Where is the System?

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Abstract

The aim of this paper is to emphasize the importance of determining the system aggregate level (global, european or national) when dealing with systemic risk. Up to now, additional supervision and regulation were established for global systemically important banks, G-SIBs. The paper highlights the need for managing domestic systemically important banks, D-SIBs. This issue is central when focusing on Europe where each country should identify its D-SIBs whereas the Basel Committee on Banking Supervision (BCBS) tags G-SIBs, not only European banks. Thus, monitoring G-SIBs does not mean we cover the systemic risk both at European and domestic level. In this paper, we show that (*i*) the popular Systemic Risk Measure (SRISK) produces similar ranking whatever the system used; (*ii*) however SRISK's values, according to the system, can be largely different underlining the need to impose the higher of either D-SIB or G-SIB higher loss absorbency (HLA) requirements; (*iii*) market-based systemic risk measures (SRMs) as the ΔCoVaR, which capture the degree of interconnectedness with the return correlation are unstable. These findings are described through an empirical application within the eurozone.

Keywords: Systemic risk, financial regulation, SRISK, G-SIBs, D-SIBs.

JEL classification: G01, G28, G32.

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1 Introduction

Since September 15, 2008 and the collapse of Lehman Brothers, extensive research has been done on systemic risk , considering its definition, measurement, or regulation. We do not have a unanimous definition[1] but each systemic risk definition agrees on three points that are summarized in the 2011 G-10 definition:

> "Systemic financial risk is the risk that an event will trigger a loss of economic value or confidence in [sic] a substantial portion of the financial system that [sic] have significant adverse effects on the real economy."

Thus, a systemic event corresponds to a *trigger point* which causes *significant disruption in the financial system* and finally *spreads out to the real economy*. The key element that concerns systemic risk is the identification of Systemically Important Financial Institutions (SIFIs), institutions threatening the system, even though we do not have an accurate and precise definition of what the system is. The question is well addressed in context of the United States, because this is a unique country composed of states. However, in Europe where we are faced with a sum of countries, the issue is central. Accordingly, considering global or domestic systemically important banks (G- or D-SIBs) does not lead to the same conclusions and raises numerous of questions. For example, should we evaluate the contribution of a given financial institution to the systemic risk at a domestic, supranational or global level? Is the identification of SIFIs identical regardless of the level of the system taken into account?

These questions are crucial for regulators. In this regard, in April 2012, the Financial Stability Board on the request of the G20 Leaders, asked that the G-SIBs framework to be extended to include D-SIBs in October 2012. The Basel Committee on Banking Supervision (BCBS) published a framework for dealing with D-SIBs in line with its previous methodology for assessing G-SIBs. This country-by-country approach asks regulators to take into account a set of new bank specific factors such as size, interconnectedness, financial institution infrastructure and complexity of a particular bank within its own financial system. Besides weighting of main contributing factors to systemic risk by domestic characteristics, BCBS emphasizes that national regulators should establish their own list of D-SIBs. By analogy, identification of the supranational-SIBs should be done by a supranational regulator[2] while identification of the G-SIBs should be done by a global regulator which assesses the system in the global context. At the global level, the regulator looks like the Eye of Providence that you can see every day on top of an unfinished pyramid on the one-dollar bill. Thus, challenge systemic risk at this level sounds tricky but one thing is sure, a bank is

[1] VanHoose distinguishes 14 standard definitions of systemic risk.

[2] Currently, BCBS develops a methodology to identify G-SIBs at the European level. Thus, we have only European banks in the list.

on top because its foundations are buried in the ground. In other words, G-SIB is automatically defined as D-SIB but the inverse is not true.

This top down approach means that additional capital or higher monitoring on G-SIBs are primordial if we want to avoid a cascade of bankruptcy which could affect the entire global system. However, because a particular bank can't be seen at this high level does not imply that its contribution to systemic risk is null. This bank is still a part of the pyramid and its impact on neighbors could be significant and eventually destabilize the whole construction. Taking D-SIBs into account in elaborating the regulation is even more important if we think that, for a given bank, its systemic contribution is probably larger in its country than abroad. That is why BCBS asks national authorities to calibrate the level of higher loss absorbency (HLA) required for D-SIBs. Consequently, the identification of SIBs changes depending on the system we focus on.

This paper addresses this issue and explicitly answers the questions about consequences of determining the system aggregate level. Our analysis relies on publicly available real-time data, using principally the Systemic Risk Measure (SRISK) of Brownlees and Engle (2012) and Acharya, Engle and Richardson (2012). Indeed, this simple but famous measure is easily adjustable to this problem and its values are expressed in cash value allowing users to quantify the amount of additional loss absorbency required for a given SIB. To the best of our knowledge, this paper is the first to apply market-based systemic risk measures (SRMs) at different levels of the system simultaneously. To avoid time lag and obtain results in the same currency we consider the eurozone counties over the last decade. This is our global level and our domestic level corresponds to each of the 10 country-members of this economic and monetary union.[3] The contributions of our paper are the following. First, we show that (*i*) the famous SRISK measure produces similar ranking regardless of determining the system aggregate level, global or local. Second, (*ii*) SRISK's values can be largely different according to the system used, underlining the importance to impose the higher of either D-SIB or G-SIB HLA requirements. Third, (*iii*) SRMs which capture the degree of interconnectedness, between a particular system and a bank that belongs to this system, as the Delta Conditional Value-at-Risk (ΔCoVaR) of Adrian and Brunnermeier (2011) are unstable.

The rest of the paper is organized as follows. Section 2 provides a brief literature review of systemic risk and introduces the general framework for identifying D-SIBs with its specifics. In Section 3, we describe the SRISK and the ΔCoVaR allowing us to highlight the presence of common factors when we use this measure to identify G-SIBs and D-SIBs. Section 4 presents the data and the main empirical findings. Section 5 summarizes and concludes.

[3] Established in January 1, 1999, the eurozone is an economic and monetary union of 17 European Union member states (in November 2012) which share a unique currency, the euro, since January 1, 2002.

2 Principles for SIBs

In this paper, we don't want to oppose the two traditional approaches to tackle systemic risk. In other words, we do not want to determine which approach is better than the other. The first approach is based only on balance sheet and stock returns data (Acharya et al., 2010, Billio et al., 2011, Adrian and Brunnermeier, 2011, Acharya, Engle and Richardson, 2012 and Brownlees and Engle, 2012), whereas the second approach requires balance sheet information disaggregated by class of assets and counterparties (Gourieroux, Heam and Monfort, 2012a-b and Greenwood, Landier and Thesmar, 2012). Furthermore, the Shapley Value can be applied on the two former approaches (Borio, Tarashev and Tsatsaronis, 2010, Drehmann and Tarashev, 2011a, Garratt, Webber and Willison, 2012, Gauthier, Lehar and Souissi, 2012 and Cao, 2010). The common feature of these different methods is that they are already included within a particular system. And the size of the network is particularly important to capture the degree of interconnectedness of a given financial institution with its neighbor. For example, Lopez-Espinosa et al. (2012) derive the CoVaR at a global level whereas Cerutti, Claessens and McGuire (2012) emphasize the need for additional data to capture international dimensions of systemic risk. In contrast, Elsinger, Lehar and Summer (2006) and Acharya and Stefen (2012) apply Marginal Expected Shortfall, Conditional Expected Shortfall and Systemic Expected Shortfall at the European level. The only paper that focuses on domestic level from Brämer and Gischer (2011) adjusts the methodology proposed by the BCBS and identifies D-SIB in the context of the Australian banking system. Engle, Jondeau and Rockinger (2012) design a specific econometric multi-factor model to address with asynchronous market. To identify G-SIFIs and D-SIFIs among European financial firms with this new model, they explain firms returns by three drivers, a country-wide index, an European index and a world index. One of our contributions is to show that this multivariate model does not outperform the traditional bivariate model when the identification of D-SIFIs is the purpose.

To assess systemic risk, BCBS develops a framework (Financial Stability Board - International Monetary Fund - Bank for International Settlements, 2009, BCBS, 2011 and Financial Stability Oversight Council, 2012) which incorporates a score based on systemic risk factors as size, interconnectedness, non-substitutability, complexity and cross-jurisdictional activity. Then following an indicator-based measurement approach, banks get a score and given this number they are thrown in a bucket in which a minimum additional loss absorbency is required. This G-SIB HLA requirement will be added to the Common Equity Tier One of the G-SIBs. In addition to this bucketing approach based on the clustering of scores produced by the methodology, addressing systemic risk means to be also careful with the behavior of those banks. With this risk, financial system face moral hazard, and being a G-SIFI or a G-SIB can be viewed as a good opportunity because banks are sure to be well capitalized and more intensively monitored. However, this surcharge can be viewed as a blessing or as a punishment because financial institutions are explicitly too big and/or too interconnected to be saved, and have to quickly raise new capital which can be very expensive. But even if banks would like to reduce their contribution, they have no strong incentive to do so. Indeed, their funding cost will increase and the reduction of risk means a loss in banks' market share, then these global actors become less competitive and could face shareholders confrontation against this strategy.

G-SIBs

[Insert Table 1]

Table 1 reports the worldwide list of G-SIFIs published by the Financial Stability Board in 2011.[4] When the SRISK is presented by its authors at a conference, they argue that this measure is close to this list of G-SIFIs and show that the ranking obtained with the SRISK is not linked to the leverage, the MES (measure of interconnection) and the size (captured by the market capitalization). Unsurprisingly, we observe that the SRISK allows us to identify 23 from 29 of these G-SIFIs. Moreover, using this measure we know which banks are the riskiest. However we show that, at this date, the ranking according to the quarterly book value of liabilities reports 26 from 29 of these G-SIFIs, whereas we have 25 banks in common between the SRISK and the quarterly book value of liabilities.[5] The idea to present this table is not to argue about the identification of G-SIFIs which is carefully done by the regulator using a thorough methodology to assess systemic risk. We also don't want to say anything about the SRISK measure which is a daily measure designed to gauge the capital expected shortfall that a given firm may have during a financial crisis. We just want to point out as Drehmann and Tarashev (2011b) did that simple indicators are able to gauge some aspects of systemic risk but not all its multifaceted. In this case, we show that the identification of G-SIB is mainly driven by the total amount of liabilities because at this global level, principal actors are big banks well known worldwide. Hence, if we trust the ability of the simple indicator to identify G-SIFIs over time, then the only interesting point to know is where we should put the threshold on those indicators. The Basel Committee uses a cut-off point by clustering the scores produced by its methodology.

Even if we agree that dealing with systemic risk means taking the multifaced threat into account, the main issue is probably not linked to the identification of G-SIFIs since one could reproduce

[4] An update can be made with the list of G-SIBs published in 2012 (Financial Stability Board, 2012) where two banks have been added to the list (BBVA and Standard Chartered) and three removed (Commerzbank, Dexia and Lloyds).

[5] According to the list of G-SIBs published in 2012, the SRISK and the quarterly book value of liabilities identify 21 over 28 of these G-SIBs whereas SRISK and quarterly book value of liabilities rankings have 25 institutions in common among the first 28 G-SIBs.

almost each future list of G-SIFIs using only simple indicators. The principal identification issue arises at a domestic level where the degree of interconnection is certainly thinner and, therefore difficult to be easily captured by simple indicators. For example in 2011, 27 banks were identified by the score indicator and 2 have been added based on home supervisory judgement (BCBS, 2011). Thus, BCBS methodology has to be modified according to the level-playing field (global or domestic).

D-SIBs

At the domestic level, Brämer and Gischer (2011) replace the cross-jurisdictional activity by the Domestic sentiment. This point of view comes from the national authority in charge of the regulation calling for a framework to deal with D-SIBs (BCBS, 2012). When a bank is identified as G-SIB, this particular bank is also D-SIB but is not necessarity well-capitalized. Then, home authorities should impose the higher of either the D-SIB or G-SIB HLA requirements in the case where the banking group has been identified as a D-SIB in the home jurisdiction as well as a G-SIB (BCBS 2012). For a given bank, one could argue G-SIB HLA has to be higher than the D-SIB HLA because at the global level, the totality of its interconnections are known and not only its domestic linkages. Thus a global shock should lead to a bigger HLA requirement. However, the marginal effect of this global shock is less than the domestic shock, a global shock is more spread out than the domestic shock. As during an earthquake where the seismic magnitude and damages are greater when you are close the epicenter, the D-SIB HLA has to be higher than the G-SIB HLA when you face a domestic shock. Moreover, D-SIB can be viewed as the worst case because a bank is penalized although it is not a global actor. Banks identified as domestic actors probably want to grow until becoming principal actors but their growth is reduced due to the HLA requirement. However, given the repartition of systemic risk in five equal parts, 20% for each systemic risk factor, a bank could reduce one of those factors to increase its degree of interconnectedness and become a global actor without being further penalized. Up to now, no incentives have been considered to reduce the degree of interconnectedness or common exposure of a given financial system to an exogenous source of risk which is the key element of systemic risk at a domestic level.

In this paper, we compute market-based systemic risk measures using publicly available data. We assume market efficiency because we want system bank-specific factors to be included into the market return, which is the only element to gauge the choice of the system. The eurozone is an ideal example to challenge all SRMs because we have to take into account not only national specifics but also supranational authorities like the ECB in charge of the monetary policy. Furthermore, dealing with national specifics become more and more important during a financial crisis because each country wants to protect its own banking system to avoid bank runs.

3 Systemic Risk Measures

In this section, we present the SRISK and the ΔCoVaR which capture the contribution of a given bank to the risk of the system, both at a global (european) and domestic (national) levels. These measures are derived within a unified framework described in Appendix A.

SRISK

The SRISK measure proposed by Brownlees and Engle (2011) and by Acharya, Engle and Richardson (2012) extend the Marginal Expected Shortfall (MES) measure taking into account both the liabilities and the size of the financial institution. The SRISK corresponds to the expected capital shortfall of a given financial institution, conditional on a crisis affecting *a particular system*. In other words, SRISK is the difference between the required capital and the available capital. In this perspective, banks with the largest capital shortfall are assumed to be the greatest contributors to the crisis. Hence, banks which are not well capitalized are considered the most systemically risky. The SRISK is defined as:

$$SRISK_{it} = k\ D_{it} - (1-k)\ W_{it}\ \left(1 - LRMES_{it}\right)\ , \tag{1}$$

where k is the prudential capital ratio (usually equal to 8%), D_{it} is the quarterly book value of total liabilities, and W_{it} is the daily market capitalization or market value of equity.[6] This systemic risk measure also considers the interconnection of a firm with the rest of *a particular system* through the long-run marginal expected shortfall (LRMES). The LRMES is based on MES and corresponds to the drop in the equity value the firm should face when the *particular market* falls by more than its Value-at-Risk (VaR). Acharya, Engle and Richardson (2012) propose to approximate the LRMES, without simulation, using the daily MES, described in Appendix B, as $LRMES_{it} \simeq 1 - \exp\left(18 \times MES_{it}\right)$. This approximation represents the firm expected loss per dollar at a time horizon of 6 month, conditional on this *particular market* falling by more than 40% in the next six months.

The nice property of this SRM is that this measure is strongly linked to the choice of the market. Thus, we can easily adapt Equation (1) according to the level of the regulation that we are dealing with. When we focus on the G-SIBs as the BCBS does, we consider a *global system* which means *global market* and we have:

$$SRISK^{G}_{it} = k\ D_{it} - (1-k)\ W_{it}\ \left(1 - LRMES^{G}_{it}\right)\ , \tag{2}$$

and similarly when we focus on the D-SIBs as the national authorities in charge of the regulation

[6] The true definition of the SRISK is $SRISK_{it} = \max[0\ ;\ k\ D_{it} - (1-k)\ W_{it}\ (1 - LRMES_{it})]$, but we work with the difference of two SRISK in the empirical illustration. Thus, we do not want to impose this minimum threshold to obtain the magnitude change.

do, we consider a *national system* which means *domestic market* and we have:

$$SRISK_{it}^{D} = k\ D_{it} - (1-k)\ W_{it}\ \left(1 - LRMES_{it}^{D}\right)\ . \tag{3}$$

Sometimes, both quantities can be expressed in terms of the same currency like in case of the eurozone. We also could adjust the SRISK's amount to the exchange rate, when we consider a global level where currencies are still linked to a sovereign monetary policy. Because both quantities are comparable for a given bank, we can take the difference between two:

$$SRISK_{it}^{D} - SRISK_{it}^{G} = (1-k)\ W_{it}\ \left(LRMES_{it}^{D} - LRMES_{it}^{G}\right)\ . \tag{4}$$

This is a useful measure since we can easily get the additional HLA requirement due to the D-SIB effect (if SRISK^D > SRISK^G) or the G-SIB effect (if SRISK^G > SRISK^D). Indeed, we anticipate that SRISK^D is greater than the SRISK^G due to lower degree of connection of a bank with the global system. In other words, bank i should be more affected by the downturn in its domestic market than the drop of the global market. To estimate systemic contribution, we use a DCC-GARCH model[7] as Brownlees and Engle (2012) and apply a nonparametric kernel estimation method[8] (Scaillet, 2005) to estimate conditional expectations.

ΔCoVaR

The ΔCoVaR measure proposed by Adrian and Brunnermeier (2011) extends the VaR methodology because it allows computing VaR conditional on a specific event. The ΔCoVaR of bank i is defined as the difference between the VaR of a *particular system* conditional on the distress of bank i and the VaR of this *particular system* conditional on bank i being in its median state. A financial institution is in distress when its loss is equal to its VaR at $\alpha\%$ level of risk, and in the normal state if its loss equal to its median return. Thus, the ΔCoVaR is defined as:

$$\Delta CoVaR_{it} = CoVaR_{it}^{m|r_{it}=VaR_{it}(\alpha)} - CoVaR_{it}^{m|r_{it}=Median(r_{it})} \tag{5}$$

$$= \gamma_{it}\ \left[VaR_{it}(\alpha) - VaR_{it}(0.5)\right]\ , \tag{6}$$

where γ_{it} corresponds to the linear projection coefficient of *a particular market* return on the firm return. This proportionality coefficient is fundamentally linked to the correlation between firm and market returns and market volatility. Appendix C describes Equation (6) in details and gives the explicit expression for γ_{it}. Like the MES, the ΔCoVaR is a measure of interconnectedness, both quantities are mainly driven by the return correlation and this coefficient is different for a

[7] We model the conditional variances σ_{it}^2 and σ_{mt}^2 according to a TGARCH specification (Rabemananjara and Zakoïan, 1993) and use a DCC model (Engle, 2002) for the time-varying correlations ρ_{it}. The model is estimated in two steps using Quasi Maximum Likelihood.

[8] We fix the bandwidth at $T^{-1/5}$ and choose the standard normal probability distribution function as a kernel function, i.e., $k(u) = \phi(u)$.

particular system. So once again, we can derive two ΔCoVaRs according to the level of the system. For the *global system:*

$$\Delta CoVaR_{it}^{G} = \gamma_{it}^{G} \; \left[VaR_{it}\left(\alpha\right) - VaR_{it}\left(0.5\right)\right] \; , \tag{7}$$

and for the *domestic system*:

$$\Delta CoVaR_{it}^{D} = \gamma_{it}^{D} \; \left[VaR_{it}\left(\alpha\right) - VaR_{it}\left(0.5\right)\right] \; . \tag{8}$$

With the ΔCoVaR, we can only compare those quantities separately without being able to subtract them because they are computed for different system aggregate level. On the one hand, we have a difference between the two conditional on *global market* returns and on the other hand, the difference is done with two conditional *domestic market* returns. To estimate systemic contributions, ΔCoVaR^{G} and ΔCoVaR^{D}, we also use a DCC-GARCH model.[9]

SRISK and ΔCoVaR capture the interconnectedness of a given bank i to a particular system through the correlation between bank and a *specific market* returns. This is the only one element directly connected to the market. Thus, as soon as we change the level playing field, the correlation also changes and affects our SRMs.

[Insert Figure 1]

Figure 1 displays the time series evolution of the conditional correlation of Alpha Bank.[10] As expected, the return correlation of this bank with its domestic market is higher than its return correlation with the global index. We observe specific changes at some point especially at the European level because the bank is less connected with this index. Thus, is return correlation able to capture all aspects of systemic risk regardless of the chosen level of the system? The purpose of the next section is to provide some answers at this question with an empirical illustration.

4 Empirical Results

In this section, we implement an empirical study about systemic risk for the eurozone area. We collect data for 44 European banks belonging to 10 countries. We extract stocks prices, annual amount of liability in book value and daily market value of equity from Datastream Worldscope. These particular banks are not selected randomly, they are included in the market indexes (domestic and eurozone) provided by Deutsche Börse on its website with the STOXX indexes. In

[9] We can also apply a quantile regression of the market return on the firm return as in Adrian and Brunnermeier (2011) and obtain a γ_i coefficient which is constant over time. In the rest of the paper, we report ΔCoVaR estimated with DCC-GARCH because results are robust to any the methodology applied. Results obtained with quantile regression without macro-variables are available upon request.

[10] Alpha Bank is the 3^{rd} bank in Greece and the 273^{th} largest bank worldwide according to the amount of assets at the end of 2011.

this application, we need 11 market indexes, one per country (domestic system) plus one for the eurozone market (global system), and this website allows us to download these market prices from January 1, 2002 to December 30, 2011.[11] We compute the log-returns on these stocks prices and market index prices. Unfortunately, none weightings of these components inside the indexes are available and the 44 selected banks do not allow us to identify D-SIB for each European countries.

None of these banks disappear over the last decade. The list of banks is constant for any level of the system because we focus on the evolution of our SRMs according to the choice of the system. Of course, for a given country, the set of banks should increase at a domestic level because the number of potential D-SIBs grows when we reduce the size of the system. To assess these changes we perform a cross sectional analysis to see if the ranking is consistent across the system aggregate level. Using time series analysis we also look at the difference between the domestic and the global SRM.

Cross-section

Table 2 reports the ranking of all banks in our sample at the national and eurozone level of the system according to the SRISK^D, SRISK^G, and the difference between both, respectively, for December 31, 2011. We observe that the ranking produced by the SRISK^D is identical to the one produced by the SRISK^G within each country and also at the eurozone level. This result is the same that Engle, Jondeau and Rockinger (2012) where they rank European financial firms by SRISK in percentage of domestic nominal Gross Domestic Product (GDP). In the first step, we see this as a bad thing since we have no additional information to extract from those lists but in the second step, we observe new information that a G-SIB is automatically a D-SIB. However, values are different and 40 out of 44 of our banks have SRISK^D greater than their SRISK^G highlighting the requirement of additional capital buffer for banks which are D-SIB. By how much should a D-SIB increase its Tier one capital to satisfy the regulation? If we trust the SRISK, the difference expressed in euro should produce exactly this additional amount. Thus, on this date and on the domestic level, the National Bank of Greece is undercapitalized by €254 million whereas the Deutsche Bank's overcapitalization is equal to €236 million, the Commerzbank is undercapitalized by €153 million due to higher SRISK^G. These two German banks are G-SIBs and tend to contribute to the risk of the eurozone more largely because of their size.

[Insert Table 2]

We can say that the total expected capital shortfall of Spain is around €2.202 billion which is

[11] This link sends users to the STOXX website where we can access to the EURO STOXX Total Market Index (TMI) which is our eurozone index. Then when we select EURO STOXX TMI components, we find all our sample of banks and finally extract the EURO STOXX TMI of our country of interest. http://www.stoxx.com/indices/index_information.html?symbol=BKXE .

still less than €2.730 billion of that of Italy but much more than the amount of undercapitalization €118 million of France. Nevertheless, according to the BCBS principles, the bigger HLA requirement should be applied although national authorities have the liberty to adjust the level of this HLA. At their discretion, they can impose a threshold to determine which banks are systemically risky for any system aggregate level and also fix the amount of additional capital required. For example, with the SRISK a natural threshold is equal to 0 (but according our results this threshold should be greater than 0). Hence, we could have a bank which goes beyond this threshold at a domestic level but not at a global level and identify a D-SIB which is not a G-SIB.

[Insert Table 3]

Table 3 reports the ranking of all our banks at the national and eurozone levels according to the ΔCoVaR^D and ΔCoVaR^G. We observe two opposite results. Domestic rankings are almost the same even though we observe some discrepancies especially for Italy, Spain and Greece whatever the system is considered. It means that both ΔCoVaR produce the same ranking of D-SIBs. However, the rankings derived from the domestic and the eurozone systems are completely different. For example, the National Bank of Greece is the 14^{th} biggest G-SIB according to the national market but only the 32^{th} G-SIB when we use the eurozone index. Results are similar for all Greeks banks, their ΔCoVaR^D are twice as much than their ΔCoVaR^G. This accentuates the great distress of the national Greek economy at the end of 2011, and emphasizes also the fact that this national system is not the most important in the eurozone with regard to its size captured by the relative GDP (relative GDP less than 3%). In contrast, Spain (relative GDP greater than 10%) and Italy (relative GDP greater than 15%) are the two countries which can significantly destabilize the eurozone, especially Spain with the ΔCoVaR^G of its G-SIBs banks like Santander and Banco Bilbao Vizcaya Argentaria being greater than their ΔCoVaR^D. In other words, the systemic contribution of these banks is larger in the eurozone than in their home country. We observe the same phenomena for French, German and Belgium banks. To sum up, global rankings based on the ΔCoVaR^D have no value as long as this eurozone ranking puts on top D-SIBs (not all, as we can see for Bankia which is in the bottom of both lists) belonging to a domestic system in distress on a particular date. Furthermore, we observe than even after the nationalization of Dexia, this bank is considered as the riskier Belgian bank based on ΔCoVaR^G but not on ΔCoVaR^D. Those results show ΔCoVaR is unstable because one bank would be G-SIB without be D-SIB.

Whatever the system is selected, SRISK produces similar rankings, which is in line with the current regulation. In contrast, ΔCoVaR leads to two different rankings, and might identify a G-SIB which is not a D-SIB.

[Insert Figure 2]

Time series

The time series analysis of these measures confirms our previous findings. In Figure 2 where we observe the evolution of both SRISKs over the last decade for Alpha Bank shows the gap between domestic and global SRISK. This difference is not constant over time although the coefficient of correlation between these two systemic risk measures is equal to 0.99. Moreover when both markets are in crisis, curves are closer. As predicted, for this bank SRISK^D is above the SRISK^G because the domestic MES is often above the eurozone MES. The correlation coefficient reported in Figure 1 is lower at a global level for a technical reason. Indeed, the weighting factor of this bank used to construct the eurozone index is lower than the one employed to build the domestic index. For this bank, we obtain a shift of €544.123 million in average over the period but the difference is twice as much in average for National Bank of Greece and EFG Eurobank Ergasias. As we observe in this figure, the potential amount of a greater capital surcharge due to the D-SIB HLA requirement could be quite important and vary over time. Thus, calculating this amount on a given date is not a good strategy. Indeed, regulation must avoid procyclicity, and to determine the additional amount of capital we have to look at a relatively long period of time. When we use this kind of measure, capital surcharge should increase during the crisis period and not before. Like the methodology to assess the Stress-VaR, the level of higher loss absorbency could be evaluated over the last financial crisis period.

[Insert Figure 3]

Figure 3 displays ΔCoVaR time series for Alpha Bank over the last decade. The correlation coefficient between the domestic ΔCoVaR^D and the eurozone ΔCoVaR^G is equal to 0.65. This coefficient is low due to the choice of our estimation method which allows us to produce a time-varying proportional coefficient between the ΔCoVaR and VaR. Indeed, if we estimate ΔCoVaR with a quantile regression with or without macro-variables, we have a perfect correlation between both ΔCoVaRs. In this case, the time series dynamic is the same at both national and eurozone systems. However, it doesn't mean that the ranking is the same because the magnitude between these curves can be large. The ΔCoVaR is extremely sensitive to the estimation method. With this figure, we show that the ΔCoVaR^G can be above the ΔCoVaR^D due to a higher interconnection between banks in the eurozone than in their own market. At the end of the period, we observe that the ΔCoVaR^D remains high whereas the ΔCoVaR^G becomes lower and less volatile. The systemic contribution of Alpha Bank is then higher within its domestic market than at the eurozone level because the return correlation with the global market decreases as we can see in Figure 1.

This empirical part shows the evidence that the choice of the system is a key factor in measuring systemic risk contribution. We also point out that the correlation between the financial institution and its sytem is the only mathematical tool to take into account this change of level. Jiang (2012) argue that the dependence among bank and market returns is nonlinear and that we need to use copula approaches to capture this dependence. Even with this methodology the level playing field is crucial.

5 Conclusion

The purpose of this paper is not to look for the best systemic risk measure. Instead, we use these simple SRMs as a tool to emphasize the importance of system aggregate level. Before dealing with systemic risk, regulators and researchers have to delimitate the perimeter of their research. A misspecification on this issue can lead to a huge turmoil, as the last financial crisis has showed. Indeed, up to now, regulation was mainly based on a micro level, where the health of each financial institution should ensure global stability. Recent events showed us this was not true. Thus a macro prudential approach is currently being developed around the world, trying to gauge the global systemic risk and identify which banks are globally systemically risky. However, assuming that we can know for sure which banks are the most significant contributors to systemic risk at a global level, this may not be enough. We have to keep in mind that when we look at the global (macro) level, we forget about the domestic (micro) level. Consequently, identifying G-SIBs is essential in order to capture the domestic contribution of a particular bank to the risk of the national system.

In this paper, we first argue that the D-SIBs monitoring is a preamble (first step) to the regulation of the G-SIB, since by only looking at an aggregate level we ignore some SIBs. Moreover, we argue that the Higher Loss Absorbency requirement should be first calibrated within the domestic market by the national regulator (over the last financial crisis period to avoid the procyclicity issue) and then calculated at the european level and whether the G-SIB HLA is greater than the D-SIB HLA then the capital requirement comes from the HLA computed at the european level. In their paper, Greenwood, Landier and Thesmar (2012) show that only equity injection is useful to reduce the vulnerability of a given bank.

Second, the SRISK produces identical rankings for any level of the system used in its computation. On the one hand, this is a conforting result because the list of SIBs is consistent according to the level of regulation (observation). On the other hand, it means that the impact of the liabilities, as well as the market value of equity, have a huge impact on this measure. This is inconsistent with our purpose (however not useless) because these main factors are bank specific and not linked to the size of the system. Only the LRMES relies on the choice of the system, and the MES of a given bank i is close to the ES of this particular system when the correlation between bank and market return is important.

Third, the change in ΔCoVaR depending on the choice of the system is also mainly driven by the correlation and the magnitude is due to the volatility of the system. Thus, individual ranking of firms for each country using the domestic system is able to produce the same global ranking as the global system. Indeed, we cannot compare and rank the individual systemic risk of bank i from country i with the individual systemic risk of bank j from country j because the union of this two systems produces an empty set at this level. However, at a higher level, the union of the different sets at the beginning can create a new set following its own rules, even if its connection with both sub-systems is still active.

Our results also have some key implications for regulation. They highlight the lack of specific factor directly connected to the system in which the bank is operating. A network approach, already used to deal with systemic risk (Eisenberg and Noe, 2001, Demange, 2011), seems to be a necessary tool to capture all characteristics of the system but this approach requires more data, and is promising as shown by Jo (2012). Thus, producing a simple SRM based on network approach should be a priority. To conclude, we show that the current systemic risk regulation is like an unfinished pyramid which requires completion.

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Appendix A: The Framework

We consider a simple bivariate model where the demeaned market return at time t, r_{mt}, and the demeaned firm return of a given bank i at time t, r_{it}, are expressed as:

$$
\begin{aligned}
r_{mt} &= \sigma_{mt}\ \varepsilon_{mt}\ , && \text{(A1)}\\
r_{it} &= \sigma_{it}\ \varepsilon_{it}\ , && \text{(A2)}
\end{aligned}
$$

where σ_{it} and σ_{mt} are the conditional standard deviations whereas ε_{it} and ε_{mt} are the conditional standardized residuals. The conditional correlation between market and bank returns ρ_{it} is equal to:

$$
\rho_{it} = \frac{\sigma_{imt}}{\sigma_{it}\ \sigma_{mt}} \Leftrightarrow \rho_{it}\ \sigma_{it} = \frac{\sigma_{imt}}{\sigma_{mt}}\ , \tag{A3}
$$

where σ_{imt} is the conditional covariance. The conditional systematic risk of a given bank β_{it} is defined as follows:

$$
\beta_{it} = \frac{\sigma_{imt}}{\sigma_{mt}\ \sigma_{mt}} = \frac{\sigma_{imt}}{\sigma_{mt}^2}\ . \tag{A4}
$$

According to the CAPM, the bank return is:

$$
\begin{aligned}
r_{it} &= \beta_{it}\ r_{mt} + \eta_{it}\\
&= \frac{\sigma_{imt}}{\sigma_{mt}^2}\ \sigma_{mt}\ \varepsilon_{mt} + \eta_{it}\\
&= \frac{\sigma_{imt}}{\sigma_{mt}}\ \varepsilon_{mt} + \eta_{it}\\
&= \rho_{it}\ \sigma_{it}\ \varepsilon_{mt} + \eta_{it}\\
&= \rho_{it}\ \sigma_{it}\ \varepsilon_{mt} + \sigma_{\eta_{it}}\ \xi_{it}\ . && \text{(A5)}
\end{aligned}
$$

Then we compute the bank variance:

$$
V(r_{it}) = \sigma_{it}^2 = \sigma_{it}^2\ \rho_{it}^2 + \sigma_{\eta_{it}}^2 \tag{A6}
$$

The first part of Equation (**A6**) corresponds to the systematic risk whereas the second part is the idiosyncratic risk. Hence, we extract the idiosyncratic risk when we substract the systematic risk from the total risk of bank i as we have in the following equation:

$$
\begin{aligned}
&\Rightarrow\quad \sigma_{\eta_{it}}^2 = \sigma_{it}^2\ [1-\rho_{it}^2] && \text{(A7)}\\
&\Rightarrow\quad \sigma_{\eta_{it}} = \sigma_{it}\sqrt{1-\rho_{it}^2} && \text{(A8)}
\end{aligned}
$$

Thus the bank return becomes:

$$
\begin{aligned}
r_{it} &= \rho_{it}\ \sigma_{it}\ \varepsilon_{mt} + \sigma_{it}\sqrt{1-\rho_{it}^2}\ \xi_{it}\\
&= \sigma_{it}\ (\rho_{it}\ \varepsilon_{mt} + \sqrt{1-\rho_{it}^2}\ \xi_{it}) && \text{(A9)}
\end{aligned}
$$

Finally, we obtain the exact same framework as Brownlees and Engle (2011):

$$
\begin{aligned}
r_{mt} &= \sigma_{mt}\ \varepsilon_{mt}\ , && \text{(A10)}\\
r_{it} &= \sigma_{it}\ \rho_{it}\ \varepsilon_{mt}\ +\ \sigma_{it}\ \sqrt{1-\rho_{it}^2}\ \xi_{it}\ , && \text{(A11)}\\
(\varepsilon_{mt},\ \xi_{it}) &\sim D\ . && \text{(A12)}
\end{aligned}
$$

where $r_{mt} \perp \xi_{it}$, the process $\nu_t = (\varepsilon_{mt}, \xi_{it})'$ is *i.i.d.* and satisfies $\mathbb{E}(\nu_t) = 0$ and $\mathbb{E}(\nu_t \nu_t') = I_2$, a two-by-two identity matrix, and D is a bivariate distribution of these standardized innovations, which is assumed to be unknown.

Appendix B: The MES Formula

According to Appendix A and the definition of the expected shortfall of a *particular market* return:

$$ES_{mt}(\alpha) = \mathbb{E}_{t-1}(r_{mt} \mid r_{mt} < C) = \sum_{i=1}^{N} w_{it}^{S}\ \mathbb{E}_{t-1}(r_{it} \mid r_{mt} < C)\ , \tag{B1}$$

where we consider N firms in a *particular system*, noted S, and we denote r_{it} the return of firm i at time t. Similarly, the market return of this *particular system* is the value-weighted average of all firm returns inuding in this *particular system*, $r_{mt} = \sum_{i=1}^{N} w_{it}^{S}\ r_{it}$, where w_{it}^{S} denotes the relative market capitalization of firm i within this *particular system*.

According to Scaillet (2004), we have the following expression for the MES of a given specific event C on the market return for a level of risk α can be expressed as:

$$\begin{aligned}
MES_{it}(\alpha) &= \frac{\partial ES_{mt}(C)}{\partial w_{it}^{S}} = \mathbb{E}_{t-1}(r_{it} \mid r_{mt} < C) \\
&= \sigma_{it}\ \mathbb{E}_{t-1}\left(\varepsilon_{it} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right) \\
&= \sigma_{it}\ \mathbb{E}_{t-1}\left(\rho_{it}\ \varepsilon_{mt} + \sqrt{1-\rho_{it}^{2}}\xi_{it} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right)\ .
\end{aligned} \tag{B2}$$

And we have:

$$\begin{aligned}
MES_{it}(\alpha) &= \sigma_{it}\ \rho_{it}\ \mathbb{E}_{t-1}\left(\varepsilon_{mt} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right) \\
&\quad + \sigma_{it}\ \sqrt{1-\rho_{it}^{2}}\ \mathbb{E}_{t-1}\left(\xi_{it} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right)\ .
\end{aligned} \tag{B3}$$

In our application, $C = VaR_{mt}(\alpha)$, the expected shortfall of the market is:

$$ES_{mt}(\alpha) = \mathbb{E}_{t-1}(r_{mt} \mid r_{mt} < VaR_{mt}(\alpha))\ . \tag{B4}$$

and the MES is equal to:

$$\begin{aligned}
MES_{it}(\alpha) &= \sigma_{it}\ \rho_{it}\ \mathbb{E}_{t-1}\left(\varepsilon_{mt} \mid \varepsilon_{mt} < \frac{VaR_{mt}(\alpha)}{\sigma_{mt}}\right) \\
&\quad + \sigma_{it}\ \sqrt{1-\rho_{it}^{2}}\ \mathbb{E}_{t-1}\left(\xi_{it} \mid \varepsilon_{mt} < \frac{VaR_{mt}(\alpha)}{\sigma_{mt}}\right)\ .
\end{aligned} \tag{B5}$$

Caporin and de Magistris (2012) show that Equation (**B5**) only holds as an approximation with log returns.

Appendix C: The CoVaR Formula

The CoVaR corresponds to the VaR of a *particular market* obtained conditional on some event $\mathbb{C}(r_{it})$ observed for firm i belongs to this *particular system*:

$$\Pr\left(r_{mt} \leq CoVaR_t^{m|\mathbb{C}(r_{it})} \;\middle|\; \mathbb{C}(r_{it})\right) = \alpha \ . \tag{C1}$$

where α is the level of risk of this conditional probability.

Given the simple bivariate process describes in Appendix A as:

$$\begin{aligned} r_{mt} &= \sigma_{mt}\ \epsilon_{mt}\ , && \text{(C2)} \\ r_{it} &= \sigma_{it}\ \epsilon_{it}\ , && \text{(C3)} \end{aligned}$$

where $(r_{mt}, r_{it}) \sim D$, D is a bivariate distribution with $\nu_t = (r_{mt}, r_{it})'$ satisfies $\mathbb{E}(\nu_t) = 0$, and $\mathbb{E}(\nu_t \nu_t') = H_t = \begin{pmatrix} \sigma_{mt}^2 & \rho_{it}\ \sigma_{it}\ \sigma_{mt} \\ \rho_{it}\ \sigma_{it}\ \sigma_{mt} & \sigma_{it}^2 \end{pmatrix}$, the conditional variance/covariance matrices.If the conditional mean function of r_{mt} is linear in r_{it}, the first two conditional moments of r_{mt} given $r_{it} = c$ can be expressed by the following:

$$\begin{aligned} \mathbb{E}(r_{mt} \mid r_{it} = c) &= \frac{cov(r_{mt}, r_{it})}{\sigma_{it}^2} \times c \\ &= \frac{\rho_{it}\ \sigma_{it}\ \sigma_{mt}}{\sigma_{it}^2} \times c \\ &= \frac{\rho_{it}\ \sigma_{mt}}{\sigma_{it}} \times c\ , && \text{(C4)} \end{aligned}$$

$$\begin{aligned} \mathbb{V}(r_{mt} \mid r_{it}) &= \mathbb{V}(r_{mt}) - \left[1 - \rho_{it}^2\right] \\ &= \sigma_{mt}^2\ \left(1 - \rho_{it}^2\right)\ . && \text{(C5)} \end{aligned}$$

We standardized this *particular market* return and we have:

$$\Pr\left(\frac{r_{mt} - \frac{\rho_{it}\ \sigma_{mt}}{\sigma_{it}} \times r_{it}}{\sigma_{mt}\ \sqrt{(1-\rho_{it}^2)}} \leq \frac{CoVaR_{it}^{m|\mathbb{C}(r_{it})} - \frac{\rho_{it}\ \sigma_{mt}}{\sigma_{it}} \times r_{it}}{\sigma_{mt}\ \sqrt{(1-\rho_{it}^2)}} \;\middle|\; \mathbb{C}(r_{it})\right) = \alpha\ . \tag{C6}$$

Thus, when bank i is in distress we have $\mathbb{C}(r_{it}) : r_{it} = VaR_{it}(\alpha)$, Equation (C6) is expressed as:

$$CoVaR_{it}^{m|r_{it}=VaR_{it}(\alpha)} = \frac{\rho_{it}\ \sigma_{mt}}{\sigma_{it}} \times VaR_{it}(\alpha) + \left(\sigma_{mt}\ \sqrt{(1-\rho_{it}^2)}\right)\ G^{-1}(\alpha)\ , \tag{C7}$$

where $G(.)$ the conditional distribution of r_{mt}.

When the bank i is just fine, $\mathbb{C}(r_{it}) : r_{it} = Median(r_{it})$, Equation (C6) becomes:

$$\begin{aligned} CoVaR_{it}^{m|r_{it}=Median_i} &= \frac{\rho_{it}\ \sigma_{mt}}{\sigma_{it}} \times Median(r_{it}) + \left(\sigma_{mt}\ \sqrt{(1-\rho_{it}^2)}\right)\ G^{-1}(\alpha) \\ &= \frac{\rho_{it}\ \sigma_{mt}}{\sigma_{it}} \times VaR_{it}(0.5) + \left(\sigma_{mt}\ \sqrt{(1-\rho_{it}^2)}\right)\ G^{-1}(\alpha)\ . && \text{(C8)} \end{aligned}$$

Finally, the systemic contribution of a given bank i to the risk of a *particular system* is equal to

$$\begin{aligned} \Delta CoVaR_{it} &= CoVaR_{it}^{m|r_{it}=VaR_{it}(\alpha)} - CoVaR_{it}^{m|r_{it}=Median(r_{it})} \\ & \frac{\rho_{it}\ \sigma_{mt}}{\sigma_{it}} \times VaR_{it}(\alpha) + \left(\sigma_{mt}\ \sqrt{(1-\rho_{it}^2)}\right)\ G^{-1}(\alpha) \\ & \quad - \frac{\rho_{it}\ \sigma_{mt}}{\sigma_{it}} \times VaR_{it}(0.5) + \left(\sigma_{mt}\ \sqrt{(1-\rho_{it}^2)}\right)\ G^{-1}(\alpha) \\ \Delta CoVaR_{it} &= \frac{\rho_{it}\ \sigma_{mt}}{\sigma_{it}}\ \left[VaR_{it}(\alpha) - VaR_{it}(0.5)\right]\ . && \text{(C9)} \end{aligned}$$

where the linear projection coefficient of *a particular market* return on the firm return is equal to $\gamma_{it} = \rho_{it}\ \sigma_{mt}\ /\ \sigma_{it}$. When we assume a location-scale distribution for r_{it}, we have $VaR_{it}\,(\alpha) = \sigma_{it}$ $F^{-1}\,(\alpha)$, with $F(.)$ the marginal distribution of ϵ_{it} (this pdf is symetric around 0) and $F^{-1}\,(\alpha)$ is the empirical quantile of the standardized innovations of r_{it}. The proportionality coefficient corresponds to $\gamma_{it} = \rho_{it}\ \sigma_{mt}$.

Appendix D: Dataset

Tickers and Company Names per Country

Austria (3)	
EBS	ERSTE GROUP BANK
OBS	OBERBANK AG
RBI	RAIFFEISEN BANK INTERNATIONAL
Belgium (3)	
BNB	BANQUE NATIONALE DE BELGIQUE
DEXB	DEXIA
KBC	KBC GRP
Germany (3)	
CBK	COMMERZBANK
DBK	DEUTSCHE BANK
DPB	DEUTSCHE POSTBANK
Spain (8)	
BCIV	BANCA CIVICA
BKIA	BANKIA
BKT	BANKINTER
BBVA	BCO BILBAO VIZCAYA ARGENTARIA
POP	BCO POPULAR ESPANOL
SAB	BCO SABADELL
SAN	BCO SANTANDER
CABK	CAIXABANK
Finland (1)	
POH1S	POHJOLA BANK
France (4)	
BNP	BNP PARIBAS
ACA	CREDIT AGRICOLE
GLE	GRP SOCIETE GENERALE
KN	NATIXIS
Greece (6)	
ALPHA	ALPHA BANK
TATT	BANK OF ATTICA
TELL	BANK OF GREECE
EUROB	EFG EUROBANK ERGASIAS
ETE	NATIONAL BANK OF GREECE
TPEIR	PIRAEUS BANK
Ireland (1)	
BIR	BANK OF IRELAND
Italy (12)	
CRG	BCA CARIGE
BMPS	BCA MONTE DEI PASCHI DI SIENA
PMI	BCA POPOLARE DI MILANO
BPSO	BCA POPOLARE DI SONDRIO
BPE	BCA POPOLARE EMILIA ROMAGNA
BP	BCO POPOLARE
CB	CREDITO BERGAMASCO
CE	CREDITO EMILIANO
CVAL	CREDITO VALTELLINESE
ISP	INTESA SANPAOLO
UBI	UBI BCA
UCG	UNICREDIT
Portugal (3)	
BPI	BCO BPI
BCP	BCO COMERCIAL PORTUGUES
BES	BCO ESPIRITO SANTO

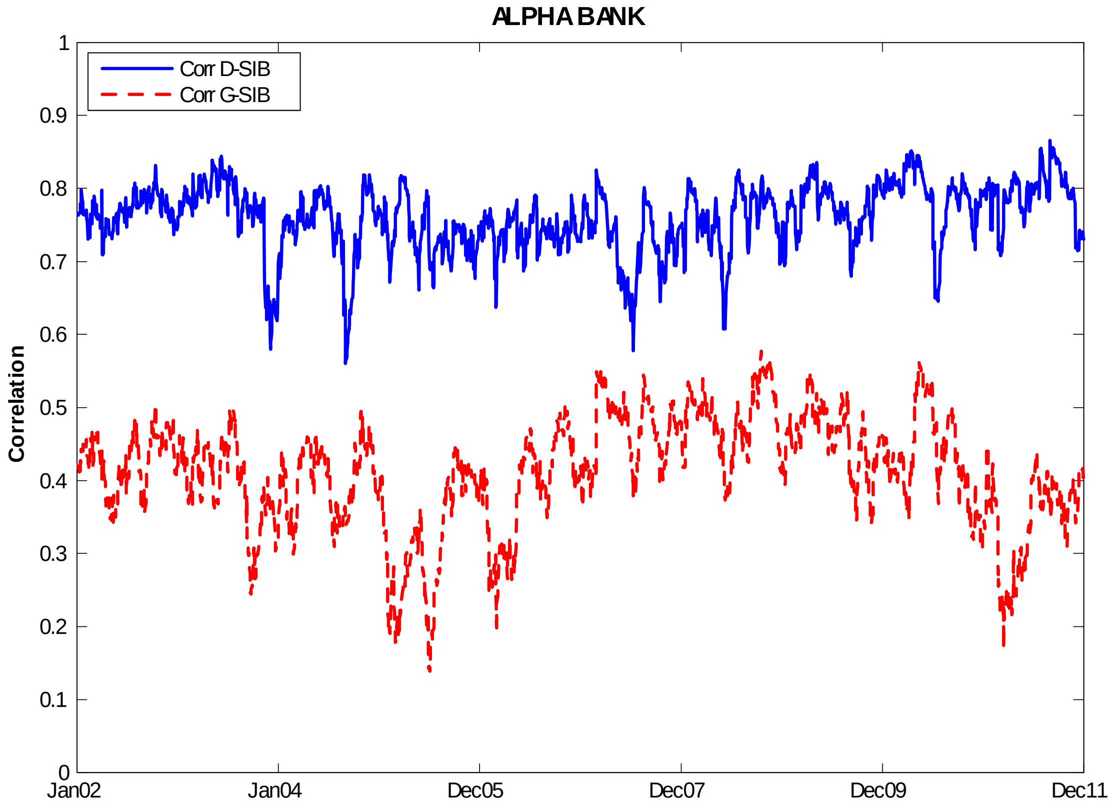

Figure 1: This figure displays the conditional correlation of Alpha Bank return with its domestic index (blue solid line) and with its eurozone index (red dashed line). The estimation period is from 01/02/2002 to 12/30/2011.

Table 1: Systemic Risk Rankings: G-SIBs

December 31, 2009		
	G-SIBs	
FSB	SRISK	Liability
Bank of America	Royal Bank of Scotland	BNP Paribas
Bank of China $^{\mp}$ $^{\pm}$	BNP Paribas	Royal Bank of Scotland
Bank of New York Mellon $^{\mp}$ $^{\pm}$	Deutsche Bank	Deutsche Bank
Banque Populaire CdE $^{\mp}$ $^{\pm}$	Group Crédit Agricole	HSBC
Barclays	Barclays	Group Crédit Agricole
BNP Paribas	Mitsubishi UFJ FG	Mitsubishi UFJ FG
Citigroup	Mizuho FG	Barclays
Commerzbank	ING Bank	Bank of America
Credit Suisse	Lloyds Banking Group	JP Morgan Chase
Deutsche Bank	Commerzbank	Citigroup
Dexia	Citigroup	Mizuho FG
Goldman Sachs $^{\mp}$	Société Générale	ING Bank
Group Crédit Agricole	UBS	Lloyds Banking Group
HSBC	Sumitomo Mitsui FG	Santander
ING Bank	HSBC	Société Générale
JP Morgan Chase	Unicredit Group	UBS
Lloyds Banking Group	Bank of America	Unicredit Group
Mitsubishi UFJ FG	Dexia	Commerzbank
Mizuho FG	Santander	Sumitomo Mitsui FG
Morgan Stanley	Credit Suisse	Wells Fargo $^{+}$
Nordea	JP Morgan Chase	Credit Suisse
Royal Bank of Scotland	Natixis $^{\mp}$ $^{+}$	Intesa Sanpaolo SpA $^{\pm}$
Santander	Danske Bank A/S $^{\mp}$	Dexia
Société Générale	Morgan Stanley	Goldman Sachs $^{+}$
State Street $^{\pm}$	Intesa Sanpaolo SpA $^{\mp}$	Banco Bilbao V. A. $^{\pm}$
Sumitomo Mitsui FG	Nordea	Morgan Stanley
UBS	KBC Groep NV $^{\mp}$ $^{+}$	Nordea
Unicredit Group	Banco Bilbao V. A. $^{\mp}$	Danske Bank A/S $^{\pm}$
Wells Fargo $^{\mp}$	Resona Holdings $^{\mp}$ $^{+}$	National Australia Bank $^{\pm}$ $^{+}$

Notes: Source: FSB and V-Lab website. In the first column, labeled FSB, we report the list in alphabetic order of the 29 G-SIBs identified according to the methodology set out in the BCBS document “Global systemically important banks: Assessment methodology and the additional loss absorbency requirement”, using data as of end-2009. To be fair we report, in the second column labeled SRISK, the publicly avalaible ranking (avalaible on the VLab website) of the first 29 G-SIBs identified by the SRISK measure for December 31, 2009. In the third column, labeled Liability, we disclose the banking based on the total amount of liabilities for December 31, 2009. The following $^{\mp}$ tags banks which are not identified by FSB and SRISK in the same time whereas $^{\mp}$ tags banks which are not jointly identified by FSB and Liability in the same time. Finally $^{+}$ tags banks which are not identified by SRISK and Liability in the same time.

Table 2: Systemic Risk Rankings: SRISK Ranking per country and over the eurozone

December 30, 2011		
$SRISK^D$	$SRISK^G$	$SRISK^D$ - $SRISK^G$
	Austria	
15-ERSTE GROUP BANK	15-EBS	5-ERSTE GROUP BANK (407.296)
20-RAIFFEISEN BANK INTERNATIONAL	20-RBI	7-RAIFFEISEN BANK INTERNATIONAL (222.588)
44-OBERBANK AG	44-OBS	36-OBERBANK AG (0.060)
	Belgium	
10-DEXIA	10-DEXB	37-BANQUE NATIONALE DE BELGIQUE (-2.070)
12-KBC GRP	BE-12-KBC	39-KBC GRP (-7.979)
22-BANQUE NATIONALE DE BELGIQUE	22-BNB	40-DEXIA (-21.247)
	Germany	
1-DEUTSCHE BANK	1-DBK	42-DEUTSCHE POSTBANK (-86.614)
7-COMMERZBANK	7-CBK	43-COMMERZBANK (-153.113)
18-DEUTSCHE POSTBANK	18-DPB	44-DEUTSCHE BANK (-236.167)
	Spain	
5-BCO SANTANDER	5-SAN	1-BCO SANTANDER (964.948)
11-BCO BILBAO VIZCAYA ARGENTARIA	11-BBVA	3-BCO BILBAO VIZCAYA ARGENTARIA (799.664)
13-BANKIA	13-BKIA	9-BCO SABADELL (141.655)
17-CAIXABANK	17-CABK	11-BCO POPULAR ESPANOL (113.238)
25-BCO POPULAR ESPANOL	25-POP	12-BANKIA (109.813)
29-BCO SABADELL	29-SAB	17-CAIXABANK (77.718)
30-BANCA CIVICA	30-BCIV	25-BANKINTER (28.431)
35-BANKINTER	35-BKT	41-BANCA CIVICA (-32.651)
	Finland	
37-POHJOLA BANK	37-POH1S	35-POHJOLA BANK (5.931)
	France	
2-BNP PARIBAS	2-BNP	19-GRP SOCIETE GENERALE (49.192)
3-CREDIT AGRICOLE	3-ACA	26-BNP PARIBAS (26.461)
4-GRP SOCIETE GENERALE	4-GLE	28-CREDIT AGRICOLE (21.941)
9-NATIXIS	9-KN	29-NATIXIS (21.184)
	Greece	
16-BANK OF GREECE	16-TELL	6-NATIONAL BANK OF GREECE (254.232)
24-NATIONAL BANK OF GREECE	24-ETE	21-ALPHA BANK (40.946)
27-EFG EUROBANK ERGASIAS	27-EUROB	24-EFG EUROBANK ERGASIAS (37.124)
31-ALPHA BANK	31-ALPHA	30-BANK OF GREECE (16.792)
32-PIRAEUS BANK	32-TPEIR	33-BANK OF ATTICA (10.208)
42-BANK OF ATTICA	42-TATT	34-PIRAEUS BANK (6.725)
	Ireland	
19-BANK OF IRELAND	19-BIR	10-BANK OF IRELAND (139.770)
	Italy	
6-UNICREDIT	6-UCG	2-INTESA SANPAOLO (905.941)
8-INTESA SANPAOLO	8-ISP	4-UNICREDIT (707.218)
14-BCA MONTE DEI PASCHI DI SIENA	14-BMPS	13-BCA MONTE DEI PASCHI DI SIENA (106.611)
21-BCO POPOLARE	21-BP	14-BCO POPOLARE (97.396)
23-UBI BCA	23-UBI	16-BCA CARIGE (85.101)
33-BCA POPOLARE EMILIA ROMAGNA	33-BPE	18-UBI BCA (56.183)
34-BCA POPOLARE DI MILANO	34-PMI	20-BCA POPOLARE EMILIA ROMAGNA (41.789)
38-BCA CARIGE	38-CRG	22-CREDITO EMILIANO (38.020)
39-CREDITO EMILIANO	39-CE	23-BCA POPOLARE DI SONDRIO (37.870)
40-CREDITO VALTELLINESE	40-CVAL	31-CREDITO VALTELLINESE (12.694)
41-BCA POPOLARE DI SONDRIO	41-BPSO	32-BCA POPOLARE DI MILANO (12.539)
43-CREDITO BERGAMASCO	43-CB	38-CREDITO BERGAMASCO (-4.300)
	Portugal	
26-BCO COMERCIAL PORTUGUES	26-BCP	8-BCO ESPIRITO SANTO (208.749)
28-BCO ESPIRITO SANTO	28-BES	15-BCO COMERCIAL PORTUGUES (95.944)
36-BCO BPI	36-BPI	27-BCO BPI (25.924)

Notes: This table displays in the first column, the ranking of banks from our sample within their country based on $SRISK^D$, the ranking based on $SRISK^G$ in the second column, listed from most to least risky. The third column reports the country ranking according to the difference between the $SRISK^D$ and the $SRISK^G$, the result of this substraction is reported in parenthesis and expressed in millions of Euro. The associated number corresponds to the rank of this bank in the eurozone. The ranking is for December 30, 2011.

Table 3: Systemic Risk Rankings: CoVaR Ranking per country and over the eurozone

December 30, 2011	
ΔCoVaR^D	ΔCoVaR^G
Austria	
24-ERSTE GROUP BANK	19-ERSTE GROUP BANK
29-RAIFFEISEN BANK INTERNATIONAL	20-RAIFFEISEN BANK INTERNATIONAL
44-OBERBANK AG	44-OBERBANK AG
Belgium	
39-BANQUE NATIONALE DE BELGIQUE	25-DEXIA
40-KBC GRP	30-BANQUE NATIONALE DE BELGIQUE
41-DEXIA	31-KBC GRP
Germany	
10-DEUTSCHE BANK	5-DEUTSCHE BANK
27-COMMERZBANK	18-COMMERZBANK
43-DEUTSCHE POSTBANK	40-DEUTSCHE POSTBANK
Spain	
3-BCO SANTANDER	1-BCO SANTANDER
4-BCO BILBAO VIZCAYA ARGENTARIA	2-BCO BILBAO VIZCAYA ARGENTARIA
9-BCO POPULAR ESPANOL	7-BCO POPULAR ESPANOL
16-BANKINTER	12-CAIXABANK
19-CAIXABANK	15-BANKINTER
25-BANCA CIVICA	16-BANCA CIVICA
31-BCO SABADELL	33-BCO SABADELL
36-BANKIA	37-BANKIA
Finland	
5-POHJOLA BANK	6-POHJOLA BANK
France	
11-BNP PARIBAS	3-BNP PARIBAS
12-GRP SOCIETE GENERALE	4-GRP SOCIETE GENERALE
15-CREDIT AGRICOLE	8-CREDIT AGRICOLE
23-NATIXIS	11-NATIXIS
Greece	
14-NATIONAL BANK OF GREECE	32-NATIONAL BANK OF GREECE
22-ALPHA BANK	34-ALPHA BANK
26-EFG EUROBANK ERGASIAS	35-PIRAEUS BANK
32-PIRAEUS BANK	39-EFG EUROBANK ERGASIAS
37-BANK OF ATTICA	42-BANK OF GREECE
38-BANK OF GREECE	43-BANK OF ATTICA
Ireland	
34-BANK OF IRELAND	22-BANK OF IRELAND
Italy	
1-INTESA SANPAOLO	9-INTESA SANPAOLO
2-UNICREDIT	10-UNICREDIT
6-BCO POPOLARE	13-UBI BCA
7-BCA MONTE DEI PASCHI DI SIENA	14-BCA MONTE DEI PASCHI DI SIENA
8-UBI BCA	17-BCO POPOLARE
13-CREDITO EMILIANO	21-CREDITO EMILIANO
17-BCA POPOLARE DI MILANO	24-BCA POPOLARE DI MILANO
18-BCA POPOLARE EMILIA ROMAGNA	26-BCA CARIGE
20-CREDITO VALTELLINESE	27-BCA POPOLARE EMILIA ROMAGNA
21-BCA CARIGE	28-CREDITO VALTELLINESE
28-BCA POPOLARE DI SONDRIO	29-BCA POPOLARE DI SONDRIO
42-CREDITO BERGAMASCO	41-CREDITO BERGAMASCO
Portugal	
31-BCO BPI	23-BCO BPI
33-BCO COMERCIAL PORTUGUES	36-BCO ESPIRITO SANTO
36-BCO ESPIRITO SANTO	38-BCO COMERCIAL PORTUGUES

Notes: This table displays in the first column, the ranking of banks from our sample within their country based on ΔCoVaR^D, and the ranking based on ΔCoVaR^G in the second column, listed from most to least risky. The associated number corresponds to the rank of this bank in the eurozone. The ranking is for December 30, 2011.

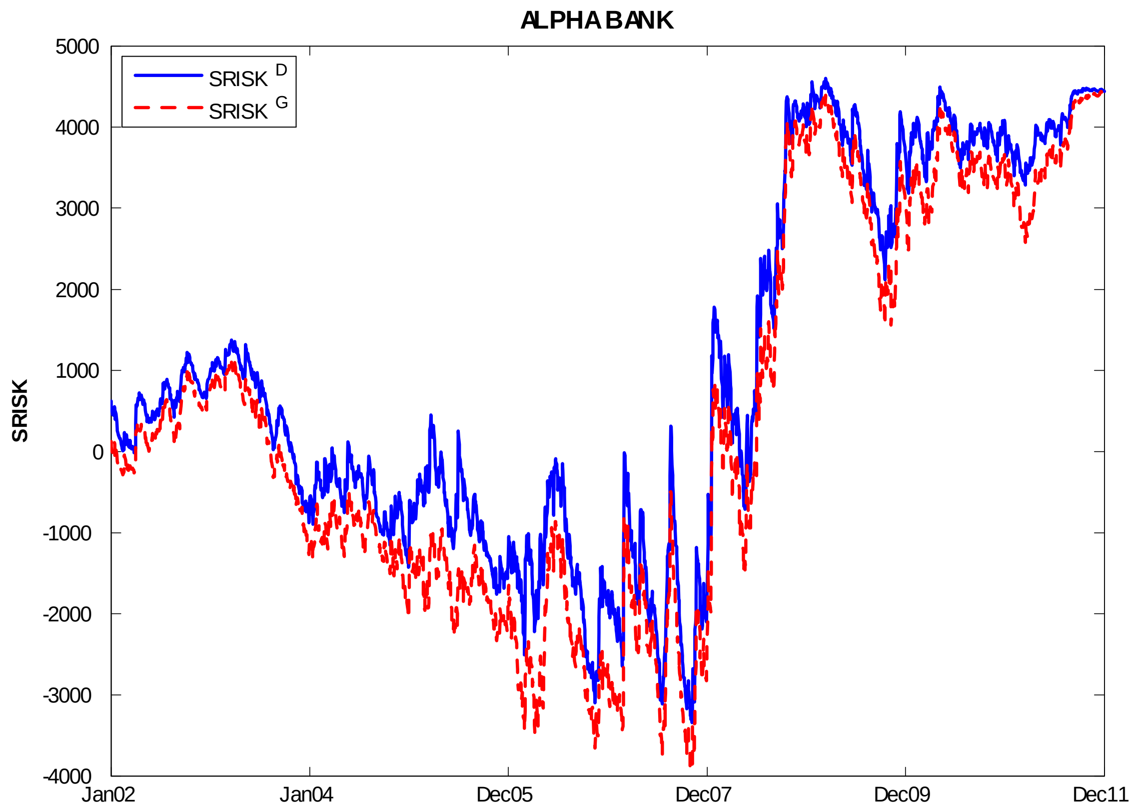

Figure 2: This figure displays the SRISK^D (blue solid line) and of the SRISK^G (red dashed line) of Alpha Bank. The estimation period is from 02/01/2002 to 12/30/2011.

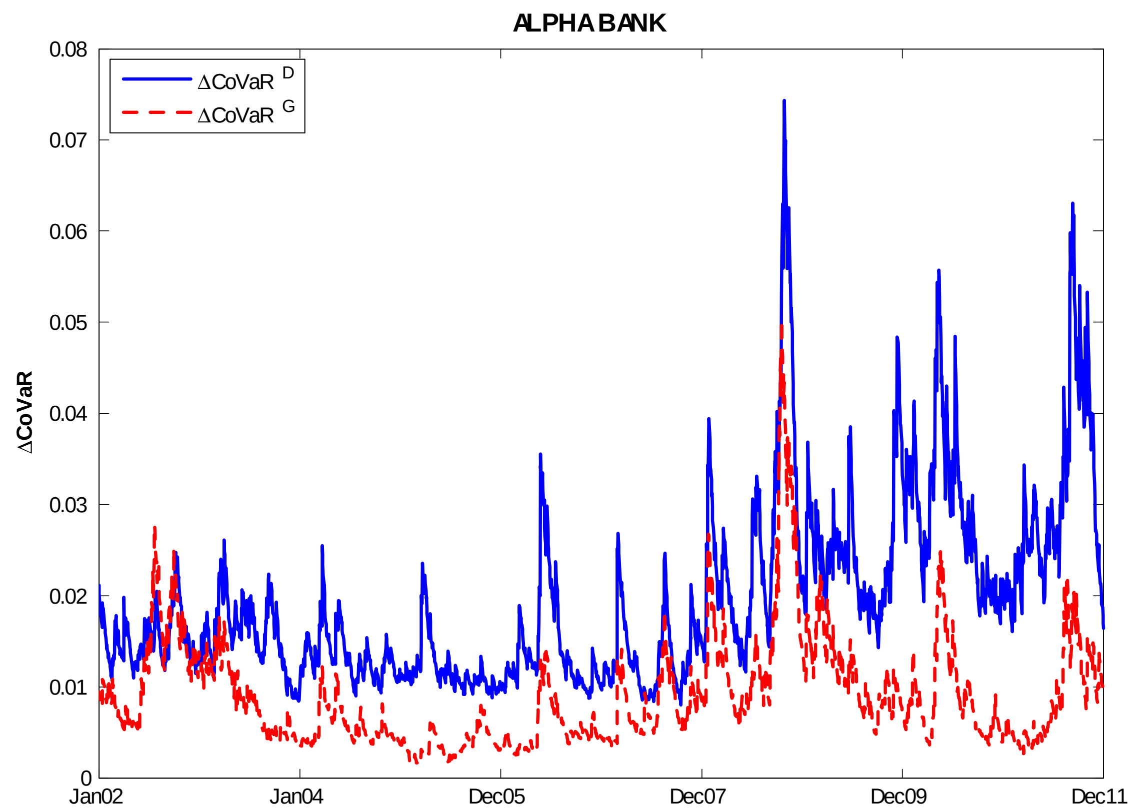

Figure 3: This figure displays the ΔCoVaR^D (blue solid line) and the ΔCoVaR^G (red dashed line) of Alpha Bank. The estimation period is from 01/02/2002 to 12/30/2011.