	−0.0115**	−0.0045	−0.0084**	−0.0120***	−0.0109***	−0.0066*	−0.0050	0.0062*	0.0037°	−0.0064°	−0.0089**	−0.0094**	−0.0081*	−0.0086***	−0.0034
	(0.0045)	(0.0038)	(0.0042)	(0.0039)	(0.0046)	(0.0037)	(0.0034)	(0.0044)	(0.0030)	(0.0040)	(0.0050)	(0.0035)	(0.0026)	(0.0042)	(0.0037)	(0.0038)	(0.0046)	(0.0028)	(0.0031)
VaR	0.1334**	0.6154***	0.4536***	0.4835***	0.2597***	0.5595***	0.3343***	0.3185**	0.4200***	0.3125***	0.5024***	0.7267***	0.5779***	0.3206***	0.6162***	0.5010***	0.3268*	0.6857***	0.5796***
	(0.0590)	(0.1287)	(0.0715)	(0.1118)	(0.0680)	(0.0836)	(0.0676)	(0.1272)	(0.1528)	(0.0834)	(0.0757)	(0.0777)	(0.0512)	(0.0473)	(0.1710)	(0.1404)	(0.1727)	(0.0743)	(0.0508)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.47	0.33	0.53	0.41	0.59	0.49	0.61	0.4	0.34	0.62	0.57	0.58	0.71	0.71	0.07	-0.04	0.16	0.57	0.67

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.40: T-B $CoVaR$ at 5% (cont)

	VIL.	RINGKJ.	FIRST.INV.	GRENKE	ALAND.	HRVAT.	ALM.BRND	BNK.ACH.	CENTR.COOP.	SPAREK.	MLP	BN.NORD.	DJURSD	SKJERN	MUTUI	KREDIT.	NORDFYN.	MOENS
(Intercept)	−0.0439***	−0.0468***	−0.0488***	−0.0433***	−0.0517***	−0.0485***	−0.0466***	−0.0458***	−0.0492***	−0.0473***	−0.0456***	−0.0502***	−0.0477***	−0.0486***	−0.0472***	−0.0497***	−0.0468***	−0.0489***
	(0.0034)	(0.0038)	(0.0042)	(0.0041)	(0.0038)	(0.0042)	(0.0037)	(0.0045)	(0.0036)	(0.0049)	(0.0046)	(0.0040)	(0.0040)	(0.0043)	(0.0051)	(0.0038)	(0.0046)	(0.0035)
CREDIT	0.0029	−0.0521*	−0.0242	0.0174	−0.0200	0.0058	−0.0091	−0.0001	0.0216	−0.0152	−0.0126	0.0219	0.0008	−0.0077	0.0418°	0.0122	−0.0007	0.0039
	(0.0289)	(0.0310)	(0.0278)	(0.0223)	(0.0251)	(0.0266)	(0.0225)	(0.0226)	(0.0242)	(0.0343)	(0.0292)	(0.0249)	(0.0284)	(0.0276)	(0.0256)	(0.0268)	(0.0300)	(0.0261)
SLOPE	0.0701°	0.0041	0.0680°	0.0265	0.0734°	0.0786°	0.0146	0.0614	0.0729°	0.0885°	0.0423	0.0906*	0.0971*	0.1040*	0.0748°	0.0574	−0.0880°	0.0761°
	(0.0451)	(0.0525)	(0.0463)	(0.0425)	(0.0533)	(0.0581)	(0.0407)	(0.0503)	(0.0560)	(0.0577)	(0.0534)	(0.0502)	(0.0540)	(0.0568)	(0.0497)	(0.0574)	(0.0540)	(0.0505)
VSTOXX	−0.0419***	−0.0279*	−0.0517***	−0.0502***	−0.0460***	−0.0687***	−0.0413***	−0.0519***	−0.0539***	−0.0645***	−0.0641***	−0.0681***	−0.0498***	−0.0579***	−0.0538***	−0.0630***	−0.0604***	−0.0570***
	(0.0136)	(0.0144)	(0.0144)	(0.0107)	(0.0157)	(0.0177)	(0.0088)	(0.0180)	(0.0130)	(0.0168)	(0.0195)	(0.0168)	(0.0172)	(0.0149)	(0.0135)	(0.0187)	(0.0145)	(0.0167)
EURO.XX	0.0370	0.1928	0.4680**	0.2406°	0.4672**	0.3428°	0.2413	0.3056	0.4353**	0.3021°	0.3597°	0.6254**	0.3557	0.3856°	0.5383***	0.5016*	0.2308	0.3888*
	(0.2163)	(0.2335)	(0.2020)	(0.1614)	(0.2113)	(0.2510)	(0.1983)	(0.2439)	(0.2084)	(0.2352)	(0.2597)	(0.2838)	(0.2779)	(0.2365)	(0.2041)	(0.2565)	(0.2571)	(0.2187)
Real.Est	0.0387	−0.0477	−0.1858	0.0408	−0.2898°	−0.2383	−0.0885	−0.2747°	−0.2058	−0.2686°	−0.1914	−0.3922*	−0.2868°	−0.3605**	−0.4311**	−0.3230*	−0.2116	−0.3413**

	VIL.	RINGKJ.	FIRST.INV.	GRENKE	ALAND.	HRVAT.	ALM.BRND	BNK.ACH.	CENTR.COOP.	SPAREK.	MLP	BN.NORD.	DJURSD	SKJERN	MUTUI	KREDIT.	NORDFYN.	MOENS
	(0.1592)	(0.2122)	(0.1589)	(0.1448)	(0.1848)	(0.1863)	(0.1749)	(0.1858)	(0.1883)	(0.1773)	(0.1721)	(0.2188)	(0.1951)	(0.1822)	(0.1857)	(0.1768)	(0.2027)	(0.1694)
EUR-OIS	−0.0116***	−0.0050	−0.0067°	−0.0040	−0.0107**	−0.0086**	−0.0049	−0.0080*	−0.0116**	−0.0108**	−0.0105*	−0.0111**	−0.0114**	−0.0127**	−0.0059	−0.0105**	−0.0070°	−0.0102*
	(0.0035)	(0.0040)	(0.0046)	(0.0040)	(0.0047)	(0.0041)	(0.0038)	(0.0042)	(0.0046)	(0.0055)	(0.0063)	(0.0045)	(0.0049)	(0.0051)	(0.0055)	(0.0047)	(0.0044)	(0.0053)
VaR	0.3957***	0.6531***	0.3251***	0.2632***	0.1926°	0.0720	0.4879***	0.2257***	0.2166***	0.2768*	0.3880***	0.2788**	0.4443*	0.2408*	0.3270***	0.1698	0.2242°	0.3193°
	(0.1235)	(0.1588)	(0.0899)	(0.0644)	(0.1357)	(0.1521)	(0.1045)	(0.0720)	(0.0772)	(0.1415)	(0.1312)	(0.1267)	(0.2402)	(0.1335)	(0.0848)	(0.1760)	(0.1492)	(0.1961)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.3	0.25	0.38	0.62	-0.11	0.15	0.33	0.43	0.17	0.01	0.21	0.09	-0.2	-0.01	0.44	-0.58	0.05	-0.06

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.41: T-B $CoVaR$ at 50%

	HSBC	BNP	CR.AGR	BAN.SAN	BARC	SOC.GEN	DEUT.	LLOYDS	INTESA	ING	UBS	UNIC.	NAT.	ST.CHA	BBVA	NORDEA	ABN	DANSKE	COMMERZ.	KBC
(Intercept)	−0.0000	−0.0005	−0.0004	−0.0003	0.0009	0.0004	0.0017°	0.0009	−0.0001	−0.0002	0.0001	0.0005	−0.0007	−0.0001	0.0011	0.0002	−0.0005	0.0012	0.0002	−0.0004
	(0.0020)	(0.0008)	(0.0009)	(0.0009)	(0.0016)	(0.0009)	(0.0011)	(0.0018)	(0.0012)	(0.0009)	(0.0016)	(0.0012)	(0.0013)	(0.0013)	(0.0015)	(0.0013)	(0.0010)	(0.0016)	(0.0011)	(0.0011)
CREDIT	−0.0184	−0.0106°	0.0011	−0.0083	−0.0151	−0.0001	0.0010	−0.0097	−0.0071	−0.0142°	−0.0095	0.0059	−0.0081	−0.0126	−0.0154	−0.0088	−0.0263***	−0.0012	−0.0160	−0.0090
	(0.0205)	(0.0073)	(0.0066)	(0.0091)	(0.0213)	(0.0092)	(0.0099)	(0.0192)	(0.0115)	(0.0092)	(0.0132)	(0.0118)	(0.0161)	(0.0157)	(0.0131)	(0.0142)	(0.0100)	(0.0173)	(0.0142)	(0.0125)
SLOPE	0.0216	0.0020	−0.0143°	0.0021	0.0318	0.0115	0.0079	0.0244	0.0025	0.0066	0.0230	0.0126	0.0176	0.0217	0.0098	0.0242°	0.0319°	0.0245	0.0270	0.0356°
	(0.0340)	(0.0176)	(0.0107)	(0.0162)	(0.0335)	(0.0161)	(0.0172)	(0.0280)	(0.0213)	(0.0153)	(0.0243)	(0.0206)	(0.0243)	(0.0239)	(0.0203)	(0.0157)	(0.0222)	(0.0206)	(0.0222)	(0.0253)
VSTOXX	0.0128	0.0018	0.0005	0.0013	0.0166°	0.0065°	−0.0055	0.0100	0.0059	0.0004	0.0031	0.0022	0.0093°	−0.0017	0.0043	0.0067°	0.0052	−0.0006	0.0018	0.0026
	(0.0100)	(0.0040)	(0.0037)	(0.0036)	(0.0117)	(0.0048)	(0.0061)	(0.0112)	(0.0048)	(0.0047)	(0.0070)	(0.0037)	(0.0057)	(0.0059)	(0.0043)	(0.0051)	(0.0046)	(0.0082)	(0.0063)	(0.0054)
EURO.XX	−0.0198	−0.0028	0.0108	−0.0897°	−0.0225	0.0167	−0.0628	−0.0650	0.0154	−0.0503	0.0171	0.0859	−0.0638	−0.1282°	−0.1069	−0.0077	−0.0817	−0.0625	0.0024	0.0184
	(0.1422)	(0.0573)	(0.0505)	(0.0606)	(0.1384)	(0.0573)	(0.0837)	(0.1357)	(0.0670)	(0.0637)	(0.1223)	(0.0794)	(0.1021)	(0.0994)	(0.1114)	(0.0855)	(0.0806)	(0.1106)	(0.1091)	(0.0755)
Real.Est	0.0520	0.0085	0.0151	0.0396	0.0513	0.0055	−0.0031	0.0571	0.0138	0.0759	0.0097	−0.0231	0.0390	0.1169	0.1395°	0.1217°	0.1100	0.0730	0.0325	0.0185
	(0.1453)	(0.0575)	(0.0435)	(0.0564)	(0.1429)	(0.0648)	(0.0835)	(0.1329)	(0.0826)	(0.0603)	(0.1554)	(0.0853)	(0.1001)	(0.1044)	(0.1064)	(0.0798)	(0.0868)	(0.1115)	(0.0919)	(0.0764)
EUR-OIS	−0.0037°	−0.0017*	−0.0025**	−0.0011	−0.0053**	−0.0003	−0.0020°	−0.0044*	−0.0004	0.0001	−0.0015	0.0007	−0.0005	−0.0010	−0.0002	−0.0016°	0.0003	−0.0003	0.0001	−0.0010
	(0.0027)	(0.0010)	(0.0010)	(0.0014)	(0.0025)	(0.0011)	(0.0015)	(0.0025)	(0.0015)	(0.0011)	(0.0018)	(0.0014)	(0.0016)	(0.0016)	(0.0016)	(0.0012)	(0.0012)	(0.0022)	(0.0015)	(0.0016)
VaR	0.2323***	0.6779***	0.6723***	0.6081***	0.1717***	0.5576***	0.4809***	0.2819***	0.6427***	0.6380***	0.6598***	0.4822***	0.4867***	0.5414***	0.5721***	0.6733***	0.5703***	0.5244***	0.4494***	0.6701***
	(0.0796)	(0.0295)	(0.0266)	(0.0255)	(0.0581)	(0.0215)	(0.0288)	(0.0588)	(0.0347)	(0.0296)	(0.0577)	(0.0263)	(0.0359)	(0.0308)	(0.0317)	(0.0386)	(0.0255)	(0.0571)	(0.0263)	(0.0495)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.01	0.72	0.68	0.67	0.35	0.73	0.67	0.25	0.6	0.67	0.43	0.71	0.57	0.49	0.61	0.4	0.57	0.31	0.68	0.53

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.42: T-B $CoVaR$ at 50% (cont)

	ERSTE	SKANDI.	SVENSKA	SWEDBNK	BANC.SAB	RAIFFEI.	BPER	BANKINT.	JYSKE	POWSZ.	MEDIOB..	BANC.COMM.	OTP	EUROBNK.	BNK.GREeCE	ALPHA	PIREUS	CREDIT.EMIL	BANK.POL.
(Intercept)	−0.0009	0.0019°	0.0012	0.0009	0.0001	−0.0003	0.0003	−0.0003	0.0001	0.0005	−0.0004	0.0012	−0.0012	0.0007	0.0001	0.0000	0.0035**	−0.0001	0.0019
	(0.0010)	(0.0013)	(0.0016)	(0.0018)	(0.0012)	(0.0016)	(0.0012)	(0.0012)	(0.0014)	(0.0017)	(0.0015)	(0.0016)	(0.0017)	(0.0018)	(0.0020)	(0.0017)	(0.0017)	(0.0016)	(0.0017)
CREDIT	−0.0184°	−0.0180°	−0.0253°	−0.0227°	0.0053	−0.0194	0.0004	−0.0110	−0.0207	−0.0057	−0.0059	0.0090	−0.0023	−0.0107	0.0057	0.0023	−0.0083	0.0074	−0.0179
	(0.0114)	(0.0136)	(0.0178)	(0.0160)	(0.0127)	(0.0161)	(0.0136)	(0.0146)	(0.0170)	(0.0214)	(0.0098)	(0.0203)	(0.0143)	(0.0158)	(0.0201)	(0.0185)	(0.0192)	(0.0164)	(0.0224)
SLOPE	0.0109	0.0138	0.0487*	0.0544*	0.0013	0.0295	0.0116	0.0204	0.0180	0.0229	0.0177	−0.0117	0.0016	0.0155	0.0050	0.0149	0.0197	0.0288	0.0040
	(0.0176)	(0.0248)	(0.0287)	(0.0283)	(0.0220)	(0.0358)	(0.0285)	(0.0203)	(0.0288)	(0.0287)	(0.0251)	(0.0287)	(0.0300)	(0.0240)	(0.0371)	(0.0330)	(0.0334)	(0.0359)	(0.0310)
VSTOXX	0.0031	0.0049	0.0082	0.0033	0.0066	0.0055	0.0067	0.0051	0.0054	0.0116°	0.0028	0.0075	0.0044	0.0028	0.0083	0.0169**	0.0105	0.0042	0.0144°
	(0.0069)	(0.0056)	(0.0083)	(0.0080)	(0.0058)	(0.0075)	(0.0058)	(0.0050)	(0.0085)	(0.0073)	(0.0050)	(0.0078)	(0.0081)	(0.0064)	(0.0091)	(0.0082)	(0.0091)	(0.0083)	(0.0101)
EURO.XX	−0.0128	−0.1492*	−0.0366	−0.1148	0.0143	−0.0739	−0.2122**	0.0133	−0.1071	−0.0027	−0.1762**	−0.0493	−0.0099	−0.1509	−0.1653	−0.1047	−0.1575	−0.0207	−0.1029
	(0.0793)	(0.0879)	(0.1268)	(0.1042)	(0.0995)	(0.1070)	(0.0824)	(0.0740)	(0.0945)	(0.1367)	(0.0844)	(0.1175)	(0.1171)	(0.1210)	(0.1412)	(0.1251)	(0.1456)	(0.1065)	(0.1362)
Real.Est	−0.0139	0.1404°	0.1167	0.1186	−0.0451	0.1540°	0.1655*	0.0024	0.0330	0.1188	0.1034	0.0241	−0.0331	0.1347	0.1581	0.0380	0.1616	0.0539	0.0622
	(0.0732)	(0.1026)	(0.1197)	(0.1059)	(0.0950)	(0.1189)	(0.0868)	(0.0927)	(0.1260)	(0.1364)	(0.0953)	(0.1209)	(0.1198)	(0.1126)	(0.1638)	(0.1257)	(0.1571)	(0.1212)	(0.1350)
EUR-OIS	−0.0017°	−0.0038**	−0.0022	−0.0009	0.0034*	−0.0024	−0.0005	0.0022°	−0.0025	−0.0018	−0.0012	−0.0011	−0.0022	−0.0032*	−0.0036°	−0.0011	−0.0041*	0.0007	−0.0020
	(0.0013)	(0.0017)	(0.0024)	(0.0018)	(0.0020)	(0.0021)	(0.0016)	(0.0015)	(0.0021)	(0.0023)	(0.0014)	(0.0019)	(0.0023)	(0.0017)	(0.0024)	(0.0026)	(0.0023)	(0.0021)	(0.0029)
VaR	0.5935***	0.7045***	0.6820***	0.4693***	0.4069***	0.4545***	0.3990***	0.6010***	0.5175***	0.4340***	0.5345***	0.3352***	0.3437***	0.1808***	0.1839***	0.2173***	0.0856***	0.6191***	0.1746***
	(0.0366)	(0.0590)	(0.0807)	(0.0872)	(0.0303)	(0.0485)	(0.0298)	(0.0368)	(0.0597)	(0.0685)	(0.0402)	(0.0363)	(0.0738)	(0.0289)	(0.0410)	(0.0313)	(0.0256)	(0.0520)	(0.0430)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.56	0.26	0.21	0.17	0.65	0.53	0.62	0.48	0.32	0.36	0.54	0.58	0.32	0.64	0.62	0.62	0.69	0.32	0.49

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.43: T-B $CoVaR$ at 50% (cont)

	SANT.	KOMER	AAREAL	ING.SLA..	MBANK	SYDBAK	MILLEN.	BRD	AKTIA	HOIST	SONDRIO	CAIXA	SUISSE	BPM	BNK.GREECE	PIC.	LANG.	MEDIO.	DEUT.PF
(Intercept)	0.0003	0.0002	0.0012	0.0010	0.0004	−0.0009	0.0014	0.0004	0.0002	0.0015	−0.0002	−0.0003	0.0023°	0.0005	0.0000	0.0017	0.0020	−0.0010	−0.0002
	(0.0018)	(0.0018)	(0.0018)	(0.0016)	(0.0017)	(0.0017)	(0.0017)	(0.0019)	(0.0018)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0014)	(0.0022)	(0.0016)	(0.0019)	(0.0015)	(0.0015)
CREDIT	0.0102	−0.0147	0.0028	−0.0109	−0.0121	−0.0164	0.0016	−0.0017	−0.0263*	−0.0100	−0.0025	−0.0085	−0.0006	−0.0160	−0.0083	0.0064	−0.0099	−0.0229°	−0.0270**
	(0.0196)	(0.0194)	(0.0167)	(0.0199)	(0.0166)	(0.0161)	(0.0200)	(0.0179)	(0.0149)	(0.0158)	(0.0143)	(0.0158)	(0.0122)	(0.0148)	(0.0185)	(0.0194)	(0.0200)	(0.0175)	(0.0130)
SLOPE	0.0522	0.0197	0.0337	0.0237	0.0300	0.0201	0.0380	0.0346	0.0192	0.0234	0.0228	0.0499*	0.0047	0.0092	0.0216	0.0036	0.0269	0.0346	−0.0101
	(0.0433)	(0.0306)	(0.0357)	(0.0377)	(0.0332)	(0.0308)	(0.0377)	(0.0323)	(0.0251)	(0.0203)	(0.0292)	(0.0300)	(0.0195)	(0.0292)	(0.0380)	(0.0264)	(0.0288)	(0.0280)	(0.0272)
VSTOXX	0.0080	0.0102°	0.0056	0.0175**	0.0167**	0.0040	0.0186**	0.0134°	0.0127°	0.0215***	−0.0020	0.0021	0.0124**	0.0041	0.0139°	0.0122	0.0165°	0.0014	0.0155**
	(0.0095)	(0.0076)	(0.0082)	(0.0074)	(0.0074)	(0.0073)	(0.0085)	(0.0100)	(0.0090)	(0.0072)	(0.0069)	(0.0052)	(0.0052)	(0.0057)	(0.0106)	(0.0101)	(0.0104)	(0.0070)	(0.0069)
EURO.XX	0.1219	−0.0527	−0.0465	0.0399	−0.1327	−0.0795	0.0950	−0.0789	−0.1568	−0.0889	−0.1036	0.0245	0.0032	−0.1005	−0.0717	−0.0352	−0.0711	0.0028	−0.0829
	(0.1399)	(0.1245)	(0.1188)	(0.1298)	(0.1279)	(0.1120)	(0.1272)	(0.1212)	(0.1482)	(0.1089)	(0.1008)	(0.0908)	(0.1127)	(0.0831)	(0.1505)	(0.1239)	(0.1526)	(0.1146)	(0.1107)
Real.Est	0.0148	0.0272	0.1056	0.0855	0.1851°	0.0650	0.0479	0.0534	0.1511	0.2068*	0.0775	0.0127	0.0351	0.0903	0.1043	0.0071	0.1033	−0.1144	0.1202°

	SANT.	KOMER	AAREAL	ING.SLA..	MBANK	SYDBAK	MILLEN.	BRD	AKTIA	HOIST	SONDRIO	CAIXA	SUISSE	BPM	BNK.GREECE	PIC.	LANG.	MEDIO.	DEUT.PF
	(0.1201)	(0.1280)	(0.1112)	(0.1365)	(0.1224)	(0.1329)	(0.1333)	(0.1378)	(0.1397)	(0.1191)	(0.1072)	(0.1008)	(0.1147)	(0.1090)	(0.1752)	(0.1479)	(0.1441)	(0.1225)	(0.0933)
EUR-OIS	−0.0009	−0.0005	−0.0042°	−0.0011	−0.0016	−0.0015	−0.0004	−0.0041*	−0.0036	−0.0026°	−0.0007	−0.0021	−0.0031*	0.0002	−0.0032	−0.0055**	−0.0037°	−0.0011	−0.0017
	(0.0020)	(0.0027)	(0.0028)	(0.0021)	(0.0020)	(0.0019)	(0.0024)	(0.0023)	(0.0028)	(0.0018)	(0.0018)	(0.0017)	(0.0016)	(0.0017)	(0.0027)	(0.0025)	(0.0025)	(0.0020)	(0.0016)
VaR	0.4151***	0.4481***	0.4873***	0.4079***	0.2758***	0.5219***	0.2672***	0.2528***	0.4531***	0.2951***	0.4470***	0.5522***	0.5682***	0.3278***	0.2766***	0.3295***	0.3549***	0.6228***	0.5379***
	(0.0523)	(0.0737)	(0.0702)	(0.0472)	(0.0363)	(0.0536)	(0.0481)	(0.0686)	(0.0650)	(0.0611)	(0.0424)	(0.0329)	(0.0427)	(0.0261)	(0.1030)	(0.0830)	(0.0980)	(0.0606)	(0.0504)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	0.38	0.06	0.35	0.22	0.47	0.32	0.45	0.13	0.03	0.44	0.5	0.57	0.58	0.64	-0.35	-0.26	-0.06	0.36	0.5

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

Table 2.44: T-B $CoVaR$ at 50% (cont)

	VIL.	RINGKJ.	FIRST.INV.	GRENKE	ALAND.	HRVAT.	ALM.BRND	BNK.ACH.	CENTR.COOP.	SPAREK.	MLP	BN.NORD.	DJURSD	SKJERN	MUTUI	KREDIT.	NORDFYN.	MOENS
(Intercept)	0.0011	−0.0001	0.0017	−0.0002	0.0008	0.0008	0.0003	0.0027	0.0010	0.0004	0.0001	0.0006	0.0003	0.0005	−0.0005	0.0014	0.0012	0.0019
	(0.0019)	(0.0017)	(0.0019)	(0.0017)	(0.0018)	(0.0018)	(0.0017)	(0.0021)	(0.0018)	(0.0020)	(0.0017)	(0.0020)	(0.0015)	(0.0019)	(0.0020)	(0.0017)	(0.0017)	(0.0018)
CREDIT	−0.0114	−0.0326*	−0.0133	0.0003	−0.0275°	−0.0025	−0.0038	−0.0045	−0.0033	−0.0063	−0.0149	−0.0083	−0.0053	−0.0015	−0.0128	−0.0062	−0.0176	−0.0148
	(0.0174)	(0.0187)	(0.0231)	(0.0153)	(0.0208)	(0.0183)	(0.0194)	(0.0209)	(0.0164)	(0.0181)	(0.0201)	(0.0196)	(0.0172)	(0.0182)	(0.0176)	(0.0185)	(0.0170)	(0.0187)
SLOPE	0.0005	0.0108	0.0046	0.0130	0.0120	0.0253	0.0115	0.0258	0.0279	0.0302	0.0299	0.0105	0.0302	0.0088	0.0138	0.0237	0.0351	0.0231
	(0.0363)	(0.0293)	(0.0345)	(0.0247)	(0.0367)	(0.0331)	(0.0334)	(0.0348)	(0.0295)	(0.0363)	(0.0298)	(0.0322)	(0.0266)	(0.0307)	(0.0312)	(0.0346)	(0.0301)	(0.0346)
VSTOXX	0.0104	0.0083	0.0064	0.0178**	0.0092	0.0133	0.0126	0.0153°	0.0090	0.0087	0.0106	0.0123	0.0109	0.0081	0.0092	0.0138°	0.0108	0.0139°
	(0.0101)	(0.0081)	(0.0096)	(0.0077)	(0.0104)	(0.0108)	(0.0104)	(0.0098)	(0.0102)	(0.0110)	(0.0105)	(0.0104)	(0.0097)	(0.0112)	(0.0113)	(0.0107)	(0.0095)	(0.0095)
EURO.XX	−0.0574	−0.2107°	−0.1482	−0.0128	−0.0813	−0.0297	−0.1350	−0.1053	−0.0662	−0.1089	−0.0454	0.0197	−0.1147	−0.1877°	−0.1224	−0.0344	−0.1710	−0.0688
	(0.1373)	(0.1383)	(0.1568)	(0.1027)	(0.1394)	(0.1424)	(0.1736)	(0.1338)	(0.1452)	(0.1348)	(0.1140)	(0.1192)	(0.1358)	(0.1336)	(0.1312)	(0.1613)	(0.1396)	(0.1448)
Real.Est	−0.0151	0.2069°	0.1188	0.0957	0.1030	0.0733	0.1747	0.1839	0.0721	0.1281	0.0518	0.0238	0.1229	0.1732	0.1594	0.0850	0.1155	0.1625
	(0.1426)	(0.1516)	(0.1412)	(0.1076)	(0.1511)	(0.1367)	(0.1759)	(0.1635)	(0.1363)	(0.1608)	(0.1405)	(0.1433)	(0.1361)	(0.1683)	(0.1448)	(0.1566)	(0.1684)	(0.1460)
EUR-OIS	−0.0064**	−0.0033*	−0.0050*	−0.0042*	−0.0035	−0.0048*	−0.0031	−0.0054*	−0.0055**	−0.0032	−0.0041*	−0.0030	−0.0046*	−0.0051*	−0.0055**	−0.0051**	−0.0048*	−0.0049**
	(0.0026)	(0.0019)	(0.0026)	(0.0023)	(0.0028)	(0.0026)	(0.0025)	(0.0028)	(0.0027)	(0.0029)	(0.0022)	(0.0025)	(0.0026)	(0.0026)	(0.0027)	(0.0025)	(0.0025)	(0.0025)
VaR	0.3242***	0.5811***	0.3053***	0.2845***	0.2050***	0.0953**	0.2697***	0.1503***	0.1439**	0.2755***	0.3206***	0.3073***	0.4118***	0.2973***	0.2357***	0.0744	0.3042***	0.1862**
	(0.0985)	(0.0699)	(0.0545)	(0.0545)	(0.0754)	(0.0482)	(0.0644)	(0.0478)	(0.0596)	(0.0963)	(0.0570)	(0.1137)	(0.1182)	(0.1070)	(0.0523)	(0.0999)	(0.0912)	(0.0763)
Num. obs.	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363	363
Pseudo R^2	-0.11	0.03	0.2	0.39	-0.09	0	0.08	0.37	0.1	-0.28	0.13	-0.14	-0.57	-0.22	0.34	-0.66	-0.17	-0.23

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $^{\circ}p < 0.2$

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Chapter 3

Disentangling Systemic Risk: Bank-Specific Factors analysis via Panel Lasso Regression.

3.1 Introduction

Bank and systemic stability do not solely depend on macro-factors, as certain idiosyncratic characteristics can render individual institutions more prone to being a threat to the system. The literature has been always recognized this dichotomy. The works of mis (2006), Laeven et al. (2016), Biase and D'Apolito (2012) and Anginer et al. (2018) have fostered this vision, which has also inspired banking regulations. Indeed, the latter has shifted from a micro-prudential perspective (Basel I and II) to a macro-prudential one (Basel III), moving towards a system-oriented approach to supervision that seeks to preserve the stability of the system by regulating aspects of the agents' operations.
However, as also highlighted by Zedda and Cannas (2020), the fundamental opened question concerns the identification and quantification of micro-level variables that affect systemic risk. This paper is positioned in this direction, aiming to determine the main specific drivers that make institutions more prone to posing a risk to the system, by leveraging the information on systemic relevance of institutions provided by the framework developed by Tobias and Brunnermeier (2016) and utilizing a model selection approach in a panel analysis.
And in this last sense, it try to contribute to the literature, developing a framework that would help isolating the real specific facets that renders systemic an istitution, freeing from the stepwise selection scheme that could induce *'cherry-picking bias'* (Taylor and Tibshirani (2015)). Another key contribution pertains to the differentiated impact of variables in different market conditions, an area that has not been fully explored except for studies by Kleinow et al. (2017) and Vazquez and Federico (2015). Indeed, considering the numerous studies on changes in systemic risk levels, particularly during crises (see, for instance, the researchs of Borri and Di Giorgio (2022) and Black et al. (2016)), it's likely that macroeconomical conjunctural events could influence the systemic risk level of firms inducing a variation of variables relathionships. Therefore, a period-differentiated analysis is more pertinent.
The paper also addresses the *'too-big-to-fail'* question and the role of size as a major determinant of systemic relevance of insitutions (Nils (2018)). Important results will be

provided on this topic, affirming the predominance of interconnectedness as a booster of the systemic impact of banks in crisis periods, reshaping the role of size, which confirms its relevance during stable periods. This raises questions about the effectiveness of the regulatory direction, which currently focuses more on large financial conglomerates than on platform regulations.
The remainder of the paper is structured as follows: Section 3.2 provides the literary review on this topic. Section 3.3 describes the developed methodology. Section 3.4 provides details about the construction of the dataset. Section 3.5 presents and discusses the results. Section 3.6 is dedicated to a focus on the importance of size and interconnectedeness in systemic risk and finally, Section 3.7 is dedicated to conclusions and comments.

3.2 Literary review

The existing literature that has attempted to understand the specific determinants influencing the systemic risk levels of financial institutions is extensive, albeit somewhat inconclusive. The main difference in sytemic driver studies is between single variable investigation studies and multivariate approaches. Laeven et al. (2016), López-Penabad et al. (2022), Kleinow et al. (2017), Weiß et al. (2014b), Calice et al. (2021), Anginer et al. (2018), Black et al. (2016) and Zedda and Cannas (2020) are the main exponents of the latter category. On the other hand Acemoglu et al. (2015),Qin and Zhou (2019), Peltonen et al. (2019),Chabot and Bertrand (2021) and Varotto and Zhao (2018) have mainly operated a unifactor (with control variables of different nature) analysis.
The resultive deductions of the first group consistently highlight one or a few factors significantly impacting the systemic nature of banks, revealing a limited spectrum of decisive idiosyncratic factors. Laeven et al. (2016) and Kleinow et al. (2017) emphasize the importance of size as the main discriminant feature, a finding corroborated by Nils (2018). Addittionally, López-Penabad et al. (2022) in their study of the impact of negative interest rates on bank risk-taking, underscore that the business model, as reflected in balance sheet performance, provides valuable insights for delineating the risk profile of banks. Both Weiß et al. (2014b) and Calice et al. (2021) in their examinations of the relationship between concentration and stability, find that higher concentration generally leads to a destabilization of the system, primarily driven by the presence of larger institutions. However, below a certain threshold, concentration initially enhances profitability and systemic resilience. Anginer et al. (2018) raise the central role of capital in mitigating the systemic jeopardaizing role of banks. On the other hand, Black et al. (2016) notice the role of capital in favor of the systemic relevance of banks during NIRP (negative interest periods), emphasizing the importance of both size and leverage in forecasting the systemic risk level one year ahead.
The second group, which primarily focuses on single-factor investigations, explores a less diverse spectrum of variables. In fact, all of them analyze the contagion network and banks' interconnectedness. Acemoglu et al. (2015),Qin and Zhou (2019), Chabot and Bertrand (2021) and Varotto and Zhao (2018) concur on the systemic relevance of these fundamental network characteristics, that is without doubt a severe vehicle of contagion especially in crisis periods.
The second main dividing element in litereature attains the regional diversity. López-Espinosa et al. (2012) discovered that wholesale funding in the first decade of twenties has

been a systemic risk factor for European banks, although these results do not necessarily apply to U.S. banks. Up to them, this is mainly driven by the new currency impulse that have inflationated the interbank market. Qin and Zhou (2019) investigated the differences in drivers explaining banking systemic risk between BRICS and non-BRICS countries. They found that the non-interest income factor is relevant for developed countries but not for BRICS. This suggests that financial innovations and financial market development play a crucial role, albeit indirectly, and should be taken into account. Varotto and Zhao (2018) explores the systemic risk in the US and EU banking markets, emphasizing the central role of dimensions in explaining systemic risk. The study does not reveal substantial geographical differences in the most crucial determinants of risks.
However, to the best of our knowledge, there is no study that has attempted to implement a formal approach for model selection and consequently variable selection. Such an approach would help disentangle the actual effects, cluster the truly impactful spectrum of covariates, and avoid the noise and imperfections of multivariate data. This approach could lead to an enhancement of the effect findings in multivariate analysis, without the necessity of being restricted to univariate approaches (which are often monothematic).

3.3 Methodology description

The methodology chosen for the analysis has been inspired by the work of Babii et al. (2022) who develop a panel regression approach augmented with a L^1-lasso penalty. The assumption of a sparse covariates' matrix is done, therefore the following regularization scheme will work as a model selection, ruling out the uneffective factors. The panel regression equation has the classical functional form:

$$y_{j,t} = \beta_0 + \boldsymbol{\beta} \boldsymbol{X_t'} + \epsilon_{j,t} \tag{3.1}$$

Where $y_{j,t}$ is the time dependent variable and $\boldsymbol{X_t'} \in \mathbb{R}^{p\times T}$ where $j = 1...p$ and $t = 1...T$. Moreover $\boldsymbol{\beta}$ is the $\mathbb{R}^{1\times p}$ vector of coefficients and β_0 is the common intercept level, meanwhile $\epsilon_{j,t}$ is the idyosincratic error, normal distributed and for which the following holds $\mathbb{E}[\epsilon_{j,t}, \epsilon_{j,i}] = 0$, for $i \neq t$ and $i \in [1, T]$.
The estimation with lasso reguralization has performed solving the following optimization problem:

$$\min_{\boldsymbol{\beta}} ||\boldsymbol{Y} - \boldsymbol{\beta} \boldsymbol{X_t'}||^2_{pT} + 2\lambda\Omega(\boldsymbol{\beta}) \tag{3.2}$$

where $\boldsymbol{Y}$ is the matrix of dependent variable, $||.||^2_{pT}$ is the empirical norm ($||.||^2/pT$ where $||.||^2$ is the L^2-norm) and $\Omega(\boldsymbol{\beta})$ is the penalty function, which has the following shape:

$$\Omega(\boldsymbol{\beta}) = \gamma|\boldsymbol{\beta}|_1 + (1-\gamma)||\boldsymbol{\beta}||^2_{\mathbb{G}} \tag{3.3}$$

with γ a constant and $|.|_1$ the L^1-norm, and $||.||^2_{\mathbb{G}}$ is the group lasso penalty (Simon et al. (2013)).
Since the intention is not to cluster covariates in different penalized groups the second term of LHS in (3.3) could be eliminated, setting γ=1.
To set the tuning parameter λ a k-fold cross validation approach has been used, considering the similar approach followed in Babii et al. (2022). The results of the tuning process for all the models implemented would be displayed in the Appendix section.

In this paper a panel data with time fixed effect will be used. This choice is mainly driven to isolate the chosen covariates set, avoiding introducing state covariates that could monopolize the statistical significance in the regression. Therefore (3.1) and (3.2) transform into the following:

$$y_{j,t} = \beta_0 + \boldsymbol{\beta}'_{time}(\boldsymbol{I_p} \otimes \boldsymbol{1})\boldsymbol{\delta_t} + \boldsymbol{\beta}\boldsymbol{X'_t} + \epsilon_{j,t} \tag{3.4}$$

$$\min_{\boldsymbol{\beta},\boldsymbol{\delta_t}} ||\boldsymbol{Y} - \boldsymbol{\beta}'_{time}(\boldsymbol{I_p} \otimes \boldsymbol{1})\boldsymbol{\delta_t} - \boldsymbol{\beta}\boldsymbol{X'_t}||^2_{pT} + 2\lambda\Omega(\boldsymbol{\beta}) \tag{3.5}$$

Where $\boldsymbol{\delta_t} = [1_{2016}, ...1_{2022}]$ is the vector of time dummy variables and $\boldsymbol{\beta}'_{time}$ is the vector of coefficients associated to the time dummy. $\boldsymbol{I_p} \in \mathbb{R}^{p \times p}$ and $\boldsymbol{1} \in \mathbb{R}^T$ are respectively the identity matrix and all-ones vector, meanwhile the $\otimes$ is the Kronecker product.
The idealized selection approach will be employed to limit the covariate set, reducing noise in the data and considering only the most predictive variables. To assess the validity of the approach, a post-penalized regression (analysis conducted using the set of covariates chosen by the shrinking approach) will be implemented. This approach, assuming that the support is sparse and that the model selection effectively recovers the support of the real $\boldsymbol{\beta}$, could be an efficient approach to make inference after shrinkage (see section 11.4 of Hastie et al. (2015)).

3.4 Variables description

The purpose of this study is to investigate the bank-specific drivers that exhibit a high statistical relationship with the systemic risk level of banks. To quantifiy this latter, the framework of Tobias and Brunnermeier (2016) that derives the $CoVaR$ and $\Delta CoVaR$ measures, that represents the market performance under distress of institutions and the contribuition to systemic risk of each institution, have been employed. These measure will be briefly discussed in the **Mathematical Appendix**.
To achieve this objective, a set of idiosyncratic indicators and ratios has been collected, primarily from the balance sheet, for each of the 54 banks involved (the sample is shown in **Table 3.8**). These data were obtained from the Bankfocus Database, and any missing data were supplemented with information from the Refinitiv Database. The data refers to the period that goes from 2016 to 2022, and are collected at yearly frequency.
The first covariate involved in the analysis is the *Total assets* (TOA), which has been appropriately transformed using the natural logarithm to standardize the variable's scale with the others. This variable is widely debated in the literature on banking systemic risk and is closely monitored by regulators due to its common usage as a proxy for bank size (Moenninghoff et al. (2015)). Moreover, size is invariably associated with the systemic relevance of institutions, given the likelihood of endangering the financial stability of larger banks (Nils (2018)). The latters often exhibit more intense interbank liability interlinkages [1], making them *'too-big-to-replace'*, and engage in a greater volume of market and real activities, a default of which could cause systemic turbulence, making them *'too-big-to-fail'* (Kleinow et al. (2017), Laeven et al. (2016)). On the other hand, there is a considerable body of literature in favor of large banks, as they can take advantage of economies of scale (Boyd and Heitz (2016)) and achieve better diversification of activities

[1]Several other interlinkages have to be considered, the interbank deposits, loans and derivatives relations are only a small part of the whole (Kaufman, 2014).

(Walter (2009)). Moreover, considering the results of Weiß et al. (2014a), the size factor appears to not be a determinant of systemic risk during a crisis. To sum up, there is no agreement regarding the effect of size on systemic risk level (Varotto and Zhao (2018)), therefore further discussion about this variable will be carried out in the next paragraphs, along whit the following factor considered in the analysis.

Interconnectedness is another major concern in banking systemic risk, often underestimated in banking regulation (Markose et al. (2012)). To represent this element I use the *Interbank Ratio (INT)*, which measures the ratio of interbank assets to interbank liabilities. It quantifies the Interbank lending as percentage of interbank borrowings, with higher values indicating a greater exposure to the system. Researchers such as Peltonen et al. (2019) and Chabot and Bertrand (2021) have suggested that a pronounced interconnection is a relevant source of instability for the financial industry, especially during period of crisis. Addittionally, Caccioli et al. (2012) have shown, exploiting the informativeness of network analysis, that systems with non-homogeneous sizes and correlated units are more susceptible to the ripple effects caused by the failure of a random institution, especially if it is one of the largest. An interesting viewpoint is presented by Haldane (2009), who argues that connectivity is a knife-edge feature of systems. In normal times, it functions as a form of mutual insurance, but during crisis periods, interconnectedness can transform into a shock amplifier.

The analysis also covers other bank-specific aspects related to the type of business conducted by banks. Specifically, we include the *Loan ratio (LOANS)* (the ratio of Loans on total assets) and the *Non-interest income ratio (NON.INT)* (the ratio of Non-interest income on operating revenues). These factors are included to investigate whether banks that engage in less *'traditional'* and more diversified revenue streams are more stable and exhibit fewer systemic effects, due to their capacity of being flexible (and less exposed to external factors such as interest rate). Or if their orientation toward market-based activities exposes them to market turmoil. While Kleinow et al. (2017) support the beneficial diversification effect, documenting a negative relationship between the quantity of non interest income and systemic contribuition, Laeven et al. (2014) and De Jonghe (2010) argue that market-centric instiutions contribute more to the crisis of the system compared to those that are less market oriented. Bats and Houben (2020) and Langfield and Pagano (2016) investigate the whole system, highlighting that bank-based financing structures are generally less resilient than market-financing-oriented systems. This vulnerability stems from the illiquidity of credit positions, resulting in high losses during fire sales, and a susceptibility to interest rate shocks due to asset-liability mismatches.

I also control for the capital level of banks. To address this, the *Total equity* (EQITY) has been taken into account for its recognized role of shock buffer (Bluhm and Krahnen (2014)). Well-capitalized banks are better equipped to withstand a contraction in their asset side of the balance sheet. Thus, if there is a depreciation of interbank assets due to a systemic shock, they can absorb it through their capital reserves. Another variable in this context is the *Tier-1 ratio* (TIER1) expressed as thee ratio of the Tier-1 capital on the Risk-weighted-assets. Unlike the total equity variable, this ratio measures the sufficiency of capital relative to the risks taken on by the bank, therefore ruling out the dimension bias. Unlike Black et al. (2016),who used the ratio of equity to assets, I rely on this risk-adjusted quantity to investigate the risk profile of banks. This approach aligns with the hypothesis put forth by Perotti et al. (2011), which suggests that banks with higher equity level, potentially due to regulators requirements, may have an incentive to invest in high risk assets exposing themselves to tail risks. Consequently, this lead to a surge of systemic contribution when these risks materialize. n the other hand, another strand of literature supports the idea of capital as a buffer that lowers the systemic riskiness of banks. This is highlighted by Chabot and Bertrand (2021), Anginer et al. (2018) and Laeven et al. (2016) emphasizing the augmented capacity of well-capitalized banks to absorb shocks and prevent their propagation to the system.

To assess the performance of banks in the analysis, we have selected the following metrics: *ROAA* (return on average assets), *ROAE* (return on average equity), *RoRwa* (return on risk weighted assets) and *CI* (Cost to income ratio). Higher bank profits can serve as leverage for enhancing bank stability and increasing capital, as demonstrated by Xu et al. (2019). To the contrary, both De Jonghe (2010) and Qin and Zhou (2019) have demonstrated that the most profitable banks, respect to both total assets and total equity, tend to be among the highest contributors to systemic risk. Therefore, raising another open question. However, this should also be considered relative to the level of risk taken, and for this purpose we include also the risk-adjusted profitability. Research by Zedda and Cannas (2020) has shown that the riskiness of assets is a significant variable for predicting the level of systemic contribution by institutions. In terms of the efficiency ratio, a higher cost structure in banks can constrain profitability, making it challenging to preserve financial stability and reduce the ability to absorb losses. This could potentially lead to destabilization of the system in the event of an institution's default (Maudos et al. (2002)).

The *NPL ratio* (the ratio of loan loss provisions on the toal value of loans) has been proven to be a relevant predictor os sytemic risk level of banks. Kleinow et al. (2017) prove that in crisis period the latter exacerbates the risk contribution of banks, in dependence of the spiral effect caused by the increase in credit losses and the simultaneous deterioration of existing credit positions (Wong et al. (2011)).This indicates that in any case a bad credit portfolio is a detrimental factor in the banking sector, especially during systemic crises.

Another omnipresent factor in systemic risk literature is the *Leverage (LEV)* level [2]. Beltratti and Stulz (2012) have shown that a high leverage ratio exposes banks to undercapitalization in the case of extreme losses, increasing the risk of loss spillovers and the likelihood of a costly bail-in or bail-out of distressed banks. Moreover, Adrian and Shin (2010) assert that the procyclical nature of banking leverage makes highly leveraged banks even more vulnerable during periods of crisis.

Bank liquidity has also been taken into account. Ispired by Kleinow et al. (2017) the *Financial Power indicator* (POWER), obtained with the ratio of net cash flow of operating activities over the total liabilities, has been considered. For sake of completiveness, *LCR* [3] has also been included, even though it may duplicate information.This decision was made to consider a less manipulable measure. The LCR has faced criticism, especially in the USA, due to the possibility of inflating High-Quality Liquid Assets (HQLA) to meet regulatory constraints (Cetina and Gleason (2015)).

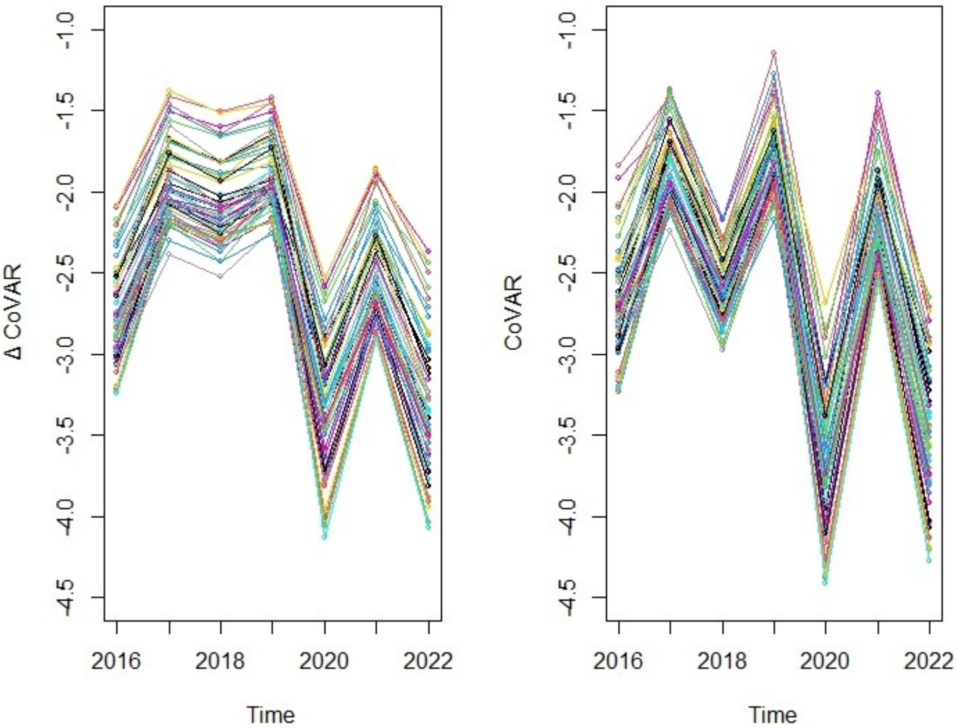
The last but not the least covariate considered is the *Deposit ratio* (DEPOSIT) (the ratio of total deposits and short term funding on total liabilities). It has been included to take into account the funding strategy of banks, so considering the business model from the liability side. According to Laeven et al. (2016), as well as for Beltratti and Stulz (2012)

[2]It's calculated by the data provider as the Tier 1 capital on a fully loaded basis as a percentage of total on and off-balance sheet items. The ratio is not adjusted for Basel guidelines.

[3]This ratio has obtained as: $LCR = \frac{HQLA}{TNCF} < 100\%$, where HQLA stands for High quality liquid asset amount and TNCF stands for total net cash flow

and Demirgüç-Kunt and Huizinga (2010) nondepository funding is associated with high systemic risk level of institutions. This would be basiccally dependent from the stability of the liability side, a soft recourse to deposit funding create, with a massive usage of wholesale funding could be highly costful and instable. Indeed, the deposit funding is more stable and highly liquid (Shleifer and Vishny (2010)).
The dependent variables used are the $\Delta CoVaR$ and the $CoVaR$, both at 5% quantile, estimated using the standard procedure developed in Tobias and Brunnermeier (2016) directly on stock market data at weekly frequency. Then the weekly estimates obtained have been converted to yearly frequency by taking their average values for each year. The decision to include also the $CoVaR$ time series is primarily motivated by the intent to incorporate an estimation of the VaR of the banking sector returns, representing a market state condition. This addittion augments and supports the information provided by the $\Delta CoVaR$, which measures the contribution to banking systemic risk of each institution. In the following **Figure 3.1** are displayed the value for each bank in time.

Figure 3.1: $\Delta CoVaR$ and $CoVaR$



Note: On the left hand panel the $\Delta CoVaR$ is displayed, on the right is shown the evolution of $CoVaR$.

As is evident in both quantities, all the banks exhibit similar patterns, suggesting there is a time effect (that would be considered as time fixed effect in the panel data). There is collapse in the $\Delta CoVaR$ in 2020, which is replicated in the 2022 due to the COVID-19 outbreak and the Ukraine-Russian war, respectively. As highlighted in the previous chapter, there is a clear regime shift starting in 2020, indicating a change in the state of the series. This shift is pronounced in the case of $\Delta CoVaR$ and somewhat less visible in the case of the $CoVaR$. Looking at the average value of dependent variable for each bank in the sample (**Figure 3.2**, **Figure 3.3**), some evidences could be trait.

Figure 3.2: Cross validation output, for CoVaR

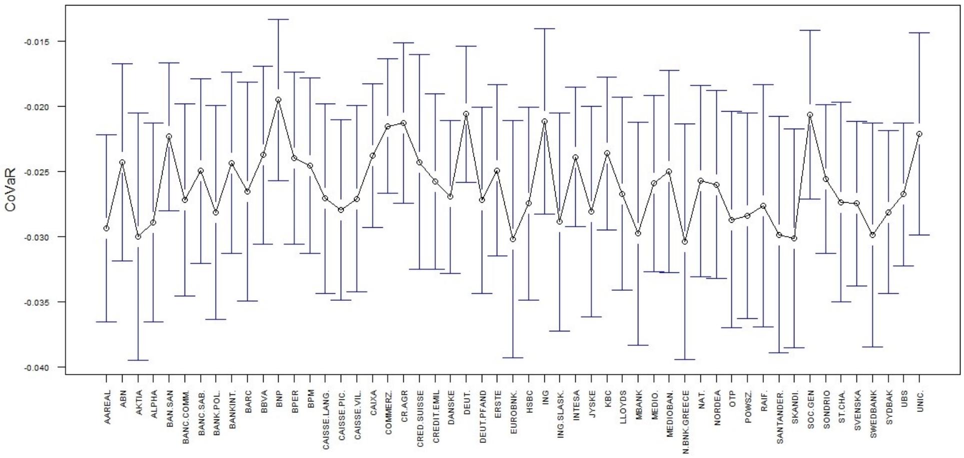
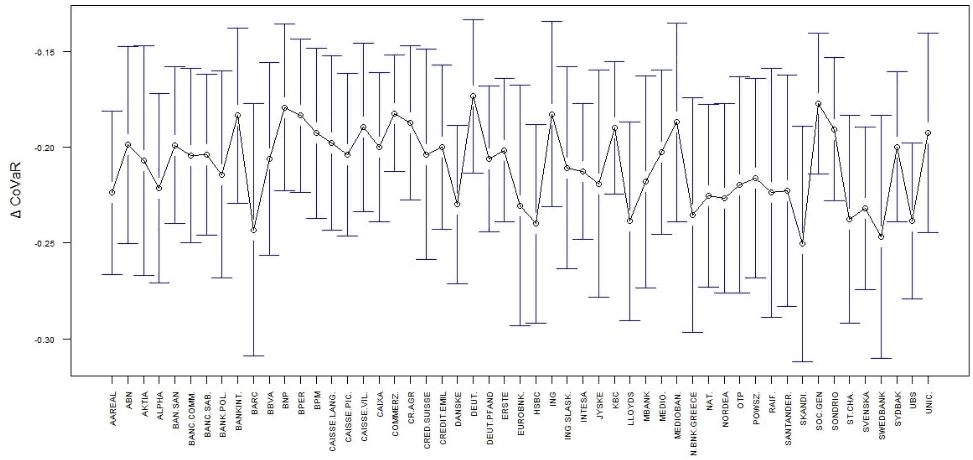


Figure 3.3: Cross validation output, for $\Delta CoVaR$



In terms of $\Delta CoVaR$, Greek banks exhibit the highest average systemic risk contribution, along with Barclays PLC, HSBC, LLOYDS and the Swedish banks. This output highlights that the Greek banking sector has not yet fully recovered from the sovereign bond crisis, further emphasizing the systemic fragility of these banks, attributable to their high non-performing loans (NPLs) and low capitalization. The results concerning english banks suggest that the Brexit event have made the banks more fragile, as reported also by Fernández et al. (2020), for several reason. This fragility can be attributed to factors such as the depreciation of the pound, which reduces the cross-border strength of banks, and the high inflation level that could have eroded the country's investments. Regarding Swedish banks, Madaschi and Pablos Nuevo (2017) have documented that banks in the *'frugal four'* primarily rely on wholesale fundings. They are particularly susceptible to monetary policy changes and have large exposures to long-term illiquid assets, especially in the housing market and household debt (Indeed, according to the analysis in the previous chapter, Skandinaviska Bank is an institution affected by the real estate changes variable.). These factors make them vulnerable to price and interest rate fluctuations, especially considering the recent rapid increase in official interest rates over the last three years.

In conclusion of the paragraph, in the next **section 3.7** the summary statistics for the covariate set is provided. For dimension uniformity of the covariates the total assets and total equity variables have been transformed with the decimal logarithm.

Table 3.1: Summary Statistics

.	Calculation	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis
TOA	$ln(Total\ assets)$	8.2874	0.6288	8.3437	6.9669	9.4259	2.4590	-0.0312	-1.2122
LOANS	$\frac{Loans}{Total\ assets}$	0.5569	0.1434	0.5865	0.1864	0.9416	0.7552	-0.5640	-0.4171
EQTY	$ln(Total\ equity)$	16.4015	1.2739	16.4010	13.2878	18.9700	5.6822	-0.1287	-0.9866
TIER1	$\frac{Tier-1\ capital}{RWA}$	16.4577	3.1233	16.0900	9.0400	28.7000	19.6600	0.6712	0.5974
DEPOSIT	$\frac{Total\ deposits}{Short-term\ fund+liab}$	0.0000	0.0000	0.0000	0.0000	0.0002	0.0002	2.5208	7.1821
NPL	$\frac{Loan\ loss\ provision}{Total\ loans}$	4.8723	7.4144	3.1000	0.0710	60.6000	60.5290	4.5327	23.8298
LEV	(Footnote 2)	4.9457	1.833	4.5625	1.2436	13.99	12.74	0.9848	2.0053
ROAA	$\frac{Net\ Income}{Avg.\ (assets)}$	0.4924	0.5457	0.4787	-4.0532	2.3772	6.4304	-2.1869	18.2126
ROAE	$\frac{Net\ Income}{Avg.\ (equity)}$	6.9870	6.6289	7.4328	-40.2252	27.1611	67.3863	-1.9923	11.6353
LCR	$\frac{HQLA}{TNCF}$	169.2854	51.1060	158.0000	81.0000	448.0000	367.0000	1.9756	5.9612
RORwA	$\frac{EBIT}{Risk-weighted\ assets}$	1.8159	1.4308	1.8712	-8.4661	8.6607	17.1268	-0.5553	8.8086
CI	$\frac{Operating\ Expenses}{Operating\ Income}$	60.8679	24.6341	60.1163	-341.0971	128.4207	469.5178	-11.4979	188.6080
POWER	$\frac{C.F\ Operating\ activities}{Total\ Liabilities}$	0.0069	0.0064	0.0066	-0.0435	0.0290	0.0725	-0.9424	11.3522
NON.INT	$\frac{Non-Interest\ Income}{Operating\ Income}$	44.5363	27.3415	42.4631	5.4622	499.9907	494.5285	12.4667	204.7539
INT	$\frac{Interbank\ assets}{Interbank\ liabilities}$	3.7868	1.0782	3.8669	0.8655	6.5458	5.6803	-0.0363	-0.1530

Note: $Avg.(x) = (Beginning + Ending\ x)/2$. C.F. stands for Cash flows

3.5 Results

Having seen the results of the previous chapter, to avoid the estimation bias due to the structural change in systemic credit measure observed in the previous chapter, the analysis has been splitted in two periods, the pre-crisis period [4] (the one that goes from 2016 to 2019) and the crisis period (from 2020 to 2022). The panel data analysis considers time fixed effects as specified in section 3.3. In the following **Table 3.2** are displayed the results of the lasso approach used.

Table 3.2: Coefficients' significance in Conditional quantile regressions for different time-lagged covariates

	(All)		(Pre crisis)		(Crisis)	
	$Covar$	$\Delta Covar$	$Covar$	$\Delta Covar$	$Covar$	$\Delta Covar$
TOA	/	0.1448	/	0.0612	0.3482	0.3684
EQTY	0.1442	/	0.0589	/	/	/
LOANS	0.7842	0.9389	/	/	/	/
TIER1	-0.0333	-0.0394	-0.0107	-0.0241	-0.0069	-0.0141

[4] Even if pre-crisis name is deprecable, since stagflation periods and low-interest periods are quite detrimental for banks

DEPOSIT	/	/	/	/		
NPL	0.01351	-0.0118	/	-0.0012	-0.0195	-0.0193
LEV	-0.0002	-0.0002	-0.0002	/	-0.00005	/
ROAA	/	/	/	/	/	/
ROAE	0.0210	0.0128	0.0141	0.01673	0.0098	/
LCR	-0.0024	-0.0023	-0.0007	-0.0007	/	/
RORwA	0.0524	0.0389	/	/	/	-0.0238
CI	0.0069	0.0072	0.0051	0.0059	/	/
POWER	/	/	/	/	/	/
NON.INT	0.0085	0.0075	/	-0.0007	-0.0021	-0.0005
INT	-0.0332	-0.0149	/	/	-0.1103	-0.0976

Note: '*All*,' '*Pre-Crisis*,' and '*Crisis*' indicate the models built on the periods from 2016 to 2022, 2019 to 2020, and 2020 to 2022, respectively.

At first glance, it appears that the sample time division has revealed some distinct effects. First of all, the deposit ratio,the Financial Power and the ROAA have been excluded in all of the model formulations, confirming the results of Kleinow et al. (2017) and Laeven et al. (2016) for the first two, and evidencing the power of the model in dealing with multicollinearity. Indeed, it has demonstrated that the information provided by the ROAE ratio perfectly supply the need for explaining systemic risk level, and that the ROAA is redundant (and not statistically relevant as discovered by Black et al. (2016)). Moreover, the loans ratio has been selected for the complete sample model but discarded in the split-time intervals. This provides further evidence of the misleading output of the entire sample, where a clear regime-switching bias is present (Hamilton (2016)).
When considering total assets and interbank liabilities, it appears that they become significant issues during crisis periods, while only the size variable has a role during pre-crisis times. This is a relatively new finding and will be extensively discussed in the following pages.
The capital level, represented by the Tier 1 ratio, is a consistently significant covariate in the analysis, consistently displaying a negative coefficient. This negative relationship will be further confirmed in the post-penalized regressions in the following sections **Table 3.4** and **Table 3.5**. All in all, this suggests that banks with higher levels of capitalization are more likely to have a more significant spillover effect on the financial system. This finding aligns perfectly with the results of Peltonen et al. (2019),and underscores how the quality of capital, as indicated by the Tier 1 ratio, surpasses the quantity of capital, represented by total equity, in explaining systemic risk.
As for the NPL and Leverage ratios, they perform as expected. These ratios consistently serve as significant predictors, helping to delineate the risk profile of banks in both crisis and pre-crisis periods. Similarly, the non-interest income ratio is selected by the model across all periods, although it's noteworthy that there is a sign misalignment of coefficients between the model estimated for the entire sample period and those estimated with period differentiation. This further supports the notion that the model on the complete sample time may be misspecified due to changing economic conditions over time, that introduce variation in coefficients' values and signs.
The analysis of covariates impact will be further explored in the following section with

the output of the post-penalized regression. As anticipated, the model selection step is employed to avoid redundancy and multicollinearity bias. Therefore, the results of the panel regressions with the covariate set constructed using this shrinkage approach will be presented. But before delving into that, to validate the hypothesis of fixed effects, two diagnostic tests are conducted: the The Lagrange multiplier test (Honda (1985)) for checking pooling and the Hausman test (Hausman (1978)) to assess the correlation of covariates with errors (random effects).

Table 3.3: Diagnostic tests

	Honda	Hausman
Unrestricted		
$CoVaR$-All	-0.37196 (0.645)	91.646 ($4.885e^{-13}$)
$CoVaR$-Pre.	-2.4042 (0.9919)	53.55 ($1.533e^{-06}$)
$CoVaR$-Crisis.	1.4928 (0.06775)	105.17 ($4.801e^{-16}$)
$\Delta CoVaR$-All	1.5661 (0.05866)	25.715 (0.04113)
$\Delta CoVaR$-Pre.	-0.83593 (0.7984)	6.6423 (0.9476)
$\Delta CoVaR$-Crisis.	5.3289 ($4.94e^{-08}$)	777.4 ($<2.2e^{-16}$)
Restricted		
$CoVaR$-All	0.01172 (0.4953)	169.75 ($<2.2e^{-16}$)
$CoVaR$-Pre.	-1.2459 (0.8936)	183.15 ($<2.2e^{-16}$)
$CoVaR$-Crisis.	-3.4941 (0.9998)	24.708 (0.00038)
$\Delta CoVaR$-All	1.3526 (0.0881)	7.9555 (0.7173)
$\Delta CoVaR$-Pre.	-0.8120 (0.7916)	13.402 (0.03708)
$\Delta CoVaR$-Crisis.	-0.2424 (0.5958)	19.966 (0.00280)

Note: The normal value (and the corresponding p value in the round brakets) of the Honda test and the chisqaured value (and the corresponding p value in the round brakets) for the Hausman test. '*All*,' '*Pre-Crisis*,' and '*Crisis*' indicate the models built on the periods from 2016 to 2022, 2019 to 2020, and 2020 to 2022, respectively.

As seen, except for the $\Delta CoVaR$-All model in both the restricted and unrestricted models, the results strongly support fixed effects and reject the random effects hypothesis. This suggests that the covariate set is highly correlated with the fixed effects, indicating time-dependent patterns in the balance-sheet factors.
In the next **Table 3.4** and **Table 3.5** are provided the results of the post-penalized regressions.

Table 3.4: Post-penalized models for *CoVaR*

	Dependent variable:					
	CoVaR					
	All		Pre-Crisis		Crisis	
	Unr.	Re.	Unr.	Re.	Unr.	Re.
TOA	0.007***		0.034*		0.021	0.002
	(0.002)		(0.019)		(0.034)	(0.004)
EQTY	−0.001	0.001***	−0.012	−0.004***	−0.004	
	(0.001)	(0.0001)	(0.008)	(0.001)	(0.015)	
LOANS	0.005***	0.003*	0.014		0.038	
	(0.002)	(0.001)	(0.014)		(0.024)	
TIER1	−0.0002***	−0.0002***	−0.002***	−0.002***	−0.003***	−0.002***
	(0.0001)	(0.0001)	(0.001)	(0.0004)	(0.001)	(0.001)
DEPOSIT	23.361***		281.952***		182.413	
	(8.883)		(76.338)		(166.591)	
NPL	−0.00002	−0.00004*	−0.0001		−0.002*	−0.002***
	(0.00003)	(0.00002)	(0.0002)		(0.001)	(0.001)
LEV	0.00000	−0.00000	0.00001	−0.00000	−0.00000	0.00000
	(0.00000)	(0.00000)	(0.00001)	(0.00001)	(0.00002)	(0.00001)
ROAA	0.001		−0.009		0.043	
	(0.001)		(0.011)		(0.026)	
ROAE	0.00000	0.0001*	0.001	0.001***	−0.003	−0.0005
	(0.0001)	(0.00004)	(0.001)	(0.0002)	(0.002)	(0.0003)
LCR	0.00000	−0.00000	0.00003	−0.00004	0.00003	
	(0.00000)	(0.00000)	(0.00003)	(0.00003)	(0.00004)	
RORwa	−0.0002	−0.0002	−0.005		0.005	
	(0.0003)	(0.0002)	(0.003)		(0.005)	
CI	0.00003***	0.00003***	0.0002***	0.0003***	0.0002***	
	(0.00001)	(0.00001)	(0.00001)	(0.0001)	(0.0001)	
POWER	0.017		0.612		−2.483	
	(0.075)		(0.630)		(1.556)	
NON.INT	0.00002***	0.00002***	0.0001		−0.00002	−0.0001
	(0.00001)	(0.00001)	(0.0001)		(0.0001)	(0.0001)
INT	−0.001***	−0.001***	−0.002		−0.006**	−0.009***
	(0.0001)	(0.0001)	(0.002)		(0.002)	(0.002)
Observations	371	371	212	212	159	159
R^2	0.481	0.458	0.276	0.213	0.239	0.197
Adjusted R^2	0.450	0.432	0.213	0.178	0.153	0.148
F Statistic	21.563***	27.104***	5.290***	9.101***	3.177***	5.220***

Note: *p<0.1; **p<0.05; ***p<0.01 .

Table 3.5: Post-penalized models for $\Delta CoVaR$

	Dependent variable:					
	$\Delta CoVaR$					
	All		Pre-Crisis		Crisis	
	Unr.	Re.	Unr.	Re.	Unr.	Re.
TOA	0.031*	0.0004*	0.041**	−0.008***	0.018	0.002
	(0.018)	(0.001)	(0.019)	(0.002)	(0.034)	(0.003)
EQTY	−0.010		−0.016**		−0.003	
	(0.008)		(0.008)		(0.015)	
LOANS	0.037***	0.041***	0.016		0.031	
	(0.013)	(0.011)	(0.014)		(0.024)	
TIER1	−0.002***	−0.002***	−0.003***	−0.003***	−0.003***	−0.002**
	(0.001)	(0.0004)	(0.001)	(0.0004)	(0.001)	(0.001)
DEPOSIT	217.106***		265.286***		170.210	
	(74.169)		(75.154)		(165.664)	
NPL	−0.0003	−0.0003*	−0.0002	−0.0002*	−0.002**	−0.002***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.001)	(0.001)
LEV	0.00001	0.00000	0.00001		−0.00000	
	(0.00001)	(0.00001)	(0.00001)		(0.00002)	
ROAA	0.011		0.004		0.048*	
	(0.011)		(0.011)		(0.026)	
ROAE	−0.0004	0.0003	0.0004	0.0005*	−0.003*	
	(0.001)	(0.0003)	(0.001)	(0.0003)	(0.002)	
LCR	0.00001	−0.00001	0.00002	−0.00004	0.00002	
	(0.00003)	(0.00002)	(0.00003)	(0.00003)	(0.00004)	
RORwa	−0.001	−0.0013*	−0.003		0.004	−0.005***
	(0.003)	(0.000)	(0.003)		(0.005)	(0.002)
CI	0.0002***	0.0003***	0.0002***	0.0003***	0.0003***	
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
POWER	−0.468		−0.120		−2.828*	
	(0.623)		(0.620)		(1.547)	
NON.INT	0.0001*	0.0002***	0.00005		−0.0001	−0.0001*
	(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)
INT	−0.003**	-0.004***	−0.001		−0.005**	−0.007***
	(0.001)	(0.001)	(0.002)		(0.002)	(0.002)
Observations	371	371	212	212	159	159
R^2	0.246	0.224	0.320	0.271	0.250	0.215
Adjusted R^2	0.201	0.187	0.260	0.238	0.165	0.173
F Statistic	7.611***	9.266***	6.508***	12.491***	3.379***	6.830***

Note: *p<0.1; **p<0.05; ***p<0.01

As mentioned earlier, the temporal division proves useful in distinguishing the relevant effects. Notably, variables like size and non-interest income exhibit contrasting effects in both the $CoVaR$ and $\Delta CoVaR$ cases between the time-segmented models and the overall time model, providing evidence that the time variation of effects should be of primary consideration. Starting analyzing systemic risk contribution, the coefficients of capital (Tier 1), interbank ratio, RoRwa, and NPL ratio (all with negative signs) exhibit the highest level of significance for the crisis specification in the restricted model. Intuitively, this means that when the interbank contagion channel is open due to a crisis, well-capitalized and high-performing banks contribute more than less-structured institutions, which are generally characterized by lower levels of asset riskiness and income performance. The business model also enters the model with a significantly negative coefficient, aligning with the perspective of De Jonghe (2010) which suggests that a market-oriented business model on the asset side makes the institution more likely to pose risks to other players. Similarly, though not to the same extent, during stable periods , the most liquid (even if liquidity has poor significance) and capitalized banks, exhibiting larger sizes and worse performances, have a greater impact on the system. An interesting finding is the significance of the efficiency ratio (CI) in the pre-crisis period, suggesting that more efficient banks also tend to be more systemically important (though this may be influenced by the economy of scale effect, as highlighted by Hughes et al. (2019)). Additionally, in both periods, a higher Non-Performing Loan (NPL) ratio is undoubtedly detrimental. NPLs are one of the main causes of losses, and in severe cases, defaults, which in turn exacerbate the systemic fragility of institutions.

The results obtained are clear and significant, revealing a differentiated effect of size between crisis and pre-crisis periods. In the latter, size exacerbates the systemic relevance of banks, suggesting a prevailing negative impact of size. However, during the crisis period, size per se appears to have an insignificant contribution to estimating the systemic risk levels of banks. This contradicts existing literature opinions (Laeven et al. (2016), Zhou (2009)) and regulatory assumptions that prioritize size as the main determinant for designating banks as systemically important. Moreover, the results regarding the system exposure (interbank ratio) are perfectly in line with the one found by Peltonen et al. (2019), suggesting that during a crisis, having strong connections with other players makes an institution more vulnerable. Meanwhile, in pre-crisis time, when no contagion channels is activated, connection is mostly irrelevant. This output confirms the idea formalized by Haldane (2009). This contagion proneness may be fueled by a significant involvement in market-based activities (Moore and Zhou (2013)). This latters, suscetible to market distortions and consequently creating less '*skin in the game*', could amplify systemic risk (Brunnermeier et al. (2020)). It's also worth noting the capital factor (Tier-1), which indicates that microprudential regulation incentivizes banks to take on more risk, unveiled during crisis periods, similarly to the findings of Black et al. (2016). Similarly, another risk-adjusted measure ($RoRWA$) has a more pronounced negative impact as its value increases. This further highlights the vulnerability of systems based on risk-adjusted measures, especially for larger banks that could take advantage of the pliability of Basel III internal models to underestimate their risks (Barucci and Milani (2018) and Vallascas and Hagendorff (2013)).

Furthermore, a mention of the leverage results is necessary, as it does not seem to play a significant role in determining the systemic risk contribution of banks. However, this result merely confirms the effectiveness of banking regulations; the banks all adhere closely to regulatory limit, and the variability (the primary information for the estimates) is low. This explains the exclusion from the model, that demonstrates the irrefutable validity of the regulation on this point [5].

For the $CoVaR$ measure, the results are similar, except for the total asset, which, in both hypothesized cases, appears to play no significant role in assessing systemic risk.

In the end, the fitting measures (R^2 and Adjusted-R^2) demonstrate the effectiveness of the model selection approach, as the difference between unrestricted and restricted models is negligible.

[5] Although the leverage specification in this paper does not take into account the weighting prescription, it is reasonable to assume that the alignment situation equally holds.

3.6 Is a matter of size or interconnection? (Or both?)

The results of the paper lead to a further consideration regarding the roles of size and interconnectedness. Interestingly, the statistical significance shifts in different directions between the crisis and pre-crisis periods. In the crisis period, interconnectedness is found to be significant, while size is not. Conversely, during the pre-crisis period, the roles are reversed. This emphasizes the critical role of the system and the information flow through contagion channels during turbulent times. However, it is important to clarify that the results from the crisis period do not exclude the role of bank size but rather reevaluate its significance. It is well-known that larger banks tend to be more interconnected (Krause and Giansante (2012)), well-capitalized, and have more market-oriented asset portfolios (Laeven et al. (2016)), that are features that this work demonstrates to be significant in predicting systemic relevance in crisis periods. Given this, it's reasonable to assume that during the crisis period, the role of bank size is indirect and secondary, thereby elevating the importance of interconnectedness. These findings are consistent with those of Acharya (2009), Caccioli et al. (2012), Krause and Giansante (2012) and Lu and Hu (2014), all of which support the predominance of network features, such as interconnectedness, over individual specific factors like bank size.

And in light of this deduction, some policy consideration could be made. After the Lehman Brothers collapse, that have had also a disruptive cross boarder effect, and the subsequent establishment of the Financial Stability Board (FSB) in 2009, the worldwide regulators have reinforced the regulations for the bigger banks, recognizing the different status and requiring them additional capital surchages to avoid that a distress could trigger a detrimental '*butterfly*' effect on the whole system. One of the most significant measures involved the imposition of additional prudential capital requirements, ranging from 1% to 3.5% based on risk-weighted assets, for entities identified as 'Systemically Important Financial Institutions' (SIFIs). These designations is made using a weighted indicator, where size and interconnectideness (of greater banks) properties accounted for more than 40% of the assessment (on Banking Supervision (2013)). In the Eurozone, for non-SIFI banks the regulation has relied mainly on countercyclical and systemic risk buffers. Introduced with Basel III, these measures may not be sufficient to contain contagions in the banking system, particularly within the cluster of non-SIFI banks, as they are generic and not estimated based on specific factors, especially the countercyclical buffer.

It's reasonable to assume that regulators were primarily motivated by the '*too big to fail*' logic, focusing on the specific characteristics of individual players rather than evaluating each player as a part of the system. Their aim appeared to be centered on preventing possible bailout costs in case of defaults rather than safeguarding the entire system as also asserted by Schwarcz (2019). It's limiting to presume that by stabilizing larger banks, systemic stability will be guaranteed against any adverse cases. As suggested by Brunnermeier et al. (2009), a systemic crisis could arise from negative spillover effects of large institutions as well as from numerous smaller defaults that are interconnected. The herding behavior of small banks, sharing risks and declining together due to contractual and interbank interlinkages, has often been overlooked. For this reason, shifting the regulatory focus from the size of individual banks to the overall systemic structure could enhance the effectiveness of preventing systemic crises. Acharya (2009), one of the pioneers in exploring optimal regulations for systemic risk events, suggests shifting away from standalone regulation and emphasizes the scrutiny of systemic interrelations, considering a system-based regulation akin to a 'Pigovian' tax approach. This system requires the observation and scrutiny of all the banks, not only the bigger ones, scaling the capital surchages or tax for taking into account the relative dimension in a systemic view. In line with this perspective, Rochet (2010) suggests that financial supervision should transition from individual screening to a more *'platform'* protection model, focusing on aspects like the soundness of the interbank market. The last two examples are better suited to address this specific phenomenon and provide a more comprehensive understanding of the complexity and determinants of the banking system.

3.7 Conclusion

The paper provides insights into which bank-specific variables actively influence the risk levels of financial institutions in the Eurozone. To achieve this, we developed a preliminary model selection approach, leveraging the structured framework developed by Babii et al. (2022). To test the validity of this approach, we conducted a post-penalized analysis by comparing the restricted set identified by the algorithm with the set of all bank features.

From the empirical results, the following conclusions can be drawn: First, dividing the analysis period into pre and post-crisis periods helps overcome bias introduced by regime-switching coefficients. Second, certain variables, such as the NPL ratio and Tier 1, have a consistent impact in both crisis and pre-crisis periods. Third, the roles of size and interconnectedness differ significantly between pre and post-crisis periods, highlighting a dynamic change in their importance in predicting systemic risk levels.

In the future, I will consider repeating the same analysis using different measures of systemic contribution. The measure used in this paper is primarily market-based. It would be interesting to extend the analysis to hybrid measures such as MES (Marginal Expected Shortfall)(Acharya et al. (2017)) or the SRISK (Brownlees and Engle (2017)).

Summary of results

Table 3.6: Summary of the principle results

Reference	Determinants	Results
	Capital	
Chabot and Bertrand (2021)	Tier 1 ratio (⇓)	Tier1 is a systemic risk amplificator in both pre and during crisis periods.
Zedda and Cannas (2020)	Regulatory Capital (⇓)	
Varotto and Zhao (2018)	Regulatory Capital (⇓)	
Anginer et al. (2018)	Regulatory Capital (⇓)	
De Jonghe (2010)	Equity ratio (⇓)	
Black et al. (2016)	Equity/Assets (⇑)	
Perotti et al. (2011)	Capital ratio (⇑)	
	Size	
Black et al. (2016)	ln(Total assets) (⇑)	Total assets is a amplificator in pre-crisis and not significant during crisis periods.
Nils (2018)	Literary review on size (⇑)	
Zedda and Cannas (2020)	Total assets (_)	
Varotto and Zhao (2018)	ln(Total assets) (_)	
Weiß et al. (2014a)	ln(Total assets) (_)	
Anginer et al. (2018)	ln(Total assets) (⇑)	
Laeven et al. (2016); Laeven et al. (2014)	ln(Total assets) (⇑)	
Kleinow et al. (2017)	ln(Total assets) (⇑)	
Biase and D'Apolito (2012)	Total assets (⇑)	
Qin and Zhou (2019)	ln(Total assets) (⇑)	
De Jonghe (2010)	ln(Total assets) (⇑)	
	NPL	
Kleinow et al. (2017)	NPL ratio (⇑)	NPL ratio is a systemic risk amplificator in both pre and during crisis periods.
Qin and Zhou (2019)	NPL ratio (⇑)	
	Leverage	
Varotto and Zhao (2018)	Leverage ratio (_)	Leverage ratio is irrelevant in both pre and during crisis periods.
Qin and Zhou (2019)	Total assets/equity (_ for US; ⇓for BRICS)	

Note: ⇓and ⇑signal that an increase in the variable induces a reduction or amplification of systemic risk, respectively. (_) implies that any significance has been found.

Table 3.7: Summary of the principle results (Continuation)

Reference	Determinants	Results
	Interconnection	
Chabot and Bertrand (2021)	Interbank assets (⇑)	Interbank raio is irrelevant in pre-crisis period, amplificator during crisis periods.
Zedda and Cannas (2020)	Interbank assets (_) Interbank Liability (⇓))	
Calice et al. (2021)	Concentration (⇑over a certain threshold)	
Boyd and Heitz (2016)	Concentration (⇑)	
Peltonen et al. (2019)	Interconnectediness (⇑)	
Qin and Zhou (2019)	Interbank assets/total assets (⇑)	
	Business model	
Kleinow et al. (2017)	Non-Interest inc. (_)	Non-interest income amplifies the systemic crisis
Black et al. (2016)	Loan/Deposit (⇑)	
Laeven et al. (2014)	Non-Interest inc. (⇓) Non-Interest inc.*ln(Total assets) (⇑)	
De Jonghe (2010)	Non-Interest inc. (⇑ Net interest margin (⇓)	
Anginer et al. (2018)	Net loans/Total assets (⇓)	
	Liquidity	
Varotto and Zhao (2018)	Liquidity ratio (_)	It's irrelevant
Kleinow et al. (2017)	Liquidity ratio (_)	
Anginer et al. (2018)	Liquid assets/Total assets (⇓)	
Biase and D'Apolito (2012)	Cash and equivalents/total assets (⇓)	
	Performance	
Black et al. (2016)	ROA (_)	It's irrelevant
Qin and Zhou (2019)	ROA (⇑)	
Biase and D'Apolito (2012)	Earning per share (⇓)	
Zedda and Cannas (2020)	RWA (⇑)	

Note: ⇓and ⇑signal that an increase in the variable induces a reduction or amplification of systemic risk, respectively. (_) implies that any significance has been found.

3.8 Appendix

Table 3.8: Financial institutions sample

Name	Abbreviation	Country	Specialisation
HSBC holdings PLC	HSBC	UK	Commercial bank
Bnp Paribas	BNP	France	Commercial bank
Credit Agricole SA	CR.ACGR	France	Cooperative bank
Banco Santander SA	BAN.SAN	Spain	Commercial bank
Barclays PLC	BARC	UK	Commercial bank
Societe Generale	SOC.GEN	France	Commercial bank
Deutsche bank ag	DEUT	Germany	Commercial bank
Lloyds banking group PLC	LLOYDS	UK	Commercial bank
Intesa Sanpaolo	INTESA	Italy	Commercial bank
ING groep NV	ING	Netherlands	Commercial bank
UBS group AG	UBS	Switzerland	Commercial bank
Unicredit spa	UNIC	Italy	Commercial bank
Natwest group PLC	NAT	UK	Commercial bank
Standard Chartered PLC	ST.CHA	UK	Commercial bank
Banco bilbao vizcaya argentaria sa	BBVA	Spain	Commercial bank
Nordea bank ABP	NORDEA	Finland	Commercial bank
ABN Amro bank NV	ABN	Netherlands	Commercial bank
Danske bank AS	DANSKE	Finland	Commercial bank
Commerzbank AG	CBK.DE	Germany	Commercial bank
KBC groep NV	KBC	Belgium	Commercial bank
ERSTE groep bank AG	ERSTE	Austria	Commercial bank
Skandinaviska enskilda banken AB	SKANDI	Sweden	Commercial bank
Swedbank AB	SWED.	Sweden	Commercial bank
Banco de sabadell sa	BANC.SAB	Spain	Commercial bank
Raiffeisen bank international ag	RAIF	Austria	Cooperative bank
Bper banca SPA	BPER	Italy	Commercial bank
Bankinter SA	BANKINT	Spain	Commercial bank
Jyske bank AS	JYSKE	Denmark	Commercial bank
Powszechna kasa oszczednosci bank polski SA	POWSZ	Poland	Commercial bank
Mediobanca SPA	MEDIOB	Italy	Commercial bank
Banco commercial portugues SA	COMM.P	Portugal	Commercial bank
OTP bank PLC	OTP	Hungary	Commercial bank
Eurobank ergasias SA	EUR.BNK	Greece	Commercial bank
National bank of greece SA	BNK.GRE	Greece	Commercial bank
Alpha SA	ALPHA	Greece	Commercial bank
Piraeus financial holdings SA	PIREUS	Greece	Commercial bank
Credito emiliano spa	CRED.MI	Italy	Cooperative bank

Bank polska kasa optieki SA	BNK.POL	poland	commercial bank
Santander bank polska	SAN	Poland	commercial bank
Aareal bank ag	AAREAL	Germany	Real.Est and mortgage inst.
Ing Bank Slaski S.A. p capital group	ING.SLA	Poland	Commercial bank
Mbank SA	MBANK	Poland	Commercial bank
Sydbank	SYDBNK	Sweden	Commercial bank
Bank millenium	MILLEN	Poland	Commercial bank
Aktia bank plc	AKTIA	Finland	Commercial bank
Banca popolare di sondrio SPA	SONDRIO	Italy	Commercial bank
Caixa bank S.A.	CAIXA	Spain	Commercial bank
Credit suisse group ag	SUISSE	Switzerland	Commercial bank
Banco bpm SA	BPM	Italy	Commercial bank
CRCAM brie picardie SC	PC	France	Cooperative bank
CRCAM du languedoc SC	LANG	France	Cooperative bank
Banca mediolanum	MEDIO	Italy	Coommercial bank
Deutsche pfandriefbank AG	DEYT.PF	Germany	Coommercial bank
CRCAM de l'ille et vilaine SA	VIL.	France	Cooperative bank

Figure 3.4: Cross validation output, for $CoVaR$ in overall period

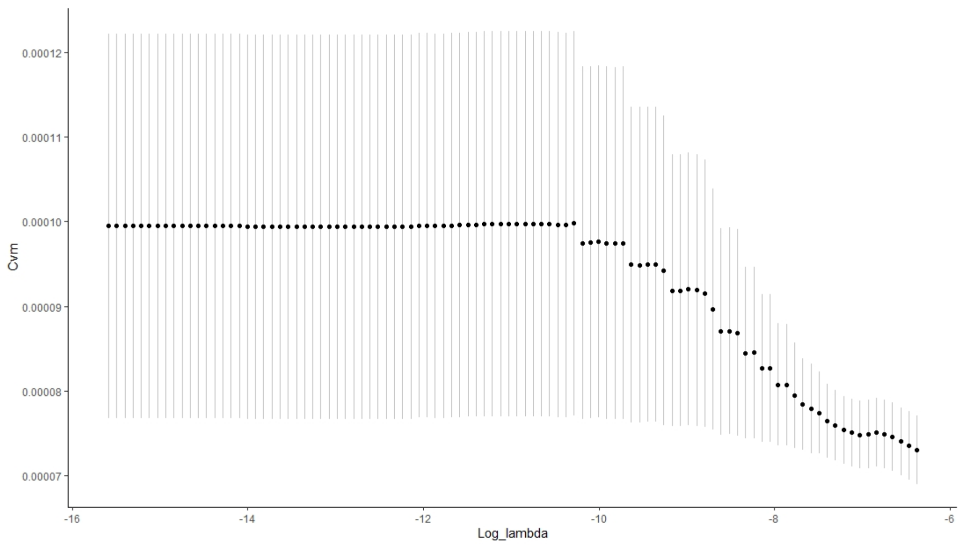


Figure 3.5: Cross validation output, for $\Delta CoVaR$ in overall period

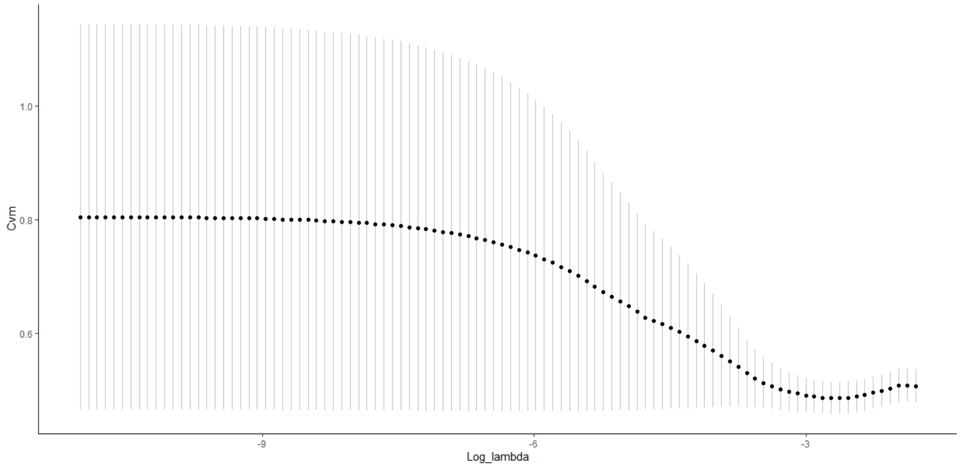


Figure 3.6: Cross validation output, for $CoVaR$ pre-crisos

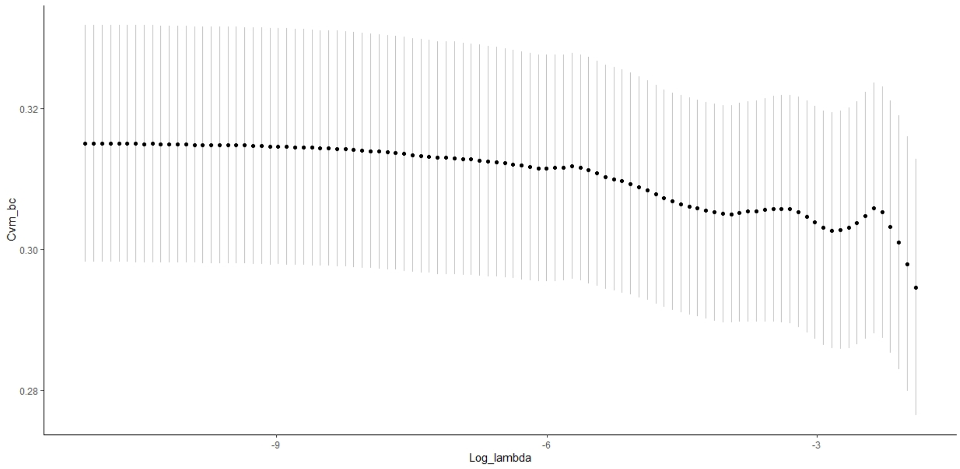


Figure 3.7: Cross validation output, for $\Delta CoVaR$ pre-crisis

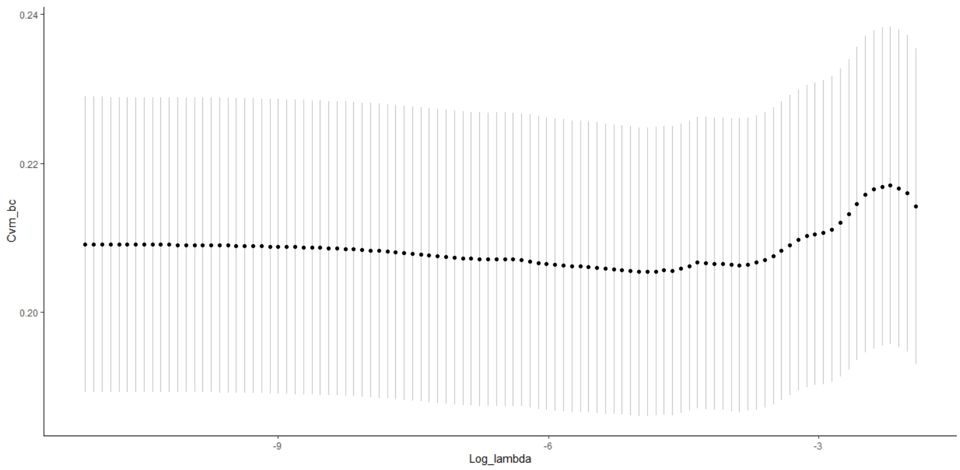


Figure 3.8: Cross validation output, for $CoVaR$ in crisis period

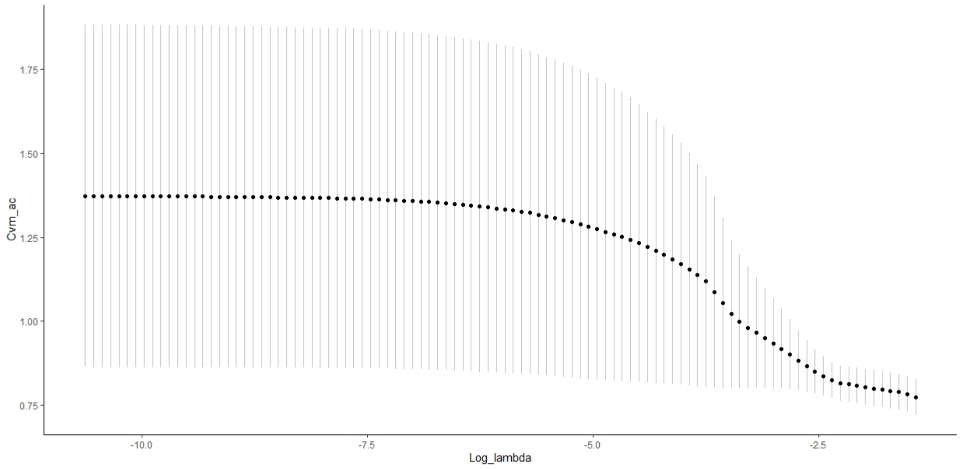
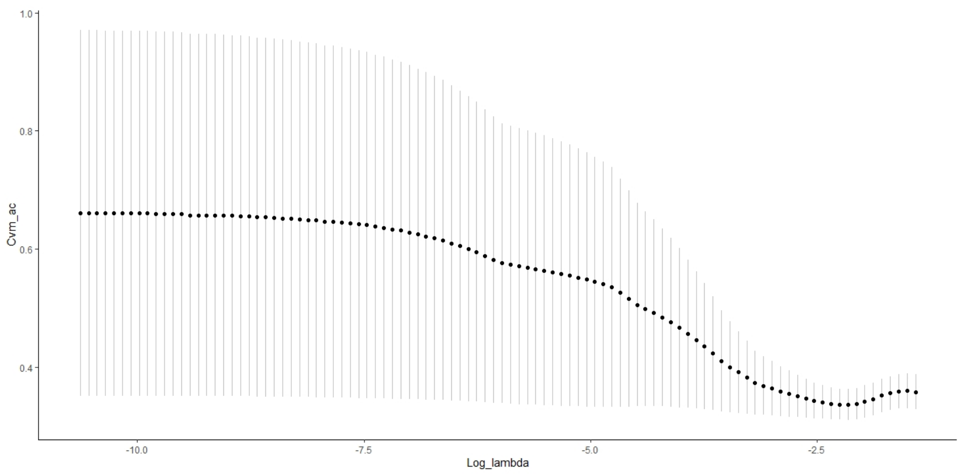


Figure 3.9: Cross validation output, for $\Delta CoVaR$ in crisis period



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