Bank ownership, financial segments and the measurement of systemic risk: An application of CoVaR

by

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Abstract

The recent financial crisis has shown that the regulatory framework that has been formulated and implemented over the last twenty years under the Basel I and II agreements has relied excessively on the monitoring of individual financial institutions. It failed to capture the contribution of systemic risk, which is considered to be the risk that is the outcome of collective behaviour of financial institutions that have significant effects on the real economy. This paper investigates whether the increased presence of foreign banks which are listed on a national stock market has contributed to the increase in the systemic risk, in particular, after the financial crisis of 2007-2009. We examine the extent to which the distress of foreign banks contributes to systemic risk for the US. In addition using relevant data for the UK we investigate the extent to which distress within different sub-segments of the financial system, namely, the banking, insurance and other financial services industries contribute to systemic risk. We conduct our analysis with the CoVaR measure of systemic risk recently developed by Adrian and Brunnermeier (2011) using daily data for the period 2 January 2000 to 31 December 2012. Furthermore, we complement our analysis with the application of two tests, the significance and dominance tests, to provide a formal comparison of the relative contribution of either the domestic or foreign banks and/or each individual financial sector. Our main results provide evidence that in the US, the non-US banks contribute to the systemic risk although most of the contribution comes from the US banks. In the case of the UK we show that the banking industry contributes relatively more to systemic risk in periods of distress than the insurance industry or the other financial services industry. Furthermore, when we examine the estimated $\Delta CoVaR$ measures, we observe that for all sectors the contribution to systemic risk has increased since 2008.

Keywords: systemic risk, CoVaR, quantile regressions, risk management, foreign banks

JEL classification: C21, C53, G20, G21, G28

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1. Introduction

The global financial crisis of 2007-2009 illustrated how distress can spread quickly through the financial system and threaten financial stability (Brunnermeier, 2009). Furthermore, Brunnermeier and Pedersen (2009) argue that the degree to which international financial institutions are linked depends on the level of market liquidity. Banks play a crucial role in the proper functioning of an economy because they provide the necessary liquidity to the markets and help to promote economic growth (Levine, 1997). Ill-functioning of the banking sector dramatically increases the costs in the real economy and historically has been a major source of financial crises, like the recent one, in both developed and emerging economies (Barth and Caprio, 2006; Demirguc-Kunt *et al*. 2009; Reinhart and Rogoff, 2009). Since October 1987, financial and banking regulation has focused on monitoring and regulating the banking industry.

The recent financial crisis has shifted the focus from the assessment of the risk management of individual financial institutions towards a more systematic or macro-prudential approach since it was made obvious that the micro-prudential regulatory framework is not sufficient to prevent world-wide contagion as a result of bank failures initially in the US and subsequently in Europe and elsewhere. The micro-prudential regulatory framework is based on the provisions of the Basle I and II agreements which imposed minimum capital requirements on the banks as a measure of prevention against unexpected losses (Pillar I). Within this framework the Basle II agreement led to the development of internal systems for measurement of market risk and such regulation looked at the soundness of individual financial institutions. However, such provisions based only on capital adequacy ignored factors such as size, degree of leverage, and interrelationships with the rest of the system. Stein (2010, p. 50) argued that "the overarching goal of financial reform must not be only to fortify a set of large institutions, but rather to reduce the fragility of our *entire system* of credit creation".

Instead, macro-prudential regulation implies that we observe the operation of the banking system as a whole (see Borio and Lowe, 2002; Borio and Drehmann, 2009; Gauthier *et al*., 2012). Moreover, as was made evident from the recent financial crisis, an important element of systemic risk is the propagation of adverse shocks to a single institution through the rest of the system. The Basle III agreement which is still under formation is expected to address most of the issues related to systemic risk and develop the appropriate framework for regulation and supervision of the financial markets based on recent experience. Therefore, for Central Banks and financial regulators, it is of great value to be able to quantify the risks that can threaten the financial system, not only on the national level but also globally. Indeed, evaluating the risk stemming from important financial institutions which are labelled as "systemic" as well as the interrelationships within the financial system is of great importance for the regulators. Specifically, capital flows globally have increased substantially over the last decade leading to an increase in the degree of contagion, and the presence of foreign banks in mature and emerging economies has led to an increase in systemic risk. Therefore, as a result of the recent financial crisis and the role of the large financial institutions, governments and monetary authorities are in the process of developing a framework for the important domestic systemic financial institutions. To this end recently capital surcharges have been imposed on global systematically important banks.

Interdependence among financial institutions becomes particularly important during periods of distress, when losses tend to spread across institutions and the whole financial system becomes vulnerable. In this respect systemic risk is defined as multiple simultaneous defaults of large financial institutions. A systemic crisis that disrupts the stability of the financial system can have serious consequences and large costs for the whole economy and the society. During financial crises, episodes of contagion among financial institutions occur very often and therefore regulators need to take them into consideration when assessing the health of the financial system. Central banks are responsible for promoting financial stability in the domestic economy and hence a central component of the central banks' activities is to follow and analyse systemic risk. The financial crisis of 2007-2009 has put increased emphasis on analysing systemic risk and developing systemic risk indicators that can be used by central banks and others as a monitoring tool. In order to evaluate the stability of the banking system, a crucial element is the measurement of the systemic risk of a financial system. According to the Group of Ten (2001, p.126):

"Systemic financial risk is the risk that an event will trigger a loss of economic value or confidence in, and attendant increases in uncertainly [sic] about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy. Systemic risk events can be sudden and unexpected, or the likelihood of their occurrence can build up through time in the absence of appropriate policy responses. The adverse real economic effects from systemic problems are generally seen as arising from disruptions to the payment system, to credit flows, and from the destruction of asset values."

Early works on this front by Lehar (2005), Goodhart *et al*. (2005, 2006) and Goodhart (2006) proposed alternative measures of financial fragility which can be implemented at both the individual and the aggregate levels. Additionally, the Financial Sector Assessment Program (a joint IMF and World Bank initiative) was set up with the purpose of increasing the effectiveness of plans to promote the soundness of financial systems in their member countries.

Arnold *et al*. (2012) also argue that key aspects of recent regulatory reforms which are under way through the Basle III agreement include measuring and regulating systemic risk and designing and implementing macro-prudential policies in an appropriate way. To this end the E.U. has established the European Systemic Risk Board and the U.S. the Financial Stability Oversight Council in order to focus on the issue of systemic risk not only in those two regions but also at the global level. The collapse of numerous financial institutions over the last five years has imposed significant negative spillovers on governments and the economy as a whole. Therefore, in measuring systemic risk we need to consider the degree of risk of financial institutions and to allocate risks and costs across them so that we take into account the negative spillovers associated with financial instability. Although the issue of stability of the banking sector is very important, there are only a few studies that examine the impact of bank regulation and supervision on banking risk, some of which find that it has little effect on minimizing banking risk. Thus, Demirguc-Kunt and Detragiache (2011), using a sample of 3000 banks from 86 countries, reject the hypothesis that better regulation and supervision results in a sounder banking system. In contrast, Klomp and de Haan (2012) also examine the issue of the effectiveness of bank regulation and supervision and find evidence in favour of its effectiveness for high-risk banks. However, when they consider low-risk banks, then they find no support in favour of the effectiveness of the regulatory framework.

The most commonly used measure of market risk is the Value-at-Risk (VaR) which calculates the monetary loss an institution may experience within a given confidence level. The problem with such a measure is that it does not consider the institution as part of a system which might itself experience instability and spread new sources of economic risk. Furthermore, it is noted that traditional measures have focused on banks' balance sheet information, including non-performing loans ratios, earnings and profitability, liquidity and capital adequacy measures which are not appropriate to evaluate the soundness of a financial system (see Huang *et al*., 2009; Sylvain *et al*., 2012).

Recently, Adrian and Brunnermeier (2011) developed CoVaR as a measure of systemic risk. CoVaR measures the contribution of a financial institution to systemic risk and its contribution to the risk of other financial institutions. CoVaR stands for Conditional Value-at-Risk, and indicates the Value-at-Risk (VaR) of financial institution i, conditional on financial institution j being in distress. Adrian and Brunnermeier (2011) argue that this is a more complete measure of risk since it is able to capture alternative sources of risk which affect institution i even though they are not generated by it. Furthermore, if we consider that institution i is the whole financial system, then ΔCoVaR is defined as the difference between the CoVaR and the unconditional VaR and it captures the marginal non-causal contribution of a particular institution to the overall systemic risk. We follow Bernal *et al*. (2013) and Castro and Ferrari (2013) and we complement the CoVaR analysis with the implementation of two formal tests to compare the relative contribution of the US banks and the non-US banks, as well as of each individual financial industry of the UK, on the real economy. This formal testing procedure is accomplished with the implementation of the Kolmogorov-Smirnov test developed by Abadie (2002), which is based on bootstrapped techniques.

Although there is no consensus on the exact definition of systemic risk, the following quote from the July 2009 testimony of Daniel Tarullo, a member of the Board of Governors of the FRB, before the

Senate Banking, Housing, and Urban Affairs Committee, provides one definition on which agreement could be made and which is one that CoVaR may captures.[1]

"Financial institutions are systematically important in the failure of the firm to meet its obligations to creditors and customers would have significant adverse consequences for the financial system and the broader economy".

In this paper we build on the CoVaR methodology which allows us to generate time-varying estimates of the systemic risk contribution of three specific sectors of the financial industry subject to different regulation and supervisory framework: banks, insurances and financial services. We employ daily data from January 2000 to December 2012 for the US and the UK, which have been seriously affected by the recent financial crisis. The US banking sector in particular has been a major source of the evolution of this crisis. In the case of the US we examine the contribution of non-US banks whose stocks are traded on the New York Stock Exchange and of the US (domestic) banks on systemic risk of the US economy. In the case of the UK we investigate how the contribution of the different financial sectors has changed following the failure of Lehman Brothers in September 2008. Specifically, the different sectors that compose the financial system are the banking, insurance and other financial services sectors. The other financial services sector includes financial companies such as broker-dealers, hedge funds and holding companies. The failure of Long-Term Capital Management (LTCM) in 1998 or of the American International Group (AIG) are examples of the impact the insurance sector or the financial services may have in increasing systemic risk in an economy. Contrary to the role of banks whose failure can lead to a worsening of credit conditions (Bernanke and Gertler, 1989; Claessens and Kose, 2013), the insurance firms do not directly influence monetary policy and credit availability but they certainly have become less stable financial institutions since they began engaging, during the last two decades, in non-traditional activities such as CDS which altered their risk profile which caused problems to the real economy (De Bandt and Hartmann, 2000; Harrington, 2009; Billio *et al*. 2012; Bernal et al. 2013). Thus, we focus on the analysis of the inter-linkages between the financial sector itself, taken as a whole, and the real

[1] http://www.federalreserve.gov/newevents/testimony /tarullo20090723a.htm

economy and whether the presence of foreign banks in an economy may increase financial instability. Applying the CoVaR analysis, we want to measure risk spillovers and model the conditional second moments of the financial sectors on the whole economy.

There are several important findings that stem from our analysis. Based on the estimation of the 1% and the 50% quantile regressions, we show that equity returns is a key determinant in triggering systemic risk episodes. In addition, in the case of the US volatility of the general index ex financials (system variable) and real estate return contribute significantly to systemic risk. There is also evidence that liquidity spread and credit spread changes have an effect although weaker. Furthermore, we show that for the US it is the US banks that contribute mostly to the systemic risk than the non-US banks whereas in the UK is the banking sector that contributes most to the systemic risk. Based on the results of ΔCoVaR estimates before and after 2008, it is observed for both economies that the contribution of each financial segment to systemic risk increased after the unfolding of the crisis. Finally, we implemented two recently developed testing procedures (Castro and Ferrari, 2013; Bernal *et al*. 2013) to examine the issues of statistical significance and dominance of the estimated $\Delta \hat{CoVaR}$. For the case of the US we show that both the US banks and the non-US banks have a significant impact on the real economy during a period of distress. Furthermore, the application of the dominance test leads to the conclusion that the US banks are systematically riskier than the non-US banks. In the UK case it is also shown that each financial sector has a significant impact on the real economy and, based on the evidence from the dominance test, we conclude that the banking sector represents a greater systemic risk than either the insurance industry or the financial services industry and that the financial services industry are systematically riskier than the insurance companies.

The structure of the paper is as follows: Section 2 presents and discusses the recent literature on CoVaR modelling. In Section 3 the CoVaR modelling approach to estimate systemic risk is discussed. Section 4 presents the data and empirical results while a summary and the concluding remarks are given in section 5.

2. Review of the literature

Achieving macroeconomic stability requires the identification of systemic risk in the financial system and the factors driving it. Although there is no consensus on the definition and measurement of systemic risk, we review the recent literature on the topic in this section (for a complete survey, see Bisias *et al*., 2012).

The recent literature has followed two main channels to analyse systemic risk. First, several studies examine the channels through which risk is transmitted from one financial institution to another. Pritsker (2000) and Forbes and Rigobon (2001) were among the first studies to explain the transmission of disturbances from one market to another over time, identifying two transmission channels which take the form either of interdependence or contagion. Within this framework we also observed the development of research on early warning indicators for both developed and emerging economies in an attempt to forecast systemic events (see for example Borio and Lowe, 2002; Alessi and Detken, 2009; Alfaro and Drehmann, 2009, Borio and Drehmann, 2009; Giesecke and Kim, 2009; Huang *et al*., 2009; Khandani *et al*., 2010; Borio *et al*., forthcoming). A second approach to measuring systemic risk using either macroeconomic data or balance sheet data has also been employed but suffers from two shortcomings. Thus, Cerutti *et al*. (2011) emphasize the problem that researchers face with the lack of useful and consistent data and suggest the creation of a common reporting template for globally systematically important financial institutions. A second shortcoming of this approach lies in the static modelling of institutional behaviour and therefore models with low frequency data are not appropriate for studying the effects of the regulatory and supervisory framework.

The second strand of literature on measuring systemic risk uses high frequency time series data. Several approaches have been proposed. Segoviano and Goodhart (2009) and Moreno and Pena (2013) argue that CDS spreads are good estimators of systemic risk. The problem with this approach is that it captures only credit risk and not market risk, which is the issue under examination in the present paper. Another approach focuses on individual measures of systemic risk, which seek to predict how much the stocks of financial institutions fall in a major market downturn. Essentially, this approach provides a framework to evaluate the co-dependence of financial institutions on a given system when a distress event occurs. The theoretical foundations of this approach were developed in Acharya and Richardson (2009), Acharya *et al*. (2010) and Acharya *et al*. (2012). Acharya *et al*. (2010) define the systemic expected shortfall as the propensity of a financial institution to be undercapitalized when the system as a whole is undercapitalized. In addition, Acharya *et al*. (2012) show that when this negative event occurs the government usually wants to minimize the resulting cost to the taxpayer. Furthermore, it is shown that this cost is a function of size, leverage and expected equity losses during a crisis. Brownlees and Engle (2011) propose a bivariate GARCH model for volatility as well as an asymmetric DCC model to capture correlation. Furthermore, they construct short- and long-run Marginal Expected Shortfall forecasts and propose the SRISK index, which is also a distress measure. Within this framework we also have the works by Tarashev *et al*. (2009) and Drehmann and Tarashev (2011) which employ the Shapley value approach.

Adrian and Brunnermeier (2011) propose the *CoVaR* methodology in order to evaluate the impact of financial units which are in distress on the whole financial system. Therefore, this approach is useful in measuring risk transmission from a financial institution to the financial system. For their empirical application they use quantile regressions to estimate the conditional models using data for 1266 US financial institutions which are distinguished into four groups: commercial banks, broker-dealers (including the investment banks), insurance companies and real estate. They conclude that systemic risk depends significantly on size, leverage and maturity mismatch. This methodology has been applied in several recent studies. Van Oordt and Zhou (2010) extended CoVaR to analyze situations at an extremely low probability level. Their analysis is based on 46 equally weighted industry portfolios including NYSE, AMEX and NASDAQ firms. Wong and Fang (2010) examine the interrelationships among eleven Asia-Pacific economies by estimating CoVaR for the CDS of their banks. Their main finding is that CoVaR measurements are higher than the respective unconditional VaR measure. Chan-Lau (2008), using a similar approach, studied the existence of spillover effects using the CDS spreads of a sample of 25 financial institutions in Europe, Japan and the United States.

Recently, Agrippino (2009) proposed the implementation of CoVaR analysis of five US commercial banks using daily data in order to distinguish between interdependence and spillovers among financial institutions. The analysis concludes that CoVaR provides superior measurement of risk compared to that estimated with the traditional VaR model, particularly in case of financial instability when negative effects are spread across institutions. Roengpitya and Rungcharoenkitkul (2011) employ panel data from six major banks of Thailand in order to examine risk spillover effects among these financial institutions. Girardi and Ergun (2013) modified the CoVaR model. They change the definition of financial distress from a financial institution i to a financial institution j, defining it as being higher, rather than equal, to its VaR estimate. They estimate the systemic risk contributions of four financial industry groups consisting of a large number of institutions. Lopez-Espinoza *et al*. (2012a) analyze the banking system responses to positive and negative shocks to the market-value balance sheets of individual banks. Lopez-Espinoza *et al*. (2012b) employ an asymmetric CoVaR methodology to deal with the characteristics sample of 54 international banks and to address the asymmetric patterns that may underlie tail dependence. Bjarnadottir (2012) studies the contribution of four major Swedish banks to the systemic risk of the Swedish financial system. Adams *et al.* (2011) propose a state-dependent sensitivity VaR to assess the spillover effects among systematically important financial institutions using data from four US financial sectors: commercial banks, investment banks, hedge funds and insurance companies and they conclude that hedge funds play an important role in the transmission of shocks to the other financial institutions. Bernal *et al*. (2013) depart from the above mentioned papers since they study systemic risk by analyzing how financial sectors of an economy that operate under different regulation systems contribute to systemic risk. Therefore, they examine the existence of inter-relationships between the financial sector and the whole, instead of focusing on individual institutions. They estimate the respective *CoVaR* model using daily data for the banking, insurance and other financial services industries of the US and the Eurozone and they find that the insurance sector contributes relatively more to the systemic risk in periods of distress as compared to the banking and other financial services industries in the former case and that the banking sector is the one that contributes most to the systemic risk relatively to the insurance and other financial services sector in the latter case. Finally, Castro and Ferrari (2013) provide an identification and ranking of the most systematically risky banks for the European financial system with the development test. They apply the proposed statistical methodology to a sample of 26 large European banks.

This paper follows Bernal *et al*. (2013) and Castro and Ferrari (2013) in evaluating the contribution to systemic risk by different aggregated components of the financial system including the banking, insurance and other financial services industries. The argument that Bernal *et al*. (2013) make is that the evaluation of the impact of shocks affecting one of these different financial industries on the whole system is important in designing appropriate regulation. We employ CoVaR analysis to study the contribution of foreign and domestic banks which are listed in the US equity market for the case of the United States as well as the impact of these three financial sectors on the whole system for the UK. A novel feature of our analysis is that we complement the Adrian and Brunnermeier (2011) analysis with two formal tests proposed by Bernal *et al*. (2013) and Castro and Ferrari (2013). The first testing procedure tests for the significance of the ΔCoVaR based on the Kolmogorov-Smirnov test and it allows us to determine whether a given financial sector or foreign or domestic banks contribute significantly to systemic risk. The second testing procedure allows us to test whether or not one particular financial sector or foreign or domestic banks contribute more to systemic risk than another.

3. Econometric methodology

During the last fifteen years there has been a voluminous literature on measuring approaches on market risk and propagation channels and causes of risk contagion effects. However, it has been shown that these traditional approaches have several modelling limitations, as well as strong assumptions with respect to the returns distribution and thus their application was proven problematic. Following the Basle II agreement, the Value-at-Risk measure became very popular to measure market risk because of its simplicity since the calculation of a single number was considered to be sufficient to quantify the minimum capital adequacy requirements for a financial institution. Intuitively, the VaR(α) is the worst loss over a target horizon that will not be exceeded with a given level of confidence 1-α (Jorion, 2007). Statistically, the VaR(α), defined for a confidence level 1-α, corresponds to the α-quantile of the projected distribution of gains and losses over the target horizon.

This was the main approach used within the context of micro-prudential regulation as proposed by the Basle I and Basle II agreements. First, VaR models only estimate their own minimum loss if tail takes place under several alternative error distribution specifications. However, these models do not bring to the surface the potential loss of systemic risk transmitted from other sectors of either the domestic economy or the global economy. A stylized fact of these models is that the error terms of the dynamic correlation model or the autoregressive conditional heteroskedasticity model are assumed to have a specific distribution which leads to a bias toward the coefficients' estimation. Second, the extreme value theory and the derived models for estimating VaR do not take into consideration the full set of observations of the sample, leading to underestimation of the respective risk measure, whereas there is also a small sample bias (see for example Wong and Fong, 2010). A final critical issue in modeling interrelationships between different sectors of the economy refers to time lag.

Given these criticisms regarding the ability of the traditional VaR model to capture systemic risk, we employ the CoVaR model (Adrian and Brunnermeier, 2011). The CoVaR model is particularly useful for measuring systemic risk by the VaR of an institution conditional on other institutions in distress. During the 2007-2009 global financial crisis, the emerging economies faced severe credit risk and major financial problems. The CoVaR model is appropriate to study risk spillovers and is therefore also a convenient measure of systemic risk.[2]

Adrian and Brunnermeier (2011) define $CoVaR_q^{j|i}$ as the VaR_q^j of institution j (or of the financial institution) conditional on some event $C(R^i)$ of institution i. Then $CoVaR_q^{j|i}$ is the q^{th} quantile of the conditional probability distribution of returns of j

[2] According to Adrian and Brunnermeier (2011) the CoVaR measure is related to the literature on volatility models and tail risk (Engle and Manganelli, 2004). It is also related to the earlier literature on contagion and volatility spillovers (see Claessens and Forbes, 2001)

$$P(R^j \leq CoVaR_q^{j|C(R^i)} \mid C(R^i)) = q \qquad (1)$$

Adrian and Brunnermeier (2011) defines $\Delta CoVaR$ as the difference between the $CoVaR$ of the financial institution j conditional on the distress of another institution i and the $CoVaR$ of institution j conditional on the normal state of institution i. Therefore, this $CoVaR$ measurement calculates how much an institution contributes to another institution's risk.

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i = VaR_q^i} - CoVaR_q^{j|X^i = Median^i} \qquad (2)$$

where $\Delta CoVaR_q^{j|i}$ denotes the VaR of institution $j's$ asset returns when institution $i's$ returns are at its normal state of their distribution (e.g. 50% percentile), and $\Delta CoVaR_q^{j|i}$ is institution $j's$ VaR when institution $i's$ returns are in a distressed or extremely bad condition such as the one experienced during the recent financial crisis. It can also be taken as the additional VaR caused by outside influences, which is above the ordinary interdependencies.

We further calculate $\Delta CoVaR$ for each institution as follows:

$$\Delta CoVar_t^{j|i}(q) = CoVaR_t^{j|i}(q) - CoVaR_t^{j|i}(50\%) = \hat{\beta}^{j|i}[VaR_t^i(q) - VaR_t^i(50\%)]. \qquad (3)$$

Adrian and Brunnermeier (2011) estimate the related $VaR_q^{j|i}$ and the respective $\Delta CoVaR_q^{j|i}$ with the use of the growth rates of market-valued total assets for an individual institution and define them as a function of a constant, lagged state variable and error term. In order to assess the link between a set of independent variables and the quantiles of the dependent variable, they employ the quantile regressions methodology developed by Koenker and Basset (1978) and extended by Koenker and Xiao (2002) and Koenker (2005).

In this paper we adopt the methodology of Adrian and Brunnermeier (2011) but instead of focusing on measuring systemic risk within the financial system we consider the real economy as the system variable. Recently, Bernal *et al*. (2013) defined systemic risk as the impact that a group of financial institutions may have on the whole economy. In this context systemic risk is measured with the estimation of $\Delta CoVaR$. Based on equations (1) and (2), 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 being equal to its level of VaR for a q^{th} - quantile. This is given by the following probability:

$$P(R^{system} \leq CoVaR_q^{systemC(R^i)} \mid C(R^i) = q. \tag{4}$$

Therefore,

$$\Delta CoVaR_q^{system|i} = CoVaR_q^{system|X^i = VaR_q^i} - CoVaR_q^{system|X^i = Median^i}. \tag{5}$$

Following Bernal *et al*. (2013) we use this modelling approach to assess risk transmission from foreign and domestic banks to the whole economy. The application of the $CoVaR$ estimation is implemented in six stages.

The first stage deals with modelling the returns R^i as a function of a set of state variables:

$$R_t^i = \alpha^i + \gamma^i M_t + \varepsilon_t^i. \tag{6}$$

where α^i is the constant, M_t represents a vector of contemporaneous control variables and ε_t^i is a white noise error term. We then estimate the 1% quantile of market return based on the quantile regressions.

The second stage involves the computation of the predicted 1% VaR for each segment of the financial system using only the statistically significant variables that were identified in the first stage. Given that the $VaR(\alpha)$ defined for a confidence level $1-\alpha$ is the quantile of the distribution of gains and losses over the target horizon, the forecast will be obtained as follows:

$$\hat{VaR} = \hat{\alpha}^i + \hat{\gamma}^i M_t. \tag{7}$$

where $\hat{\alpha}^i$ and $\hat{\gamma}^i$ are the coefficient estimates from equation (6).

We then move to third stage of our analysis in which we estimate the system's returns using the following equation:

$$R_t^{system} = \alpha^{system|i} + \beta^{system|i} R_t^i + \gamma^{system|i} M_t + \varepsilon_t^{system|i} . \qquad (8)$$

where $\alpha^{system\backslash i}$ is the constant, β gives the contribution of the return R_t^i of each financial sector to the real economy, M_t is a set of contemporaneous control variables and $\varepsilon_t^{system|i}$ is a white noise error term. Again the 1% quantile of returns is obtained from the quantile regression.

In the next stage we compute the predicted CoVaR of the system which as we have already discussed is the VaR of the system conditional to a situation of distress within either one of the individual financial sectors, represented by the computed 1% quantiles. Therefore, the estimation of CoVaR requires the use of the computed VaR (1%) from equation (7), given all the significant control variables obtained from equation (8).

$$\hat{CoVaR}_t^{\,i} = \hat{\alpha}^{sytem|i} + \hat{\beta}^{systemi} \hat{VaR}_t^{\,i} + \hat{\gamma}^{system|i} M_t . \qquad (9)$$

where $\hat{\alpha}^{system|i}$, $\hat{\beta}^{system|i}$ and $\hat{\gamma}^{system|i}$ are derived from equation (8).

The fifth stage of the estimation process involves the computation of ΔCoVaR which, as we explained above, is the difference between the CoVaR at the 1% quantile and the CoVaR at the 50% quantile. The calculation of CoVaR at the 50% quantile is conducted as it is done for the 1% quantile with the only difference being that we take 50% of the returns at each stage. This estimated CoVaR at the 50% quantile can be considered to be a conditional event at a median state given in formulation (5) which is required in order to compute the systemic risk measure. Therefore, ΔCoVaR is the marginal contribution of the domestic and foreign banks or each financial sector to systemic risk, i.e.

$$\Delta \hat{CoVaR}_t^{\,i}(q) = \hat{CoVaR}_t^{\,i}(1\%) - \hat{CoVaR}_t^{\,i}(50\%) . \qquad (10)$$

During a financial crisis, portfolio returns of all financial institutions are at their VaR level. Therefore, the CoVaR model is particularly appropriate for capturing risk contagion from a systemic crisis. Because the credit risk faced by financial institutions is more severe when there is a dramatic fall in prices and therefore returns, we focus on the downside risk of the changes in prices and thus, $\Delta \hat{CoVaR}$ takes negative values because it is computed from the 1% returns of the domestic and foreign banks or each financial industry. Within this framework we consider that the financial sector with the largest absolute $\Delta \hat{CoVaR}$ is the sector that contributes the most to systemic risk in periods of turbulence. We also follow this testing approach when we consider the contribution of domestic or foreign banks to systemic risk.

In the sixth and final stage we follow Bernal *et al*. (2013) and Castro and Ferrari (2013) to test for the significance and the stochastic dominance of the ΔCoVaRs in order to rank the domestic and foreign banks or each financial sector according to their contribution to systemic risk.[3] This test amounts to the examination of the estimated ΔCoVaR conditional on either the domestic banking sector or the foreign banking sector for the case of the US and which financial sector for the case of the UK. We test the null hypothesis that the estimated ΔCoVaR is not statistically different from 0 (i.e. the given banking or financial sector is not systematically risky) against the alternative that is statistically different from 0.[4] Given that according to quantile regression approach the coefficient of each explanatory variable is different depending on the quantile of interest, the above testing procedure is equivalent to testing the null hypothesis that the difference of the cumulative distribution functions (CDFs) of the CoVaR at the 1% quantile and 50% quantile are statistically equal to zero. Abadie (2002) developed a bootstrap Kolmogorov-Smirnov (KS) test which is suitable to test the specific null hypothesis. Following Bernal *et al*. (2013) the significance test based on the two-sample KS statistic is defined as follows:

$$D_{mm} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} \sup_{x} |F_m(x) - G_n(x)| \tag{11}$$

[3] For a detailed analysis of the significance and dominance of ranking testing procedure, see Bernal *et al*. (2013, Appendix A) and Castro and Ferrari (2013).

[4] Castro and Ferrari (2013) developed an alternative approach to test statistical significance and they use a joint exclusion Wald test on the coefficient parameters without taking into account the set of control variables employ. However, as in Bernal *et al*. (2013) we want to take into account all the significant explanatory variables of the CoVaR.

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 denote the size of each sample, respectively with the null hypothesis defined above given by:

$$H_0 : \Delta CoVaR_t^{system|i}(q) = CoVaR_t^{system|i}(1\%) - CoVaR_t^{system|i}(50\%) = 0 . \tag{12}$$

The second testing procedure, the dominance test, is employed in order to test the statistical significance of the rankings obtained from the $\Delta CoVaR$ s. Therefore, the application of this test will help us to evaluate whether a given financial sector i contributes more to systemic risk than another financial sector j. This testing procedure is also based on the bootstrap KS test developed by Abadie (2002). Following again Bernal *et al*. (2013) the two-sample KS test statistic for the dominance test is defined as follows:

$$D_{mn} = \left(\frac{mn}{m+n} \right)^{\frac{1}{2}} \sup_x |A_m(x) - B_n(x)| \tag{13}$$

where $A_m(x)$ and $B_n(x)$ are the CDFs of the $\Delta CoVaR$ s related to two financial sectors m and n are the size of the two samples with the null hypothesis defined above given by:

$$H_0 : |\Delta CoVaR_t^{system|i}(q)| > |\Delta CoVaR_t^{system|j}(q)| \tag{14}$$

Thus, we are able to compare the CDs of the $\Delta CoVaR$ s in relation to two financial sectors. Finally, given that the estimated $\Delta CoVaR$ s are negative, the interpretation of our results will rely on the absolute values of $\Delta Co\hat{V}aR$.

4. Description of the data

Following the works of Roengpitya and Rungcharoenkitkul (2011), Bernal *et al*. (2013), Girardi and Ergun (2013) and Castro and Ferrari (2013), we use a stock market index as a proxy of the real economy (system variable). For the case of the US we take the S&P 500 ex-Financial index and for the UK the FTSE 100 ex-financial index. In both indices, financial companies are excluded from the index to avoid spurious correlations between our variables of interest. The use of this index as a proxy of the real economy is based on the argument that stock market movements can be considered as a leading indicator of expected changed of the economy as a whole. We employ daily data for the period January 2, 2000 to December 31, 2012.

The US data are described as follows. With respect to the domestic (US) and foreign (non-US) banks we rely on the "Bank Fundamentals Annual" of COMPUSTAT database to identify domestic and foreign banks whose shares are traded in the US stock market. The headquarters of the foreign banks are based in the following countries: Argentina, Australia, Bermuda, Brazil, Canada, Chile, Germany, Greece, India, Ireland, Italy, Japan, Korea, Luxemburg, Netherlands, Panama, Peru, Portugal, Spain and UK. We obtain price and return data for each bank from the CRSP database. We then construct the non-US bank index, the US bank index and the total bank index (all indices are equally-weighted).[5] The total number of daily bank observations is 2,067,694. The rest of the data is extracted from the Bloomberg database. VIX is the volatility index; the liquidity spread variable is the difference between the 3-month US repo rate and the 3-month US T-Bill rate; the 3-month T-bill spread variation variable is the difference between the 3-month US T-Bill rate in time t and the 3-month US T-Bill in time $t-1$; the yield spread change variable is the difference between the 10-year US Treasury Bond rate and the 3-month US T-Bill rate; The credit spread change variable is defined as the difference between the 10-year Moody's BBB US corporate bond rate and the 10-year US Treasury Bond yield; The equity return variable is the S&P 500 index returns and the real estate return variable is the Dow Jones US Real Estate index returns.

[5] The total index which we constructed differs from the Dow Jones US Banks Index since it includes all banks whose shares are traded in the US.

For the case of the UK we also retrieve data from the Bloomberg and Datastream. The banking index is the FTSE all shares banks Index. The insurance industry index is the FTSE Insurance Index and the financial services index is the FTSE Financial Services Index. The FTSE 100 Volatility Index is the volatility index; the liquidity spread variable is the difference between the 3-month UK repo rate and the 3-month UK T-Bill rate; the 3-month T-bill spread variation variable is the difference between the 3-month UK T-Bill rate in time t and the 3-month UK T-Bill in time $t-1$; the yield spread change variable is the difference between the 10-year UK Treasury Bond rate and the 3-month UK T-Bill rate; The credit spread change variable is defined as the difference between the 10-year BBB UK corporate bond rate and the 10-year UK Treasury Bond yield; The equity return variable is the FTSE 100 index returns and the real estate return variable is the FTSE UK Real Estate index returns.[6]

4.1. Quantile regressions

Table 1 reports quantile regressions results for the 1% and 50% quantile returns for the US banks and non-US banks whereas Table 5 reports quantile regressions results for the banking, insurance and other financial services industries for the UK Furthermore, Tables 1 and 5 also report estimates for the system's returns in which the S&P 500 stock market index and the FTSE 100 stock market index excluding financial services is used to proxy each country's real economy. In addition, Tables 1 and 5 report the pseudo-R^2 in order to assess the goodness-of-fit of quantile regressions. This measure has a similar interpretation as the standard R^2. The pseudo-R^2 is derived using the distances from data points to estimates in each quantile regression at each point along the R_t^i - distribution. The estimated pseudo-

[6] For the case of the UK we could not provide similar analysis as we did for the US due to lack of relevant data. Specifically, we searched for foreign banks whose stocks are traded on the London Stock Exchange as follows: We combine the database of the London Stock Exchange Companies and Issuers Archived List of Companies http://www.londonstockexchange.com/statistics/companies-and-issuers/companies-and-issuers.htm and the Bank Ownership Database compiled by Claessens and Van Horen, http://www.dnb.nl/en/onderzoek-2/databases/index.jsp (details with respect to this database can be found in Claessens and Van Horen, forthcoming). In addition, we use the Bank of England List of Banks, the UK Foreign Bank Members Association and the Depositors Protection List compiled by the UK's Financial Services Compensation Scheme. This detailed data search led to the conclusion that there are no foreign banks listed in the London Stock Exchange. Specifically, foreign banks operate either through a branch, and in this case their stocks are traded overseas or they have established a subsidiary which however is not listed in the London Stock Exchange. Therefore, we provide our analysis of the effects of the domestic financial sectors on the UK economy.

R^2 obtained values imply that our estimated models have the appropriate specification. The estimation of the models is conducted using the bootstrapped quantile regressions developed by Buchinsky (1995). This estimation method has the advantage that does not assume that the estimated standard errors are i.i.d. which may not be true when we consider financial data (Koenker, 2005).

Results for the US banks index show that liquidity spread, credit spread change and real estate return and equity returns have a positive impact on the 1% quantile returns of the banking index whereas volatility has a negative impact. With respect to the US Banks index at 50% (normal state), we observe that liquidity spread, credit spread change, real estate return and equity return still have a positive impact and volatility has a negative impact. Turning now to the S&P 500 ex Financials 1% quantile returns, we note that liquidity spread, credit spread change, real estate return, equity returns and the US bank index total return are statistically significant with a positive sign whereas volatility is statistically significant and with a negative sign. With respect to the 50% quantile returns for the S&P 500 ex Financials, liquidity spread, credit spread change, real estate return and equity returns remain statistically significant with a positive influence and volatility and bank index total return have a negative impact. The situation of the non-US banks is somehow weaker since the only statistically significant control variables are volatility and the equity return for the 1% and 50% quantile returns for the non-US Banks index. In the case of the S&P 500 ex Financial Services we observe that volatility is statistically significant with a negative sign and the non-US bank index total return has a positive sign at the 1% and the same evidence is derived for the 50% (normal state).

The evidence for the UK economy also provides interesting arguments for the regulators. Looking into the banking industry we see that the 1% quantile returns of the banking index are influenced positively by the real estate returns and equity returns and negatively by volatility, liquidity spread and credit spread change. In the case of the banking index at the 50% quantile returns, both real estate returns and equity returns still have a statistically significant impact whereas volatility and liquidity spread have a negative impact. For the case of the 1% quantile returns of the FTSE 100 ex Financials, the real estate index and equity returns and the bank index total returns enter positively and volatility has a statistically significant negative sign while for the 50% quantile returns volatility, liquidity spread, real estate returns enter and bank index returns have a positive effect.

The results for the UK insurance industry are summarized as follows. For both the 1% and 50% quantile returns, liquidity spread, real estate returns and equity returns positively affect the insurance index and for the latter case, the index is influenced negatively by volatility, the yield spread change and the credit spread change. For the 1% quantile returns for the FTSE 100 ex Financials index, the yield spread change, the real estate returns insurance index total returns positively affect the insurance index whereas volatility enter the relationship with a significant negative sign. For the 50% quantile volatility, the yield spread change, the real estate returns and the UK insurance index total returns all enter significantly with a positive sign.

Looking at the financial services industry for the UK, our results indicate that the financial services 1% quantile returns are negatively related to volatility and positively to real estate returns and equity returns. The 50% quantile returns are positively related to real estate returns and equity returns and negatively related to volatility. The FTSE 100 ex Financials 1% and 50% quantile returns are positively influenced by real estate returns and by the financial index total returns whereas in the 50% quantile, the FTSE 100 ex Financials returns are influenced positively by real estate returns and the financial index total returns and negatively by the credit spread change.

4.2. $\Delta \hat{CoVaR}$ estimates

In this section we present and discuss the $\Delta \hat{CoVaR}$ estimates based on our presentation in Section 3. We define that a $\Delta \hat{CoVaR}$ with a value of zero implies that none of the financial industries contributes to the systemic risk. Therefore, if the value is different from zero, we then consider the case that the financial industry which has the largest absolute estimate of $\Delta \hat{CoVaR}$ is taken to be the sector that contributes relatively the most to systemic risk in periods of distress.

In Table 2 we report descriptive statistics of the estimated $\Delta \hat{CoVaR}$ for US Banks and non-US Banks**.** We observe that the absolute value of the estimated $\Delta \hat{CoVaR}$ conditional to the US banks is larger than the corresponding values for the non-US banks. This finding suggests that when a distress situation occurs in the domestic banking segment, it will increase the value of the VaR in the US as a whole as compared to the normal state. Looking at the case of the UK economy, it is documented from Table 6 that the estimated $\Delta \hat{CoVaR}$ conditional to the banking industry has the largest absolute value and therefore it is this segment of the financial sector that contributes most to the systemic risk in the UK economy during financial turmoil.

An additional interesting result we can derive from the results in Table 2 is that when we split the full sample into two periods, before and after the financial crisis with the year 2008 as the break point, then we note that the absolute values of the estimated $\Delta \hat{CoVaR}$ for all cases in the period prior to the financial crisis are smaller as compared to those obtained for the post-crisis period. This implies that the contribution to systemic risk is increased for both US banks and non-US banks. This finding is reinforced in the case of the UK since it is clear that the banking, insurance and other financial services, when in distress, contribute more to the systemic risk as the financial crisis moves into full swing.

4.3. Significance and dominance tests

As explained in Section 3 the results which we obtain from the estimation of $\Delta \hat{CoVaR}$ must be further analysed in order to get clearer evidence on whether non-US banks are systematically riskier than US banks over the whole sample. This is due to the fact that our conclusions so far are based on the average of $\Delta \hat{CoVaR}$ values. Moreover, as Castro and Ferrari (2013) and Bernal *et al*. (2013) point out, this analysis is based on daily $\Delta \hat{CoVaR}$ estimated values**.** They argue that when we take into account the corresponding confidence interval, then it is possible that a financial sector that displays a positive $\Delta \hat{CoVaR}$ absolute value may not be a significant source of risk for the system.

Table 3 reports the results of the significance test for US banks and non-US banks. It shows the KS statistics and the corresponding bootstrapped p-value under the null hypothesis that the $CoVaR$ estimate during the period of crisis (1% quantile) and the $CoVaR$ estimate in normal time (50% quantile) are equal. The results show that the null hypothesis for both U.S. banks and non-US banks could be rejected at the 1% significance level. This finding allows us to argue that each sector, the US banks and the non-US banks, has a significant impact on the real economy during a period of turmoil. Therefore, both banking sub-sectors contribute significantly to systemic risk in the US. Table 4 reports the results of the dominance test. Based on the bootstrapped p-value, the null hypothesis is rejected at 1% and we conclude that the US banks are systematically riskier than the non-US banks.

Turning now to the results obtained for the case of the UK, Tables 7 and 8 provide the results of the significance and dominance tests. With respect to the significance test the p-values is rejected at the 1% significance level, which means that each financial sector has a significant impact on the real economy during a crisis, which implies that all three financial sectors significantly contribute to systemic risk in the UK. In the case of the dominance test three pairs are formed. For the first pair the p-value indicates that the null hypothesis is rejected at the 1% critical value, implying that banks are systematically riskier than the insurance industry. With respect to the two other pairs we report that the null hypothesis is rejected at the 1% level of significance, which leads to the conclusion that banks are riskier than financial services and that financial services are systematically riskier than insurance companies in the UK.

5. Summary and concluding remarks

The recent financial crisis led to the understanding that financial intermediary distress documented in extreme (tail) events tend to spillover to financial institutions, financial industries and - through - them to the whole economy. It also made clear that such spillovers are the results of an increase in the risk-appetite of banks, insurances and other financial services, either individually or at the industry level. Another important aspect of these negative effects is the need for a new regulatory framework that is currently under development within the context of Basle III, in order to embody the main factors of systemic risk. Following the failure of the micro-prudential regulatory framework, there has been a shift to the development of macro-prudential regulations. An important issue of macroprudential policy, aimed at reducing the risk resulting from the systemic banks alone and their emerging interconnections, is the determination of the institutions which are systematically important (see also Castro and Ferrari, 2013).

In this paper we adopt ΔCoVaR, a recent econometric methodology developed by Adrian and Brunnermeier (2011). This is a parsimonious measure of systemic risk that complements measures designed for individual financial institutions and also extends risk measurement to allow for a macro-prudential approach. Although recent studies investigate many aspects of the financial crisis in relation to developed economies, less research has been done with respect to emerging economies. Following Bernal *et al.* (2013), we do not study systemic risk in the context of individual financial institutions. We consider the contribution of the banking, insurance and other financial services industries that may be in distress to the systemic risk. The ΔCoVaR analysis allows us to investigate the additional level of risk that the economy as a whole faces when at least one of the financial sectors is in distress.

We implement this new measure of systemic risk on financial and macroeconomic data for the US and the UK using daily data for the period January 2000 to December 2012. Our analysis pays particular attention to the period of the recent financial crisis 2007-2009. We examine the extent to which the distress of foreign banks contributes to systemic risk for the US. In addition, using relevant data for the UK, we investigate the extent to which distress within different sub-segments of the financial system, namely, the banking, insurance and other financial services industries, contribute to systemic risk. The main findings, based on the estimation of the 1% and the 50% quantile regressions, show that equity returns is a key determinant in triggering systemic risk episodes. In addition in the case of the US, volatility of the general index ex financials (system variable), and real estate returns contribute significantly to systemic risk. There is also evidence that liquidity spread, and credit spread change have an effect, although a weaker one. Furthermore, we show that for the US, it is the US banks that contribute most to systemic risk whereas in the UK it is the banking sector that contributes most to systemic risk.

Based on the results of ΔCoVaR estimates before and after 2008, it is observed that the contribution of the US banks and the non-US banks to systemic risk for the US economy and the contribution of each financial industry to systemic risk for the UK economy increased after the unfolding of the crisis. Finally, we implemented two recently developed testing procedures (Castro and Ferrari, 2013; Bernal *et al*. 2013) to examine the issues of statistical significance and dominance of the estimated $\Delta \hat{CoVaR}$. For the case of the US, we show that both the US banks and the non-US banks have a significant impact on the real economy during a period of distress. Furthermore, the application of the dominance test leads to the conclusion that the US banks are systematically riskier than the non-US banks. In the UK case it is also shown that each financial sector has a significant impact on the real economy and, based on the evidence from the dominance test, we conclude that the banking sector represents a greater systemic risk than the insurance industry or the financial services industry and that the financial services industry is systematically riskier than the insurance companies industry.

Our results are of interest to regulators since they show that the different financial industries have an important and negative impact on the economy as a whole. It is emphasized that regulatory authorities should be able to identify the different segments of the financial sector of the economy which represent different risks for the system. Therefore, there is a need for regulatory provisions to reduce the risk to the whole economy emanating from these financial industries which are in distress.

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Table 1. Quantile regressions for the United States

Panel A: Quantile regressions for US banks

	Quantile Regression 1%		Quantile Regression 50%	
Variable	R_t^i	R_t^{system}	R_t^i	R_t^{system}
Volatility	-0.0893** (0.03262)	-0.3845** (0.01298)	-0.01256** (0.0356)	0.0155* (0.0067)
Liquidity spread	0.9532** (0.4779)	0.2236** (0.0543)	0.3933* (0.1567)	0.0109* (0.0068)
Three-month rate change	-0.6899 (1.0892)	-0.7891* (0.1339)	-0.1944 (0.7211)	0.0098 (0.0346)
Yield spread change	-0.0378 (0.9291)	-0.0970* (0.0416)	-0.0312 (0.0858)	-0.0005 (0.0056)
Credit spread change	0.6411*** (0.0332)	0.3822*** (0.0289)	0.3367*** (0.0211)	0.5366*** (0.0545)
Real Estate return	0.5562*** (0.1455)	0.3945** (0.1712)	0.4489** (02114)	0.3376** (0.0233)
Equity return	0.8312*** (0.1745)	-	0.7988*** (0.0699)	-
R_t^i		0.0912*** (0.0095)		0.0886*** (0.0035)
Pseudo- R^2	0.4981	0.9438	0.4468	0.9399

Notes: The R_t^i and the R_t^{system} are respectively the weekly market returns of the US banks index and the weekly market returns of the general index excluding the financial index. (***), (**) and (*) denotes significance at the 1%, 5% and 10% critical level, respectively.

Panel B: Quantile regressions for non-US banks

	Quantile Regression 1%		Quantile Regression 50%	
Variable	R_t^i	R_t^{system}	R_t^i	R_t^{system}
Volatility	1.9518*** (0.2089)	-0.3052*** (0.0893)	-0.2444*** ().0789)	0.1261*** (0.0334)
Liquidity spread	0.298 (0.3178)	-0.0702 (0.1123)	0.0012 (0.0306)	-0.0028 (0.0308)
Three-month rate change	-0.899 (1.5983)	-0.0406 (0.1138)	0.0203 (0.3331)	-0.0902 (0.0608)
Yield spread change	-1.4609 (1.3224)	0.0678 (0.0788)	-0.0022 (0.0387)	0.0013 (0.0094)
Credit spread change	-1.735 (1.7761)	-0.0503 (0.2988)	0.0508 (0.3446)	-0.0889 (0.0702)
Real Estate return	-1.0003 (1.3889)	0.0509 (0.0993)	-0.0407 (1.3442)	0.0028 (0.0101)
Equity return	0.9003*** (0.0026)	-	0.1125*** (0.0202)	-
R_t^i		0.1298*** (0.0299)		0.0433*** (0.0058)
Pseudo- R^2	0.1935	0.9445	0.2613	0.9335

Notes: The R_t^i and the R_t^{system} are respectively the weekly market returns of the non-US bank index and the weekly market returns of the general index excluding the financial index. (***), (**) and (*) denotes significance at the 1%, 5% and 10% critical level, respectively.

Table 2. $\Delta \widehat{CoVaR}$ **estimates for the United States**

	2000-2012		2000-2007		2008-2012	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
$\Delta CoVaR$ US banks	-2.099	0.665	-1.776	0.442	-2.779	0.776
$\Delta CoVaR$ non-US banks	-1.667	0.774	-1.045	0.308	-1.988	0.556

Notes: All the figures above are in percentages.

Table 3. Significance test for the United States

	Stat	p-value
H_0 : ΔCoVaR US Banks $= 0$	0.901	0.001
H_0 : ΔCoVaR non-US banks $= 0$	0.603	0.001

Notes: The bootstrapped Kolmogorov-Smirnov tests the null hypothesis of the equality of the cumulative distribution functions (CDFs) of the $CoVaR$s related to the 1% and 50% quantiles.

Table 4. Dominance test for the United States

	Stat	p-value
H_0 : US banks $\leq$ non US banks	0.455	0.001

Notes: The null hypothesis means that the $\Delta CoVaRs$ related to the US banks are lower (or equal to), in absolute value, than the $\Delta CoVaRs$ related to the non-US banks. Therefore, the null hypothesis implies that the US banks are less or equally systematically risky that the non-US banks

Table 5. Quantile regressions the United Kingdom

Panel A: Quantile regressions for UK Banks

	Quantile Regression 1%		Quantile Regression 50%	
Variable	R_t^i	R_t^{system}	R_t^i	R_t^{system}
Volatility	-0.0688** (0.0244)	-0.1782** (0.0612)	-1.2346*** (0.366)	0.0986*** (0.0144)
Liquidity spread	-0.0688** (0.0298)	-0.0446* (0.0266)	-0.0356** (0.0103)	0.0905** (0.0495)
Three-month rate change	-0.3866 (1.4056)	0.0483 (0.0636)	0.5282 (0.3741)	-0.0097 (0.0104)
Yield spread change	0.0124 (0.4426)	0.0275 (0.0310)	-0.0717 (0.0894)	0.0006 (0.0032)
Credit spread change	-0.0696** (0.0356)	0.009591 (0.01987)	-0.0399** (0.0105)	-0.002566 (0.00459)
Real Estate return	0.4215*** (0.0176)	1.2356*** (0.0905)	0.6554*** (0.2878)	0.3977*** (0.0982)
Equity return	1.3989*** (0.679)	-	0.7800*** (0.0588)	-
R_t^i		0.1368*** (0.0092)		0.2110*** (0.0062)
Pseudo-R^2	0.2967	0.9689	0.3335	0.9231

Notes: The R_t^i and the R_t^{system} are respectively the weekly market returns of the financial services index and the weekly market returns of the general index excluding the financial index. (***), (**) and (*) denotes significance at the 1%, 5% and 10% critical level, respectively.

Panel B: Quantile regressions for UK Insurance Companies

	Quantile Regression 1%		Quantile Regression 50%	
Variable	R_t^i	R_t^{system}	R_t^i	R_t^{system}
Volatility	-0.4553*** (0.0389)	-0.0477*** (0.0156)	0.6736** (0.2347)	0.2475** (0.098)
Liquidity spread	1.9368** (0.7615)	1.4582 (1.7674)	1.1806* (0.6295)	0.0365 (0.1107)
Three-month rate change	-0.6919 (0.8920)	-0.9109 (1.2612)	-0.7650 (1.5235)	0.0987 (0.0780)
Yield spread change	-0.2272*** (0.0069)	0.6850*** (0.1271)	2.1883*** (0.5541)	0.5993*** (0.0114)
Credit spread change	-0.0778*** (0.0123)	-1.2566 (1.335)	-0.966** (0.2454)	1.198** (0.675)
Real Estate return	0.3356*** (0.0432)	1.5567*** (0.778)	0.7882*** (0.0116)	1.6642*** (0.4431)
Equity return	1.5370*** (0.2262)	-	0.7712*** (0.0780)	-
R_t^i		0.1809*** (0.0125)		0.1623*** (0.0031)
Pseudo-R^2	0.4186	0.9151	0.3179	0.9246

Notes: The R_t^i and the R_t^{system} are respectively the weekly market returns of the banks index and the weekly market returns of the general index excluding the financial index. (***), (**) and (*) denotes significance at the 1%, 5% and 10% critical level, respectively.

Panel C: Quantile regressions for UK Financial Services

	Quantile Regression 1%		Quantile Regression 50%	
	R_t^i	R_t^{system}	R_t^i	R_t^{system}
Volatility	-0.07123*** (0.02678)	-0.02198 (0.3235)	-0.9023*** (0.0771)	0.0475 (0.0955)
Liquidity spread	-0.0889 (0.0901)	-0.09821* (0.07674)	0.00122 (0.0625)	0.0365 (0.1107)
Three-month rate change	-0.6919 (1.8920)	0.1029 (0.3412)	-0.3992 (0.5385)	0.0399 (0.0680)
Yield spread change	0.3872 (0.5987)	0.2887 (03981)	0.3464 (0.5839)	0.0535 (0.0892)
Credit spread change	0.03787 (0.02678)	-0.03944 (0.06733)	0.00098 (0.0077)	-0.02345* (0.0098)
Real Estate return	0.4876** (0.1921)	0.09123*** (0.0235)	0.5367*** (0.02813)	0.3476** (0.15634)
Equity return	1.2320*** (0.3233)	-	0.9501*** (0.0656)	-
R_t^i		0.1989*** (0.0295)		0.1823*** (0.0051)
Pseudo- R^2	03186	0.9156	0.2279	0.9256

Notes: The R_t^i and the R_t^{system} are respectively the weekly market returns of the banks index and the weekly market returns of the general index excluding the financial index. (***), (**) and (*) denotes significance at the 1%, 5% and 10% critical level, respectively.

Table 6. $\Delta \hat{CoVaR}$ **estimates for the United Kingdom**

	2000-2012		2000-2007		2008-2012	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
$\Delta CoVaR$ banks	-2.098	0.728	-1.322	0.372	-2.398	0.773
$\Delta CoVaR$ insurance	-1.687	0.640	-0.901	0.453	-1.877	0.691
$\Delta CoVaR$ financial services	-1.810	0.588	-1.108	0.354	-1.983	0.561

Notes: All the figures above are in percentages

Table 7. Significance test for the United Kingdom

	Stat	p-value
H_0 : ΔCoVaR Banks = 0	0.791	0.001
H_0 : ΔCoVaR Insurance = 0	0.545	0.001
H_0 : ΔCoVaR Financial Services = 0	0.621	0.001

Notes: The bootstrapped Kolmogorov-Smirnov tests the null hypothesis of the equality of the cumulative distribution functions (CDFs) of the $CoVaR$ s related to the 1% and 50% quantiles.

Table 8. Dominance test for the United Kingdom

	Stat	p-value
H_0 : Banks $\leq$ Insurance	0.455	0.001
H_0 : Banks $\leq$ Financial Services	0.455	0.001
H_0 : Financial Services $\leq$ Insurance	0.455	0.001