Are Market-Based Measures of Global Systemic Importance of Financial Institutions Useful to Regulators and Supervisors?

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Abstract

We analyze whether four market-based measures of the global systemic importance of financial institutions offer early warning signals during three financial crises. The tests based on the 2007/2008 crisis show that only one measure (Δ CoVaR) consistently adds predictive power to conventional early warning models. However, the additional predictive power remains small and it is not normally confirmed for the Asian and the 1998 crises. We conclude that it is problematic to identify a market-based measure of systemic importance that remains valid across crises with different features. The same criticism also applies to several conventional proxies of systemic importance, of which size is the most consistent performer.

1 INTRODUCTION

The recent global financial crisis has highlighted the sheer scale of the negative externalities that might result from instabilities in the financial industry. Numerous countries have been forced to rely on very significant amounts of public funds to bailout financial institutions and have suffered from a dramatic slowdown in economic growth and social unrest (Dieckmann and Plank 2012, Ötker-Robe and Podpiera 2013, Veronesi and Zingales 2010). While there seems to be a plurality of causes of this global turmoil (Allen and Carletti 2010, Brunnermeier 2009, Purnanandam 2011), it is widely believed that the inadequacy of the financial regulatory framework has exacerbated the effects of the crisis (Acharya et al. 2009, Houston, Lin and Ma 2012).¹ Therefore, it is not surprising that one key response to the global financial crisis has been the design of a new regulatory framework that aims to enhance the resilience of both individual banks and the whole financial system to shocks (Basel Committee 2011, Keys et al. 2009).

A crucial component of the new regulatory framework is a stricter regime for systemically important financial institutions. These are conventionally defined as institutions "whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity" (Financial Stability Board 2011). The regulatory focus, given the worldwide negative effects produced by the defaults of large and international financial institutions during the crisis, is in particular on "Global Systemically Important Financial Institutions" (GSIFIs), that have the potential to generate negative effects across different countries (Basel Committee 2011, Financial Stability Board 2009).ⁱⁱ A potential support to the regulatory and supervisory activity in dealing with global systemically important financial institutions might come from the numerous market based measures of systemic importance that have been mostly proposed in the aftermath of the global crisis (see for instance Acharya, Engle, and Richardson 2012, Adrian and Brunnermeier 2011, Brownlees and Engle 2012, Huang, Zhou, and Zhu 2012, Lopez-Espinosa et al. 2012, Puzanova and Düllmann 2012).

The potential use of the market-based measures by regulators and supervisors varies with the theoretical perspectives that they adopt on how to define how much each financial institution is responsible for financial instability. More specifically, some of these measures focus on the implications of a financial institution's distress on the rest of the financial system and are then potentially useful to control ex-post systemic damages that might arise from distress conditions at the firm level (see for instance the measures in Adrian and Brunnermeier 2011 and Lopez-Espinosa et al. 2012). Hence, they can be regulatory tools to guide timely actions in periods of systemic crises. Other measures emphasize the degree of vulnerability of a financial institution in the case of a systemic shock (see Acharya, Engle, and Richardson 2012, Brownlees and Engle 2012, Huang, Zhou, and Zhu 2012, Puzanova and Düllmann 2012, and Lehar 2005). It follows that they are supposed to be useful when the purpose of supervisors is to design ex-ante interventions that help to reduce the number of defaults in the financial industry when a systemic crisis materializes. In spite of the highlighted theoretical differences, all types of measures have to satisfy a key requirement if they aim at being incorporated as valuable tools within the regulatory and supervisory framework; namely, they have to offer information that is not already present in more conventional risk proxies. In other words, they have to signal something not already known to regulators and supervisors on the basis of conventional drivers of systemic risk that are available at the firm level.

In this paper, we assess whether the above key requirement is satisfied by four market-based measures of systemic importance that we apply to a global setting. More precisely, we conduct a comparative assessment for an international sample of large financial institutions of the additional early warning signals of systemic importance that these market-based measures might offer to regulators and supervisors before the eruption of a financial crisis. In our empirical setting, therefore, the incorporation within the regulatory and supervisory framework of these market-based measures is justified by their ability to offer early warning signals on systemic importance that are not already provided by simpler firm characteristics that have been conventionally linked to systemic risk.

To conduct our analysis, we employ four measures of systemic importance that have been recently proposed in the literature that we compute for an international sample of large financial institutions representing, during the analyzed period, on average around 80% of the total assets and market capitalization of the worldwide listed financial companies. More specifically, we select two types of measures that differ in their possible use by regulators and supervisors. The first type includes $\Delta CoVaR$ as proposed by Adrian and Brunnermeir (2011) and its variant ΔA _CoVaR suggested by Lopez-Espinosa et al. (2012) and captures risk-spillovers from a financial institution to the rest of the financial system. Hence, these measures are supposed to signal the potential systemic damages associated with distress conditions at the firm level so as to help timely regulatory interventions during systemic crises. The second type includes the SRISK indicator proposed by Brownlees and Engle (2012) and further developed by Acharya, Engle, and Richardson (2012) and the contribution to the variance of the systemic Expected shortfall (EXSHORT) as in Lehar (2005). These measures quantify the degree of vulnerability of financial institutions in the presence of a systemic shock and consequently they are expected to be useful when the purpose is to design ex-ante supervisory interventions to reduce the number of defaults from a systemic shock. More generally, these four measures share two attributes that are desirable to regulators. First, they can be computed with readily available data (as they simply rely on market and accounting information) that can be obtained over a long time period. Second, in contrast to other methodologies (see for instance, Drehmann and Tarashev 2011b), their computation does not impose any restriction in terms of sample size. Therefore, these measures can be easily computed for our extensive worldwide sample of large financial institutions including banks, insurance companies and other financial institutions - selected over the period from 1992 to 2006.

We start our empirical analysis by using the global financial crisis as a laboratory to test whether the predictive performance of an early warning model (where different measures of the *realized* systemic importance of financial institutions during this crisis are used as the dependent variable) based on firm characteristics improves when one of the market-based measures of global systemic importance is included as an additional explanatory variable. We define the *realized* systemic importance during the crisis on the basis of measures that mostly capture the potential systemic damages that can derive from an insolvency condition at the firm level and with measures of degree of vulnerability of a financial institution to the exposure of a systemic shock. The first proxies of *realized* systemic importance are expected to be primarily predicted by Δ CoVaR and Δ A_CoVaR, while the second set of measures of the *realized* systemic importance should be predicted, in particular, by SRISK and EXSHORT.

The results of these tests identify Δ CoVaR as the only market-based measure that significantly explains the different notions of *realized* systemic importance computed over the global financial crisis event. Δ CoVaR, therefore, offers early warning signals not only of the potential ex-post systemic damages that can arise from financial institution distress, as implied by its theoretical foundations, but also in terms of the vulnerability of these institutions to the occurrence of a systemic shock. Overall, the additional predictive power remains, however, rather small compared to more conventional firm characteristics, and in particular to firm size.

The other three market-based measures of systemic importance show generally much less additional predictive power when compared to firm characteristics. The asymmetric version of the conventional Δ CoVaR only occasionally demonstrates some predictive power, while SRISK and EXSHORT show some significant predictive ability only when the focus is on a specific definition of vulnerability; that is, the vulnerability of financial institutions in terms of capital shortfall. By contrast, they do not show any predictive power when the vulnerability is based on the decline in market value suffered during the crisis. These conclusions hold when the analysis is limited to the sub-sample of banks, when the prediction models are extended with the addition of further firm characteristics and when we follow Acharya, Engle, and Pierret (2014) and Engle, Jondeau, and Rockinger (2014) to control for the potential distortions generated on our results by the use of the International Financial Reporting Standards (IFRS) by some of the financial institutions in our sample.

Next, we conduct a second set of tests with the purpose of evaluating whether the predictive performances of the selected market-based measures of systemic importance during the global crisis, and in particular the ability of Δ CoVaR to enter (all prediction models) with a significant coefficient, reflect a general economic rationale or are the result of an optimal methodology design that captures the specificities of the global crisis. This concern is motivated by the fact that three out the four market-based measures we analyze in this study have been proposed in the aftermath of the global financial crisis with an obvious focus on those aspects of systemic risk that have emerged as pivotal during this crisis.

We, therefore, evaluate whether these market-measures show similar predictive performances as for the global financial crisis when we focus on other crisis episodes by employing a similar empirical strategy. We select two crises that occurred in the nineties that are normally recognized as having global relevance and that have often been at the core of previous empirical studies on systemic risk and bank performance (Fahlenbrach, Prilmeier, and Stulz 2012, Sedunov 2012, Weiß, Bonstandzic, and Neumann 2014): the Asian financial crisis that erupted in the second half of 1997 and the Russian and the Long Term Capital Management (LTMC) crisis that started in the second half of 1998. Notably, in our sample the Asian crisis has a significantly milder impact than the 1998 crisis and this allows us to also evaluate whether the severity of a crisis plays any role in the predictive power of the chosen market-based measures of systemic importance.

In these additional tests, we find a very low degree of consistency compared to the results for the global financial crisis. Δ CoVaR does not confirm its ability to consistently predict different notions of the *realized* degree of systemic importance, suggesting that some of its predictive power during the global crisis can be indeed explained by the specificities of this crisis. Furthermore, all measures show very disappointing predictive power in the majority of the tests on the 1998 crisis; namely, they do not offer particular support to regulators and supervisors especially in the crisis event that appears closer to the recent crisis in terms of its negative impact on the financial institutions included in our sample. Overall, putting together the results of the three crisis tests we observe that some degree of consistency only emerges when the focus is on the prediction of a narrow definition of the vulnerability of financial institutions in terms of capital adequacy. In this respect a key role is played by SRISK and, to a minor extent, by EXSHORT.

Our tests highlight the difficulty of identifying a market-based measure of systemic importance that remains valid across financial crises that present different features. From our analysis, however, it seems that this also applies to several conventional proxies employed by regulators to identify the most global systemically important financial institutions. Among these conventional measures, size is the most consistent performer across the recent global crisis and the 1998 crisis; namely, in those crises with the largest impact on the financial institutions included in our sample. This result of firm size being a more consistent performer than marketbased measures of systemic importance echoes Danielsson et al's (2014) conclusion that the use of basic firm-characteristics is preferable to the adoption of more complex approaches in shaping regulatory actions.

The rest of the paper is structured as follows. Section 2 describes the empirical setting of our tests -including the selected market measures of systemic importance, the data and the main dependent and explanatory variables employed in the prediction tests. Section 3 presents the empirical results and robustness tests for the prediction analysis that employs the global financial crisis as a laboratory, while Section 4 reports additional tests for two further crisis episodes: the Asian crisis that erupted in the second half of 1997 and the 1998 crisis. Section 5 discusses our key findings and offers conclusions.

2 EMPIRICAL METHODOLOGY, SAMPLE AND CONTROL VARIABLES

2.1 Empirical Methodology

We assess the usefulness of four market-based measures of systemic importance for regulators and supervisors by their ability to offer early warning signals of global systemic importance over and above what can be obtained by employing more conventional risk-drivers based on firm characteristics. Essentially, we argue that the ability of market-based measures to offer early warning signals is a necessary but not a sufficient condition for their incorporation in the regulatory framework if similar signals can be obtained by using alternative and simpler indicators of systemic importance. Our empirical framework is, therefore, based on the estimation of a prediction model where measures of the *realized* systemic importance during episodes of financial crises, which we define in section 2.3, are explained by firm characteristics. We then assess whether the prediction performance of these models improves when one market-based measure of systemic importance is included as an additional predictor. In other words, we evaluate i) the degree of significance of the market-based measures of systemic importance when they are added to benchmark models based on conventional firm characteristics and ii) the related additional explanatory power (R-squared) that it is provided to these models.

The market-based measures of systemic importance include in the analysis consist of the Δ CoVaR measure as in Adrian and Brunnermeier and its variant formulated by Lopez-Espinosa et al. (2012), named henceforth Δ A_CoVaR, with the addition of the measures proposed by Brownlees and Engle (2012) and Lehar (2005), named as respectively SRISK and EXSHORT in the following sections. Δ CoVaR and Δ A_CoVAR are examples of a bottom-up approach (Drehmann and Tarashev; 2011a) in quantifying systemic importance; namely, the degree of systemic importance is quantified on the basis of the negative implications for the system produced by the distress conditions of a financial institution. Under this approach, therefore, the

theoretical causation runs from the financial institution to the system. SRISK and EXSHORT are instead examples of a top-down approach in quantifying systemic importance where the preliminary step to the assessment process is the quantification of the total amount of systemic risk that is then allocated to different components of the financial system. Thus, the theoretical causation runs from the system to the financial institution. We provide details of the estimation method that has been adopted in this study for each measure in the Appendix.

We select these four measures on the basis of two criteria. First, computations have to rely on readily available data that can be collected over an extensive time period. Second, a measure can be computed for a large sample of financial institutions in a *global* system. These criteria exclude the estimation of any contribution approach that uses Shapley Values to allocate systemic risk – this is due to the dimensionality problem associated with this type of analysis.ⁱⁱⁱ Similarly, models that require the estimation of the joint probabilities of failures, as in Segoviano and Goodhart (2009) and Zhou (2010), are excluded as their estimation becomes problematic in large datasets. These criteria also exclude measures that require the computation of the implied default probability from Credit Default Swaps (CDS) as in Huang, Zhou, and Zhu (2012). This is because CDS are not normally available for a long time period and an extensive international sample of financial institutions

Our initial and main tests employ the global financial crisis as a laboratory. We estimate the additional informative content that regulators and supervisors would have obtained by using these market based measures as additional predictors of the *realized* systemic importance of financial institutions during this crisis. Following Beltratti and Stulz (2012) and Fahlenbrach, Prilmeier, and Stulz (2012), the length of the crisis spans from 2nd July 2007 to 31st December, 2008. The prediction model is then estimated on the basis of accounting and market data available at the end of 2006. More precisely, to avoid forward looking bias, we estimate daily values for the four market measures of systemic importance with the accounting and market data available up to the end of 2006 using an estimation window of five years. In essence, we take the

perspective of a regulator/supervisor that has opted to measure the degree of systemic importance of financial institutions at the end of year 2006 before the eruption of the global shock. We then use the average values of these measures in year 2006 as an additional control in our prediction model. Notably, our results remain qualitatively unchanged if we employ a longer estimation window to estimate the market measures of systemic importance.

As detailed in the Appendix, some of these measures, namely, SRISK and EXSHORT require the use of both market and accounting data in the estimation process. This raises a possible bias in the measurement of systemic importance due to the fact that before the global crisis some companies in our sample have moved to the International Financial Reporting Standard (IFRS). This is, in particular, the case of numerous European financial institutions for which the adoption of IFRS became compulsory since 2005. While our initial tests on the global financial crisis do not deliberately control for this possible bias, in section 3.3 we conduct additional analyses that aim to remove any concerns over the impact of accounting standards on our results. In particular, as IFRS is supposed to have an impact on the size of a company balance sheet, we follow Acharya, Engle, and Pierret (2014) and Engle, Jondeau, and Rockinger (2014) and adopt a milder 5.5% minimum capital requirement rather than the 8% for all the companies that at the end of 2006 claimed to follow these accounting principles in the estimation of capital shortfall. As this adjustment implies that the values of total liabilities under IFRS are around 45% larger than under other accounting principles, we then re-estimate EXSHORT with an increase in the value of debt of 45% for IFRS companies. Notably, the problem of accounting standards can also potentially affect the estimation of the two $\Delta CoVaR$ measures. As suggested by Adrian and Brunnermeier (2011) and Danielsson et al. (2014), Δ CoVaR can be implemented both by using observable equity returns or estimated asset returns that are then influenced by accounting data. We have opted to follow Danielsson et al. (2014) and estimate these measures by using easily observable equity returns given that this reduces errors-in-variables problems including those related to differences in accounting principles across companies.^{1V}

A second set of tests evaluates whether the predictive performance of the selected marketbased measure of systemic importance during the global crisis is motivated by a general economic rationale or is simply the result of an optimal methodology design that simply captures the specificities of the global crisis. This is because the majority of the market-based measures of systemic importance we analyze have been proposed in the aftermath of the global financial crisis with a focus on those aspects of systemic risk that have emerged as pivotal during this crisis. We, therefore, test whether these market-measures predict the *realized* systemic importance of financial institutions in other crisis episodes by adopting a similar empirical strategy as used for the global financial crisis. We focus on the two crises that occurred in the nineties that are normally recognized as having an international relevance and that have often been at the core of previous empirical studies on systemic risk and bank performance (Fahlenbrach, Prilmeier, and Stulz 2012, Sedunov 2012, Weiß, Bonstandzic, and Neumann 2014): the Asian financial crisis erupted in the second half of 1997 and the Russian and the LTCM crisis that started in the second half of 1998.

We identify the start of the Asian crisis on the 2nd of July 1997, as in Weiß, Bonstandzic, and Neumann (2014) and the start of the 1998 crisis on the 3rd of August, as in Fahlenbrach, Prilmeier, and Stulz (2012). More problematic, however, is the identification of an end date for these two crises. We address this issue by following an approach similar to Fahlenbrach, Prilmeier, and Stulz (2012). They quantify the performance of a financial institution under the 1998 crisis from the 3rd of August 1998 to the day of the lowest return at the company level up to December 1998. We modify this approach to maintain a consistent time frame across companies and to focus on the systemic dimension of these two crises. As a result, for each episode the end day is the lowest value of the Datastream World index for the financial industry; the 12th November 1997 for the Asian crisis and the 5th October 1998 for the 1998 crisis.

It is worth noting that the two crises appear quite different in terms of global impact. During the period from July 1997 to 12th November, 1997, the global financial sector index declined by around 10%, while from August 1998 to 5th October, 1998, the decline in value was equal to about 30%. This difference in the crises gives us the opportunity to assess whether, outside the global financial crisis, the predictive performance of the four market-measures of systemic importance varies with the severity of the crisis episode. This is particularly important from a regulatory and supervisory perspective given that it would be preferable that these measures offer more effective early warning signals when a crisis might generate a more severe impact on the stability of the global financial system. As in our main test, to conduct these additional analyses, we estimate the four market-based measures of systemic importance using accounting and market information for the five years before the eruption of the shock and the average for the last available year is then employed as the predictor in our empirical tests.

2.2 Data

We conduct our analyzes on an international sample of large financial institutions and employ market and accounting data for the period spanning from 1, January, 1992 to 31, December, 2006. More precisely, our initial tests based on the global financial crisis require data for the period from 2002 to 2006 to estimate our market-based measures of systemic importance, while the additional tests to evaluate the performance of these measures under different crises periods such as the Asian Crisis in 1997 and the 1998 crisis are based, respectively, on the periods 1992-1996 and 1993-1997.

In the selection of financial institutions, similar to Brownlees and Engle (2012), we start the sampling process from the list of publicly traded financial institutions at the end of 2006 as available from Datastream International. The list includes banks, insurance companies and financial services firms, such as investment banks, consumer finance companies and firms engaged in asset management. From this group of financial institutions, we select financial firms in the list of the top 300 institutions in terms of both total assets and market capitalization. The application of this criterion, which has led to an initial sample of 240 financial institutions, might,

however, introduce some survivorship bias in the selection process as it does not consider large financial institutions that have been delisted before 2006. Therefore, the initial sample has been complemented with the addition of any financial firm that was in the list of the top 300 financial institutions (in terms of total assets and market capitalization) in any year from 1992 to 2005. This has led to the selection of a further 122 financial institutions and to a total sample size of 362 units.

Next, as in Adrian and Brunnermeier (2011), we only retain in the sample financial institutions with sufficient data to estimate the measures of systemic importance over a period of five consecutive years - 54 sampling units were lost due to the application of this criterion. Finally, though the measures of systemic importance proposed in the literature focus on the tail of the distribution of stock returns, we exclude from the sample financial institutions suffering from thin trading – that is, they have less than 80% of non-zero returns over the sample period (see De Jonghe, 2010). This criterion reduces the sample size by five units. The sample of selected companies consists of 303 financial institutions.

[Table 1]

Table 1 reports the distribution of the final sample by country and sector. The sample is dominated by US financial institutions with a share of 26% of the total sample, followed by Japanese financial institutions (about 16% of the total sample). The distribution by sector shows that 65% of the sampling units are commercial banks, followed by insurance companies (22% of the sample). Overall the sample is equivalent to an average share of approximately 80% of total assets and market capitalization of the listed financial companies and is, therefore, very representative of the international financial system.

2.3 The Estimation of Benchmark Models: Measures of Realized Systemic Importance and Control Variables

The assessment of the usefulness of market-based measures of systemic importance requires the preliminary estimation of benchmark models where proxies of the *realized* degree of systemic importance during a crisis event are explained by conventional risk-drivers. To this end, when the focus is on the global financial crisis, we employ as dependent variables four measures that aim to capture the *realized* systemic importance of financial institutions: i) the *realized* covariance risk; ii) the bailout of financial institutions via public funds; iii) the *realized* market value loss and iv) the *realized* capital shortfall. For the other two crisis episodes analyzed in this paper we replicate the prediction tests with the same set of dependent variables with the exclusion of ii) given the lack of a sufficient number of public rescues during these two crises.

The selection of the above measures of *realized* systemic importance is justified by two key reasons. First, some of these measures have been employed in previous studies to assess the degree of systemic risk at the firm level associated with firm characteristics. Second, in the context of our analysis they offer the opportunity to assess the contribution of the market-based measures of systemic importance in terms of the predictability of the potential ex-post systemic damages that can be associated with insolvency at the firm level and in terms of the predictability of which institutions are more vulnerable under a systemic event and, consequently require exante interventions as highlighted in the introduction.

In particular, the *realized* covariance risk and the bailout of financial institutions via public funds appear to be closer proxies for the potential systemic damages that can derive from distress conditions in financial institutions. Essentially, the failure of a bank with a higher covariance risk is supposed to affect the remaining banks more than the failure of a bank with a lower covariance risk and, hence, it is likely to generate negative spillover risk for other entities. Similarly, the regulatory decision to bailout financial institutions should reflect regulatory concerns over the systemic implications of the failure of a financial institution. It follows that these first two proxies of the *realized* degree of systemic importance are expected to be related specially to those market-based measures (Δ CoVaR and Δ A_CoVaR) that capture the riskspillover between a financial institution and the rest of the financial system. The other two measures of the degree of systemic importance during crises, the *realized* market value loss and the *realized* capital shortfall, are instead more likely to reflect the vulnerability of financial firms when a systemic shock materializes. Consequently, they are expected to be better explained by top-down market-based measures (SRISK and EXSHORT) where the causation runs from the system to the bank.

We measure the *realized* covariance risk as the covariance between the daily returns of each financial institution and the daily returns of the value weighted portfolio of all institutions in the sample. A similar measure has been used by Adrian and Brunnermeier (2011) to quantify the degree of interdependency between a financial institution and the whole financial system to be used as an indicator of the impact of a financial institution on systemic risk during the financial crisis.

Next, for the global financial crisis we construct a dummy variable (BAILOUT) that takes a value equal to one when a financial institution has been bailed out by means of public funds during the global crisis. The data on bailouts are collected on government-funded recapitalizations from ProPublica (http://projects.propublica.org/bailout/list) for U.S. financial institutions, Petrovic and Tutsch (2009) for European financial institutions, and annual reports as well as company websites for the remainder of the sample. Furthermore, in the case of the US, we consider as bailed out institutions only those that received capital support outside the Capital Purchase Program (CPP), such as AIG, Freddie Mac and Fannie Mae, and/or institutions that were "forced" to receive public funds on October 14, 2008 in the context of this program. Financial institutions that instead took part in the CPP voluntarily have not been qualified as bailed out entities (for a detailed description of the program see Bayazitova and Shivdasani 2012).^v While the selection for the CPP was driven both by the banks' voluntary decision to

submit an application and by the Treasury's and direct banking regulators' approval to participate in the program, Bayazitova and Shivdasani (2012) find clear evidence of self-selection by banks. Furthermore, CPP banks had stronger fundamentals compared to non-CPP banks both prior to and during the program's initiation period (Ng, Vasvari, and Moerman 2011), and they had significantly stronger asset quality than banks that were not approved for CPP injections, suggesting that capital was not provided to banks with high levels of troubled assets (Bayazitova and Shivdasani 2012). These results are in line with the argument of the US Treasury that the CPP was not aimed at supporting poorly performing banks. Notably, after the applications of these criteria, out of the 245 institutions for which data are available to compute the pre-crisis market measures of systemic importance, 40 had been bailed out during the crisis.

The third measure of *realized* systemic importance is taken from Acharya et al. (2010) and is computed as the buy and hold return (BHR) during the length of a crisis. Institutions that suffered from the largest decline in market valuation during the crisis are then identified as the most systemically important. Differently from Acharya et al. (2010) we employ in our regression analysis the value of BHR multiplied by minus one to ease the comparability with other proxies of *realized* systemic importance; namely, higher values denote a larger *realized* systemic importance during the crisis.

The fourth measure of *realized* systemic risk contribution follows the logic behind the construction of SRISK where the contribution to systemic risk is related to the return that each institution realizes during a crisis event and to its leverage. Essentially we employ equation (2A) in the appendix to quantify the capital shortfall at the firm level during a crisis episode. More precisely, this capital shortfall is a function of the book value of liabilities before the eruption of a shock, the market value of equity and the decline in equity value suffered as a consequence of the systemic event (this decline in market value is expressed by the company BHR observed during the crisis period).

We estimate our benchmark models by regressing the measures of *realized* systemic importance on a set of explanatory variables that has been selected with the purpose of capturing conventional drivers of systemic risk while maintaining in the sample the largest number of financial institutions. We start our analysis by estimating a linear model where we include only financial institution size (**SIZE**) as an explanatory variable, measured via the log of total assets (in millions of US dollars). This first step of our analysis is motivated by the growing focus on size as a key driver of systemic importance in the aftermath of the global crisis (Laeven, Ratnovski, and Tong 2014, Viñals et al. 2013). The empirical evidence normally suggests that the larger financial institutions are more exposed to systemic shocks (De Jonghe 2010, Vallascas and Keasey 2012) and hence, a positive relationship is expected between SIZE and the measures of *realized* systemic importance.

Next, we include in the regression analysis capital strength, volatility and basic indicators of the degree of interconnectedness in the global financial system. By estimating this second model we can, therefore, evaluate the additional contribution of additional firm characteristics in explaining the *realized* systemic importance during a crisis event. In section 3.3 we conduct additional tests to show that our results do not vary when we include other control variables. A financial institution's capital strength (**EQUITY**) is measured by the ratio between total equity and total assets. The degree of systemic importance should be decreasing in EQUITY as under a systemic shock, highly leveraged financial institutions might be forced to de-leverage by liquidating assets at fire-sale prices in response to the increasing credit rationing by creditors facing liquidity constraints (Acharya and Viswanathan 2011, Shleifer and Vishny 2010). In line with this interpretation, Adrian and Brunnermeier (2011) find that higher leverage is generally associated with an increase in systemic importance as measured by Δ CoVaR and Benoit et al. (2013) find that the SRISK ranking of the top 10 US financial institutions resembles a leveragebased ranking. The next control variable is the volatility of daily stock returns computed for the year 2006 (**VOLATILITY**) that captures financial institution total risk. More risky institutions are likely to be more prone to failure during systemic events and then exacerbate the effects of financial crises. Finally, we control for the degree of interconnectedness of a firm with the rest of the financial industry. The degree of interconnectedness is recognized as an important potential driver of systemic risk as it amplifies the externalities caused by financial distress via contagion risk.^{vi} We employ the approach proposed by Billio et al. (2012) to derive measures of the degree of interconnectedness of a financial system. Essentially we apply a Granger causality test on daily stock returns for a period of three years to estimate the number of financial institutions that a financial institution is 'causing' before the crisis event (**CAUSING_OTHERS**). For each pairs of stocks we estimate a linear specification with two lags of stock returns. We then interpret a larger number of CAUSING_OTHERS as indicating a higher degree of interconnectedness. As an additional control we also include the number of financial institutions causing the stock returns of a financial institution over the calendar year 2006 (**CAUSED_BY_OTHERS**) that we estimate in a similar manner.

While the described controls can be computed for all financial institutions in our sample, banks are characterized by some key distinguishing features. One, for instance, is the need to comply with the Basel capital requirements that offer the opportunity to compute different and probably more appropriate measures of capital strength compared to **EQUITY**. Furthermore, banks tend to combine different types of business lines by operating in interest-based (lending) and non-interest-based (commission, fee and trading) activities and from a systemic perspective, several theoretical studies argue that the development of diversified financial institutions may be detrimental to financial stability. For instance, Wagner (2010) shows that while diversification may reduce the default risk of an individual institution, it may increase the risk of joint failures in the banking system by raising bank exposure to common sources of risks. Similarly, Ibragimov, Jaffee, and Walden (2011) show that there is a threshold above which the individual benefits

related to diversification strategies are lower than the costs due to an increasing risk of joint bank failures in the banking system.

Therefore, to control for the specificities of banks we estimate a bank-specific model that differs from the baseline specification in two aspects. First, we control for bank capital strength by means of the ratio between total regulatory capital and risk-weighted assets (**REG_RATIO**) as required by the Basel regulations. Second, we add into the regression model an index of revenue diversification (**DIVERSIFICATION**) that, following previous studies (see for instance Stiroh and Rumble 2006), is defined as one minus the Herfindhal index of income concentration between net interest-based activities and non-interest sources. Notably, the accounting information needed to construct these variables, especially those related to the regulatory capital ratio, are only available for a sufficient number of observations for the most recent years. We can, therefore, estimate this additional specification only for the test on the global financial crisis.

We estimate benchmark prediction models of the *realized* systemic importance during the global crisis for the full sample and for the sub-sample of banks that is then extended with the inclusion of one of the market-based measures analyzed in this paper. All models are estimated via OLS with robust standard errors clustered at the country level to control for within country correlation in systemic importance. The only exception to this general framework refers to the prediction of BAILOUT; given the dichotomous nature of the dependent variable, we estimate a logit regression with robust standard errors clustered at the country level.

[Table 2]

In Table 2 we report definitions and summary statistics for the variables employed in our empirical tests including the four market-based measures of systemic importance computed before the eruption of each crisis episode. It is worth noting that EXSHORT is expressed in US\$ mln and shows an extremely skewed distribution in all time periods. Consequently, the following empirical tests employ its log transformation rather than raw values. Finally, the

summary statistics confirm that the Asian crisis had a much milder global reach than the 1998 crisis. For instance, during the Asian crisis the financial institutions in our sample lost on average 1.90% in market value compared to approximately 22.70% during the 1998 crisis, with an average covariance of 0.84 versus 3.52 in 1998.

3 THE PREDICTIVE PERFORMANCE OF MARKET-BASED MEASURES OF SYSTEMIC IMPORTANCE DURING THE GLOBAL FINANCIAL CRISIS

This section presents tests on the prediction of measures of *realized* systemic importance during the global financial crisis. We start with the models that employ as dependent variables proxies of systemic importance that capture the risk of potential ex-post systemic damages in the case of a financial institution distress. Next, the analysis focuses on measures of vulnerability to systemic shocks. The last sub-section is devoted to additional tests to assess the robustness of our key findings.

3.1 The Predictability of Covariance Risk and Bailouts during the Global Crisis

Panel A of Table 3 reports the OLS estimates of the prediction model for the full sample where the dependent variable is the covariance risk during the global financial crisis. We start the analysis in columns (1) and (2) where we report two benchmark models that include, respectively, only size and size plus a set of additional conventional indicators of risk as explanatory variables. Next, we include alternative market-based measures of systemic importance as explanatory variables in an attempt to quantify their additional contribution to the regulatory and supervisory activity.

The results of this analysis show that only Δ CoVaR offers an additional contribution in explaining the covariance risk during the global crisis. This market-based measure enters the model with a positive and significant coefficient indicating that a higher Δ CoVaR in 2006 was associated with a significantly higher covariance risk during the global financial crisis. Nevertheless, when compared to the model reported in column (2), we observe that the addition of Δ CoVaR as a predictor only increases the explanatory power of the prediction model by about 3 percentage points (with the R-squared increasing from 45.3% to 48.5%).

[Table 3]

For the remaining market measures their information content is generally already captured by SIZE, VOLATILITY and CAUSING OTHERS that enter the specifications with the expected sign and with highly significant coefficients. It is worth, in particular, noting that the fact that CAUSING OTHERS is positive and significant suggests that the *realized* covariance risk during the global crisis reflects the potential spillover risk (and the related collateral damages) from a financial institution to the rest of the system. Furthermore, SIZE confirms its pivotal role during the recent global crisis - being able to capture about 50% of the total variance explained by the model in column (2).

In Panel B, we repeat the analysis for the full sample of banks controlling for bank capital strength in terms of Basel requirements and for the degree of bank income diversification. The results are generally consistent with the findings for the full sample. The model confirms SIZE, VOLATILITY and CAUSING OTHERS as key determinants of *realized* covariance risk during the global crisis though it also suggests that an increase in this risk is produced by higher values of income diversification. More importantly, Δ CoVaR still enters the model with a positive and significant coefficient (at the 5% level), though the increase in the explanatory power of the model is, however, smaller (from 52.9% to 54.1%) compared to the full sample analysis. Furthermore, when the focus is only on banks, Δ A_CoVaR also appears to provide a (marginal) contribution to the prediction model.

The additional information content of Δ CoVaR when the focus is on the prediction of *realized* measures of systemic importance that capture the potential systemic implications of bank failures is also confirmed by the regression results reported in Panel A of Table 4 where the dependent variable is BAILOUT. The models, estimated for the full sample according to a logit specification, with clustered standard errors at the country level, show that only Δ CoVaR enters the specification with a positive and significant coefficient (at the 10% level) indicating a higher probability of being bailed out for institutions having a higher pre-crisis Δ CoVaR.

The remaining market-based measures do not show any significant effect on the probability of being bailed out during the global crisis and the analysis suggests that the decision by regulators to rescue financial institutions is largely explained by size. This is clearly highlighted by the high pseudo R-squared of the model reported in the first column of Table 4 where SIZE is used as the only predictor of the probability of regulatory rescue and by the fact that size remains the only significant predictor in column (2).

The conclusions remain similar when we limit the analysis to the sub-sample of banks: only CoVAR shows a significant coefficient (at the 5% level) in the prediction model, while none of the remaining market-based measures of systemic importance add any information to what it is already embedded in more conventional firm characteristics. Notably, when Δ CoVaR is added to the baseline specification we also observe a lower probability of receiving capital support by banks characterized by a higher regulatory capital ratio in 2006.

[Table 5]

To evaluate the importance of the additional information offered by Δ CoVaR under the logit specification that predicts the bailout of financial institutions, we compare the percentage of correctly classified institutions by the model in column (3) in Table 4, with the percentage of institutions correctly classified by the two benchmark models reported in columns (1) and (2). More precisely, Panel A of Table 5 focuses on the full sample analysis and employs the value of the ratio between the number of bailout institutions (40) and the total number of observations (245) as a cut-off point to identify those institutions that have been correctly classified. In Panel B we repeat a similar analysis for the sub-sample of banks.

Overall, the additional tests suggest that when the analysis is conducted for the full sample, the percentage of correctly classified bailed out institutions increases substantially when Δ CoVaR is added as an explanatory variable. In particular, moving from a model with only SIZE to a model with additional conventional controls increases the percentage of correctly classified institutions by only 2.5 percentage points (from 67.50% to 70%), while the inclusion of Δ CoVaR increases this percentage by a further 7.5 percentage points. The improvement is, however, smaller when we focus on the total number of correctly classified institutions in column (2). Furthermore, we observe that Δ CoVaR appears less effective as an additional control when the analysis is limited to the sub-sample of banks. In this latter case, column (2)

in Panel B shows that while there is an improvement in terms of overall classification compared to the benchmark model based on SIZE of approximately 2.0 percentage points, the results in column (1) show that such an improvement is not observed in terms of the classification of the sub-set consisting only of the group of bailout institutions.

In summary, the results of this section identify Δ CoVaR as the only market-based measure of systemic importance that provides additional information compared to what is already embedded in more conventional indicators of the potential degree of systemic relevance of a financial institution. Nevertheless, despite the degree of significance observed across all specifications, Δ CoVaR does not often add a particularly high explanatory power to our benchmark prediction models based on firm characteristics. The additional information content seems low especially when the analysis is conducted only on the sub-sample of banks.

3.2 The Predictability of Buy and Hold Returns and Realized Capital Shortfall during the Global Crisis

In this section we analyze the contribution of the four market-based measures of systemic importance in predicting proxies of the degree of vulnerability of financial institutions during the global crisis. As in the previous section we first estimate for the full sample a benchmark model with conventional explanatory variables that we then progressively extend with the addition of market-based measures of systemic importance. This empirical framework is extended to the sub-sample of banks with the addition of bank specific controls.

[Table 6]

Our first set of tests, reported in Panel A of Table 6, employ as the dependent variable the negative values of the buy and hold returns computed over the crisis period, with higher values denoting a larger vulnerability to the global crisis. Despite this variable, in theory, capturing the causation running from the system to banks in assessing systemic importance, from the results reported in Panel A we still observe that only Δ CoVaR enters the prediction model with a positive and significant coefficient (at the 5% level) with an increase in the explanatory power of the model (comparing columns (2) and (3)) of 2.2 percentage

points. Hence, a larger pre-crisis Δ CoVaR was associated with a larger decline in market valuation during the global crisis.

While none of the other mark-based measures of systemic importance show a significant impact on the crisis performance of financial institutions, we find that conventional explanatory variables have a significant predictive ability. In particular, larger and more volatile financial institutions generally performed worse during the global crisis by suffering from a larger decline in market valuation. Once again, our results emphasize the importance of SIZE: as shown in the first column of Panel A of Table 6 when we employ only the size of financial institutions as an explanatory variable in the prediction model we obtain a R-squared that is equal to 18.4%, equivalent to around 75% of the R-square of the model in column 3) that includes other firm characteristics and Δ CoVaR as additional controls.

Panel B of Table 6 offers similar conclusion for the sub-sample of banks. In essence, we still observe that among the market-based measures of global systemic importance only Δ CoVaR predicts bank performance during the financial crisis contributing with an additional 3.4 percentage points to the explanatory power of the model (from 24.2% to 27.6%). We do not find that the two additional bank specific variables (the regulation ratio and the income diversification of a bank) help to predict (the negative value of) buy-and-hold returns during the crisis; rather these additional tests confirm the importance of size and volatility as significant predictors. Overall, it appears that the key findings are not affected by changes in the sample composition.

The results are substantially different when we measure the degree of vulnerability of a financial institution in terms of capital shortfall suffered during the global financial crisis. Under this framework, the results reported in Panel A of Table 7 for the full sample support the view that especially SRISK and EXSHORT can provide early warning indications as to which institutions should be subject to more stringent ex-ante regulatory interventions as they are likely to be heavily affected by the eruption of a systemic shock through an erosion of their capital adequacy.

[Table 7]

More specifically, both SRISK and EXSHORT enter the regression model with a positive and significant coefficient and add, respectively, 23.2 and 6 percentage points to the explanatory power of the prediction model. Hence, it is in particular, SRISK that appears as an effective predictor and under this

setting it completely subsumes the importance of size in the prediction model. SIZE remains, however, largely significant in all other specifications and it is the only conventional variable that explains cross-sectional variation in the value of the *realized* capital shortfall. It is also worth noting that both Δ CoVaR and Δ A_CoVaR add some, though marginal, contribution to the prediction model estimated under this empirical setting. In essence, SRISK and EXSHORT seem to work as early warning signals only under a specific setting, while Δ CoVaR shows a potential contribution to the activity of regulators and supervisors under a range of possible scenarios.

Once again, the conclusions for the full sample are largely confirmed when the estimation is only conducted for the sub-sample of banks, the only exception being the lack of significance associated with ΔA _CoVaR. Furthermore, bank diversification shows in some specifications a negative and significant coefficient denoting a lower capital shortfall in more diversified banking firms.

Taken together the findings of this section, with the evidence shown by the previous tests, confirm that Δ CoVaR is the only metric of global systemic importance that enters all the estimated models with a significant coefficient and offers an improvement to the explanatory power of these models that is captured by more conventional firm characteristics. Δ CoVaR, therefore, offers early warning signals not only of the potential ex-post systemic damages that a financial institution distress can produce, as implied by its theoretical foundations, but also on the vulnerability of financial institutions when a systemic shock materializes. By contrast, the remaining market based measures show some ability to offer support to the regulatory and supervisory activity only under an empirical setting focusing on a specific definition of firm vulnerability. More precisely, SRISK and EXSHORT are effective as early warning devices only when the focus is on the *realized* capital shortfall - while in the remaining cases they appear to be characterized by a lack of additional information content especially with respect to financial institution size.

3.3 Additional Tests

We conduct several additional tests to evaluate whether our results are confirmed under alternative model specifications. First, we test whether our findings are influenced by the heterogeneity in accounting standards and in particular by the adoption of IFRS by numerous companies (103 financial institutions) in our sample. This adoption is supposed to have an impact on the size of a company balance sheet, and consequently, on its leverage. This could affect the estimation of SRISK and EXSHORT as they are based on both market and accounting data. As mentioned in section 2.1, in adjusting the estimation of SRISK, we follow Acharya, Engle, and Pierret (2014) and Engle, Jondeau, and Rockinger (2014) and adopt a milder 5.5% minimum capital requirement rather than 8% for all companies that at the end of 2006 follow IFRS. Furthermore, as this adjustment implies that the values of total liabilities under IFRS are around 45% larger than under other accounting principles, we then re-estimate EXSHORT with an increase in the value of debt of 45% for IFRS companies. We then reestimate the prediction models by using these IFRS-adjusted measures rather than our initial measures of systemic importance. The above tests show that SRISK and EXSHORT do not improve their predictive performance after the IFRS adjustments. This is not surprising given that the IFRS-adjusted measures present a correlation well above 95% with the original measures of systemic importance. As a further test to control for heterogeneity in accounting standards, we repeat our analysis with the inclusion of a dummy variable equal to one if a financial institution has adopted IFRS and zero otherwise. Again, we do not find that SRISK and EXSHORT improve their predictive performance.

Next, we estimate the models with additional control variables. We include a measure of funding composition defined by the ratio between short-term funding over total debts or a measure of maturity mismatch as defined in Adrian and Brunnermeier (2011). Both measures are only available for a sub-set of our sample (equal to 238 financial institutions). Furthermore, we control for the book-to-market ratio at the end of 2006, as Brunnermeier et al. (2012) show that this variable appears to be a significant determinant of systemic importance for a sample of US banks. Essentially, a higher book-to-market ratio is found to reduce the degree of systemic importance. These variables enter occasionally with a significant coefficient but this does not generally modify our key conclusion: we still continue to observe that Δ CoVaR performs generally better than the other market-based measures of systemic importance. In particular we

find that a higher value of the ratio between short-term funding and total liabilities significantly increases the probability to receive government support and increases the loss in market values suffered during the crisis. One consequence of the inclusion of these additional controls is the loss in the predictive power of Δ CoVaR of the bailouts of financial institutions but only when the analysis is conducted for the full sample. By contrast, in the case of banks, we still observe that a higher pre-crisis Δ CoVaR increases the probability to receive government support.

Furthermore, for the sub-sample of banks we replace the regulatory capital ratio with a bank capital buffer: namely, the difference between the regulatory capital ratio and the minimum regulatory capital ratio imposed at the country level. This allows us to control more precisely for differences in capital regulation across countries. However, this control rarely enters any specification with a significant coefficient and, more importantly, does not influence the findings on the impact of the four market-based measures of systemic importance on our proxies of *realized* systemic importance during the global financial crisis.

We then evaluate whether the aggregation of the four measures of systemic risk via principal component analysis is preferable to using a single indicator. Consequently, the derived systemic importance score, measured by the first principal component across the four measures, is employed as an explanatory variable in lieu of the single indicators. This analysis generally suggests that the aggregation does not deliver additional information compared to the use of a single measure of systemic importance: when a market based measure appears as a significant predictor of *realized* measures of systemic importance, its inclusion in the model is normally preferable to the inclusion of an aggregate score of systemic importance.

Finally, we have used a year of data to construct our pre-crisis measures of systemic importance with the purpose of removing the influence of temporary factors which might raise the degree of systemic importance of a financial institution over a very short time period and offer misleading signals to regulators and supervisors. However, this choice is not without drawbacks. In particular, it might lead to reducing the predictive power of market-based

measures of systemic importance by ignoring the additional information content that could be associated with a sudden increase in the degree of systemic importance of a financial institution. Thus, we evaluate whether a shorter-time perspective in conducting our tests might contribute to increasing the information for regulators by using as predictors the average of each market-based measure computed during December 2006. In other words, we repeat the analysis by ignoring the information that these measures offer in the first eleven months of 2006 under the assumption that the most recent values incorporate newer information on the degree of systemic importance. Nevertheless, the re-estimation of the prediction models under this new empirical setting does not show any improvement in the prediction performance of market-based measure of systemic importance.

4 THE PREDICTIVE PERFORMANCE OF MARKET-BASED MEASURES OF SYSTEMIC IMPORTANCE IN OTHER CRISIS EPISODES

In this section we focus on the predictive performance of the four market-based measures of systemic importance in two other crisis episodes: the Asian Crisis in the second half of 1997 and the Russian default and the related rescue of LTCM in 1998. More precisely, we focus on the predictability of three out of four measures of *realized* systemic importance that we have examined for the global financial crisis: covariance risk, the (negative value of) buy and hold return, and a proxy of the *realized* capital shortfall. Furthermore, similarly as in the previous tests we start by estimating benchmark models based on firm characteristics observed at the end of 1996 for the Asian crisis and at the end of 1997 for the 1998 crisis and then we add one of the market-based measures as an additional predictor.

[Table 8]

Table 8 reports the prediction tests of covariance risk with Panel A that focuses on the Asian crisis and Panel B on the results for the 1998 crisis. The results for the Asian Crisis suggest that

 Δ CoVaR does not confirm its predictive ability observed during the global financial crisis while several firm characteristics predict the *realized* covariance risk in the second half of 1997. Nevertheless, the size factor seems to play a much lower role than in the recent crisis. Overall, some additional explanatory power comes only from SRISK - when added to the firm characteristics variables it increases the R-squared by approximately 2.5 percentage points. Even more disappointing is the predictive performance of the market measures of systemic importance when the analysis is conducted on the 1998 crisis: none of the market measures enter the model with a significant coefficient. It is worth noting, however, that in this prediction test, conventional firm characteristics also perform particularly poorly with the exception of CAUSING OTHERS; this variable shows an ability to predict covariance risk in all three of the crisis episodes we have analyzed in this study.

[Table 9]

Table 9 reports the regression results when the negative value of the buy-and-hold returns is the dependent variable in the prediction model. Only for the Asian crisis does the analysis offer a picture that shows some similarity with the global crisis: Δ CoVaR appears to be the marketmeasure that offers the best additional information content compared to more conventional drivers of systemic importance, followed by Δ A_CoVaR. Nevertheless, under the 1998 crisis none of the four measures enters the prediction model with the expected sign and with a significant coefficient. By contrast Δ CoVaR offers misleading indications to regulators and supervisors: a higher Δ CoVaR in 1997 is associated with better performance (a lower decline in value) during the 1998 crisis. Interestingly, during the 1998 crisis where the loss in value suffered by financial institutions is on average 12 times larger than during the Asian crisis (22.70% versus 1.90%), size emerges as significant predictor of the buy-and-hold returns. Overall, the results appear substantially different across the two crisis episodes and, more importantly, often not fully aligned with the evidence obtained in the previous section for the global financial crisis. Finally, more similarities with the recent financial crisis emerge when we employ the *realized* capital shortfall as our dependent variable in the prediction test. The results reported in Panel A of Table 10 suggest that the two top-down measures (SRISK and EXSHORT), that are supposed to capture vulnerability conditions under systemic events, significantly predict the *realized* capital shortfall during the Asian crisis, with SRISK providing the highest additional explanatory power to the prediction model. We achieve a similar conclusion in Panel B when the prediction test is conducted for the 1998 crisis. However, in such a context the others two market measures of systemic importance exhibit some additional predictive power. Overall, SRISK and EXSHORT appear to have only a specific use for regulators and supervisors - that is, when the need is to assess the vulnerability of the capital adequacy of financial institutions to systemic shocks and the related design of ex-ante interventions in terms of capital requirements.

In summary, this section suggests that outside the global crisis Δ CoVaR does not confirm its ability to consistently predict all the different notions of *realized* systemic importance employed in our prediction tests. More importantly, it does not perform particularly well even when the measure of *realized* systemic importance should reflect the potential for ex-post damages stemming from individual distress conditions and is thus closer to the theoretical design of Δ CoVaR. More generally, all the market-based measures perform very poorly in predicting covariance risk and the loss in market value when the tests are based on a severe crisis event such as the 1998 crisis where on average the financial institutions in our sample lost 22% in market valuation. Some predictive power emerges occasionally under the Asian crisis, a clearly milder crisis event from a global perspective. Furthermore, a consistent picture across different tests emerges only when the definition of vulnerability of financial institutions to systemic shocks is based on capital shortfall.

All in all, the identification of the crisis episode is crucial in influencing the predictive performance of the market-based measure of systemic importance. This highlights the difficulties in identifying a measure of systemic importance that remains a valid regulatory and supervisory tool over time. It is interesting to note that this finding is also in line with the evidence reported by Rose and Speigel (2011) of the weak predictive ability of key macro drivers of the global financial crisis when applied to other periods of turmoil.

5 DISCUSSION AND CONCLUSIONS

Numerous market based measures that attempt to quantify the degree of systemic importance of financial institutions have been proposed in the aftermath of the global financial crisis. The purpose of these measures is to offer regulators and supervisors additional, and more effective, tools to monitor systemic risk at the firm level. From a theoretical perspective, some of these measures focus on the implications of a financial institution's distress on the rest of the financial system and are consequently designed to be useful to control ex-post systemic damages from individual distress conditions. Others emphasize the degree of vulnerability of a financial institution in the case of a systemic shock and are then supposed to be useful when the purpose of supervisors is to design ex-ante interventions that reduce the potential number of defaults when a crisis materializes.

To be beneficial for regulators and supervisors, however, both types of measures have to offer information that is not already incorporated in more conventional risk proxies; namely, they have to signal something not already known on the basis of conventional drivers of systemic risk at the firm level. This paper shows that this requirement is not fully satisfied by a number of the most recent market-based measures of systemic importance and often questions the additional contribution that these measures provide with respect to simpler indicators of systemic importance. This conclusion emerges from a comprehensive comparison, conducted across three different financial crises (the global financial crisis, the Asian crisis and the 1998 crisis related to the Russian default and to the rescue of LTCM), of two measures that are expected to be beneficial in controlling ex-post systemic damages (Δ CoVaR and asymmetric

 Δ CoVaR) from the distress of financial institutions and two measures that are instead more likely to be useful in signaling the need for ex-ante supervisory interventions (SRISK and EXSHORT).

More precisely, the tests that employ the global financial crisis as a laboratory identify Δ CoVaR as the only market-based measure that is able to significantly explain the different notions of *realized* systemic importance computed over this crisis event. Δ CoVaR, therefore, offers early warning signals not just in terms of potential ex-post systemic damages that can arise from financial institution distress but also in terms of the vulnerability of these institutions to the occurrence of a systemic shock. Nevertheless, in terms of magnitude, the contribution of this measure compared to more conventional firm characteristics, and in particular to firm size, remains rather small.

During the global financial crisis, however, more disappointing is the performance of the other three market-based measures of systemic importance. The asymmetric version of Δ CoVaR only very seldom offers some additional predictive power to the early warning models, while SRISK and EXSHORT show some significant predictive ability only when the focus is on a specific definition of vulnerability; that is, the vulnerability of financial institutions in terms of capital shortfall. By contrast, they do no show any predictive power when the vulnerability is based simply on the decline in market value suffered during the crisis.

The overall picture becomes even more complex when the analysis focuses on the Asian crisis and the 1998 crisis. In these additional tests, Δ CoVaR does not confirm its ability to consistently predict different notions of systemic importance, suggesting that some of its predictive power during the global crisis is due to the specificities of this crisis. Furthermore, all measures perform especially poorly in two out of three tests conducted on the 1998 crisis; namely, they do not offer particular support to regulators and supervisors especially in the crisis event that appears closer to the recent crisis in terms of negative impact on the financial institutions included in our sample. All in all, if we put together the results of the three crisis tests we conclude that some degree of consistency only emerges when the focus is on the predictability of the vulnerability of financial institutions narrowly defined in terms of capital adequacy. In this respect, SRISK and, to a minor extent, EXSHORT seem to offer a valuable support to design ex-ante supervisory interventions on firm-specific capital requirements.

In conclusion, the key message from our tests is that it is problematic to identify a marketbased measure of systemic importance that remains valid across financial crises with different features and across different measures of *realized* systemic importance. It is worth noting, however, that our analysis shows that this criticism also applies to more conventional proxies employed by regulators to identify the most systemically important financial institutions. In this respect, size seems the most consistent indicator among the conventional measures - especially under severe global systemic events such as the recent global crisis and the 1998 crisis.

APPENDIX: ESTIMATION OF GLOBAL SYSTEMIC IMPORTANCE

In this section we provide details on the estimation procedures of the four market-based measures of systemic importance. Each measure is estimated on a daily frequency. In each prediction test, we construct the four measures on the basis of 5 years of data and we then employ the average computed over the last calendar year before the year of the eruption of the crisis in our prediction test.

 Δ **CoVaR and** Δ **A CoVaR** - the two bottom-up CoVaR approaches share some key characteristics. In particular, CoVaR denotes the Value at Risk of the financial system conditional on the performance of an institution *i*. Furthermore the performance on institution *i* is expressed as the Value at Risk computed on X_i that normally refers to equity returns or asset returns. This implies that the $CoVaR_{q,i}^{System|C(x^i)}$ is defined by the q-quantile of the conditional probability distribution:

$$Pr\left(X_{t}^{System} \leq C_{\theta} VaR_{q}^{System|C\left(X_{t}^{i}\right)} \middle| C\left(X_{t}^{i}\right)\right) = q_{t}^{'}$$
(A1)

It follows that the degree of systemic importance of an institution *i* is obtained by subtracting the CoVaR of the system when *i* is in "normal" conditions, expressed by a value of X_t equal to the median, from the value of the CoVaR when a distress condition in *i* is observed:

$$\Delta CoVaR_{q,t}^{System|i} = CoVaR_q^{System|X_t^i = VaR_{q,t}^i} - CoVaR_q^{System|X_t^i = Median_t^i}$$
(A2)

As in Adrian and Brunnermeier (2011) $CoVaR_q^{System|X_i^t=VaR_{q,i}^t}$ and $CoVaR_q^{System|X_i^t=Median_i^t}$ are estimated via quantile regression where X_i is regressed on a vector of lagged 'state variables' M_{i-i} describing the economic environment:

$$X_{t}^{i} = \boldsymbol{\alpha}_{q}^{i} + \boldsymbol{\gamma}_{q}^{i} M_{t-1} + \boldsymbol{\varepsilon}_{t,q}^{i},$$

$$X_{t}^{system} = \boldsymbol{\alpha}_{q}^{system/i} + \boldsymbol{\beta}_{q}^{system/i} X_{t}^{i} + \boldsymbol{\gamma}_{q}^{system/i} M_{t-1} + \boldsymbol{\varepsilon}_{t,q}^{system/i}.$$
(A3)

Given the purpose of the empirical tests discussed in this paper, the state variables in Adrian and Brunnermeier (2011) have been modified with the aim of describing the 'global' economic environment. In particular, the global stock market conditions are described by the return of a World Market Index from Datastream and by the volatility of this index (estimated by the GJR-GARCH model). The performance of the global real estate sector is measured by the annual cumulative return of a World Real Estate Index from Datastream. The change in the risk free rate is the GDP weighted average of the 3 month government yield rate for the G7 countries (US, UK, Germany, Canada, France, Italy and Japan), while the default risk is the GDP weighted average of the 3-month interbank rate and the 3 month government yield rate. The change in the global yield is the G7 GDP weighted average of the difference between the ten-year and the 3-month government yield rate. Finally, the proxy for the global liquidity risk is the change in the GDP weighted average difference between the 2-month and 1 –month interbank rates for the G7 countries.

The quantification of the degree of systemic importance is then derived employing the predicted values from (11), expressed as follows:

$$\begin{aligned} VaR_{t}^{i}(q) &= \hat{\alpha}_{q}^{i} + \hat{\gamma}_{q}^{i}M_{t-1}, \\ CoVaR_{q}^{System|X_{t}^{i}=VaR_{q,t}^{i}} &= \hat{\alpha}_{q}^{system/i} + \hat{\beta}_{q}^{system/i}VaR_{t}^{i}(q) + \hat{\gamma}_{q}^{system/i}M_{t-1}. \end{aligned}$$
(A3)

The major difference between the original CoVaR and the asymmetric approach (A_CoVaR) proposed by Lopez-Espinosa et al. (2012) refers to the underlying assumption that is used to model the relationship between the VaR of the financial system and the returns of an institution i. Adrian and Brunnermeier (2011) assume that the VaR of the financial system is affected in the same way by positive and negative returns realized by an institution i while Lopez-Espinosa et al. (2012) assume that the VaR of the financial system is more sensitive to negative returns realized by firm i than to positive returns. Therefore, the quantile regression for X_i^{system} has been modified as reported below:

$$X_{t}^{\text{system}} = \alpha_{q}^{\text{system/i}} + \beta_{q}^{\text{system/i}} X_{t}^{i} I_{(X_{t}^{i}<0)} + \beta_{q}^{\text{system/i}} X_{t}^{i} I_{(X_{t}^{i}\geq0)} + \gamma_{q}^{\text{system/i}} M_{t-t} + \varepsilon_{t,q}^{\text{system/i}}$$
(A4)

SRISK - Brownlees and Engle (2012), building upon Acharya et al. (2010), measure the degree of systemic importance of a financial institution via its participation in the systemic capital shortfall during a crisis. More specifically, for firm i at time t, under a prudential equity to asset ratio equal to k, the capital buffer is equal to:

$$Capital Buffer_{i,t} = k(TA_{i,t}) - W_{i,t}$$
(A5)

where TA is equivalent to the sum of risky debts (RD), guaranteed debts (GD) and the amount of equity capital $W_{i,t}$. The expected capital shortfall (CS) in period t+1 under a crisis event, defined as a drop in the market return below a certain threshold C, is then measured as follows:

$$CS_{i,t} = E_1 \Big[k \Big(TA_{i,t} \Big) - W_{i,t+1} \Big| Crisis \Big] =$$
(A6)

$$= E_1 \underbrace{\acute{e}k} \left(RD_{i,t} + GD_{i,t} + W_{i,t+1} \right) - W_{i,t+1} \left| Crisis \underbrace{\acute{e}} \right|$$
(A6.1)

$$= k \Big(RD_{i,t} + GD_{i,t} \Big) - (1-k) W_{i,t} \Big[1 + E_1 \Big(R_{i,t+1} \Big| R_{m,t+1} < C \Big) \Big]$$
(A6.2)

where $R_{i,t+1}$ and $R_{m,t+1}$ are the firm and market (arithmetic) returns in period t+1. $E_t(R_{i,t+1}|R_{m,t+1} < C)$ is the Marginal Expected Shortfall (MES); namely, the tail expectation of the firm return conditional on the market being in its left tail. To model MES, as in Brownlees and Engle (2012), the firm and market returns (measured as the value weighted average return of the financial institutions in the sample) are described as follow:

$$R_{m,t} = \sigma_{m,t} \varepsilon_{m,t}$$

$$R_{i,t} = \sigma_{i,t} \rho_{i,t} \varepsilon_{m,t} + \sigma_{i,t} \sqrt{1 - \rho_{i,t}^2} \xi_{i,t}$$
(A7)

where $\sigma_{m,t}$ and $\sigma_{i,t}$ are the volatility for the market and firm *i* at date *t*, $\rho_{i,t}$ is the correlation between the returns of market and firm *i* at date *t*, and $\varepsilon_{m,t}$ and $\xi_{i,t}$ are residuals following independent and identical normal distributions with zero mean, unit variance and zero covariance. Therefore, MES can be decomposed as follows:

$$MES_{i,t}(C) = E_{t} \left(R_{i,t+1} | R_{m,t+1} < C \right) = \sigma_{i,t+1} E_{t} \left(\varepsilon_{i,t+1} | \varepsilon_{m,t+1} < C / \sigma_{m,t+1} \right) = \sigma_{i,t+1} E_{t} \left(\rho_{i,t+1} \varepsilon_{m,t+1} + \sqrt{1 - \rho_{i,t+1}^{2}} \xi_{i,t+1} | \varepsilon_{m,t+1} < C / \sigma_{m,t+1} \right) = \sigma_{i,t+1} \rho_{i,t+1} E_{t} \left(\varepsilon_{m,t+1} | \varepsilon_{m,t+1} < C / \sigma_{m,t+1} \right) + \sigma_{i,t+1} \sqrt{1 - \rho_{i,t+1}^{2}} E_{t} \left(\xi_{i,t+1} | \varepsilon_{m,t+1} < C / \sigma_{m,t+1} \right)$$
(A8)

Following Brownlees and Engle (2012) the estimates of $\sigma_{m,t}$ and $\sigma_{i,t}$ are based on the GJR-GARCH model while $\rho_{i,t}$ is derived from a Dynamic Conditional Correlation (DCC) model. Finally, the tail expectation $E_t(\varepsilon_{m,t+1}|\varepsilon_{m,t+1} < C/\sigma_{m,t+1})$ and $E_t(\xi_{i,t+1}|\varepsilon_{m,t+1} < C/\sigma_{m,t+1})$ have been estimated with a nonparametric kernel estimation approach. The first 1000 observations are required to estimate the tail behavior to draw the first estimates for MES.

Finally, as formalized below, the degree of systemic importance of a financial institution is defined as the portion of the total expected system capital shortfall which a firm *i* participates in during a crisis:

$$SRISK = \frac{Capitalshortfall_{i}}{\sum_{i} Capitalshortfall} = \frac{Max(0, CS_{i})}{\sum_{i} Max(0, CS_{i})}$$
(A9)

EXSHORT – a top-down framework is also characterized in the measure proposed by Lehar (2005). The author defines the degree of systemic importance of a financial institution in terms of the share of the total volatility of the expected shortfall for the system that expresses the risk exposure of a hypothetical regulator. More specifically, the expected shortfall for the system is defined as the total present value of the amount of debt that cannot be covered by the assets of the financial institution in the case of default. Under the Merton (1977) framework, for a bank i this is equivalent to the value of a put option expressed by the following equation:

$$S_t^i = B_t^i N\left(-d_t + \sigma \sqrt{t}\right) - V_t^i N\left(-d_t\right)$$
(A10)

Where B_t^i is the book value of total debts, σ is the value of asset volatility, V_t^i is the market value of total assets and d_t is equal to $\frac{\left[ln\left(V_t^i/B_t^i\right) + \sigma^2/2\right]T}{\sigma\sqrt{T}}$.

The volatility of the expected shortfall for the banking system, that is the sum of S_t^i across all the banks in the system, is then computed through the variance-covariance matrix (Σ) of the returns on the bank's asset portfolios, whose components are based on an exponentially weighted moving average (EWMA) model with a decay factor (λ) equal to 0.94, and using the vectors δ_t of partial derivatives $(V_i^i \partial S_t^i / \partial V_i^i)$.

Then, using first order terms, the Dollar-volatility of the expected shortfall z_t can be approximated as follows:

$$z_t = \sqrt{\delta_t \sum_t \delta_t'} \tag{A11}$$

Lehar (2005) decomposes z_t on the basis of the standard concept of component value at risk where the vector of contributions to the expected shortfall risk is measured by means of the following equation:

$$\varsigma_{t} = \frac{1}{\gamma_{t}} \left(\sum_{i} \delta_{i}^{'} \right) * \delta_{i}^{'} \tag{A12}$$

Where * is the element wise-product of two vectors and the total sum of the elements of ζ_t , that quantify the degree of systemic importance at the firm level, is equal to z_t .

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42

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TABLES

TABLE 1: SAMPLE DISTRIBUTION BY COUNTRY AND SECTOR

	Full	sample	Comn	nercial	Insu	rance	Financi	al services
		-	baı	ıks	com	panies	com	panies
	Ν	%	Ν	%	Ν	%	Ν	%
Australia	8	2.64	6	3.05	0	0.00	2	5.26
Austria	1	0.33	1	0.51	0	0.00	0	0.00
Belgium	4	1.32	3	1.52	1	1.47	0	0.00
Brazil	1	0.33	1	0.51	0	0.00	0	0.00
Canada	11	3.63	6	3.05	5	7.35	0	0.00
China	3	0.99	3	1.52	0	0.00	0	0.00
Denmark	3	0.99	3	1.52	0	0.00	0	0.00
Finland	2	0.66	1	0.51	1	1.47	0	0.00
France	11	3.63	6	3.05	4	5.88	1	2.63
Germany	15	4.95	6	3.05	7	10.29	2	5.26
Greece	4	1.32	4	2.03	0	0.00	0	0.00
Hong Kong	3	0.99	3	1.52	0	0.00	0	0.00
Hungary	1	0.33	1	0.51	0	0.00	0	0.00
India	2	0.66	2	1.02	0	0.00	0	0.00
Ireland	3	0.99	2	1.02	1	1.47	0	0.00
Israel	2	0.66	2	1.02	0	0.00	0	0.00
Italy	16	5.28	12	6.09	4	5.88	0	0.00
Japan	45	14.85	29	14.72	5	7.35	11	28.95
Luxembourg	2	0.66	2	1.02	0	0.00	0	0.00
Malaysia	3	0.99	3	1.52	0	0.00	0	0.00
Mexico	1	0.33	1	0.51	0	0.00	0	0.00
Netherlands	3	0.99	1	0.51	2	2.94	0	0.00
Norway	3	0.99	3	1.52	0	0.00	0	0.00
Portugal	5	1.65	5	2.54	0	0.00	0	0.00
Russia	1	0.33	1	0.51	0	0.00	0	0.00
Singapore	3	0.99	3	1.52	0	0.00	0	0.00
South Africa	8	2.64	4	2.03	3	4.41	1	2.63
South Korea	8	2.64	7	3.55	0	0.00	1	2.63
Spain	6	1.98	6	3.05	0	0.00	0	0.00
Sweden	5	1.65	4	2.03	1	1.47	0	0.00
Switzerland	6	1.98	2	1.02	4	5.88	0	0.00
Taiwan	6	1.98	4	2.03	2	2.94	0	0.00
Thailand	4	1.32	4	2.03	0	0.00	0	0.00
Turkey	4	1.32	3	1.52	0	0.00	1	2.63
United Kingdom	17	5.61	10	5.08	5	7.35	2	5.26
USA	83	27.39	43	21.83	23	33.82	17	44.74
Total	303	100.00	197	100.00	68	100.00	38	100.00

TABLE 2: VARIABLE DEFINITIONS	S AND DESCRIPTIVE STATISTICS
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		Ν	Mean	Median	St.Dev.	P1	P99
Panel A: Variables employed	for the tests on the Global Financial Crisis						
ΔCoVaR	Market measure of systemic importance based on Adrian and Brunnermeier (2011)	245	0.52	0.54	0.29	-0.03	1.12
ΔA_CoVaR	Market measure of systemic importance based on Lopez-Espinosa et al., (2012)	245	0.84	0.82	0.47	-0.08	1.90
SRISK	Market measure of systemic importance based on Brownlees and Engle (2012)	245	0.40	0.13	0.71	0.00	3.59
EXSHORT	Market measure of systemic importance based on Lehar (2005): US\$ mln	245	4542.44	73.57	16663.61	-214.49	98955.86
LN(EXSHORT)	Log of Market measure of systemic importance based on Lehar (2005)	245	7.41	6.90	1.19	6.56	11.51
COVARIANCE	Covariance between daily stock returns of financial institution i with the return of the value weighted remaining financial institutions in the sample 2 nd July 2007 to 31 st December 2008	245	4.73	4.55	2.52	0.13	11.06
BAILOUT	Dummy Equal to one if a financial institution has received capital support via public funds	245	0.16	0.00	0.37	0.00	1.00
NBHR	Minus the buy and hold returns computed from 2 nd July 2007 to 31 st December 2008 (%)	245	49.64	52.00	28.59	-26.16	97.70
CAP_SHORTFALL	Realized capital shortfall 2 nd July 2007 to 31 st December 2008. Based on Brownlees and Engle (2012) (%)	241	0.41	0.06	0.91	0.00	4.49
SIZE	Log of Total assets measured in millions of US \$	245	11.77	11.54	1.18	9.55	14.40
EQUITY	Equity over total assets (%)	245	7.78	6.55	5.38	1.43	28.49
VOLATILITY	Equity returns volatility (%)	245	25.20	23.80	9.39	10.99	53.7
CAUSING OTHERS	Number of financial institutions caused by financial institution <i>i</i> based on linear Granger causality tests on daily stock returns with two lags.	245	73.71	68.00	50.16	4.00	182.0
CAUSED BY OTHERS	Number of financial institutions that are causing financial institution <i>i</i> based on linear Granger causality tests on daily stock returns with two lags.	245	70.84	55.00	52.70	4.00	177.0
REG_RATIO	Regulatory capital divided by risk-weighted assets	155	12.24	11.80	2.62	8.79	25.0
DIVERSIFICATION	1 minus the Herfindhal index of income concentration between interest and non-interest						
	income	155	0.43	0.46	0.09	0.14	0.5
Panel B: Variables employed	for the tests on the Asian Financial Crisis						
$\Delta CoVaR$	Market measure of systemic importance based on Adrian and Brunnermeier (2011)	219	0.641	0.609	0.348	-0.182	1.34
ΔA_CoVaR	Market measure of systemic importance based on Lopez-Espinosa et al., (2012)	219	1.210	1.247	0.756	-0.345	2.91
SRISK	Market measure of systemic importance based on Brownlees and Engle (2012)	219	0.46	0.21	0.73	0.00	3.9
EXSHORT	Market measure of systemic importance based on	219	1512.40	87.50	3995.36	0.00	19522.4
LN(EXSHORT)	Lehar (2005): US\$ mln Log of Market measure of systemic importance based on Lehar (2005)	219	4.52	4.49	2.74	0.70	9.8
COVARIANCE	Covariance between daily stock returns of financial institution i with the return of the value weighted remaining financial institutions in the sample from 2 nd July 1997 to 12 th November 1997	219	0.84	0.84	0.39	-0.08	1.7
NBHR	July 1997 to 12 th November 1997 (%)	219	1.90	-1.79	26.21	-61.42	62.6
CAP_SHORTFALL	Realized capital shortfall from 2 nd July 1997 to 12 th November 1997. Based on Brownlees and Engle (2012) (%)	219	0.46	0.00	1.16	0.00	5.6
SIZE	Log of Total assets measured in millions of US \$	219	10.68	10.64	1.08	8.19	13.1
EQUITY	Equity over total assets (%)	219	7.59	6.34	5.71	1.76	31.0
VOLATILITY	Equity returns volatility (%)	219	1.44	1.37	0.42	0.78	3.0
CAUSING OTHERS	Number of financial institutions caused by financial institution <i>i</i> based on linear Granger causality tests on daily stock returns with two lags.	219	36.02	26.00	28.26	7.00	121.0
CAUSED BY OTHERS	Number of financial institutions that are causing financial institution <i>i</i> based on linear Granger causality tests on daily stock returns with two lags.	219	36.02	31.00	20.03	9.00	97.0

Notes: Panels A, B and C of this Table report the variable definitions and the summary statistics of the market measures of systemic importance, the measures of *realized* systemic importance and the control variables, employed for, respectively, the Global Financial Crisis Tests, the Asian Crisis Tests and the 1998 Crisis Tests.

Table 2: CONTINUED

ΔCoVaR	Market measure of systemic importance based on Adrian and Brunnermeier (2011)	219	0.61	0.56	0.35	-0.21	1.4
ΔA_CoVaR	Market measure of systemic importance based on Lopez-Espinosa et al., (2012)	219	1.10	1.07	0.68	-0.30	2.7
SRISK	Market measure of systemic importance based on Brownlees and Engle (2012)	219	0.37	0.02	0.93	0.00	4.0
EXSHORT	Market measure of systemic importance based on Lehar (2005): US\$ mln	219	4541.68	171.78	27096.20	-57.41	13385 2
LN(EXSHORT)	Log of Market measure of systemic importance based on Lehar (2005)	219	6.59	6.13	1.37	5.45	11.8
COVARIANCE	Covariance between daily stock returns of financial institution i with the return of the value weighted remaining financial institutions in the sample from 3^{rd} August 1998 to 5^{th} October 1998	219	3.52	3.76	2.09	-0.85	7.
NBHR	Minus the buy and hold returns computed from 3^{rd} August 1998 to 5^{th} October 1998 (%)	219	22.70	23.17	18.16	-28.29	56.
CAP_SHORTFALL	Realized capital shortfall from 3 rd August 1998 to 5 th October 1998. Based on Brownlees and Engle (2012) (%)	219	0.46	0.00	1.19	0.00	5.1
SIZE	Log of Total assets measured in millions of US \$	219	10.70	10.56	1.09	8.26	13.0
EQUITY	Equity over total assets (%)	219	8.04	6.30	7.56	2.23	29.3
VOLATILITY	Equity returns volatility (%)	219	2.17	1.86	0.95	1.05	5.4
CAUSING OTHERS	Number of financial institutions caused by financial institution <i>i</i> based on linear Granger causality tests on daily stock returns with two lags.	219	48.37	34.00	38.26	8.00	149.
CAUSED BY OTHERS	Number of financial institutions that are causing financial institution <i>i</i> based on linear Granger causality tests on daily stock returns with two lags.	219	49.02	46.00	24.77	9.00	100.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample						
SIZE	1.010***	0.879***	0.707***	0.853***	1.049***	0.963***
	(6.98)	(8.62)	(8.15)	(8.22)	(9.50)	(12.28)
EQUITY		0.040	0.041	0.035	0.039	0.038
		(1.16)	(1.38)	(1.02)	(1.05)	(1.01)
VOLATILITY		0.040*	0.038*	0.040*	0.043**	0.043*
		(1.96)	(2.03)	(1.99)	(2.21)	(1.93)
CAUSING OTHERS		0.024***	0.015***	0.021***	0.024***	0.023***
		(5.69)	(4.80)	(6.57)	(5.49)	(6.08)
CAUSED BY OTHERS		-0.002	-0.001	-0.001	-0.001	-0.002
		(0.31)	(0.23)	(0.14)	(0.24)	(0.46)
$\Delta CoVaR$			2.450***			
			(3.60)			
ΔA_CoVaR				0.495		
				(1.30)		
SRISK					-0.365	
					(1.30)	
Ln (EXSHORT)						-0.143
						(0.80)
Constant	-7.166***	-8.496***	-7.160***	-8.462***	-10.441***	-8.417***
	(3.66)	(5.46)	(5.64)	(5.75)	(9.58)	(4.95)
Observations	245	245	245	245	245	245
R-squared	0.224	0.453	0.485	0.457	0.458	0.456
Panel B: Banks						
SIZE	0.904***	0.778***	0.842***	1.084***	1.077***	0.904***
	(8.13)	(6.71)	(7.26)	(8.17)	(10.04)	(8.13)
REG_RATIO	0.054	0.030	0.041	0.056	0.043	0.054
	(1.33)	(0.76)	(1.01)	(1.34)	(0.97)	(1.33)
DIVERSIFICATION	4.129***	3.376**	4.299***	3.754**	3.210*	4.129***
	(2.89)	(2.39)	(3.10)	(2.24)	(1.72)	(2.89)
VOLATILITY	0.062***	0.060***	0.060***	0.064***	0.070***	0.062***
	(3.73)	(3.54)	(3.83)	(3.90)	(4.03)	(3.73)
CAUSING OTHERS	0.024***	0.018***	0.020***	0.024***	0.024***	0.024***
	(7.55)	(6.15)	(7.55)	(7.06)	(7.30)	(7.55)
CAUSED BY OTHERS	-0.005	-0.005	-0.004	-0.005	-0.005	-0.005
	(1.21)	(1.16)	(1.18)	(1.12)	(1.26)	(1.21)
$\Delta CoVaR$		1.505**				
		(2.04)	0 == 1 + 1			
ΔA_CoVaR			0.751*			
0			(1.94)			
SRISK				-0.331		
				(1.26)		
Ln (EXSHORT)					-0.261	
					(1.32)	
Constant	-11.181***	-9.477***	-10.721***	-13.113***	-10.912***	-11.181***
	(5.47)	(4.78)	(5.54)	(6.80)	(4.55)	(5.47)
Observations	155	155	155	155	155	155
R-squared	0.529	0.541	0.539	0.533	0.536	0.529

TABLE 3: REALIZED COVARIANCE RISK DURING THE GLOBAL FINANCIAL CRISIS AND MARKET MEASURES OF GLOBAL SYSTEMIC IMPORTANCE BEFORE THE CRISIS

Notes: This Table reports the regression results of the relationship between the **covariance risk** during the global financial crisis (July 2007-December 2008) and the degree of systemic importance in 2006 according to market measures. **SIZE** is defined as the log transformation of firm total assets at the end of 2006, **EQUITY** is the ratio between equity capital and total assets, **VOLATILITY** is the stock return volatility computed with daily stock returns, **CAUSING OTHERS** is the number of financial institutions that a financial institution A is causing during year 2006 according to Granger causality tests based on daily stock returns, **CAUSED BY OTHERS** is the number of financial institutions that are a financial institution A during year 2006 according to Granger causality tests based on daily stock returns, **REG_RATIO** is regulatory capital divided by risk-weighted assets, and **DIVERSIFICATION** is 1 minus the Herfindahl index of income concentration between interest and non-interest income. Robust t statistics clustered at the country level are reported in round brackets and *** (**;*) indicates significant at 1%(5%;10%).

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample						
SIZE	1.155***	0.998***	0.800*	0.948**	1.425***	1.101***
	(3.69)	(2.87)	(1.74)	(2.39)	(2.63)	(2.78)
EQUITY		-0.100	-0.120	-0.114	-0.120	-0.119
		(1.19)	(1.19)	(1.17)	(1.35)	(1.34)
VOLATILITY		0.016	0.016	0.015	0.021	0.021
		(0.56)	(0.59)	(0.52)	(0.73)	(0.74)
CAUSING OTHERS		0.002	-0.006	-0.001	0.001	0.001
		(0.41)	(0.75)	(0.09)	(0.27)	(0.27)
CAUSED BY OTHERS		-0.009	-0.010	-0.009	-0.008	-0.010
		(1.23)	(1.18)	(1.07)	(1.00)	(1.27)
ΔCoVaR			2.763*			
			(1.69)			
∆A_CoVaR			(,	0.704		
				(0.79)		
SRISK				(0.17)	-0.621	
					(1.52)	
Ln (EXSHORT)					(-0.138
						(0.84)
Constant	-15.789***	-13.172***	-11.636*	-12.943**	-18.131**	-13.304***
Jonstant	(3.94)	(2.60)	(1.93)	(2.39)	(2.53)	(2.59)
Observations	245	245	245	245	245	245
Pseudo R-squared	0.249	0.283	0.313	0.289	0.295	0.286
Panel B: Banks	0.247	0.205	0.515	0.207	0.275	0.200
	1 000***	1 051***	0 742*	1 007***	1 (15***	1 1/5**
SIZE	1.008***	1.051***	0.742*	1.007***	1.645***	1.145**
	1.008*** (3.31)	(3.25)	(1.75)	(2.83)	(2.60)	(2.49)
		(3.25) -0.190	(1.75) -0.287*	(2.83) -0.204	(2.60) -0.171	(2.49) -0.200
REG_RATIO		(3.25) -0.190 (1.34)	(1.75) -0.287* (1.71)	(2.83) -0.204 (1.31)	(2.60) -0.171 (1.30)	(2.49) -0.200 (1.36)
REG_RATIO		(3.25) -0.190 (1.34) -0.092	(1.75) -0.287* (1.71) -2.959	(2.83) -0.204 (1.31) 0.014	(2.60) -0.171 (1.30) -1.175	(2.49) -0.200 (1.36) -0.525
REG_RATIO DIVERSIFICATION		(3.25) -0.190 (1.34) -0.092 (0.03)	(1.75) -0.287* (1.71) -2.959 (0.67)	(2.83) -0.204 (1.31) 0.014 (0.00)	(2.60) -0.171 (1.30) -1.175 (0.32)	(2.49) -0.200 (1.36) -0.525 (0.15)
REG_RATIO DIVERSIFICATION		(3.25) -0.190 (1.34) -0.092 (0.03) 0.038	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043
REG_RATIO DIVERSIFICATION VOLATILITY		(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04)	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83)	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038 (1.02)	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22)	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06)
REG_RATIO DIVERSIFICATION VOLATILITY		(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04) 0.002	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83) -0.014	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038 (1.02) -0.001	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22) 0.002	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06) 0.002
REG_RATIO DIVERSIFICATION VOLATILITY CAUSING OTHERS		(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04) 0.002 (0.37)	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83) -0.014 (1.35)	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038 (1.02) -0.001 (0.18)	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22) 0.002 (0.33)	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06) 0.002 (0.32)
REG_RATIO DIVERSIFICATION VOLATILITY CAUSING OTHERS		(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04) 0.002 (0.37) -0.006	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83) -0.014 (1.35) -0.007	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038 (1.02) -0.001 (0.18) -0.006	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22) 0.002 (0.33) -0.004	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06) 0.002 (0.32) -0.007
REG_RATIO DIVERSIFICATION VOLATILITY CAUSING OTHERS CAUSED BY OTHERS		(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04) 0.002 (0.37)	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83) -0.014 (1.35) -0.007 (0.73)	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038 (1.02) -0.001 (0.18)	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22) 0.002 (0.33)	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06) 0.002 (0.32)
REG_RATIO DIVERSIFICATION VOLATILITY CAUSING OTHERS CAUSED BY OTHERS		(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04) 0.002 (0.37) -0.006	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83) -0.014 (1.35) -0.007 (0.73) 4.560**	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038 (1.02) -0.001 (0.18) -0.006	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22) 0.002 (0.33) -0.004	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06) 0.002 (0.32) -0.007
REG_RATIO DIVERSIFICATION VOLATILITY CAUSING OTHERS CAUSED BY OTHERS ACoVaR		(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04) 0.002 (0.37) -0.006	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83) -0.014 (1.35) -0.007 (0.73)	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038 (1.02) -0.001 (0.18) -0.006 (0.73)	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22) 0.002 (0.33) -0.004	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06) 0.002 (0.32) -0.007
REG_RATIO DIVERSIFICATION VOLATILITY CAUSING OTHERS CAUSED BY OTHERS ACoVaR		(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04) 0.002 (0.37) -0.006	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83) -0.014 (1.35) -0.007 (0.73) 4.560**	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038 (1.02) -0.001 (0.18) -0.006 (0.73)	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22) 0.002 (0.33) -0.004	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06) 0.002 (0.32) -0.007
REG_RATIO DIVERSIFICATION /OLATILITY CAUSING OTHERS CAUSED BY OTHERS ACoVaR		(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04) 0.002 (0.37) -0.006	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83) -0.014 (1.35) -0.007 (0.73) 4.560**	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038 (1.02) -0.001 (0.18) -0.006 (0.73)	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22) 0.002 (0.33) -0.004	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06) 0.002 (0.32) -0.007
REG_RATIO DIVERSIFICATION /OLATILITY CAUSING OTHERS CAUSED BY OTHERS ACoVaR		(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04) 0.002 (0.37) -0.006	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83) -0.014 (1.35) -0.007 (0.73) 4.560**	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038 (1.02) -0.001 (0.18) -0.006 (0.73)	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22) 0.002 (0.33) -0.004	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06) 0.002 (0.32) -0.007
REG_RATIO DIVERSIFICATION /OLATILITY CAUSING OTHERS CAUSED BY OTHERS ACoVaR		(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04) 0.002 (0.37) -0.006	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83) -0.014 (1.35) -0.007 (0.73) 4.560**	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038 (1.02) -0.001 (0.18) -0.006 (0.73)	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22) 0.002 (0.33) -0.004 (0.53)	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06) 0.002 (0.32) -0.007
REG_RATIO DIVERSIFICATION VOLATILITY CAUSING OTHERS CAUSED BY OTHERS ACoVaR AA_CoVaR SRISK		(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04) 0.002 (0.37) -0.006	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83) -0.014 (1.35) -0.007 (0.73) 4.560**	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038 (1.02) -0.001 (0.18) -0.006 (0.73)	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22) 0.002 (0.33) -0.004 (0.53)	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06) 0.002 (0.32) -0.007
SIZE REG_RATIO DIVERSIFICATION VOLATILITY CAUSING OTHERS CAUSED BY OTHERS ACoVaR AA_CoVaR SRISK Ln (EXSHORT)		(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04) 0.002 (0.37) -0.006	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83) -0.014 (1.35) -0.007 (0.73) 4.560**	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038 (1.02) -0.001 (0.18) -0.006 (0.73)	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22) 0.002 (0.33) -0.004 (0.53)	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06) 0.002 (0.32) -0.007 (0.80)
REG_RATIO DIVERSIFICATION VOLATILITY CAUSING OTHERS CAUSED BY OTHERS ACoVaR AA_CoVaR SRISK Ln (EXSHORT)		(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04) 0.002 (0.37) -0.006	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83) -0.014 (1.35) -0.007 (0.73) 4.560**	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038 (1.02) -0.001 (0.18) -0.006 (0.73)	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22) 0.002 (0.33) -0.004 (0.53)	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06) 0.002 (0.32) -0.007 (0.80)
REG_RATIO DIVERSIFICATION VOLATILITY CAUSING OTHERS CAUSED BY OTHERS ACoVaR AA_CoVaR SRISK En (EXSHORT)	(3.31) -13.689***	(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04) 0.002 (0.37) -0.006 (0.78)	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83) -0.014 (1.35) -0.007 (0.73) 4.560** (2.31)	(2.83) -0.204 (1.31) 0.014 (0.00) 0.038 (1.02) -0.001 (0.18) -0.006 (0.73) 0.651 (0.72)	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22) 0.002 (0.33) -0.004 (0.53) -0.800 (1.63) -19.398****	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06) 0.002 (0.32) -0.007 (0.80) -0.110 (0.45) -12.649**
REG_RATIO DIVERSIFICATION VOLATILITY CAUSING OTHERS CAUSED BY OTHERS ACoVaR AA_CoVaR SRISK	(3.31)	(3.25) -0.190 (1.34) -0.092 (0.03) 0.038 (1.04) 0.002 (0.37) -0.006 (0.78)	(1.75) -0.287* (1.71) -2.959 (0.67) 0.036 (0.83) -0.014 (1.35) -0.007 (0.73) 4.560** (2.31)	$\begin{array}{c} \textbf{(2.83)}\\ -0.204\\ (1.31)\\ 0.014\\ (0.00)\\ 0.038\\ (1.02)\\ -0.001\\ (0.18)\\ -0.006\\ (0.73)\\ \end{array}$	(2.60) -0.171 (1.30) -1.175 (0.32) 0.044 (1.22) 0.002 (0.33) -0.004 (0.53)	(2.49) -0.200 (1.36) -0.525 (0.15) 0.043 (1.06) 0.002 (0.32) -0.007 (0.80)

TABLE 4: BAILOUTS DURING THE GLOBAL FINANCIAL CRISIS AND MARKETMEASURES OF GLOBAL SYSTEMIC IMPORTANCE BEFORE THE CRISIS

Notes: This Table reports the regression results of the relationship between **bailouts** during the global financial crisis and the degree of systemic importance in 2006 according to market measures. **SIZE** is defined as the log transformation of firm total assets at the end of 2006, **EQUITY** is the ratio between equity capital and total assets, **VOLATILITY** is the stock return volatility computed with daily stock returns, **CAUSING OTHERS** is the number of financial institutions that a financial institution A is causing during year 2006 according to Granger causality tests based on daily stock returns, **CAUSED BY OTHERS** is the number of financial institutions that are a financial institution A during year 2006 according to Granger causality tests based on daily stock returns, **REG_RATIO** is regulatory capital divided by risk-weighted assets, and **DIVERSIFICATION** is 1 minus the Herfindahl index of income concentration between interest and non-interest income. Robust t statistics clustered at the country level are reported in round brackets and **** (**;*) indicates significant at 1%(5%;10%).

	(1)	(2)
	% Bailout institutions correctly classified	% All institutions correctly classified
Panel A: Full sample		
Only SIZE	67.50	74.29
SIZE + additional conventional variables	70.00	74.29
SIZE + additional conventional variables +CoVAR	77.50	78.37
Panel B: Banks		
Only SIZE	76.67	76.13
SIZE + additional conventional variables	73.33	76.77
SIZE + additional conventional variables +CoVAR	76.67	78.71

TABLE 5: CLASSIFICATION STATISTICS FROM THE LOGIT PREDICTION MODELS

Notes: This Table reports the percentage of correctly classified institutions on the basis of the prediction model reported in columns from 1) to 3) in Table 4. The cut-off point to identify the number of institutions that are correctly classified is defined by the ratio between the number of bailout institutions and the total number of observations (40/245).

N (A 17 11 - 1	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample						
SIZE	10.401***	9.669***	8.048***	9.661***	12.016***	10.446***
	(4.52)	(4.93)	(4.27)	(5.10)	(4.31)	(5.89)
EQUITY		-0.362	-0.355	-0.364	-0.384	-0.388
		(0.69)	(0.72)	(0.70)	(0.73)	(0.72)
VOLATILITY		0.516***	0.492**	0.516***	0.552***	0.544**
		(2.87)	(2.59)	(2.89)	(3.16)	(2.69)
CAUSING OTHERS		0.103	0.025	0.103*	0.105	0.099
		(1.52)	(0.47)	(1.87)	(1.52)	(1.55)
CAUSED BY OTHERS		-0.021	-0.016	-0.021	-0.016	-0.026
		(0.28)	(0.22)	(0.26)	(0.22)	(0.36)
ΔCoVaR			23.210**			
			(2.22)			
ΔA_CoVaR				0.155		
				(0.03)		
SRISK					-5.021	
					(1.68)	
Ln (EXSHORT)						-1.308
						(0.71)
Constant	-72.771**	-80.113***	-67.453**	-80.102***	-106.901***	-79.388***
	(2.53)	(2.77)	(2.46)	(2.78)	(2.86)	(2.75)
Observations	245	245	245	245	245	245
R-squared	0.184	0.224	0.246	0.224	0.231	0.226
Panel B: Banks						
SIZE	9.543***	9.101***	6.580**	8.568***	11.473**	8.915***
	(3.23)	(3.62)	(2.34)	(3.67)	(2.54)	(4.01)
REG_RATIO		-1.353	-1.836	-1.463	-1.334	-1.342
		(1.28)	(1.61)	(1.40)	(1.25)	(1.26)
DIVERSIFICATION		27.111	12.131	28.567	22.154	28.098
		(1.03)	(0.44)	(1.03)	(0.81)	(0.93)
VOLATILITY		0.591***	0.554**	0.574***	0.614***	0.583**
		(2.94)	(2.45)	(2.89)	(3.01)	(2.52)
CAUSING OTHERS		0.026	-0.089	-0.011	0.030	0.026
		(0.43)	(1.61)	(0.21)	(0.47)	(0.43)
CAUSED BY OTHERS		-0.126	-0.115	-0.121	-0.118	-0.126
		(1.24)	(1.18)	(1.21)	(1.21)	(1.24)
ΔCoVaR		(1.21)	29.962**	(1.21)	(1.21)	(1.21)
			(2.39)			
ΔA_CoVaR			(2.57)	6.439		
				(1.06)		
SRISK				(1.00)	-4.374	
5K15K						
L - (EVCLIOD'T)					(0.91)	0.200
Ln (EXSHORT)						0.280
	(0.107	50.010	24.005	54044	04.255	(0.09)
Constant	-62.407	-58.818	-24.885	-54.866	-84.355	-59.108
	(1.62)	(1.34)	(0.51)	(1.31)	(1.33)	(1.31)
Observations	155	155	155	155	155	155
R-squared	0.162	0.242	0.276	0.248	0.248	0.243

TABLE 6: BUY AND HOLD RETURNS DURING THE GLOBAL FINANCIAL CRISIS AND MARKET MEASURES OF GLOBAL SYSTEMIC IMPORTANCE BEFORE THE CRISIS

Notes: This Table reports the regression results of the relationship between **buy and hold returns** during the global financial crisis (July 2007-December 2008) and the degree of systemic importance in 2006 according to market measures. **SIZE** is defined as the log transformation of firm total assets at the end of 2006, **EQUITY** is the ratio between equity capital and total assets, **VOLATILITY** is the stock return volatility computed with daily stock returns, **CAUSING OTHERS** is the number of financial institutions that a financial institution A is causing during year 2006 according to Granger causality tests based on daily stock returns, **CAUSED BY OTHERS** is the number of financial institutions that are a financial institution A during year 2006 according to Granger causality tests based on daily stock returns, **REG_RATIO** is regulatory capital divided by risk-weighted assets, and **DIVERSIFICATION** is 1 minus the Herfindahl index of income concentration between interest and non-interest income. Robust t statistics clustered at the country level are reported in round brackets and *** (**;*) indicates significant at 1%(5%;10%).

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample						
SIZE	0.549***	0.556***	0.527***	0.545***	0.101	0.409***
	(6.56)	(5.44)	(5.49)	(5.63)	(1.24)	(5.54)
EQUITY		-0.002	-0.002	-0.005	0.001	0.002
		(0.27)	(0.24)	(0.52)	(0.32)	(0.19)
VOLATILITY		0.006	0.006	0.006	-0.001	0.000
		(1.28)	(1.23)	(1.32)	(0.30)	(0.08)
CAUSING OTHERS		0.001	-0.001	-0.000	0.000	0.001
		(0.45)	(0.39)	(0.27)	(0.36)	(0.80)
CAUSED BY OTHERS		0.000	0.000	0.001	-0.001	0.001
		(0.40)	(0.65)	(0.88)	(1.01)	(0.98)
$\Delta CoVaR$			0.437**			
			(2.08)	0.040*		
ΔA_CoVaR				0.242*		
SRISK				(1.80)	0.963***	
SKISK						
Ln (EXSHORT)					(5.89)	0.241***
LII (EASITORI)						(3.55)
Constant	-6.059***	-6.362***	-6.144***	-6.360***	-1.128	-6.382***
Constant	(6.31)	(5.18)	(5.30)	(5.53)	(1.08)	(6.73)
Observations	241	241	241	241	241	241
R-squared	0.506	0.510	0.517	0.517	0.742	0.570
Panel B: Banks	0.500	0.510	0.517	0.517	0.712	0.570
SIZE	0.622***	0.640***	0.589***	0.625***	0.106	0.391***
SIZE	(4.91)	(4.97)	(4.59)	(4.84)	(1.29)	(4.08)
REG_RATIO	(4.91)	0.000	-0.010	-0.003	-0.005	0.015
		(0.01)	(0.53)	(0.17)	(0.59)	(0.91)
DIVERSIFICATION		-1.270*	-1.581**	-1.230*	-0.158	0.040
		(1.90)	(2.28)	(1.93)	(0.48)	(0.06)
VOLATILITY		0.004	0.003	0.004	-0.001	-0.007
		(0.68)	(0.56)	(0.62)	(0.32)	(1.31)
CAUSING OTHERS		0.001	-0.001	-0.000	0.000	0.001
		(0.41)	(0.57)	(0.06)	(0.11)	(0.59)
CAUSED BY OTHERS		0.001	0.001	0.001	-0.001	0.001
		(0.67)	(0.87)	(0.77)	(0.79)	(0.86)
$\Delta CoVaR$		· · /	0.619*	~ /	()	
			(1.73)			
ΔA_CoVaR			× ,	0.182		
				(1.20)		
SRISK				~ /	0.976***	
					(5.44)	
Ln (EXSHORT)					` '	0.371***
· · · ·						(4.56)
Constant	-6.873***	-6.785***	-6.095***	-6.680***	-1.035	-7.131***
	(4.73)	(4.09)	(3.67)	(4.08)	(0.97)	(4.66)
Observations	154	154	154	154	154	154

TABLE 7: CAPITAL SHORTFALLS DURING THE GLOBAL FINANCIAL CRISIS AND MARKET MEASURES OF GLOBAL SYSTEMIC IMPORTANCE BEFORE THE CRISIS

Notes: This Table reports the regression results of the relationship between **capital shortfalls** during the global financial crisis (July 2007-December 2008) and the degree of systemic importance in 2006 according to market measures. **SIZE** is defined as the log transformation of firm total assets at the end of 2006, **EQUITY** is the ratio between equity capital and total assets, **VOLATILITY** is the stock return volatility computed with daily stock returns, **CAUSING OTHERS** is the number of financial institutions that a financial institution A is causing during year 2006 according to Granger causality tests based on daily stock returns, **CAUSED BY OTHERS** is the number of financial institutions that are a financial institution A during year 2006 according to Granger causality tests based on daily stock returns, **REG_RATIO** is regulatory capital divided by risk-weighted assets, and **DIVERSIFICATION** is 1 minus the Herfindahl index of income concentration between interest and non-interest income. Robust t statistics clustered at the country level are reported in round brackets and *** (**;*) indicates significant at 1%(5%;10%).

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Asian crisis						
SIZE	0.121***	0.131**	0.131**	0.132**	0.063	0.145**
	(3.34)	(2.75)	(2.23)	(2.65)	(1.36)	(2.59)
EQUITY		0.011**	0.011**	0.011**	0.010**	0.010**
		(2.50)	(2.44)	(2.46)	(2.25)	(2.35)
VOLATILITY		0.239***	0.239***	0.239***	0.234***	0.246***
		(3.13)	(3.08)	(3.13)	(3.03)	(3.11)
CAUSING OTHERS		0.005***	0.005***	0.004***	0.005***	0.004***
		(5.75)	(6.04)	(5.52)	(5.66)	(5.10)
CAUSED BY OTHERS		0.004**	0.004**	0.004**	0.003*	0.003**
		(2.27)	(2.11)	(2.23)	(2.00)	(2.23)
ΔCoVaR			0.005		. ,	. ,
			(0.04)			
ΔA_CoVaR				-0.010		
				(0.25)		
SRISK					0.129***	
					(3.82)	
Ln (EXSHORT)						-0.009
						(0.73)
Constant	-0.452	-1.296**	-1.292*	-1.289**	-0.595	-1.388**
	(1.04)	(2.23)	(1.99)	(2.26)	(1.07)	(2.22)
Observations	219	219	219	219	219	219
R-squared	0.108	0.304	0.304	0.305	0.329	0.306
Panel B: 1998 crisis						
SIZE	0.430**	0.259	0.331	0.320	0.190	0.327
	(2.74)	(1.04)	(1.18)	(1.22)	(0.67)	(1.00)
EQUITY	~ /	0.015	0.017	0.014	0.014	0.016
		(0.54)	(0.62)	(0.52)	(0.47)	(0.57)
		· · ·	-0.099	· · ·	-0.202	· · ·
VOLATILITY		-0.199	-0.099	-0.107	-0.202	-0.141
VOLATILITY						
		-0.199 (0.79) 0.024***	(0.28) 0.026***	-0.107 (0.31) 0.024***	(0.79) 0.025***	-0.141 (0.43) 0.023***
		(0.79) 0.024***	(0.28) 0.026***	(0.31) 0.024***	(0.79) 0.025***	(0.43) 0.023***
CAUSING OTHERS		(0.79)	(0.28)	(0.31)	(0.79)	(0.43)
CAUSING OTHERS		(0.79) 0.024*** (3.64) 0.009	(0.28) 0.026*** (3.88) 0.011	(0.31) 0.024*** (4.16) 0.011	(0.79) 0.025*** (3.93) 0.010	(0.43) 0.023*** (3.24) 0.009
CAUSING OTHERS CAUSED BY OTHERS		(0.79) 0.024*** (3.64)	(0.28) 0.026*** (3.88) 0.011 (1.20)	(0.31) 0.024*** (4.16)	(0.79) 0.025*** (3.93)	(0.43) 0.023*** (3.24)
CAUSING OTHERS CAUSED BY OTHERS		(0.79) 0.024*** (3.64) 0.009	(0.28) 0.026*** (3.88) 0.011 (1.20) -0.836	(0.31) 0.024*** (4.16) 0.011	(0.79) 0.025*** (3.93) 0.010	(0.43) 0.023*** (3.24) 0.009
CAUSING OTHERS CAUSED BY OTHERS ΔCoVaR		(0.79) 0.024*** (3.64) 0.009	(0.28) 0.026*** (3.88) 0.011 (1.20)	(0.31) 0.024*** (4.16) 0.011 (1.25)	(0.79) 0.025*** (3.93) 0.010	(0.43) 0.023*** (3.24) 0.009
CAUSING OTHERS CAUSED BY OTHERS ΔCoVaR		(0.79) 0.024*** (3.64) 0.009	(0.28) 0.026*** (3.88) 0.011 (1.20) -0.836	(0.31) 0.024*** (4.16) 0.011 (1.25) -0.446	(0.79) 0.025*** (3.93) 0.010	(0.43) 0.023*** (3.24) 0.009
CAUSING OTHERS CAUSED BY OTHERS ΔCoVaR ΔΑ_CoVaR		(0.79) 0.024*** (3.64) 0.009	(0.28) 0.026*** (3.88) 0.011 (1.20) -0.836	(0.31) 0.024*** (4.16) 0.011 (1.25)	(0.79) 0.025*** (3.93) 0.010 (1.03)	(0.43) 0.023*** (3.24) 0.009
CAUSING OTHERS CAUSED BY OTHERS ΔCoVaR ΔΑ_CoVaR		(0.79) 0.024*** (3.64) 0.009	(0.28) 0.026*** (3.88) 0.011 (1.20) -0.836	(0.31) 0.024*** (4.16) 0.011 (1.25) -0.446	(0.79) 0.025*** (3.93) 0.010 (1.03) 0.161	(0.43) 0.023*** (3.24) 0.009
CAUSING OTHERS CAUSED BY OTHERS ΔCoVaR ΔΑ_CoVaR SRISK		(0.79) 0.024*** (3.64) 0.009	(0.28) 0.026*** (3.88) 0.011 (1.20) -0.836	(0.31) 0.024*** (4.16) 0.011 (1.25) -0.446	(0.79) 0.025*** (3.93) 0.010 (1.03)	(0.43) 0.023*** (3.24) 0.009 (0.95)
CAUSING OTHERS CAUSED BY OTHERS ΔCoVaR ΔΑ_CoVaR SRISK		(0.79) 0.024*** (3.64) 0.009	(0.28) 0.026*** (3.88) 0.011 (1.20) -0.836	(0.31) 0.024*** (4.16) 0.011 (1.25) -0.446	(0.79) 0.025*** (3.93) 0.010 (1.03) 0.161	(0.43) 0.023*** (3.24) 0.009 (0.95)
CAUSING OTHERS CAUSED BY OTHERS ΔCoVaR ΔΑ_CoVaR SRISK Ln (EXSHORT)	-1 082	(0.79) 0.024*** (3.64) 0.009 (1.01)	(0.28) 0.026*** (3.88) 0.011 (1.20) -0.836 (1.00)	(0.31) 0.024*** (4.16) 0.011 (1.25) -0.446 (1.07)	(0.79) 0.025*** (3.93) 0.010 (1.03) 0.161 (0.96)	(0.43) 0.023*** (3.24) 0.009 (0.95) -0.089 (0.44)
CAUSING OTHERS CAUSED BY OTHERS ΔCoVaR ΔΑ_CoVaR SRISK Ln (EXSHORT)	-1.082 (0.50)	(0.79) 0.024*** (3.64) 0.009 (1.01)	(0.28) 0.026*** (3.88) 0.011 (1.20) -0.836 (1.00) -1.242	(0.31) 0.024*** (4.16) 0.011 (1.25) -0.446 (1.07) -0.982	(0.79) 0.025*** (3.93) 0.010 (1.03) 0.161 (0.96) 0.079	(0.43) 0.023*** (3.24) 0.009 (0.95) -0.089 (0.44) -0.779
VOLATILITY CAUSING OTHERS CAUSED BY OTHERS ΔCoVaR ΔΑ_CoVaR SRISK Ln (EXSHORT) Constant Observations	-1.082 (0.50) 219	(0.79) 0.024*** (3.64) 0.009 (1.01)	(0.28) 0.026*** (3.88) 0.011 (1.20) -0.836 (1.00)	(0.31) 0.024*** (4.16) 0.011 (1.25) -0.446 (1.07)	(0.79) 0.025*** (3.93) 0.010 (1.03) 0.161 (0.96)	(0.43) 0.023*** (3.24) 0.009 (0.95) -0.089 (0.44)

TABLE 8: REALIZED COVARIANCE RISK DURING THE ASIAN CRISIS AND THE 1998CRISIS AND PRE-CRISES MARKET MEASURES OF GLOBAL SYSTEMIC IMPORTANCE

Notes: Panel A of this Table reports the regression results of the relationship between the **realized covariance risk** during the Asian crisis (2 nd July 1997-12th November 1997) and the degree of systemic importance in 1996 according to market measures. Panel B reports a similar test for the 1998 crisis (3rd August 1998 - 5th October 1998) using predictors the degree of systemic importance in 1997 according to market measures. **SIZE** is defined as the log transformation of firm total assets at the end of 2006, **EQUITY** is the ratio between equity capital and total assets, **VOLATILITY** is the stock return volatility computed with daily stock returns, **CAUSING OTHERS** is the number of financial institutions that a financial institution A is causing during year 2006 according to Granger causality tests based on daily stock returns, **CAUSED BY OTHERS** is the number of financial institutions that are a financial institution A during year 2006 according to Granger causality tests based on daily stock returns. Robust t statistics clustered at the country level are reported in round brackets and *** (**;*) indicates significant at 1%(5%;10%).

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Asian crisis						
SIZE	2.443	3.801	0.673	2.891	2.435	8.190**
	(0.91)	(1.09)	(0.22)	(0.83)	(0.64)	(2.56)
EQUITY		0.167	0.091	0.323	0.132	-0.217
		(0.54)	(0.30)	(1.06)	(0.38)	(0.50)
VOLATILITY		8.408	7.853	8.447	8.299	10.475
		(0.87)	(0.82)	(0.86)	(0.85)	(1.06)
CAUSING OTHERS		-0.155	-0.075	-0.051	-0.148	-0.212
		(1.19)	(0.84)	(0.50)	(1.18)	(1.63)
CAUSED BY OTHERS		0.361**	0.280*	0.350**	0.349**	0.271*
CAUSED DI OTTIERS		(2.19)	(1.89)	(2.20)	(2.16)	(1.93)
ΔCoVaR		(2.19)	24.955***	(2.20)	(2.10)	(1.95)
AA C-M-D			(2.80)	0 755*		
ΔA_CoVaR				8.755*		
OD ICIZ				(1.76)	0.507	
SRISK					2.586	
					(0.67)	
Ln (EXSHORT)						-2.911**
						(2.40)
Constant	-24.192	-59.501	-40.658	-64.966*	-45.500	-87.961**
	(0.91)	(1.60)	(1.22)	(1.76)	(1.11)	(2.57)
Observations	219	219	219	219	219	219
R-squared	0.010	0.144	0.229	0.193	0.147	0.184
Panel B:1998 crisis						
SIZE	4.493***	5.590***	6.449***	6.231***	4.439**	5.193*
	(2.99)	(3.17)	(3.40)	(3.13)	(2.16)	(2.02)
EQUITY		0.293	0.321	0.279	0.271	0.285
		(1.09)	(1.22)	(1.12)	(0.99)	(0.99)
VOLATILITY		0.428	1.631	1.409	0.380	0.089
		(0.17)	(0.56)	(0.46)	(0.15)	(0.03)
CAUSING OTHERS		-0.046	-0.025	-0.048	-0.030	-0.041
		(0.65)	(0.40)	(0.79)	(0.47)	(0.61)
CAUSED BY OTHERS		0.027	0.050	0.044	0.028	0.030
		(0.23)	(0.44)	(0.40)	(0.25)	(0.26)
ΔCoVaR		(0.23)	-10.045**	(0.10)	(0.23)	(0.20)
			(2.58)			
ΔA_CoVaR			(2.30)	-4.761		
				(1.59)		
CDICK				(1.59)	2///	
SRISK					2.666	
					(1.29)	0.504
Ln (EXSHORT)						0.524
	07.0T/			10.0701	ao =a ((0.23)
Constant	-25.374	-39.504	-47.552*	-43.878*	-28.726	-38.291
	(1.49)	(1.64)	(1.82)	(1.71)	(1.01)	(1.48)
Observations	219	219	219	219	219	219
R-squared	0.073	0.096	0.125	0.122	0.111	0.097

TABLE 9: BUY AND HOLD RETURNS DURING THE ASIAN CRISIS AND THE 1998 CRISISAND PRE-CRISES MARKET MEASURES OF GLOBAL SYSTEMIC IMPORTANCE

Notes: Panel A of this Table reports the regression results of the relationship between the **buy and hold returns** during the Asian crisis (2nd July 1997-12th November 1997) and the degree of systemic importance in 1996 according to market measures. Panel B reports a similar test for the 1998 crisis (3rd August 1998 - 5th October 1998) using predictors the degree of systemic importance in 1997 according to market measures. **SIZE** is defined as the log transformation of firm total assets at the end of 2006, **EQUITY** is the ratio between equity capital and total assets, **VOLATILITY** is the stock return volatility computed with daily stock returns, **CAUSING OTHERS** is the number of financial institutions that a financial institution A is causing during year 2006 according to Granger causality tests based on daily stock returns, **CAUSED BY OTHERS** is the number of financial institutions that are a financial institution A during year 2006 according to Granger causality tests based on daily stock returns, **CAUSED BY OTHERS** is the number of financial institutions that are a financial institution A during year 2006 according to Granger causality tests based on daily stock returns, **CAUSED BY OTHERS** is the number of financial institutions that are a financial institution A during year 2006 according to Granger causality tests based on daily stock returns, **CAUSED BY OTHERS** is the number of financial institutions that are a financial institution A during year 2006 according to Granger causality tests based on daily stock returns. Robust t statistics clustered at the country level are reported in round brackets and **** (**,*) indicates significant at 1%(5%;10%).

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Asian crisis						
SIZE	0.554**	0.619***	0.611***	0.606***	0.111	0.464**
	(2.70)	(3.15)	(2.89)	(3.09)	(0.91)	(2.29)
EQUITY		-0.003	-0.004	-0.001	-0.016*	0.010
		(0.32)	(0.33)	(0.12)	(1.77)	(0.93)
VOLATILITY		0.290***	0.289***	0.291***	0.249**	0.217
		(2.89)	(2.85)	(2.93)	(2.23)	(1.68)
CAUSING OTHERS		-0.011***	-0.011***	-0.010***	-0.009***	-0.009***
		(4.41)	(3.83)	(3.72)	(4.72)	(3.57)
CAUSED BY OTHERS		0.004	0.004	0.004	-0.001	0.007
		(0.83)	(0.79)	(0.81)	(0.15)	(1.40)
ΔCoVaR		(0100)	0.064	(0.01)	(0110)	()
200741			(0.33)			
ΔA_CoVaR			(0.00)	0.122		
				(1.63)		
SRISK				(1.00)	0.962***	
					(5.79)	
Ln (EXSHORT)					(0117)	0.103*
						(2.05)
Constant	-5.461**	-6.272***	-6.224***	-6.348***	-1.063	-5.269**
Constant	(2.64)	(2.91)	(2.78)	(2.96)	(0.77)	(2.35)
Observations	219	219	219	219	219	219
R-squared	0.262	0.361	0.361	0.365	0.519	0.385
Panel B: 1998 crisis	0.202	01001	0.001	01000	01017	01000
SIZE	0.627***	0.669***	0.626***	0.643***	0.439*	0.349
512L	(2.83)	(3.04)	(2.97)	(2.91)	(1.76)	(1.65)
EQUITY	(2.05)	0.010	0.009	0.011	0.006	0.003
		(0.96)	(0.79)	(0.98)	(0.71)	(0.39)
VOLATILITY		0.251***	0.191***	0.212***	0.242***	-0.022
VOLMITATI		(3.51)	(3.78)	(3.57)	(3.02)	(0.25)
CAUSING OTHERS		-0.003	-0.004**	-0.003	0.000	0.001
encourte o minis		(1.55)	(2.59)	(1.58)	(0.23)	(0.78)
CAUSED BY OTHERS		0.006	0.005	0.006	0.007*	0.009**
CITCULD DI OTTILIO		(1.55)	(1.28)	(1.35)	(1.83)	(2.24)
ΔCoVaR		(1.55)	0.501***	(1.55)	(1.05)	(2:24)
			(2.82)			
ΔA_CoVaR			(2.02)	0.193**		
				(2.64)		
SRISK				(2.07)	0.531***	
onon					(4.46)	
Ln (EXSHORT)					(07.70)	0.423***
Constant	-6.254***	-7.508***	-7.107***	-7.331***	-5.362*	(3.71) -6.531***
Constant						
Observations	(2.80)	(3.04)	(3.00)	(2.94)	(1.90)	(3.35)
Observations	219	219	219	219	219	219
R-squared	0.329	0.419	0.435	0.429	0.550	0.530

TABLE 10: REALIZED CAPITAL SHORTFALL DURING THE ASIAN CRISIS AND THE 1998CRISIS AND PRE-CRISES MARKET MEASURES OF GLOBAL SYSTEMIC IMPORTANCE

Notes: Panel A of this Table reports the regression results of the relationship between the **realized capital shortfall** during the Asian Crisis (2nd July 1997-12th November 1997) and the degree of systemic importance in 1996 according to market measures. Panel B reports a similar test for the 1998 crisis (3rd August 1998 - 5th October 1998) using predictors the degree of systemic importance in 1997 according to market measures. **SIZE** is defined as the log transformation of firm total assets at the end of 2006, **EQUITY** is the ratio between equity capital and total assets, **VOLATILITY** is the stock return volatility computed with daily stock returns, **CAUSING OTHERS** is the number of financial institutions that a financial institution A is causing during year 2006 according to Granger causality tests based on daily stock returns, **CAUSED BY OTHERS** is the number of financial institutions that are a financial institution A during year 2006 according to Granger causality tests based on daily stock returns. Robust t statistics clustered at the country level are reported in round brackets and *** (**;*) indicates significant at 1%(5%;10%).

ENDNOTES

ⁱ See also "Lax Oversight Caused Crisis, Bernanke Says" in New York Times, January 3, 2010.

ⁱⁱ One such rule has been established by the Basel Committee (2011) on banking supervision, in a document published in July 2011, which has called for more stringent capital requirements on banks deemed to be globally systemically important.

ⁱⁱⁱ The Shapley Value approach is a game-theoretic instrument which have been used to assesses how important each financial institution is for the overall system and what payoff it can expect from interacting with other financial institutions. The purpose is to quantify how financial institutions contribute to a systemic event given the possibility that a financial institution adds to the propagation of shocks in the system and because it is itself exposed to propagated shocks (Drehmann and Tarashev, 2011a). The Shapley Value approach, however, suffers from a dimensionality problem; namely, for a system of N banks there are 2N possible subsystems for which the systemic risk indicator needs to be calculated. Therefore, applications of the contribution approach (see Tarashev, Borio, and Tsatsaronis 2010; Drehmann and Tarashev, 2011; Gauthier, Lehar, and Souissi 2012) are generally limited to small samples of financial institutions.

^{iv} Danielsson et al. (2014) identify several additional sources of errors-in-variables related to the use of asset returns rather equity returns that do not refer to the heterogeneity of accounting principles. In particular, the estimation of asset returns requires ad-hoc interpolation to transform annual (or at best quarterly) accounting data to daily asset return observations. In addition, some ad hoc method is also required to transform book data to market data. Furthermore, publicly reported asset values do not consider off-balance sheet items that can be very substantial in financial institutions.

^v As reported by Ng, Vasvari, and Moerman (2011), the capital support was initially provided to ten banks: Bank of America, Bank of New York Mellon, Citigroup, Goldman Sachs, JP Morgan, Merrill Lynch, Morgan Stanley, State Streets, Wachovia Corporation and Wells Fargo. Merrill Lynch and Wachovia Corporation were then acquired by Bank of America and Wells Fargo, respectively, with deals completed by December 2008. As a result, the capital infusions planned for Merrill Lynch and Wachovia Corporation went to the acquiring banks.

^{vi} In line with this view, the proposal of the Basel Committee (2011) on the design of capital requirements for systemically important banks recognizes a key role for proxies of the degree of interconnectedness of a firm.