Assessing the contribution of banks, insurance and other financial services to systemic risk*

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Abstract

The aim of this paper is to contribute to the debate on systemic risk by assessing the extent to which distress within the main different financial sectors, namely, the banking, insurance and other financial services industries contribute to systemic risk. To this end, we rely on the $\Delta CoVaR$ systemic risk measure introduced by Adrian and Brunnermeier (2011). In order to provide a formal ranking of the financial sectors with respect to their contribution to systemic risk, the original $\Delta CoVaR$ approach is extended here to include the Kolmogorov-Smirnov test developed by Abadie (2002), based on bootstrapping. Our empirical results reveal that in the Eurozone, for the period ranging from 2004 to 2012, the banking sector contributes relatively the most to systemic risk at times of distress affecting this sector. By contrast, the insurance industry is the most systemically risky financial sector in the United States for the same period. Moreover, the three financial sectors contribute significantly to systemic risk, both in the Eurozone and in the United States. Finally, the insurance industry appears to impact relatively less systemic risk than the other financial services industry in the Eurozone, while banks contribute the least to systemic risk in the United States.

Keywords: Systemic risk, $CoVaR$, Quantile regression, Stochastic dominance test

JEL codes: C21, E44, G01, G20, G28

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1 Introduction

The financial system plays a central role in the proper functioning of modern economies. To the same extent that it can contribute to the fostering of economic growth (Levine, 1997), failures within the financial system, as has been crystalized by the recent financial crisis, can be devastating for the global economy, especially within a framework of highly interconnected economic agents. The need for the implementation of effective regulation is therefore obvious. Such a regulatory framework is, however, hard to design and to implement in practice. Indeed, historical evidence suggests that the response of the authorities to financial crises may engender perverse behaviors, insofar as safety measures can, in fact, encourage individual risk-taking (Barth et al., 2006; Demirgüc-Kunt et al., 2009). Furthermore, as suggested by Reinhart and Rogoff (2009), financial crises have been recurrent in economic history, implying that the fundamental roots of the current turmoil lie in the propensity of the financial system to be subject to episodes of extreme fragility rather than in the accumulation of exotic and risky financial products.

Risk within the financial system appears, in fact, to be more than the sole aggregation of risks related to individual institutions and includes a non-negligible component consisting of the endogenous risk that results from the collective behavior of financial institutions, i.e. the "systemic risk". In this respect, in the case of the banking industry, it is misleading that the historical focus of the regulators has been on imposing minimum levels of capital for banks as a cushion against unexpected losses (the so-called "Pillar I" in the Basel I and II agreements). This has meant that until only very recently, the systemic importance of individual institutions resulting from factors such as size, the degree of leverage, and the interconnectedness with the rest of the system has been ignored. In this respect, addressing Stein's concern regarding "the overarching goal of financial reform [which] must be not just to fortify a set of large institutions, but rather to reduce the fragility of our entire system of credit creation" (Stein, 2010), undoubtedly calls for a systemic approach to the problem that would contrast with most regulation attempts made so far.

Against this background, understanding the main causes of the system's fragility is essential in the quest for a proper regulatory framework and this remains one of the main challenges posed to policymakers, practitioners and the academic community. Regarding systemic risk, in a statement at the Economic and Monetary Affairs Committee of the European Parliament in 2009, Jean-Claude Trichet claimed that at least three major issues needed to be addressed: (i) the measurement of the degree of procyclicality in the financial system, (ii) the analysis of the inter-linkages between the financial sector itself, taken as a whole, and the real economy, and (iii) more generally, the assessment of systemic risk determinants. This paper aims to address the second and third issues by examining the contribution to overall risk arising from the different sectors that compose the financial system, i.e. the banking, insurance and other financial services sectors, in both the Eurozone and the United States. The other financial services sector contains financial companies other than banks and insurance companies, such as broker-dealers, hedge funds and holding companies for example. The main motivation behind this paper is the fact that in a globalized and financialized economy, economic agents are becoming increasingly more interconnected. This favors the spread of adverse shocks occurring in one or several financial sectors not only to the entire financial system but also to the real economy, as was illustrated by the Dotcom and subprime crises.

Addressing these issues requires not only the examination of the way shocks propagate within a given sector (i.e. how the distress of a given bank or insurance company spreads to other banks or insurance companies) but also the way shocks within a given financial sector affect other financial sectors or the real economy as a whole (i.e. how the distress of a given bank spreads to insurance companies or to other financial companies). As discussed extensively in the literature, a collapse of the banking system can lead to a worsening of credit conditions either through a "credit crunch" (Claessens and Kose, 2013), i.e. a sudden contraction of credit provided to private agents, or through a rise in the cost of credit (Bernanke and Gertler, 1989), which is likely to drive down corporate investment and household consumption. Although the literature focuses on the banking industry, the breakdown of companies other than banks, such as hedge funds or insurers, can also have a critical impact on the real economy, as was illustrated by the failures or near-failures of Long-Term Capital Management (LTCM) in 1998 or more recently of American International Group (AIG). The mechanisms involved may, however, differ. Unlike banks, insurers do not play a role in the monetary or payment systems and their activities are usually viewed as being safer than those of banker, as they rely on longer-term liabilities and on a strong operating cash flow. However, mutations in the insurance industry over recent years – characterized by an increased engagement in non-traditional activities such as credit default swaps – have significantly altered the risk profile of insurers. This has activated channels through which adverse shocks affecting the insurance industry may significantly harm the real economy (Billio et al., 2012; Harrington, 2009). Hedge funds can also impact the real economy through specific channels. In particular, the multiple financial activities of hedge funds (e.g. borrowing, their role as a counterparty in the derivatives markets or securities transactions) create exposures for other institutions. Illustrating this in terms of the real exposure channel (De Bandt and Hartmann, 2000), a negative shock hitting the hedge fund industry that, for instance, results in a series of defaults to creditors may affect the whole financial system and in turn the real economy. Hedge funds can also impact the economy through the so-called market channel in which the propagation of risk arises from the usual aggressive trading strategies used in hedge funds. These trading strategies have the potential to feed financial bubbles and to exacerbate price declines during correction phases. In fact, hedge funds, in particular, are suspected to have played a role in the development and the spread of mortgage-backed securities (MBSs) and of collateralized debt obligations

(CDOs), which contributed to the build-up and collapse of the housing bubble in the United States in the early 2000's (Kambhu et al., 2007; Dixon et al., 2012).

The existing literature has investigated extensively the transmission mechanisms of risks from one institution to another within the same sector (see, for instance, the literature on bank runs, Diamond and Dybvig, 1983, or the detailed discussion concerning the insurance industry in Allen and Gale, 2006). Nevertheless, empirical evidence is still scarce regarding how disruptions in one particular sector can spread to the entire economy and whether a specific sector is more or less risky than another. Our paper is designed to fill this gap. To this end, using data for the Eurozone and the United States for a specific period, we first estimate the extent of the contribution to systemic risk of the banking, insurance and other financial services industries and second, we establish which of these industries contribute the most to systemic risk.

The empirical strategy developed in the paper to assess the contribution of the banking, insurance and other financial services sectors to systemic risk relies on the $\Delta CoVaR$ systemic risk measure recently proposed by Adrian and Brunnermeier (2011). There is one significant limitation of the original $\Delta CoVaR$ measure of systemic risk, i.e. the absence of a formal test to compare the relative contribution of each individual financial institution or financial sector. Importantly, we deal with this limitation by implementing the Kolmogorov-Smirnov test developed by Abadie (2002), which is based on bootstrapping techniques. Using daily data from September 21, 2004 to March 16, 2012 for the United States and the Eurozone, our empirical results show that each financial sector contributes significantly to systemic risk, with the insurance sector displaying the largest contribution in the United States. In the Eurozone, banks are found to be the most systemically risky financial sector. Interestingly, the impact of the different financial sectors on systemic risk is found to increase after 2008. These results emphasize the need for financial regulatory authorities to adopt a simple, clear and easy to implement systemic risk measure. Regulatory authorities need to be aware that the different financial sectors represent different risks to the system and that specific actions may be needed to reduce the impact in terms of risk to the whole economy of these financial sectors.

The remainder of the paper is structured as follows. Section two discusses the literature on systemic risk measures and more precisely on the $\Delta CoVaR$ measure of systemic risk. The third section of the paper outlines the data employed in this empirical analysis. Section four lays out the empirical estimation framework of the $\Delta CoVaR$ and the procedure of a formal ranking of the different financial sectors with respect to their contribution to systemic risk. Section five presents our empirical findings and the results of the specific tests. Section six discusses results and section seven concludes.

2 Literature review

The European Central Bank (ECB, 2009) defines systemic risk as a risk of financial instability "so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially". In this paper, we do not limit our definition of the system to the banking sector or to the financial system, as is often the case in the literature, but rather focus on the second part of the definition, which is related to spillovers into the real economy itself. Accordingly, in the remainder of the paper, we use "the system" to refer to the real economy. Consequently, our main objective is to assess the impact on the real economies of both the Eurozone and the U.S. of adverse shocks affecting one of the different sectors in the financial system (i.e. the banking, insurance and other financial services sectors).

Addressing this issue obviously requires the use of a relevant measure of systemic risk. A large number of systemic risk measures have been proposed in the literature (see Bisias et al., 2012 for a complete and comprehensive survey). In this section, we briefly review the main measures of systemic risk developed in the literature. One set of measures concerns network analysis, which is centered on existing linkages between agents and focuses on the balance sheet data of financial institutions in order to detect tensions and potential problems within a given financial sector. Scientific contributions in this vein include, among others, Elsinger et al. (2006), Aikman et al. (2009) and Gauthier et al. (2012), who rely on a network-based model for the Austrian, British and Canadian banking systems and interbank markets. Two important shortcomings regarding this literature should, however, be highlighted. The first is the lack of data concerning existing linkages between the cross-exposures of financial institutions. In response to this shortcoming, Cerutti et al. (2011) propose the creation of a common reporting template for global systemically important financial institutions. A second important shortcoming is the static modeling of institutional behavior. Models relying on low frequency data can scarcely capture rapid changes in the dynamics of economic and financial variables, thereby missing an important dimension of risk management.

Economic and financial conditions may change over time and so does underlying risk, meaning that models and indicators of risk must adjust to these evolutions. In this respect, systemic risk measures in the literature that can be updated on a daily or intraday basis are valuable real-time indicators of fragility in emerging crises. Some authors use Credit Default Swaps (CDS) in order to have a daily systemic risk measure. Segoviano and Goodhart (2009) construct a banking stability index to estimate interbank dependence for tail events using CDS data. Huang et al. (2009) construct the Distress Insurance Premium (DIP) by using publicly available financial market data such as the Probability of Default (PD) derived from each institution's CDS spreads and the asset return correlations among banks estimated from equity price co-movements. Moreno and Peña (2012) also find that CDS spreads are good estimators of systemic risk.

While studies relying on CDS data are important, it is essential to point out that they reflect and capture only one type of risk, namely credit risk. Another important strand of the literature relies on stock market data to identify potential spillover effects between financial institutions. In particular, Tarashev et al. (2009) conduct simulations of a stylized banking system and use the Shapley value, a concept originating from game theory. Billio et al. (2012) rely on principal-components analysis and Granger-causality tests to study the interconnectedness between different financial sectors. Acharya et al. (2010) introduce the Systemic Expected Shortfall (SES) indicator, which represents the downside risk of a single financial firm in the event of market turmoil. In the same vein, Brownlees and Engle (2012) develop a systemic risk measure (called the SRISK). These last two market-based systemic risk measures – SES and SRISK – can be seen as "top-down measures" in the sense that they aim to determine the impact of distress occurring at the level of the financial system on an individual financial institution.

By contrast, the $\Delta CoVaR$ measure of systemic risk proposed by Adrian and Brunnermeier (2011) might be seen as a "bottom-up" measure of systemic risk in that it assesses the impact of distress at the level of a single financial institution and the transmission of the associated risks to the entire financial system. Adrian and Brunnermeier (2011) use traditional quantile regressions to estimate their conditional models and rely on accounting data to determine the weekly market-valued asset returns for a period ranging from 1986 to 2010 for 1266 U.S. financial institutions of four different types, i.e. commercial banks, broker-dealers, insurance companies and real estate companies. Their results indicate that size, level of leverage, maturity mismatch and market-to-book value ratio are important factors contributing to systemic risk.

There is a growing literature on the $\Delta CoVaR$ systemic risk measure. The first strand follows strictly the $\Delta CoVaR$ methodology developed by Adrian and Brunnermeier (2011). Roengpitya and Rungcharoenkitkul (2011) use panel data regressions to quantify the spillover risk of six major Thai commercial banks within the Thai financial system. Their findings indicate that the different individual banks of interest impose additional risk on the Thai financial system and that there is some evidence that larger banks contribute more to systemic risk in Thailand. More recently, Castro and Ferrari (2013) identify and rank the most systemically risky banks for the European financial system by developing both a significance and a dominance test. The significance test aims to determine whether the $\Delta CoVaR$ related to a specific bank is different from zero, meaning that this bank has an impact on the financial system (i.e. the bank is systemically risky). The dominance test allows to determine whether a given bank is systemically riskier than another. Their findings indicate that very few banks can be ranked on the basis of the $\Delta CoVaR$.

The second strand in the literature on the $\Delta CoVaR$ systemic risk measure departs slightly from the original $\Delta CoVaR$ methodology. Girardi and Ergün (2013) consider the conditional financial distress of the $CoVaR$ definition to be a situation in which the return of the conditional institution is higher (in absolute terms) than its Value-at-Risk, rather than being equal to it, as specified in Adrian and Brunnermeier (2011). Girardi and Ergün (2013) analyze the contribution of four financial groups in the U.S. (i.e. depositories, insurers, broker-dealers and other non-depository institutions) to the risk of the financial system. Their results reveal that depositories contribute the most to systemic risk. Other authors use an asymmetric $CoVaR$ to capture the contribution of both positive and negative shocks to the banking system. In particular, López-Espinoza et al. (2012a,b) and Bjarnadottir (2012) investigate respectively 54 international large-scale complex banks, a large sample of U.S. banks and four major Swedish banks in order to evaluate their contribution to the risk of their respective financial system. Their findings reveal that the asymmetric $CoVaR$ does not underestimate systemic risk by comparison with the initial $CoVaR$.

Finally, several authors have attempted to extend the $\Delta CoVaR$ methodology. In particular, Chan-Lau (2008) adopts an approach based on Credit Default Swap spreads to investigate the spillover effects of a sample of 25 financial institutions in Europe, Japan and the United States. Wong and Fong (2010) investigate the interconnectivity between the economies of eleven Asia-Pacific countries and estimate the $CoVaR$ for the CDS of Asia-Pacific banks. Their results show that, for most of the economies of interest, the conditional risk measure is significantly higher than the unconditional risk measure (i.e. traditional Value-at-Risk). Adams et al. (2011) focus on four different financial institutions (i.e. commercial banks, investment banks, hedge funds and insurance companies). They propose a state-dependent sensitivity VaR ($SDSVaR$) to quantify the spillover effects among systemically important financial institutions. Their empirical findings suggest that hedge funds play an important role in the transmission of shocks to the other financial institutions. Agrippino (2009) computes the $CoVaR$ of five U.S. commercial banks in two ways in order to distinguish between interdependence and contagion in the financial system. Using quantile regressions coupled with a logit model, Boyson et al. (2010) find strong evidence of spillover effects across hedge fund styles in the United States.

This paper builds on the $\Delta CoVaR$ methodology. This choice is motivated by two main factors. First, the $\Delta CoVaR$ relies on high-frequency stock market data and is therefore a highly reactive systemic risk measure. Second, this measure is particularly well suited for analyzing the extent to which distress within a given financial sector (i.e. the banking, insurance and other financial services sectors) is transmitted to the real economy of the Eurozone and the United States.

To sum up, our empirical approach in this paper departs from existing analyses using the $\Delta CoVaR$ methodology in four principal ways. First, we propose a formal test of significance of the $\Delta CoVaR$ based on the Kolmogorov-Smirnov (KS) test to determine whether a given financial sector contributes significantly to systemic risk. We also propose a test of dominance that aims to assess whether or not one particular financial sector contributes more to systemic risk than another. In order to deal with the Durbin problem (Durbin,

1973) that occurs in the implementation of the KS test when two cumulative density functions are not distribution-free, we follow the bootstrapping strategy developed by Abadie (2002). An alternative strategy is adopted by Castro and Ferrari (2013). While this approach offers interesting features such as the correct inference for the KS test, it relies on questionable assumptions (see Appendix A) that are not required with the bootstrapping approach (Abadie, 2002). Bootstrapping therefore appears to be particularly well suited for conducting significance and dominance tests within the framework of the $\Delta CoVaR$. Second, in line with the definition of systemic risk proposed by the ECB (2009), the system is not restricted to the financial or the banking system, as usually happens in the literature, but is extended rather to the real economy. Third, the determinants of systemic risk are examined for both the Eurozone and the U.S. economies. Since these two regions, which were at the center of the recent financial crisis, display different regulatory frameworks, comparing the propagation of risks in each area should provide interesting insights regarding the existing link between systemic risk and the standards that financial institutions are expected to meet. Finally, we compare the contribution of the main components of the financial system, i.e. the banking, insurance and other financial services sectors to systemic risk rather than focusing on the contribution of individual financial institutions to systemic risk. All in all, our approach is likely to be highly relevant to governments and central banks for regulatory purposes.

3 Data

As in the paper of Girardi and Ergün (2013) (see also Roengpitya and Rungcharoenkitkul, 2011; Castro and Ferrari, 2013), we use a stock market index as a proxy for the system, namely the S&P 500 Ex-Financial index for the United States and the STOXX Europe 600 ex Financials index for the Eurozone.[1] In both indices, financial companies are naturally excluded from the index to avoid spurious correlations between our variables of interest.[2]

The Eurozone and U.S. stock market indices related to the three financial sectors are presented respectively in Tables 1 and 2. Their related state variables used in quantile regressions are also defined in these tables. The empirical analysis spans the period from September 21, 2004 to March 16, 2012. Overall, the sample is made up of 1765 daily observations for the Eurozone and 1813 daily observations for the United States.

[1]The most appropriate market index would be the EURO STOXX 50 ex Financials but this index only contains 37 companies, which is not completely representative of the real economy within the Eurozone. We therefore use the STOXX Europe 600 ex Financials index, which contains 462 components. This choice, however, is likely to have a limited effect on the rest of the study as, in practice, the EURO STOXX 50 ex Financials and the STOXX Europe 600 ex Financials index are highly correlated.

[2]Keeping financial companies within the global index means that a shock affecting financial sectors would mechanically impact the global index even in the absence of spillover effects between the financial sector and the real economy.

Table 1: Eurozone variables

Variable	Definition	Source
R_t^i: Market daily returns of the three financial sectors and of the system		
Banks	EURO STOXX Banks index	Bloomberg
Insurance	EURO STOXX Insurance index	Bloomberg
Financial services	EURO STOXX Financial Services index	Bloomberg
System	STOXX Europe 600 ex Financials index	Bloomberg
M_t: State variables		
VDAX	Volatility index	Bloomberg
Liquidity spread	Difference between the 3-month Euro Area repo rate and the 3-month Germany bond rate	Bloomberg and Macrobond
3-month GerBill spread variation	Difference between the 3-month Germany bond rate in time t and the 3-month Germany bond rate in time t-1	Bloomberg
Yield spread change	Difference between the 10-year Germany bond rate and the 3-month Germany bond rate	Bloomberg
Credit spread change	Difference between the 10-year Macrobond BBB Euro Area corporate bond rate and the 10-year Germany bond rate	Bloomberg and Macrobond
Equity return	EURO STOXX 50 index returns	Bloomberg
Real Estate return	EURO STOXX Real Estate index returns	Bloomberg

Notes: The spreads and the spread changes are expressed in basis points and the returns are expressed as a percentage.

Table 2: U.S. variables

Variable	Definition	Source
R_t^i: Market daily returns of the three financial sectors and of the system		
Banks	Dow Jones U.S. Banks index	Bloomberg
Insurance	Dow Jones U.S. Insurance index	Bloomberg
Financial services	Dow Jones U.S. Financial Services index	Bloomberg
System	S&P 500 Ex-Financial index	Bloomberg
M_t: State variables		
VIX	Volatility index	Bloomberg
Liquidity spread	Difference between the 3-month U.S. repo rate and the 3-month U.S. T-Bill rate	Bloomberg
3-month T-bill spread variation	Difference between the 3-month U.S. T-Bill rate in time t and the 3-month U.S. T-Bill rate in time t-1	Bloomberg
Yield spread change	Difference between the 10-year U.S. Treasury Bond rate and the 3-month U.S. T-Bill rate	Bloomberg
Credit spread change	Difference between the 10-year Macrobond BBB U.S. corporate bond rate and the 10-year U.S. Treasury Bond yield	Bloomberg and MacroBond
Equity return	S&P500 index returns	Bloomberg
Real Estate return	Dow Jones U.S. Real Estate index returns	Bloomberg

Notes: The spreads and the spread changes are expressed in basis points and the returns are expressed as a percentage.

4 Methodology

The following sections introduce the $\Delta CoVaR$ (Section 4.1) and detail the six-step procedure (Section 4.2) used in this paper in order to estimate the absolute and relative contribution to systemic risk of the banking, insurance and other financial services industries. This procedure extends the one proposed by Adrian and Brunnermeier (2011) to include a formal test of significance and dominance.

4.1 Definition of $\Delta CoVaR$

The conditional Value-at-Risk ($CoVaR$) was introduced by Adrian and Brunnermeier (2011) to analyze risk transmission from one individual financial institution to another or to the financial system as a whole. This concept is based on the Value-at-Risk, denoted $VaR(\alpha)$, the most popular measure of risk used by professionals to evaluate market risk. Intuitively, the $VaR(\alpha)$ is the worst loss over a target horizon that will not be exceeded with a given level of confidence $1-\alpha$ (Jorion, 2007). Statistically, the $VaR(\alpha)$ defined for a confidence level $1-\alpha$ corresponds to the α-quantile of the projected distribution of gains and losses over the target horizon.

The $CoVaR$ approach offers broad flexibility for describing risk spillovers between individual institutions or a group of institutions, and appears to be particularly convenient for identifying the factors contributing to systemic risk. $CoVaR_q^{j|i}$, as defined by Adrian and Brunnermeier (2011), is the VaR_q^j of an institution j (or of the financial system) conditional on an event $C(R^i)$ affecting an institution i, which is materialized by the return for this institution (R^i) being equal to its level of VaR for a q^{th} quantile (i.e. $R^i = VaR_q^i$). $CoVaR_q^{j|i}$ is defined by the q^{th} quantile of the conditional probability distribution of returns of j:

$$Pr(R^j \leq CoVaR_q^{j|C(R^i)} | C(R^i)) = q \tag{1}$$

Along these lines, the $\Delta CoVaR$ is defined by Adrian and Brunnermeier (2011) as the difference between the $CoVaR$ of the financial system j when a given financial institution i is in distress – i.e. when it reaches an adverse level of VaR (e.g. 1%) – and the $CoVaR$ of the same financial system conditional on the normal state of the same institution, i.e. when institution i is at its median state (i.e. 50%):

$$\Delta \mathrm{CoVaR}_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=Median^i} \tag{2}$$

This measure provides, in this case, the marginal contribution of a financial institution to the risk of the financial system when the financial institution is facing a stress situation instead of a normal situation. In order to estimate the related VaR_q^i and their $\Delta CoVaR_q^{j|i}$, Adrian and Brunnermeier (2011) use the growth rates of market-valued total assets for an individual institution, which are defined as a function of lagged state variables. Quantile regressions (Koenker and Basset, 1978) are used to estimate the link between a set of independent variables and specific quantiles of the dependent variable.

4.2 Six-step procedure

Following equations (1) and (2) above, we define $CoVaR_q^{system|i}$ as the VaR_q^{system} of the whole system conditional on an event $C(R^i)$ affecting a financial sector i (the return for this financial sector (R^i) being equal to its level of VaR for a q^{th} quantile):

$$Pr(R^{system} \leq CoVaR_q^{system|C(R^i)}|C(R^i)) = q \tag{3}$$

We can then define $\Delta CoVaR_q^{system|i}$ as the difference between the $CoVaR$ of the whole system conditional on distress affecting a given financial sector i (i.e. banks, insurance companies or other financial services) and the $CoVaR$ of the same system conditional on a normal situation for the financial sector of interest:

$$\Delta CoVaR_q^{system|i} = CoVaR_q^{system|X^i=VaR_q^i} - CoVaR_q^{system|X^i=Median^i} \tag{4}$$

Step 1 Daily market returns of one of the three financial sectors of interest (denoted R_t^i), are estimated using a 1% quantile regression (see Section 3 for a description of the three financial sectors):

$$R_t^i = \alpha^i + \gamma^i M_t + \varepsilon_t^i \tag{5}$$

Where α^i is the constant and M_t represents a vector of contemporary state variables (see Section 3). The error term ε_t^i is assumed to be i.i.d with zero mean and unit variance and is also independent of M_t. Results of the quantile regression estimates are presented in Tables 9 to 14 (see Appendix B). The 1% quantile of returns is obtained using the quantile regression framework.

Step 2 We compute the predicted 1% Value-at-Risk for each financial sector using exclusively the significant variables found in step 1:

$$\widehat{VaR}_t^i = \hat{\alpha}^i + \hat{\gamma}^i M_t \tag{6}$$

Where $\hat{\alpha}^i$ and $\hat{\gamma}^i$ are obtained from equation 5.

Step 3 The system's returns within a 1% quantile regression framework are then estimated:

$$R_t^{system} = \alpha^{system|i} + \beta^{system|i} R_t^i + \gamma^{system|i} M_t + \varepsilon_t^{system|i} \tag{7}$$

We approximate the macro-economic dynamics using the returns of stock market indices of the system of interest (R_t^{system}). In equation (7), $\alpha^{system|i}$ is the constant, R_t^i is the return of a financial sector index, M_t represents a vector of contemporary state variables and $\varepsilon_t^{system|i}$ is the error term. The state variables are the same as in equation 5, excluding the S&P 500 index and the EURO STOXX 50 index. The 1% quantiles of returns are again obtained from quantile regressions.

Step 4 We compute the predicted $CoVaR$ of the system, which is the VaR of the system conditional on a situation of distress within the banking, insurance or other financial services sector (represented by the 1% quantile regressions obtained in the previous steps). To this end, we insert the estimated $VaR(1\%)$ obtained in equation (6) into equation (8) along with all the significant explanatory variables from equation (7):

$$\widehat{CoVaR}_t^{system|i}(1\%) = \hat{\alpha}^{system|i} + \hat{\beta}^{system|i} \widehat{VaR}_t^i + \hat{\gamma}^{system|i} M_t \tag{8}$$

Where $\hat{\alpha}^{system|i}$, $\hat{\beta}^{system|i}$ and $\hat{\gamma}^{system|i}$ are obtained from equation (7).

Step 5 The $\Delta\widehat{CoVaR}$ is estimated by taking the difference between the predicted $CoVaR$ at a 1% quantile and the one at a 50% quantile. The second value is obtained by implementing steps 1 to 4 with a 50% quantile (i.e. by using the same methodology as for the 1% $CoVaR$ but by taking the 50% quantile of the returns at each step). This $CoVaR$ at a 50% quantile describes a median-state conditioning event. Eventually, the $\Delta\widehat{CoVaR}$ represents the marginal contribution of the banking, insurance or other financial services sectors to systemic risk:

$$\Delta\widehat{CoVaR}_t{}^{system|i}(q) = \widehat{CoVaR}_t^{system|i}(1\%) - \widehat{CoVaR}_t^{system|i}(50\%) \tag{9}$$

In the empirical results, the $\Delta\widehat{CoVaR}s$ are negative because they are computed from the worst 1% returns of the three financial sectors of interest. Along these lines, the sector of the financial system with the largest $\Delta\widehat{CoVaR}$ absolute value is the segment that contributes relatively the most to systemic risk during periods of distress. In order to generalize these results, a final step is dedicated to statistical inference.

Step 6 We test the significance and the stochastic dominance of the $\Delta CoVaRs$ in order to rank the financial sectors of interest according to their contribution to systemic risk (for more details, see Appendix A). The significance test aims to identify a systemically risky financial sector. We examine the $\Delta CoVaR$ conditional on a given financial sector to check whether it is either statistically equal to 0 (meaning that the given financial sector is not systemically risky) or statistically different from 0. Unlike Castro and Ferrari (2013), who use a joint exclusion Wald test on the coefficient parameters without taking into account the set of control variables, we want to take into account all the significant explanatory variables of the $CoVaR$ (i.e. the returns as well as the state variables). Since the coefficient of each explanatory variable differs according to the quantile of interest, we test whether or not the cumulative distribution functions (CDFs) of the $CoVaRs$ at a 1% quantile and at a 50% quantile are different from each other. In order to do this, we use the bootstrap Kolmogorov-Smirnov (KS) test developed by Abadie (2002). For the significance test, the two-sample Kolmogorov-Smirnov statistic is defined as follows:

$$D_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} sup_x \left|F_m(x) - G_n(x)\right| \tag{10}$$

Where $F_m(x)$ and $G_m(x)$ are the CDFs of the $CoVaRs$ related to the 1% and 50% quantiles respectively and m and n are the size of the two samples. The null hypothesis is the equality of the CDFs of the $CoVaRs$ related to the 1% and 50% quantiles:

$$H_0 : \Delta CoVaR_t^{system|i}(q) = CoVaR_t^{system|i}(1\%) - CoVaR_t^{system|i}(50\%) = 0 \tag{11}$$

The dominance test aims to test the significance of the ranking obtained from the $\Delta CoVaRs$ in order to check whether a given financial sector i does indeed contribute more to systemic risk than another financial sector j. We again rely on the bootstrap KS test of Abadie (2002) to compare the CDFs of the $\Delta CoVaRs$ in relation to two financial sectors. The two-sample Kolmogorov-Smirnov test statistic for the dominance test is defined as follows:

$$D_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} sup_x \left|A_m(x) - B_n(x)\right| \tag{12}$$

Where $A_m(x)$ and $B_m(x)$ are the CDFs of the $\Delta CoVaRs$ related to two financial sectors and m and n are the size of the two samples. The null hypothesis is defined as follows:

$$H_0 : \left|\Delta CoVaR_t^{system|i}(q)\right| > \left|\Delta CoVaR_t^{system|j}(q)\right| \tag{13}$$

Given that the estimated $\Delta CoVaRs$ are negative, in order to make for an easier discussion, the interpretation of the null hypothesis and the comparison of the results of the bootstrap KS tests will rely on the

$\Delta\widehat{CoVaR}$ absolute values.

5 Empirical results

This section presents the quantile regression estimates (Section 5.1), the results of the $\Delta CoVaR$ estimates and the conclusions of the two-sample Kolmogorov-Smirnov tests (Section 5.2).

5.1 Quantile regressions

Tables 9 to 11 and 12 to 14 in Appendix B provide quantile regression results for the 1% and 50% quantile returns of the respective indices for the Eurozone and the U.S. banking, insurance and other financial services sectors. Moreover, these tables contain estimates for the system's returns in which the STOXX Europe 600 ex Financials index and the S&P 500 Ex-Financial are used to proxy the Eurozone and U.S. economies respectively.

Results for the **Eurozone banking sector** indicate that volatility, liquidity spread and credit spread changes negatively influence the 1% quantile returns of the EURO STOXX Banks index. Real estate and equity returns, on the other hand, have a positive impact. Concerning the 50% quantile returns of the EURO STOXX Banks index, some differences appear with volatility and liquidity spread not influencing returns while yield spread changes display a positive impact. Looking at the 1% quantile returns of the STOXX Europe 600 ex Financials index (used to proxy the Eurozone's risk), the EURO STOXX Banks index total returns, yield spread changes and real estate are significant and have a positive coefficient. By contrast, volatility has a negative impact. Regarding the 50% quantile returns for the EURO STOXX 50 ex Financials index, three month rate changes, yield spread changes, real estate returns and the EURO STOXX Banks index total returns have a positive effect. The situation of the **U.S. banking sector** is, however, somewhat different. Volatility has a significant and negative impact, while the real estate and equity returns positively influence the 1% quantile returns of the Dow Jones U.S. Banks index. Looking at the specification of the 50% quantile returns, volatility again has a negative effect, while yield spread changes, real estate and equity returns have a positive and significant coefficient. Results for the S&P 500 Ex-Financial index (used as a measure for the U.S. risk) again indicate that volatility negatively influences both the 1% and the 50% quantile returns. Three-month rate changes, real estate returns and the Dow Jones U.S. Banks index total returns, on the other hand, display a positive coefficient. Yield spread changes only influence positively 50% quantile returns.

Looking at the **insurance sector in the Eurozone**, the empirical results indicate that the 1% quantile returns of the EURO STOXX Insurance index are negatively influenced by volatility, yield and credit spread changes, while real estate and equity returns have a positive coefficient. 50% quantile returns seem to be positively influenced only by real estate and equity returns. The 1% and 50% returns for the STOXX Europe 600 ex Financials index are both positively influenced by the EURO STOXX Insurance index total returns, real estate and yield spread changes. Volatility has a negative impact only on 1% quantile returns. 50% quantile returns are also impacted positively by credit spread changes. Results for the **U.S. insurance sector** show that the 1% returns for the Dow Jones U.S. Insurance index are negatively influenced by volatility on the one hand, with real estate and equity returns having a positive influence on the other hand. Looking at the 50% quantile returns, three-month rate changes, yield spread changes, real estate and equity returns all display a positive coefficient. The S&P 500 Ex-Financial index is positively impacted by the Dow Jones U.S. Insurance total returns and negatively impacted by volatility. Regarding the 50% quantile returns, three-month rate changes, yield spread changes and real estate returns have a positive coefficient. Credit spread changes, on the other hand, have a negative influence.

Finally, the estimates for the **other financial services sector in the Eurozone** show that both the 1% and the 50% quantile returns for the EURO STOXX Financial Services index are negatively influenced by volatility, while the real estate and equity returns have a positive and significant coefficient. Concerning the STOXX Europe 600 ex Financials index, the EURO STOXX Financial Services index total returns positively influence both the 1% and the 50% quantile returns. Three-month rate changes positively influence both the 1% and the 50% quantile returns. Liquidity spread has a negative impact on the 1% quantile returns. Yield spread changes and real estate returns influence positively only the 50% quantile returns. Credit spread changes negatively impact the 50% quantile returns. **In the United States**, the 1% quantile returns of the Dow Jones U.S. Financial Services index are negatively influenced by volatility, while the real estate and equity returns display a positive and significant coefficient. Regarding the 50% quantile returns, the three-month rate changes, real estate and equity returns all display a positive coefficient. Concerning the 1% quantile returns of the S&P 500 Ex-Financial index, volatility and liquidity spread have a negative influence, while three-month rate changes, yield spread changes and Dow Jones U.S. Financial Services total returns have a positive impact. Regarding the 50% quantile returns, volatility and credit spread changes display a negative coefficient. Liquidity spreads, yield spread changes, real estate returns and Dow Jones U.S. Financial Services total returns have a positive coefficient.

In order to evaluate the goodness of fit of the quantile regressions, we rely on the pseudo-R^2, which can be interpreted similarly to the traditional R^2. The pseudo-R^2 is based on the distances from data points to estimates in each quantile regression at each point along the y variable's distribution. This is a relevant goodness of fit measure for quantile regressions, and good levels of pseudo-R^2 are obtained from the different quantile regression estimates, which allows us to be confident regarding the specification of the models. In fact, the pseudo-R^2 ranges from 37.99% to 72.22% with a mean of 56.03% for Eurozone economy. For the U.S. economy, it ranges from 37.87% to 79.49% with a mean of 60.42%.

5.2 $\Delta CoVaR$ measures and statistical tests

We now turn to the analysis of the $\Delta CoVaR$. The discussion will be conducted in two steps. We will first comment on the estimated values of the $\Delta CoVaR$, i.e. $\Delta\widehat{CoV}aR$. We will then use statistical significance and dominance tests to draw general conclusions regarding the contribution to systemic risk of the different sectors under study.

As discussed in Section 4.2, $\Delta\widehat{CoV}aR$ is the estimated additional Value-at-Risk imposed on the system by a given financial sector when it faces a situation of distress. Since $\Delta\widehat{CoV}aR$ is computed from the worst 1% returns of the three financial sectors under study, mostly only negative values were obtained. Therefore, our interpretation of the results relies on the absolute values of $\Delta\widehat{CoV}aR$. Along these lines, $\Delta\widehat{CoV}aR \neq 0$ for a given sector means that the sector contributes to systemic risk in our sample. Importantly, the financial sector with the largest $\Delta\widehat{CoV}aR$ absolute value is the sector that contributes relatively the most to systemic risk during periods of distress.

Table 3 below provides descriptive statistics concerning the $\Delta\widehat{CoV}aRs$ in the Eurozone where the median-state conditioning event (i.e. a 50% quantile) represents a normal situation. Appendix C provides robustness checks on the $\Delta\widehat{CoV}aRs$ where the normal situation is defined by other quantiles than the median (i.e. the 40%, 45%, 55% and 60% quantiles). The $\Delta\widehat{CoV}aR$ mean of the banking sector is -1.916% and -1.723% and -1.223% respectively for other financial services and the insurance industry. Accordingly, Eurozone banks seem to be riskier for the real economy than the two other financial sectors, i.e. the absolute $\Delta\widehat{CoV}aR$ mean is higher. In order to check whether our findings are sensitive to the sample period, we split the entire period into smaller sub-periods corresponding respectively to the pre-subprime crisis period (2004-2007) and the post-subprime crisis period (2008-2012). As reported in Table 3, the main conclusions remain valid. Interestingly, in absolute terms, the $\Delta\widehat{CoV}aR$ mean of each of the financial sectors is smaller before than after the financial crisis burst.

Table 3: $\Delta\widehat{CoVaR}$ for the Eurozone

	2004-2012		2004-2007		2008-2012	
	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.
$\Delta\widehat{CoVaR}\,Banks$	-1.916	0.614	-1.561	0.238	-2.181	0.672
$\Delta\widehat{CoVaR}\,Insurance$	-1.223	0.630	-0.862	0.271	-1.492	0.684
$\Delta\widehat{CoVaR}\,Financial\ Services$	-1.723	0.612	-1.459	0.291	-1.919	0.708

Notes: The table shows the mean and standard deviation for each $\Delta\widehat{CoVaR}$ related to the different financial sectors in the Eurozone. The whole sample period 2004-2012 includes two periods: the pre-subprime crisis (2004-2007) and the post-subprime (2008-2012). All the figures are expressed as a percentage.

The results discussed in the previous paragraph need to be treated with caution for two reasons. First, using the average of the $\Delta\widehat{CoVaR}$ values does not allow the conclusion that one sector is systemically riskier than another over the whole sample. Second, the above analysis relies exclusively on daily estimated values of the $\Delta CoVaR$, i.e. $\Delta\widehat{CoVaR}$. It is therefore possible that once the confidence interval associated with each estimated value has been taken into account, a sector displaying a positive $\Delta\widehat{CoVaR}$ absolute value would in fact not be a significant source of risk for the system. Extrapolating from the sample requires the use of statistical tests on the $\Delta CoVaRs$, something that is usually neglected in the literature, with the notable exception of Castro and Ferrari (2013).

In this paper, we deal with this issue by implementing two tests: a significance test and a stochastic dominance test. The first test aims to assess whether a sector is statistically significantly risky for the system. The second test compares the contributions of the different financial sectors to the risk of the real economy. Both tests are based on the principle that the $\Delta CoVaR$ is the difference between two conditional estimated quantile functions, which can be interpreted as a two-sample quantile treatment effect (Castro and Ferrari, 2013). As discussed in Section 4.2, we rely on the bootstrapped Kolmogorov-Smirnov tests (KS) developed by Abadie (2002) for implementing the tests.

Concerning the significance test, Table 4 shows the KS statistics and the associated bootstrapped p-values under the null hypothesis of no difference between the $CoVaR$ during a period of stress (i.e. a 1% quantile) and the $CoVaR$ in normal time (i.e. a 50% quantile), i.e. $\Delta CoVaR = 0$. For each of the financial sectors of interest within the Eurozone, the null hypothesis could be rejected at the 1% significance level, which means that each financial sector has a significant impact on the real economy during a period of distress. In other words, the three financial sectors of interest significantly contribute to systemic risk in the Eurozone.

Table 4: Significance test for the Eurozone

	Stat	p-value
$H_0 : \Delta CoVaR\, Banks = 0$	0.802	0.001
$H_0 : \Delta CoVaR\, Insurance = 0$	0.570	0.001
$H_0 : \Delta CoVaR\, Financial\, Services = 0$	0.813	0.001

Note: In this case, the bootstrapped Kolmogorov-Smirnov test aims to determine whether or not the cumulative distribution functions (CDFs) of the $CoVaRs$ at a 1% quantile and at a 50% quantile are different from each other. The null hypothesis is the equality of the CDFs of the $CoVaRs$ related to the 1% and 50% quantiles.

In the case of the dominance test, the bootstrap KS test aims to compare the CDFs of the $\Delta CoVaRs$ related to two different financial sectors. Results are given in Table 5. We test whether the banking sector is less or equally risky for the system than the insurance industry. The p-value shows that the null hypothesis is rejected at the 1% significance level, meaning that banks are systemically riskier than insurance companies. In other words, we can conclude that the banking sector represents a greater systemic risk than the insurance sector within the Eurozone. Results concerning the two following comparisons, i.e. $Banks \leq Financial\, Services$ and $Financial\, Services \leq Insurance$, are more straightforward. The null hypothesis is rejected at the 1% significance level in each case, confirming that banks are systemically riskier than financial services and that financial services are also systemically riskier than insurance companies within the Eurozone. Results of the dominance tests also mean that, for each comparison pair, the contributions of each financial sector to systemic risk are statistically different from each other.

Table 5: Dominance test for the Eurozone

	Stat	p-value
$H_0 : Banks \leq Insurance$	0.630	0.001
$H_0 : Banks \leq Financial\, Services$	0.212	0.001
$H_0 : Financial\, Services \leq Insurance$	0.509	0.001

Notes: The null hypothesis "$Banks \leq Insurance$" simply means that the $\Delta CoVaRs$ related to the banking sector are lower (or equal to), in absolute value, than the $\Delta CoVaRs$ related to the insurance sector. Therefore, the null hypothesis signifies that the banking sector is less or equally systemically risky than the insurance sector.

Looking at the United States, Table 6 provides descriptive statistics concerning the $\Delta\widehat{CoV}aRs$ where the median-state conditioning event (i.e. a 50% quantile) represents a normal situation. Appendix D provides robustness checks on the $\Delta\widehat{CoV}aRs$ where the normal situation is defined by other quantiles than the median (i.e. the 40%, 45%, 55% and 60% quantiles). Our results show that with a value of -2.283%, the mean of the $\Delta\widehat{CoV}aR$ related to the insurance sector is higher in absolute terms than the average $\Delta\widehat{CoV}aR$ of the banking sector and of the other financial services sectors, which are equal to -1.807% and -1.866% respectively. These results remain valid when splitting the entire period into the smaller sub-periods, as discussed in the previous paragraphs.

Table 6: $\Delta\widehat{CoVaR}$ for the United States

	2004-2012		2004-2007		2008-2012	
	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.
$\Delta\widehat{CoVaR}\,Banks$	-1.807	0.881	-1.223	0.311	-2.258	0.891
$\Delta\widehat{CoVaR}\,Insurance$	-2.283	0.983	-1.632	0.356	-2.786	1.018
$\Delta\widehat{CoVaR}\,Financial\,Services$	-1.866	0.895	-1.359	0.526	-2.257	0.925

Notes: The table shows the mean and standard deviation for each $\Delta\widehat{CoVaR}$ related to the different financial sectors in the United States. The whole sample period 2004-2012 includes two periods: the pre-subprime crisis (2004-2007) and the post-subprime (2008-2012). All the figures are expressed as a percentage.

Similarly to the Eurozone, statistical tests on the $\Delta CoVaR$ confirm that distress in one of the three financial sectors can propagate through the system (Table 7). The three financial sectors of interest also significantly contribute to systemic risk in the United States.

Table 7: Significance test for the United States

	Stat	p-value
$H_0 : \Delta CoVaR\,Banks = 0$	0.789	0.001
$H_0 : \Delta CoVaR\,Insurance = 0$	0.851	0.001
$H_0 : \Delta CoVaR\,Financial\,Services = 0$	0.763	0.001

Note: In this case, the bootstrapped Kolmogorov-Smirnov test aims to determine whether or not the cumulative distribution functions (CDFs) of the $CoVaRs$ at a 1% quantile and at a 50% quantile are different from each other. The null hypothesis is the equality of the CDFs of the $CoVaRs$ related to the 1% and 50% quantiles.

KS bootstrap statistics and p-values for the stochastic dominance are reported in Table 8. Results of these tests indicate that the insurance sector is systemically riskier than the banking sector in the United States. Financial services turn out to be systemically riskier than banks but they represent a lower risk for the economy than insurance companies.

Table 8: Dominance test for the United States

	Stat	p-value
$H_0 : Insurance \leq Banks$	0.316	0.001
$H_0 : Financial\,Services \leq Banks$	0.077	0.001
$H_0 : Insurance \leq Financial\,Services$	0.265	0.001

Notes: The null hypothesis "$Insurance \leq Banks$" simply means that the $\Delta CoVaRs$ related to the insurance sector are lower (or equal to), in absolute value, than the $\Delta CoVaRs$ related to the banking sector. Therefore, the null hypothesis signifies that the insurance sector is less or equally systemically risky than the banking sector.

6 Discussion

The original testing procedure proposed in the paper allows shedding light on both the absolute and relative contribution of the banking, insurance and other financial services sectors to systemic risk. Overall, our empirical methodology and testing procedure clearly show that each financial sector significantly impacts the global system in period of stress. This finding holds for both the Eurozone and the United States.

When comparing the contribution of each financial industry, banks appear to be the major source of systemic risk in Europe, followed by the financial services sector and by the insurance sector. These results are in line with theoretical arguments usually developed in the literature (Geneva Association Systemic Risk Working Group, 2010). The banking sector is usually seen as being systemically riskier than the insurance sector (among others, Girardi and Ergün, 2013; Adams et al., 2011; Geneva Association Systemic Risk Working Group, 2010). Their core business and especially credit activity to households and corporate companies along with short-term funding make banks particularly fragile institutions. By contrast, insurers mainly fund themselves through long-term premiums. Another argument is that balance sheets of banks are highly volatile and exposed to economic cycles while insurance companies usually present simple and economically stable balance sheets due to their long-term oriented business. More recently, the literature has pointed out the fact that banks are also much more interconnected than insurance companies through interbank lending such as the repo market. Eventually, the size of the banking sector much greater than the one of the insurance sector can also be a factor explaining that banks appear as the most systematically risky in our study. In 2012, total banking assets reached more than €32,000bn and total assets of the insurance sector within the Eurozone accounted for €5,928bn (ECB, 2013a,b).

Our results regarding the systemic role of the three financial sectors in the United States are consistent with recent argument raised in the literature emphasizing the risk associated to fast growing non-core activities (such as credit derivatives) of insurance companies (Bell and Keller, 2009; Geneva Association Systemic Risk Working Group, 2010; Cummins and Weiss, 2013). The non-core activities of U.S. insurance firms highly increased over the last decade. Another reason why the insurance industry appears as the most systemically risky in our study might be due to its relatively larger size in the U.S. in comparison with the Eurozone. As a matter of fact, in 2011, the insurance penetration ratio (i.e. the ratio of total premiums collected and GDP) was equal to 11.4% while it was of 6.4% in the Eurozone (OECD, 2013; Ernst & Young, 2012). In fact, the U.S. insurance market alone represents almost half (48.23%) of the whole insurance market among OECD countries (OECD, 2013).

7 Conclusion

This paper aims to assess the contribution of the different sectors of the financial system to systemic risk. To that end, we split the financial system into three sectors corresponding respectively to the banking, insurance and other financial services industries. The impact of distress within any one of these sectors is measured using the $\Delta CoVaR$ systemic risk measure proposed by Adrian and Brunnermeier (2011). More precisely, $\Delta CoVaR$ is defined in this paper as the difference between the $CoVaR$ of the whole system conditional on distress affecting banks, insurance or other financial services, and the $CoVaR$ of the same system conditional on banks, insurance or other financial services being in a "normal" situation. $\Delta CoVaR$ can therefore be interpreted as the additional level of risk faced by the whole economy (both in the Eurozone and in the United States) arising from the distress of one of the different financial sectors of interest.

Empirical results are obtained from quantile regressions (Koenker and Basset, 1978) and reveal that in the Eurozone, for the period ranging from 2004 to 2012, the banking sector contributes relatively the most to systemic risk during periods of distress affecting this sector. By contrast, the insurance industry is the most systemically risky financial sector in the United States for the same period of time. Furthermore, the insurance industry appears to impact systemic risk relatively less than the other financial services industry in the Eurozone, while banks contribute the least to systemic risk during periods of distress affecting the banking sector in the United States.

We develop a significance and a dominance test for the empirical results using the bootstrap Kolmogorov-Smirnov test proposed by Abadie (2002). The significance test indicates that the $\Delta CoVaRs$ are significantly different from zero, which means that each financial sector of interest has a significant impact on the whole economy during a period of distress, in the Eurozone as well as in the United States. The dominance test provides evidence that the ranking is significant, confirming the qualitative conclusions regarding the contribution to systemic risk of the different financial sectors of interest.

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Appendix A: Testing the significance and the dominance of rankings

Introduction

With the notable exception of Castro and Ferrari (2013), studies using the $\Delta CoVaR$ methodology test neither the significance of the contribution to systemic risk that is estimated using the $\Delta CoVaR$ methodology nor the dominance of one sector or institution over others with respect to their contribution to systemic risk. In this paper, $\Delta\widehat{CoV}aR$ (see equation 9) is the difference between two conditional estimated quantile functions, which can be interpreted as a two-sample quantile treatment effect (Castro and Ferrari, 2013). Consequently, we propose to test significance and dominance using the bootstrap Kolmogorov-Smirnov (KS) test developed by Abadie (2002).

As explained below, the standard KS test cannot be applied in this case. This test is based on the difference of two cumulative density functions and does not rely on any assumption regarding the underlying distribution, meaning that the test is asymptotically distribution-free and is based only on the empirical distribution function (i.e. the KS test is a non-parametric distribution test). Within the quantile regression framework, the KS test compares two cumulative quantile functions. In other words, it measures the discrepancy between two cumulative quantile functions by using the point at which these two distributions show the largest divergence.

In this paper, we rely on estimated distributions that introduce an unknown nuisance parameter into the null hypothesis. This nuisance parameter (also called the Durbin problem; Durbin, 1973) can jeopardize the distribution-free character of the test, and the parameters cannot be estimated without violating the distribution-free nature of the standard KS test (Koenker and Xiao, 2002).

In a two-sample treatment control model such as the $\Delta CoVaR$, the two distributions differ either by a location shift or by a location-scale shift (Koenker, 2005). Therefore, we want to check whether there is a location-scale shift (and not a shape shift because covariates have no effect on the shape of the conditional distribution) that characterizes the treatment and the control distributions (i.e. the two conditional quantile functions) (Koenker, 2005).

There are two main solutions to restoring the asymptotic distribution-free character of the KS test (Koenker and Xiao, 2002). The first solution is proposed by Khmaladze (1981) and uses the Doob-Meyer Martingale decomposition of the parametric empirical process to transform the distributions of interest into an asymptotically distribution-free process. The second solution suggests obtaining critical values from the resampling of the test statistic under conditions consistent with the null hypothesis. Along these lines, Abadie (2002) proposes a method for investigating treatment effects in a two-sample setting. Since the Kolmogorov-Smirnov non-parametric distance tests generally have good power properties but asymptotic distributions of the test statistics under the null hypotheses that are generally unknown (because they depend on the underlying distributions of the data), Abadie (2002) proposes the adoption of a bootstrap strategy. More precisely, he suggests using a nonparametric i.i.d. block bootstrap in stochastic dominance tests, in which data are divided into blocks that are resampled to replicate the time-dependent structure of the original data.

Significance and dominance tests

The significance test aims to identify a systemically risky financial sector. We look at the $\Delta CoVaR$ conditional on a given financial sector to check whether it is equal to 0 (meaning that the given financial sector is not systemically risky) or statistically different from 0.

Castro and Ferrari (2013) use a joint exclusion Wald test on the coefficient parameters. Nevertheless, in performing the Wald test, they do not take into account the set of control variables, meaning that the $CoVaR$ depends only on a constant term and on the returns of a given financial institution for their test. Moreover, they also assume the equality of the coefficients.

In our case, we want to take into account all the significant explanatory variables of the $CoVaR$ (i.e. returns as well as state variables). Since the coefficient of each explanatory variable differs according to the quantile of interest, we test whether or not the cumulative distribution functions (CDFs) of the $CoVaRs$ at a 1% quantile and at a 50% quantile are different from each other. To do this, we use the bootstrap Kolmogorov-Smirnov (KS) test developed by Abadie (2002). For the significance test, the two-sample Kolmogorov-Smirnov statistic is defined as follows:

$$D_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} sup_x \left|F_m(x) - G_n(x)\right| \tag{14}$$

Where $F_m(x)$ and $G_m(x)$ are the CDFs of the $CoVaRs$ related to the 1% and 50% quantiles respectively and m and n are the size of the two samples. The null hypothesis is the equality of the CDFs of the $CoVaRs$ related to the 1% and 50% quantiles:

$$H_0 : \Delta CoVaR_t^{system|i}(q) = CoVaR_t^{system|i}(1\%) - CoVaR_t^{system|i}(50\%) = 0 \tag{15}$$

The dominance test aims to test the significance of the ranking obtained from the $\Delta CoVaRs$ in order to check whether a given financial sector i contributes more to systemic risk than another financial sector j. We again rely on the bootstrap KS test of Abadie (2002) to compare the CDFs of the $\Delta CoVaRs$ related to two financial sectors. The two-sample Kolmogorov-Smirnov test statistic for the dominance test is defined as follows:

$$D_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} sup_x \left|A_m(x) - B_n(x)\right| \tag{16}$$

Where $A_m(x)$ and $B_m(x)$ are the CDFs of the $\Delta CoVaRs$ related to two financial sectors and m and n are the size of the two samples. The null hypothesis is defined as follows:

$$H_0 : \left|\Delta CoVaR_t^{system|i}(q)\right| > \left|\Delta CoVaR_t^{system|j}(q)\right| \tag{17}$$

Given that the estimated $\Delta CoVaRs$ are negative, in order to make for an easier discussion, we use the $\Delta \widehat{CoV}aR$ absolute values in the interpretation of the null hypothesis and in the comparison of the results of the bootstrap KS tests.

Appendix B: Quantile Regressions

Table 9: Quantile regressions for Eurozone Banks

	Quantile Regression 1%		Quantile Regression 50%	
	R_t^i	R_t^{system}	R_t^i	R_t^{system}
VDAX	-0.07232***	-0.0376941***	-0.00351	0.00054
	(0.01668)	(0.013806)	(0.00414)	(0.00352)
Liquidity spread	-0.04240***	-0.00651	-0.00238	0.000910
	(0.01223)	(0.004128)	(0.00239)	(0.00244)
Three-month rate change	-0.02014	0.046065	0.00529	0.017305**
	(0.03140)	(0.032868)	(0.00933)	(0.007230)
Yield spread change	0.00840	0.0463694**	0.01591***	0.01198**
	(0.01521)	(0.018844)	(0.00515)	(0.005269)
Credit spread change	-0.05853***	0.008481	-0.02258**	-0.003843
	(0.02157)	(0.017389)	(0.00895)	(0.006233)
Real Estate Return	0.19487***	0.301887***	0.11771***	0.235177***
	(0.06110)	(0.07432)	(0.02563)	(0.019666)
Equity return	1.06290***	-	1.08031***	-
	(0.10218)	-	(0.02732)	-
R_t^i	-	0.1486521***	-	0.28751***
	-	(0.06530)	-	(0.02108)
Pseudo-R^2	0.7181	0.5461	0.5857	0.3799

Notes: The R_t^i and the R_t^{system} are respectively the daily market returns of the EURO STOXX Banks index and the daily market returns of the STOXX Europe 600 ex Financials index. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Table 10: Quantile regressions for Eurozone Insurance companies

	Quantile Regression 1%		Quantile Regression 50%	
	R_t^i	R_t^{system}	R_t^i	R_t^{system}
VDAX	-0.10256***	-0.03747***	-0.00019	-0.001248
	(0.01827)	(0.013813)	(0.00391)	(0.002365)
Liquidity spread	0.00112	-0.00704	0.00153	0.000478
	(0.00640)	(0.00466)	(0.00196)	(0.001762)
Three-month rate change	-0.03685	0.04649	0.00893	0.00671
	(0.02976)	(0.03431)	(0.00861)	(0.006816)
Yield spread change	-0.03266**	0.05124**	0.00769	0.00893**
	(0.01351)	(0.02109)	(0.00605)	(0.00418)
Credit spread change	-0.06039**	0.00329	-0.01161	-0.009929**
	(0.02899)	(0.01909)	(0.00839)	(0.00418)
Real Estate Return	0.22247***	0.26732***	0.05656***	0.17698***
	(0.07435)	(0.06639)	(0.01975)	(0.018907)
Equity return	1.05407***	-	1.09849***	-
	(0.12351)	-	(0.02767)	-
R_t^i	-	0.189461***		0.375047***
	-	(0.0595)		(0.01780)
Pseudo-R^2	0.7222	0.5513	0.6214	0.4288

Notes: The R_t^i and the R_t^{system} are respectively the daily market returns of the EURO STOXX Insurance index and the daily market returns of the STOXX Europe 600 ex Financials index. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Table 11: Quantile regressions for Eurozone Financial Services

	Quantile Regression 1%		Quantile Regression 50%	
	R_t^i	R_t^{system}	R_t^i	R_t^{system}
VDAX	-0.06845***	-0.014606	-0.00578*	0.00244
	(0.01282)	(0.013604)	(0.00312)	(0.00299)
Liquidity spread	-0.00675	-0.012689***	0.00198	0.00001
	(0.00816)	(0.004847)	(0.00155)	(0.00177)
Three-month rate change	0.03798	0.047116**	0.00715	0.01853**
	(0.03485)	(0.02111)	(0.00706)	(0.00767)
Yield spread change	0.02967	0.02594	0.00532	0.019679***
	(0.02302)	(0.02249)	(0.00521)	(0.004552)
Credit spread change	0.03007	-0.03932	0.00052	-0.012687***
	(0.02475)	(0.02711)	(0.00555)	(0.003679)
Real Estate Return	0.32959***	0.094284	0.47186***	0.147548***
	(0.10611)	(0.08354)	(0.02513)	(0.022727)
Equity return	0.75374***	-	0.49785***	-
	(0.12691)	-	(0.02738)	-
R_t^i	-	0.37153***	-	0.44434***
	-	(0.08486)	-	(0.02169)
Pseudo-R^2	0.6650	0.5591	0.5420	0.4050

Notes: The R_t^i and the R_t^{system} are respectively the daily market returns of the EURO STOXX Financial Services index and the daily market returns of the STOXX Europe 600 ex Financials index. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Table 12: Quantile regressions for U.S. Banks

	Quantile Regression 1%		Quantile Regression 50%	
	R_t^i	R_t^{system}	R_t^i	R_t^{system}
VIX	-0.19095***	-0.06878***	-0.00948**	-0.00474*
	(0.030792)	(0.010068)	(0.004228)	(0.002457)
Liquidity spread	0.00890	-0.00221	-0.00075	0.001499
	(0.00932)	(0.0053676)	(0.001816)	(0.000948)
Three-month rate change	0.03360	0.03114*	0.00517	0.01449***
	(0.03332)	(0.0185163)	(0.00769)	(0.005063)
Yield spread change	-0.01145	0.01100	0.01216**	0.01402***
	(0.0270024)	(0.015164)	(0.006163)	(0.003294)
Credit spread change	0.02044	-0.03911	0.01349	-0.04948***
	(0.0672458)	(0.036241)	(0.01603)	(0.009637)
Real Estate Return	0.40297***	0.22692***	0.36450***	0.24308***
	(0.1437747)	(0.054827)	(0.03907)	(0..01757)
Equity return	1.05768***	-	0.94513***	-
	(0.1952553)	-	(0.05631)	-
R_t^i	-	0.08371**	-	0.14307***
	-	(0.041925)	-	(0.01594)
Pseudo-R^2	0.7198	0.6684	0.4604	0.3787

Notes: The R_t^i and the R_t^{system} are respectively the daily market returns of the Dow Jones U.S. Banks index and the daily market returns of the S&P 500 Ex-Financials index. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Table 13: Quantile regressions for U.S. Insurance

	Quantile Regression 1%		Quantile Regression 50%	
	R_t^i	R_t^{system}	R_t^i	R_t^{system}
VIX	-0.09828***	-0.04863***	0.00090	-0.00401*
	(0.01398)	(0.00860)	(0.00296)	(0.00236)
Liquidity spread	-0.00904	-0.00438	-0.00035	0.00122
	(0.00907)	(0.00350)	(0.00127)	(0.001005)
Three-month rate change	0.00516	0.01630	0.01098*	0.01684***
	(0.02818)	(0.01536)	(0.00626)	(0.00509)
Yield spread change	-0.00531	0.0021	0.006375*	0.01809***
	(0.02174)	(0.01176)	(0.00371)	(0.00367)
Credit spread change	-0.05777	-0.01246	0.0073	-0.02446***
	(0.04537)	(0.02921)	(0.01086)	(0.00849)
Real Estate Return	0.23256**	0.05577	0.18006***	0.13886***
	(0.11051)	(0.04225)	(0.02125)	(0.02204)
Equity return	0.86059***	-	0.91880***	-
	(0.2275)	-	(0.03382)	-
R_t^i	-	0.45403***	-	0.39369***
	-	(0.05918)	-	(0.02387)
Pseudo-R^2	0.6992	0.7178	0.5497	0.4571

Notes: The R_t^i and the R_t^{system} are respectively the daily market returns of the Dow Jones U.S. Insurance index and the daily market returns of the S&P 500 Ex-Financials index. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Table 14: Quantile regressions for U.S. Financial Services

	Quantile Regression 1%		Quantile Regression 50%	
	R_t^i	R_t^{system}	R_t^i	R_t^{system}
VIX	-0.09777***	-0.04415***	-0.00016	-0.00474**
	(0.0104)	(0.0089)	(0.00276)	(0.00229)
Liquidity spread	-0.00476	-0.01070*	-0.00131	0.00152
	(0.006515)	(0.00586)	(0.00132)	(0.00093)
Three-month rate change	-0.01716	0.04250**	0.00939*	0.00824
	(0.02367)	(0.01751)	(0.00554)	(0.0057)
Yield spread change	-0.01098	0.02508*	0.00279	0.00828*
	(0.01778)	(0.01481)	(0.00368)	(0.00456)
Credit spread change	-0.00602	0.01373	-0.00563	-0.02714***
	(0.03952)	(0.03206)	(0.00882)	(0.01047)
Real Estate Return	0.37383***	0.01782	0.33623***	0.06531***
	(0.06708)	(0.05245)	(0.01899)	(0.01851)
Equity return	1.06362***	-	0.93226***	-
	(0.14051)	-	(0.03224)	-
R_t^i	-	0.37475***	-	0.39785***
	-	(0.065997)	-	(0.02368)
Pseudo-R^2	0.7949	0.7102	0.6358	0.4589

Notes: The R_t^i and the R_t^{system} are respectively the daily market returns of the Dow Jones U.S. Financial Services index and the daily market returns of the S&P 500 Ex-Financials index. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Appendix C: Robustness checks on the $\Delta\widehat{CoVaRs}$ within the Eurozone

Table 15: $\Delta\widehat{CoVaR}$ for the Eurozone (40% $CoVaR$)

	2004-2012		2004-2007		2008-2012	
	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.
$\Delta\widehat{CoVaR}\,Banks$	-1.847	0.580	-1.509	0.224	-2.099	0.633
$\Delta\widehat{CoVaR}\,Insurance$	-1.157	0.605	-0.815	0.264	-1.413	0.659
$\Delta\widehat{CoVaR}\,Financial\,Services$	-1.567	0.590	-1.326	0.280	-1.747	0.688

Notes: The table shows the mean and standard deviation for each $\Delta\widehat{CoVaR}$ (where the 40% $CoVaR$ represents the level for normal market) related to the different financial sectors in the Eurozone. The whole sample period 2004-2012 includes two periods: the pre-subprime crisis (2004-2007) and the post-subprime (2008-2012). All the figures are expressed as a percentage.

Table 16: $\Delta\widehat{CoVaR}$ for the Eurozone (45% $CoVaR$)

	2004-2012		2004-2007		2008-2012	
	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.
$\Delta\widehat{CoVaR}\,Banks$	-1.861	0.590	-1.520	0.231	-2.115	0.644
$\Delta\widehat{CoVaR}\,Insurance$	-1.223	0.634	-0.862	0.275	-1.491	0.690
$\Delta\widehat{CoVaR}\,Financial\,Services$	-1.651	0.598	-1.394	0.281	-1.842	0.694

Notes: The table shows the mean and standard deviation for each $\Delta\widehat{CoVaR}$ (where the 45% $CoVaR$ represents the level for normal market) related to the different financial sectors in the Eurozone. The whole sample period 2004-2012 includes two periods: the pre-subprime crisis (2004-2007) and the post-subprime (2008-2012). All the figures are expressed as a percentage.

Table 17: $\Delta\widehat{CoVaR}$ for the Eurozone (55% $CoVaR$)

	2004-2012		2004-2007		2008-2012	
	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.
$\Delta\widehat{CoVaR}\,Banks$	-1.916	0.609	-1.560	0.233	-2.181	0.666
$\Delta\widehat{CoVaR}\,Insurance$	-1.225	0.637	-0.864	0.275	-1.494	0.696
$\Delta\widehat{CoVaR}\,Financial\,Services$	-1.740	0.664	-1.454	0.294	-1.953	0.774

Notes: The table shows the mean and standard deviation for each $\Delta\widehat{CoVaR}$ (where the 55% $CoVaR$ represents the level for normal market) related to the different financial sectors in the Eurozone. The whole sample period 2004-2012 includes two periods: the pre-subprime crisis (2004-2007) and the post-subprime (2008-2012). All the figures are expressed as a percentage.

Table 18: $\Delta\widehat{CoVaR}$ for the Eurozone (60% $CoVaR$)

	2004-2012		2004-2007		2008-2012	
	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.
$\Delta\widehat{CoVaR}\,Banks$	-1.916	0.610	-1.560	0.236	-2.182	0.665
$\Delta\widehat{CoVaR}\,Insurance$	-1.225	0.627	-0.864	0.264	-1.495	0.683
$\Delta\widehat{CoVaR}\,Financial\,Services$	-1.862	0.639	-1.577	0.281	-2.075	0.740

Notes: The table shows the mean and standard deviation for each $\Delta\widehat{CoVaR}$ (where the 60% $CoVaR$ represents the level for normal market) related to the different financial sectors in the Eurozone. The whole sample period 2004-2012 includes two periods: the pre-subprime crisis (2004-2007) and the post-subprime (2008-2012). All the figures are expressed as a percentage.

Appendix D: Robustness checks on the $\Delta\widehat{CoVaR}s$ in the United States

Table 19: $\Delta\widehat{CoVaR}$ for the United States (40% $CoVaR$)

	2004-2012		2004-2007		2008-2012	
	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.
$\Delta\widehat{CoVaR}\,Banks$	-1.652	0.815	-1.121	0.375	-2.062	0.826
$\Delta\widehat{CoVaR}\,Insurance$	-2.052	0.912	-1.446	0.328	-2.519	0.943
$\Delta\widehat{CoVaR}\,Financial\,Services$	-1.684	0.817	-1.231	0.502	-2.034	0.842

Notes: The table shows the mean and standard deviation for each $\Delta\widehat{CoVaR}$ (where the 40% $CoVaR$ represents the level for normal market) related to the different financial sectors in the United States. The whole sample period 2004-2012 includes two periods: the pre-subprime crisis (2004-2007) and the post-subprime (2008-2012). All the figures are expressed as a percentage.

Table 20: $\Delta\widehat{CoVaR}$ for the United States (45% $CoVaR$)

	2004-2012		2004-2007		2008-2012	
	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.
$\Delta\widehat{CoVaR}\,Banks$	-1.733	0.853	-1.168	0.376	-2.169	0.864
$\Delta\widehat{CoVaR}\,Insurance$	-2.169	0.968	-1.524	0.348	-2.667	0.999
$\Delta\widehat{CoVaR}\,Financial\,Services$	-1.784	0.865	-1.315	0.541	-2.146	0.894

Notes: The table shows the mean and standard deviation for each $\Delta\widehat{CoVaR}$ (where the 45% $CoVaR$ represents the level for normal market) related to the different financial sectors in the United States. The whole sample period 2004-2012 includes two periods: the pre-subprime crisis (2004-2007) and the post-subprime (2008-2012). All the figures are expressed as a percentage.

Table 21: $\Delta\widehat{CoVaR}$ for the United States (55% $CoVaR$)

	2004-2012		2004-2007		2008-2012	
	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.
$\Delta\widehat{CoVaR}\,Banks$	-1.957	0.949	-1.339	0.434	-2.435	0.963
$\Delta\widehat{CoVaR}\,Insurance$	-2.416	1.042	-1.721	0.373	-2.953	1.057
$\Delta\widehat{CoVaR}\,Financial\,Services$	-2.008	0.963	-1.454	0.550	-2.436	0.995

Notes: The table shows the mean and standard deviation for each $\Delta\widehat{CoVaR}$ (where the 55% $CoVaR$ represents the level for normal market) related to the different financial sectors in the United States. The whole sample period 2004-2012 includes two periods: the pre-subprime crisis (2004-2007) and the post-subprime (2008-2012). All the figures are expressed as a percentage.

Table 22: $\Delta\widehat{CoVaR}$ for the United States (60% $CoVaR$)

	2004-2012		2004-2007		2008-2012	
	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.
$\Delta\widehat{CoVaR}\,Banks$	-1.967	0.944	-1.319	0.410	-2.432	0.953
$\Delta\widehat{CoVaR}\,Insurance$	-2.474	1.058	-1.782	0.407	-3.008	1.097
$\Delta\widehat{CoVaR}\,Financial\,Services$	-1.983	0.958	-1.451	0.578	-2.393	0.991

Notes: The table shows the mean and standard deviation for each $\Delta\widehat{CoVaR}$ (where the 60% $CoVaR$ represents the level for normal market) related to the different financial sectors in the United States. The whole sample period 2004-2012 includes two periods: the pre-subprime crisis (2004-2007) and the post-subprime (2008-2012). All the figures are expressed as a percentage.