EUROPEAN CENTRAL BANK

EUROSYSTEM

WORKING PAPER SERIES

NO 1546 / MAY 2013

HOW USEFUL IS THE MARGINAL EXPECTED SHORTFALL FOR THE MEASUREMENT OF SYSTEMIC EXPOSURE?

A PRACTICAL ASSESSMENT

Julien Idier, Gildas Lamé and Jean-Stéphane Mésonnier

In 2013 all ECB publications feature a motif taken from the €5 banknote.

MACROPRUDENTIAL RESEARCH NETWORK

Macroprudential Research Network

This paper presents research conducted within the Macroprudential Research Network (MaRs). The network is composed of economists from the European System of Central Banks (ESCB), i.e. the national central banks of the 27 European Union (EU) Member States and the European Central Bank. The objective of MaRs is to develop core conceptual frameworks, models and/or tools supporting macro-prudential supervision in the EU.

The research is carried out in three work streams: 1) Macro-financial models linking financial stability and the performance of the economy; 2) Early warning systems and systemic risk indicators; 3) Assessing contagion risks.

MaRs is chaired by Philipp Hartmann (ECB). Paolo Angelini (Banca d'Italia), Laurent Clerc (Banque de France), Carsten Detken (ECB), Simone Manganelli (ECB) and Katerina Šmídková (Czech National Bank) are workstream coordinators. Javier Suarez (Center for Monetary and Financial Studies) and Hans Degryse (Katholieke Universiteit Leuven and Tilburg University) act as external consultants. Fiorella De Fiore (ECB) and Kalin Nikolov (ECB) share responsibility for the MaRs Secretariat.

The refereeing process of this paper has been coordinated by a team composed of Gerhard Rünstler, Kalin Nikolov and Bernd Schwaab (all ECB).

The paper is released in order to make the research of MaRs generally available, in preliminary form, to encourage comments and suggestions prior to final publication. The views expressed in the paper are the ones of the author(s) and do not necessarily reflect those of the ECB or of the ESCB.

Acknowledgements

We thank Alain Monfort for stimulating discussions at the starting phase of this project. We also thank Christophe Boucher, Etienne Bordeleau, Robert Engle, Adrian Pop, Stephan Straetmans and an anonymous referee for useful comments, as well as seminar participants at Banque de France, French Economic Society 2011, Paris School of Economics, Poitiers University, French Finance Association AFFI 2012 and IFABS 2012 in Valencia. Béatrice Saes, Aurélie Touchais and Guillaume Retout provided valuable assistance with the data. The views expressed herein are those of the authors and do not necessarily reflect those of the Banque de France, the ECB or INSEE.

Julien Idier

European Central Bank; e-mail: julien.idier@ecb.europa.eu

Gildas Lamé

INSEE - National Institute for Statistics and Economic Studies.

Jean-Stéphane Mésonnier

Banque de France; e-mail: jean-stephane.mesonnier@banque-france.fr

Address	Kaiserstrasse 29, 60311 Frankfurt am Main, Germany
Postal address	Postfach 16 03 19, 60066 Frankfurt am Main, Germany
Telephone	+49 69 1344 0
Internet	http://www.ecb.europa.eu
Fax	+49 69 1344 6000

ISSN	1725-2806 (online)
EU Catalogue No	QB-AR-13-043-EN-N (online)

This paper can be downloaded without charge from http://www.ecb.europa.eu or from the Social Science Research Network electronic library at http://ssrn.com/abstract_id=1944043.

Information on all of the papers published in the ECB Working Paper Series can be found on the ECB's website, http://www.ecb.europa.eu/pub/scientific/wps/date/html/index.en.html

Abstract

We explore the practical relevance from a supervisor's perspective of a popular market-based indicator of the exposure of a financial institution to systemic risk, the marginal expected shortfall (MES). The MES of an institution can be defined as its expected equity loss when the market itself is in its left tail. We estimate the dynamic MES recently proposed by Brownlees and Engle (2011) for a panel of 65 large US banks over the last decade and a half. Running panel regressions of the MES on bank characteristics, we first find that the MES can be roughly rationalized in terms of standard balance sheet indicators of bank financial soundness and systemic importance. We then ask whether the cross section of the MES can help to identify *ex ante*, i.e. before a crisis unfolds, which institutions are the more likely to suffer the most severe losses *ex post*, i.e. once it has unfolded. Unfortunately, using the recent crisis as a natural experiment, we find that standard balance-sheet metrics like the tier one solvency ratio are better able than the MES to predict equity losses conditionally to a true crisis.

Keywords: MES, systemic risk, tail correlation, balance sheet ratios, panel.

JEL Classification: C5, E44, G2.

Non technical summary

The financial crisis of 2007-2008 has pushed concerns about systemic risk and its measurement at the forefront of both academic research and supervisory policy agenda. In particular, ongoing work by the Basel Committee and the Financial Stability Board striving to set new regulatory requirements for Systemically Important Financial Institutions (SIFI) requires that an agreement can be reached on which characteristics make a financial institution more prone than others to be severely hit by system-wide shocks (systemic resilience or participation) or to propagate such shocks to other institutions, thereby amplifying their overall impact (systemic contribution). Recently, several academic contributions have proposed high frequency measures of individual institutions' systemic importance and systemic exposure that rely exclusively on public market information (like bank stock prices or CDS premia), using sophisticated econometric techniques. While they have received notable attention, given the real-time monitoring they allow, these market-based systemic risk measures remain complex tools in which the determinants of the vulnerability of a given institution to systemic events remain undefined. As such, they do not fully meet the needs of regulators, which would have an easier task if they could rely on indicators based on more usual metrics of the financial soundness of institutions. Nor is it clearly established that these indicators, which are generally highly procyclical, can prove forward-looking enough to provide valuable early warning signals to bank regulators ahead of a financial turmoil.

We look in this paper at one particular but popular statistical measure of systemic resilience, the so-called Marginal Expected Shortfall (MES) of Acharya et al. (2010) and assess empirically for a large sample of big US banks how well this indicator meets such practical concerns.

We first estimate Brownlees and Engle's (BE) dynamic version of the MES on a daily basis over the period from 1996 to 2010 for a sample of 65 large US bank holding companies, for which we have access to detailed balance-sheet information. We then run panel regressions of quarterly bank MES on selected bank balance-sheet variables that are routinely monitored by bank regulators, thus putting the MES to a weak form of market efficiency test. The regression results suggest that the information delivered by the MES is consistent with characteristics that are intuitively viewed as sources of bank fragility, like reliance on wholesale funding, low profitability and low quality of assets. The effects of a low profitability and of a larger share of non-performing loans on the MES were significantly amplified during the recent crisis.

Finally, using the 2007-2009 crisis as a natural experiment, we ask whether the MES as measured before the crisis (i.e. taking an *ex ante* view) would have been useful to identify which institutions were the most likely to be severely hit should a crisis occur. Based on cross-sectional rank correlations as well as cross-sectional regressions, we conclude that some standard balance-sheet ratios already routinely monitored by regulators, like the ratio of tier-one capital to risk-weighted assets would have been more useful than the MES at predicting which banks were bound to suffer the most severe equity losses during the crisis.

1 Introduction

The financial crisis of 2007- and in particular the widespread disruption of financial markets triggered by the bankruptcy of Lehman Brothers in the Autumn of 2008 has pushed concerns about systemic risk and its measurement at the forefront of both academic research and supervisory policy agenda. In particular, ongoing work by the Basel Committee and the Financial Stability Board striving to set new regulatory requirements for Systemically Important Financial Institutions (SIFI) requires that an agreement can be reached on which characteristics make a financial institution more prone than others to be severely hit by system-wide shocks (systemic resilience or participation) or to propagate such shocks to other institutions, thereby amplifying their overall impact (systemic contribution).[1] Recently, several academic contributions have aimed to account for the interconnectedness of institutions as well as the rapidity of contagion of a systemic event and proposed high frequency measures of individual institutions' systemic importance and systemic exposure that rely exclusively on public market information (like bank stock prices or CDS premia), using sophisticated econometric techniques (cf. e.g. Adrian and Brunnermeier, 2009, Brownlees and Engle, 2010, Goodhart and Segoviano, 2009, Huang et al., 2010). While they have received notable attention, given the real-time monitoring they allow, these market-based systemic risk measures remain complex tools in which the determinants of the vulnerability of a given institution to systemic events remain undefined. As such, they do not fully meet the needs of regulators (Drehman and Tarashev, 2010), which would have an easier task if they could rely on indicators based on more usual metrics of the financial soundness of institutions. Nor is it clearly established that these indicators, which are generally highly procyclical, can prove forward-looking enough to provide valuable early warning signals to bank regulators ahead of a financial turmoil.

We look in this paper at one particular but popular statistical measure of systemic resilience, the so-called Marginal Expected Shortfall (MES) and assess empirically for a large sample of big US banks how well this indicator meets such practical concerns. First, we investigate how the MES reconciles with more standards measures of financial weaknesses

[1] Analytically, one may want to distinguish between situations where bank A reacts more than others to an exogenous shock and situations where Bank A is a source or an amplifyer of endogenous systemic events. Both dimensions of systemic importance are in practice clearly inter-related. The participation vs contribution approach was proposed by Drehman and Tarashev (2010).

as computed from individual institutions' balance-sheet information.[2] Second, we check whether the MES is of greater help than more standard balance-sheet indicators to identify *ex ante* which institution would be the most affected should systemic risk really materialize.

Recently adapted to systemic risk measurement from an earlier literature on risk-management at the firm level (cf. notably Tasche, 2000), the MES of a financial institution is defined as the expected equity loss per dollar invested in this firm if the overall market declines by a certain substantial amount (then identified to a "tail event" in the market). To overcome the limitations of historical measures of the MES, in particular their lack of flexibility, Brownlees and Engle (2010) recently proposed a multi-step modeling approach based on GARCH, Dynamic Conditional Correlations (DCC) and non-parametric tail estimators. Recently, Acharya et al. (2010) found that the MES of a large sample of US financial firms (banks and non-banks), as measured on the verge of the last crisis, was a good predictor of the total decline in equity valuation that these firms actually experienced during the crisis.

We first estimate Brownlees and Engle's (BE) MES on a daily basis over the period from 1996 to 2010 for a sample of 65 large US bank holding companies, for which we have access to detailed balance-sheet information. A simple look at the median MES confirms that this indicator does a good job in tracking episodes of financial turmoil, which makes it a potentially relevant coincident indicator of the exposure of individual banks to systemic risk. Interestingly, we find that the half-decade leading up to the crisis was characterized by a very low level of average MES, reflecting in turn extraordinary low levels of bank stock volatility, as well as a very low dispersion of individual MES. We view this as indicative of a phase of exacerbated optimism where investors in bank equity did not pay enough attention to individual sources of bank vulnerability.

We then run panel regressions of quarterly bank MES on selected bank balance-sheet variables that are routinely monitored by bank regulators, thus putting the MES to a weak form of market efficiency test. The regression results suggest that the information delivered by the MES is consistent with characteristics that are intuitively viewed as sources of bank fragility or systemic importance. Indeed, banks that generally rely more on wholesale funding, are less profitable, have a higher share of non-performing loans and lend more to corporates turn out to have a higher MES on average. The effects of a low profitability and

[2] De Jonghe (2010) runs a similar exercise for a sample of European banks to explore the determinants of heterogeneity in another measure of systemic risk exposure, the tail beta.

of a larger share of non-performing loans on the MES were significantly amplified during the recent crisis.

Finally, using the 2007-2009 crisis as a natural experiment, we ask whether the MES as measured before the crisis (i.e. taking an *ex ante* view) would have been useful to identify which institutions were the most likely to be severely hit should a crisis occur. Based on cross-sectional rank correlations as well as cross-sectional regressions, we conclude that some standard balance-sheet ratios already routinely monitored by regulators, like the ratio of tier-one capital to risk-weighted assets would have been more useful than the MES at predicting which banks were bound to suffer the most severe equity losses during the crisis. Although we focus in this paper on a specific model-based approach of the MES (the dynamic MES of BE), it is important to note that this conclusion still holds whether we look at the dynamic MES we estimated using the BE method, a simple historical version of the MES, or, for a sub-sample of banks also considered in the rankings posted on the Systemic risk website of NYU Stern, using the simulated long-run extension of the MES recently advocated by Acharya et al. (2012).[3]

The rest of the paper is organized as follows. In section 2 we estimate daily MES for a panel of large US banks. In section 3 we present our bank balance-sheet dataset and explore the link between balance sheet indicators of bank financial fragility and quarterly version of the MES for our panel of banks. In section 4, using rank tests, we assess the predictive power of the MES compared with usual standard banking risk metrics in the light of the last crisis. Finally, section 5 concludes.

2 The Marginal Expected Shortfall

2.1 Definition

We focus in this study on a specific measure of the sensitivity of a financial firm to systemic risk called Marginal Expected Shortfall (MES). While alternative metrics have been proposed in the burgeoning literature on systemic risk measurement, we think that the MES

[3] Our findings thus echoe those of Danielsson et al. (2012) who focus specifically on the model risk associated with usual metrics of the systemic risk contribution of financial insitutions, including the MES. They find that, because of this source of uncertainty, these metrics provide unreliable measures of banks' riskiness in both absolute and relative terms. Although the exercise they run is quite different from ours, they also conclude that a bank regulator concerned with identifying systematically important institutions would be better off monitoring some simple leverage ratios.

deserves a particular attention because of both the large audience gained by its dynamic version as developped by Brownlees and Engle (2010) (not least thanks to the regular updates of MES-based rankings of the systemic importance of US institutions posted on the website of NYU) and also recent claims by Acharya et al. (2010) that the MES would have been able to predict the cross section of losses incurred by US financial firms during the 2007-2009 crisis.

Following Acharya et al. (2010), we define the MES of a financial firm as its short-run expected equity loss conditional on the market taking a loss greater than its Value-at-Risk at $\alpha\%$. Let us denote $r_{i,t}$ the daily (log) stock return of the firm and $r_{m,t}$ the daily index return of the larger market the firm belongs to. Then the MES reads:

$$MES_{i,t} = E_t \left(r_{i,t+1} \mid r_{m,t+1} < q_{\alpha,t} \left(r_{t+1} \right) = C \right) \tag{1}$$

or

$$MES_{i,t} = E_t \left(r_{i,t+1} \mid r_{m,t+1} < C \right) \tag{2}$$

where C is a constant corresponding to what we want to define as "tail risk" in the market.

Let us also define the Expected shortfall of the market (ES) as the expected loss in the index conditional on this loss being greater than C, that is: $ES_t = E_t \left(r_{t+1} \mid r_{t+1} < C \right)$. Whenever all the considered firms belong to the market, it is straightforward to see that the MES of one firm is simply the derivative of the market's ES with respect to the firm's market share (or capitalization), hence the term "marginal". Note that in this case, the MES of a firm can be interpreted as reflecting its participation in overall systemic risk. However, it is still possible to define the same statistic whenever the observed firm does not belong to the market index. Rather than a measure of how a particular firm's risk adds to the market risk, the MES should then be viewed simply as a measure of the sensitivity (or resilience) of this firm's stock price to exceptionally bad market events.

2.2 Data and estimation

We follow closely the econometric methodology developed by Brownlees and Englee (BE, 2010) to estimate the dynamic MES. This approach is essentially an application of the asymmetric DCC-GARCH model of Engle and Sheppard (2008) to the issue of systemic risk measurement. We first estimate individual bank MES with a daily frequency for the panel of large US bank holding companies (BHCs, "banks" in the following) that we consider throughout. The modelling approach is presented in details in Appendix A. Note that in contrast with BE however, we assume here that innovations to stock returns follow a Student-t distribution instead of a Gaussian one, so as to better account for the evidence of fat tails in stock returns, notably during the recent crisis.[4]

In this study, we focus specifically on banks, as opposed for instance to insurance companies or broker-dealers, both because of their intrinsic economic significance and because detailed balance-sheet information on a long period of time is available for that category of financial institutions only (thanks to the Federal Reserve's Call reports). We pick up our selection of banks from the list of the 100 biggest BHCs as measured by their capitalization in May 2010. We keep in our sample all the BHCs for which we have almost complete Call Report data over the period of study (1996q1-2010q1).[5] Companies such as Goldman Sachs, other broker-dealers and some BHCs that acquired their current status between 1996 and 2010 are thus excluded from our sample. We also excluded 7 BHCs which are subsidiaries of foreign banks (e.g. HSBC, Santander). Financial arms of industrial conglomerates or banking branches of insurance companies are not included in our sample (e.g. Ally Financial or Metlife). This sort-out leaves us with a representative sample of 65 large institutions. Appendix B lists the selected banks, together with statistics on their share of total US bank assets and their market capitalization at sample end. Note that all institutions present in the sample have a market capitalization larger than \$500 million as of May 2011. Our sample includes most major US BHCs, accounting for some 66% of total banking assets in 2010 Q1.

We estimate these individual bank MES over the period from January 1996 to March 2010.[6] Banks' stock prices are taken from Datastream. System-wide events are gauged using fluctuations in the S&P500 Financials index returns. In the rest of the paper, we set

[4] Nevertheless, we cheched that all our results remain qualitatively unchanged if we stick to the genuine BE specification.

[5] For the sake of representativity, we thus keep in our sample five banks for which some balance sheet variables are missing over a few quarters in 1996 or in the early 2000s, as well as three banks that were closed or acquired as a consequence of the 2007-2009 crisis (like e.g. Wachovia corporation). Overall, our bank panel remain however highly balanced. Besides, we checked that our regression results remained unchanged when excluding these eight banks one by one from the sample or when interpolating linearly the missing observations for some regressors.

[6] Actually, the data used for the estimation also include the last 100 days of 1995 so that we obtain an estimate of the MES on the first day of 1996 (See appendix for details on the kernel estimation).

the constant threshold C that defines a "systemic" tail event to a daily loss larger than 2.91%. This threshold corresponds to the VaR at 95% of the S&P Financials index over the period from 1996 to 2010, or to the VaR at 97.5% of the same index over the pre-crisis period (prior to August 2007). As a consequence, it is important to note that the estimated MES captures banks' equity sensitivity to tail market events that, although "extreme", remain relatively frequent (i.e. market losses that occured on a long run average less often than once in two months in the pre-crisis world).

Figure 1 shows the fluctuations in the US financial stock market index from 1996Q1 to 2010Q1, together with vertical lines signalling "tail" daily losses larger than 2.91%. As expected, well identified episodes of financial distress, such as the LTCM failure in 1998, the burst of the dot com bubble in 2001 and the following bankruptcies of Enron and Wordlcom in 2002, are associated with clusters of larger falls in the S&P Financials index, but the 2007-2009 crisis is clearly outstanding in terms of size and frequency of extreme daily market losses.

Figure 2 shows the fluctuations in the median and interquartile range of estimated individual banks' MES through time, while Figure 3 shows the median values of two key ingredients of individual MES: the volatility of a bank's stock and its dynamic correlation with the market index (see Appendix A for a decomposition of the MES into its components). Figure 2 suggests that, as most available statistical measures of systemic importance or resilience, the dynamic MES tends to be procyclical, as protracted periods of financial distress are generally associated with higher MES.[7] First, over the late 1990s and early 2000s, the median sensitivity to system-wide shocks proved relatively low, although some variability can be accounted for by some of the events mentioned above, while cross-sectional heterogeneity was high, at least when compared to the median value. Then cross-sectional heterogeneity in banks' MES collapsed to low levels over the five years preceding the last crisis, which may be viewed as a signal that equity investors were then paying (too) little attention to idiosyncratic factors of bank fragility. Finally, the outburst of the last crisis triggered a surge in the median MES associated with a general surge in stock market volatility, but also a rise in cross-sectional heterogeneity.

[7] Adrian and Brunnermeier (2010) also find that their $\Delta CoVar$ is procyclical.

3 Bank characteristics and MES: exploring the missing link

In this section, we investigate how the MES, which is a statistical indicator of the sensitivity of bank equity valuation to tail market events, can be related to commonly considered measures of bank balance-sheet vulnerability and risk-taking. In other words, we aim to rationalize the assessment of banks' exposure to systemic risk provided by the MES. In their paper, BE raised the issue already, but they limited their investigation to a preliminary regression, focusing on only two main sources of financial firms' heterogeneity: the size of the institution, as gauged by its market capitalization, and its total leverage at market prices. They conclude that bigger and more leveraged firms (banks and non-banks) have a larger MES and that the positive correlation between leverage and MES is higher when the market is bearish.

We broaden and systematize here their analysis, while focusing more specifically on BHCs (as opposed to investment banks and shadow banks), and regress our estimated MES on a comprehensive set of balance-sheet ratios that are usually monitored by regulators to assess banks' financial soundness. Since balance-sheet information is only available at a quarterly frequency, we consider in the following a quarterly version of the estimated daily individual MES series, simply taking the median of the MES over a quarter. Thus, for each bank, we define:

$$MES_i^{quarter\ j} = \mu_{\frac{1}{2}}\{MES_{i,t} : t \in quarter_j\} \tag{3}$$

3.1 Balance-sheet variables and preliminary statistics

We take all the balance-sheet information from the Consolidated Financial Statements for Bank Holding Companies (FR Y-9C), or "Call Reports", as compiled and provided by the US Federal Reserve. In order to ensure consistency between stock prices and balance-sheet variables, we thus use the quarterly consolidated statistics at the level of BHCs (as opposed to the institution based statistics). Some important explanatory variables, like the tier 1 solvency ratio, are not available before 1996. In the following, we thus restrict the sample to the period from 1996Q1 to 2010Q1.

As candidate explanatory variables of systemic fragility, we consider the usual suspects in the large empirical literature on the determinants of bank default probability and/or bank risk-taking at large (e.g. Purnanandam, 2007, Laeven and Levine, 2009, Demirgüc-

Kunt and al., 2008, Buch and al., 2010, Delis and Kouretas, 2011, for recent examples). We thus model the MES as a function of (1) bank capitalization or book leverage, that we assess in this section using both a simple book equity capital to book assets ratio (CAR) or the supervisory ratio of tier 1 equity to risk weighted assets (CARTIER1), (2) profitability (ROA), measured by the return on assets ratio, (3) asset quality (NPL), as proxied by the ratio of non-performing loans to total loans and (4) asset liquidity (LIQ), taken as the ratio of liquid assets (defined as the sum of cash, US Treasuries, Fed Funds sold and securities purchased under agreement to resell) to total assets. The recent crisis, and notably the early failure of Northern Rock in September 2007 in the UK, has revealed how an excessive reliance on wholesale funding may prove to be a major source of bank fragility in times of systemic liquidity stress. We thus also include among our regressors (5) a ratio of wholesale (non-deposit short term) funding to total liabilities (WFUND). We also proxy for the degree of sectorial diversification of assets and lending business profiles using two additional ratios of (6) commercial and industry loans (CIL) and (7) mortgage loans (HOL) to total assets. Finally, since the biggest banks in our sample account for a non-negligible share of the S&P500 Financials, omitting size in MES regressions could importantly bias the estimated coefficients of other bank characteristics. We thus take (8) the log of total assets to capture size effects (SIZE).

Bank balance sheet datasets typically exhibit many outlier observations which may reflect mergers and acquisitions (M&A), other unobserved structural changes in banks' operating business, or even statistical errors. Using the BHC M&A database compiled by the Federal Reserve Bank of Chicago, we identified 60 important M&A operations for our sample of banks since 1996. These operations appeared to explain most of the outliers that we could filter out using a simple preliminary statistical detection procedure.[8] As shown in Table 1, the impact of a M&A in terms of quarterly total assets growth of the acquiring bank varies substantially, with a median impact of around 46%. On the basis of this evidence, we sorted identified M&A observations into two categories, denoted as small mergers and large mergers respectively, and included the corresponding dummies in our regressions below. We then dropped the remaining unexplained outlier observations (0.3% of all observations).

An important institutional change for US banks was the adoption of the Gramm-Leach-Bliley Financial Services Modernization Act of 1999 (GLB Act). The latter act relaxed

[8] We defined here an outlier obsevation as a bank-quarter observation with a total assets growth exceeding 25% over a quarter: 70 outliers were detected out of 3659 observations (1.9%).

the provisions of the 1933 Glass-Steagall Act requiring separation of banking and securities activities while attempting to maintain special safety-net protections for depository institutions. It allowed Bank holding companies (BHC) that met some supervisory standards to become Financial holding companies (FHC). Switching to the FHC status authorizes a bank to engage in a range of new financial and non-financial activities, then possibly affecting both its business model and level of risk. Using again information provided by the Federal Reserve, we identified 42 changes from BHC to FHC status in our sample of banks and created a dummy variable taking the value of one for the observations under FHC status.

Table 2 presents some summary statistics for our variables over the period from 1996 to 2010. Consistently with the exceptionally high levels of the MES observed after mid-2007, statistics for the crisis period and for the more quiet times before the onset of the crisis are presented separately. A first look at the right panel proves enough that, even in quiet times and although we restricted our sample to some of the largest US banks, our bank data still present a substantial degree of heterogeneity, notably regarding leverage, size and bank assets structure. Furthermore, comparing statistics for crisis vs normal times highlights important changes in some variables. Notably, the crisis period is associated with a significant surge in non-performing loans. Interestingly, the average capitalization ratio increases by 1.3 percentage points during the crisis, which is consistent with both stories of deleveraging during that period and with capital injections by the US authorities as part as the official packages launched to shore up the US banking system after the Lehman panic.

Table 3 displays the pooled correlations between balance-sheet variables for two subsamples: the pre-crisis period (upper panel) and the last NBER recession of 2007-2009 (lower panel). Results for the pre-crisis period confirm the already documented fact that bigger US banks tend to be more liquid but less capitalized than smaller ones, at least in normal times (see e.g. Kashyap and Stein, 2000). Solvency (tier one capital) ratios are then negatively correlated with the proportion of C&I loans on the asset side, which in turn is consistent with the higher regulatory risk weights that are put on loans to non-financial firms under the Basel I and to some extent the Basel II regulations. Both measures of leverage (CAR and CARTIER1) are strongly positively correlated, which suggests not to include them simultaneously in our regressions. As expected, the return on assets is negatively correlated with the ratio of non-performing loans in all times, but the correlation becomes strongly negative during the crisis only.

3.2 Estimation and results

In this section, we present our panel regressions of individual MES on bank characteristics in more details. The empirical model reads as follows:

$$MES_{i,t} = \alpha_0 + \alpha_i + \beta.Z_{i,t-1} + \gamma.Z_{i,t-1}.I_{t\in\ Crisis} \tag{4}$$

$$+ \delta_1.I_{(i,t)\in\ Merger1} + \delta_2.I_{(i,t)\in\ Merger2} + \delta_3.I_{(i,t)\in FHC} + \tag{5}$$

$$\theta_2.I_{Q1} + \theta_3.I_{Q2} + \theta_4.I_{Q4} + u_{i,t} \tag{6}$$

where $Z_{i,t}$ is the vector of bank balance-sheet variables detailed in section 3.1 above.

Note that instead of using directly the SIZE variable, we first orthogonalize it with respect to all other bank variables given the high and significant correlation with the other banking variables in order to better capture true size effects, as in De Jonghe (2010). Beside the dummy variables correcting for small and large mergers as well as for the FHC status, quarterly dummies were also added to control for seasonal effects (notably end of year effects) as balance sheet variables are not seasonally adjusted. As said, running this regression can be viewed as weak rationality test of the market-based measure of bank riskiness provided by the MES, by comparing the MES with at least a part of the information set available to investors. We thus lag all regressors (except dummies) by one quarter to take into account the fact that investors may react with some delay to changes in banks' financial conditions due to reporting lags, so that the current MES is more likely to reflect balance-sheet information about the previous quarter.[9]

The first two columns of Table 4 present the results of regressions of individual MES on selected bank characteristics over the period from 1996 to 2010, while the last two columns refer to regressions that also include bank characteristics interacted with a crisis dummy. In each case, bank leverage is measured alternatively as the unweighted equity to capital ratio or as the regulatory ratio of tier-one equity to risk-weighted assets. As suggested by preliminary Hausmann tests, we include fixed bank-effects in our regressions. Standard errors are robust to intra-cluster autocorrelation.

The results first show that the MES is roughly consistent with intuitive balance sheet

[9] Lagging regressors does also to some extent mitigate potential endogeneity issues. Whatever, regressions run with contemporaneous explanatory variables yield similar results.

measures of bank fragility, as balance-sheet variables explain up to 66% of the variance in individual MES (at least when the non-linearities associated with the extreme volatility episode of the 2007-2009 crisis are accounted for) and turn out to be significant with the intuitively expected sign. Indeed, a higher sensitivity of bank equity to tail market events is significantly associated with a larger reliance on wholesale funding, a larger exposure to corporate lending, riskier assets and a lower profitability. Furthermore, the impact of non-performing loans and profitability is exacerbated during the crisis episode. Size matters but only when unweighted leverage is not taken into account and only during the crisis. This last result has to be compared with recent findings by other authors (Drehman and Tarashev, 2011, BE, 2010) who suggest that the size of a bank is a good proxy of its systemic importance. Caution is however always required regarding the systemic relevance of size, since this positive correlation may also reflect composition effects in the market index used as a measure of the "system". Lastly, capitalization, whatever its measure, is positively associated with the MES during the crisis. While this may first sound counter-intuitive, it may also reflect the fact that teetering banks were forced to recapitalize from end 2008 onward as part of the TARP program of the US Treasury and the SCAP program (the 2009 "stress tests") of the US Federal Reserve.

Finally, note that we checked the robustness of our results to changes in the definition of systemic tail events (i.e. the value of C). They remain qualitatively unchanged for smaller and larger thresholds between 2% and 4%, although stricter thresholds lead mechanically to less precise coefficient estimates. In addition, we run some robustness checks related to the model. Alternative specification as (i) estimating the panel with contemporaneous data, (ii) controlling for the potential instability of the intercept, and (iii) implemeting robust standard errors as in Driscoll & Kraay (1998), do not change the results previously discussed.[10]

4 Does the MES predict bank losses when facing a systemic event?

The previous section shows that the information summarized by the MES can be broadly reconciled with usual balance sheet indicators of bank weakness. This is however not enough

[10] Robustness check results are available on request from the authors.

to convince regulators that monitoring bank MES fluctuations and the associated rankings is worthwile. Indeed, it remains to check that individual MES is a reliable predictor, at least in relative terms, of the losses banks would face in case of a true systemic event. Remember that the MES assesses the expected losses of an institution conditionally to unfrequent, but not extremely rare events in the market. In contrast, an event like the Lehman panic clearly belongs to the "tail of the tail" of market risks that materialize once or twice a century only. Due to obvious data limitations, the sensitivity of banks' returns to this "tail of the tail" market risk is very difficult to estimate. However, whether the MES estimated over normal times can be a useful proxy of expected losses conditional to a true crisis remains an open empirical issue.

We look closer at this issue in the following, notably asking whether the MES is more useful in this respect than the usual balance-sheet indicators of bank financial conditions. This doing, we follow on Acharya et al. (2010), who take the recent crisis as a natural experiment for testing their theory of the link between the MES in normal times and what they call the "systemic expected shortfall", or SES, in exceptional, system-wide distress times. On the basis of a large and very heterogenous sample of US financial firms (including insurance companies, broker-dealers, stock exchanges etc.), they notably find that individual institutions' MES as estimated just before the 2007 turmoil (what we denote in what follows as their *ex ante* MES) predicts the cross section of capital losses during the 2007-2009 crisis (their *ex post* losses). They also document that excessive leverage was another important determinant of distress during the crisis. To illustrate the point, Figure 4 shows a scatter-plot of the cumulated equity returns during the crisis versus the ex-ante MES in our sample of BHCs. As Acharya et al. (2010), although for a different, less heterogenous sample of institutions, we find a (slightly) negative relationship between the ex-ante MES and the *ex post* returns under conditions of extreme system-wide stress (i.e. a slightly positive correlation with the *ex post* losses).

We then investigate in more details the relative merits of the MES and other bank soundness indicators as predictors of the actual losses borne during the crisis. Two preliminary scatter plots illustrate the results. Figure 5 plots the solvency ratio (CARTIER1) as measured in June 2007 against the cumulated stock return over the September 2007- June 2009 period. The regression line is clearly trending upward, meaning that higher returns over the crisis (i.e. smaller losses) could have been predicted on the basis of higher solvency ratios before the crisis. Figure 6 confirms the intuition that bigger banks were *ex ante* riskier and had to face lower returns (higher losses) *ex post*.

In a more systematic way, we then compute the correlations between the *ex post* cumulated equity losses over the crisis period of 2007 Q3-2009 Q2 (the SES variable) and the bank characteristics, including their estimated MES, as they could be measured in real time at different dates before the crisis, between June 2006 and June 2007. Beside the usual Pearson correlation coefficients, we also compute Spearman rank correlation coefficients, which describe the degree of rank correlation between two variables, thus accomodating possible non-linear relationships. Table 5 presents the results for all banks.[11] Looking at the first column, we find that the rank of tier one solvency ratios in 2007Q2 would have been a relatively good advanced indicator of the rank of losses to come, with a Spearman rank correlation coefficient above 50% in absolute value. Size, non-performing loans and liquidity of assets as measured *ex ante* also exhibit good predictive properties of the rank of losses under systemic stress, with absolute rank correlation coefficients between 35% and 40%. In contrast, the correlation of the MES before the crisis with the cumulated losses borne during the crisis is below 20% and not significant.

Importantly, although our measure of the MES is model-based (and closely follows BE's dynamic approach), this last result is not model-dependent, since we obtain similar results when we replace the dynamic MES with a simple historical measure of the MES as computed over a three-year rolling window. Column 2 also shows that the results remain qualitatively unchanged when we use the more common Pearson correlation coefficient.

The rest of the Table provides correlations of the *ex post* losses with *ex ante* bank MES and balance sheet characteristics as measured at earlier dates. While the overall picture remains the same, we note that the correlation with the *ex ante* solvency ratio tends to increase, not decrease, with longer forecasting horizons, while the correlation with the MES eventually drops to zero.[12]

While the MES as measured before a major crisis is less correlated with equity losses observed *ex post* than other indicators, it may be the case that it nevertheless contains some

[11] Note that, for consistency, we limit the exercise here to the 61 banks that remain listed up to June 2009. Some institutions in the sample (namely Wachovia, National City Corp, Commerce Bancorp, Unionbancal) were indeed merged into other banking groups during the crisis. We checked however that the results of the ranking tests remain unchanged when these four BHC are included in the sample.

[12] For robustness, we checked that our results still qualitatively hold when we split our set of banks by size (above/below the median). See the related table in Appendix C

useful information at the margin. To check this, Table 8 shows the results of cross-sectional regressions of observed SES over the crisis period on *ex ante* MES and bank balance sheet ratios, as measured at different points in time before the crisis. Again, we find that the marginal explanatory power of the MES is insignificant, while *ex ante* standard ratios alone can predict some 45% of the cross-sectional variance in cumulated equity losses during the crisis.

As a financial crisis unfolds, it may be of crucial importance for the regulator to be able to identify quickly the few most endangered institutions. With this in mind, we compare in Table 6 the rankings of the top 10 most severely hurt banks in our sample during the crisis with the rankings suggested before the crisis on the basis of various alternative indicators. For each indicator, we compute the success ratio, i.e. the ratio of the *ex post* worst 10 that would have been identified as such on the basis of the indicator. In line with our previous results, the solvency ratio (CARTIER1) performs well with a success ratio of 50%, while the MES would have helped to identify only three of the ten most fragile banks. These findings suggest that, in cross-section, standard banking risk metrics do a better job than the MES in predicting which institution is going to be less resilient in case of an adverse systemic event.

Last, in a recent contribution, Acharya, Engle and Richardson (2012) expressed concern that the dynamic MES as defined above is merely a short-run indicator, and they proposed two complementary indicators meant to be more forward-looking: the long-run MES (LRMES) and the associated measure of the expected capital shortfall of a bank conditionally to a crisis, or SRISK (in dollars). Based on the same model as before, the LRMES is computed using Monte-Carlo simulations of the market and bank returns for six months in the future. Only scenarios whenever the broad market index falls by more than 40% over the next six months are kept and the LRMES is then the average cumulated expected return in the stock price of an individual bank over all these simulated crisis scenarios. The associated expected capital shortfall SRISK is then directly calculated by assuming that the book value of debt remains broadly constant over the six months period. Note that the SRISK measure incorporates both the LRMES and a measure of bank (market) leverage:

$$
\begin{aligned}
SRISK_{i,t} &= E(k.(Debt_{i,t} + Equity_{i,t}) - Equity_{i,t}|Crisis) \\
&= k.Debt_{i,t} - (1-k).(1-LRMES).Equity_{i,t}
\end{aligned}
$$

where k stands for the capital ratio imposed by the regulator (8% in their baseline).

The Systemic risk website of NYU Stern (dubbed "VLab") provides with time series of estimated LRMES and SRISK for some 100 US financial institutions, 19 of them being BHCs that are also present in our sample. As a last robustness check, Table 7 then presents similar correlations as Table 5 but this time looking at the predictive power of these new systemic risk indicators for this reduced sample of 19 banks. The results suggest that the LRMES and SRISK indicators do not fare better than the original MES.

To conclude, and based on all this evidence, we thus strongly doubt that the MES can really help regulators identify systematically important banks on the eve of a future severe systemic crisis.

5 Conclusion

The marginal expected shortfall (MES) of a bank's stock return in case of market tail losses is a popular indicator among several recent proposals to help to monitor banks' exposure to systemic risk. Since a fall in a bank's stock return dents its equity basis, the MES hints at future probabilities of default and can be used to gauge expected losses for banks' non-financial creditors.[13] However, for the MES to be of any practical use for macroprudential analysis and regulation, we need to better understand how it is related to usual balance-sheet measures of bank fragility and we also need to check if the MES can help to predict disasters to come.

In this paper, we replicated the dynamic version of the MES proposed by Brownlees and Engle (2010), which is based on the estimation of GARCH volatilities and dynamic conditional correlations of individual bank stock returns with a stock market index of financial institutions. Using a panel of 65 large US bank holding corporations over the period 1996-2010, we first regressed quarterly MES on selected balance-sheet ratios and various

[13] See Drehman and Tarashev (2011) for such an extension of various indicators of systemic importance like the MES.

controls. Our results first confirm that the MES can be brodaly rationalized in terms of standard indicators of bank fragility or systemic exposure, like a high degree of reliance on wholesale funding or a low profitability, although some a priori intuitive balance sheet indicators, like the share of non-performing loans and the size of assets, matter only during the recent crisis.

This being said, a regulator should be more inclined to monitor the MES of large banks if there is sufficient indication that this metric can help identify *ex ante*, i.e. before a crisis unfolds, which institutions are more likely to suffer the most severe losses *ex post*, i.e. once it has unfolded. Unfortunately, using the recent crisis as a natural experiment, we find that standard balance-sheet metrics like the tier one solvency ratio are better able than the MES to predict equity losses conditional to a true and rare systemic market event. Overall, our results hence tend to weaken the case for a practical use of the MES for supervisory purposes.

A Appendix: Estimation procedure of the Marginal Expected Shortfall

To estimate the MES, we first model the bivariate process of firm and market returns:

$$r_{m,t} = \sigma_{m,t}\varepsilon_{m,t} \tag{7}$$

$$\begin{aligned} r_{i,t} &= \sigma_{i,t}\varepsilon_{i,t} && (8)\\ &= \sigma_{i,t}\rho_{i,t}\varepsilon_{m,t} + \sigma_{i,t}\sqrt{1-\rho_{i,t}^2}\xi_{i,t} && (9) \end{aligned}$$

$$\left(\varepsilon_{m,t}, \xi_{i,t}\right) \sim F \tag{10}$$

where $r_{i,t}$ and $r_{m,t}$ are the stock price returns of the institution i and the market respectively. $\sigma_{m,t}$ and $\sigma_{i,t}$ are the volatilities of the market and financial institution i at time t; $\rho_{i,t}$ the correlation at time t between $r_{i,t}$ and $r_{m,t}$.

In this model, the disturbances $\left(\varepsilon_{m,t}, \xi_{i,t}\right)$ are assumed to be independently and identically distributed over time and have zero mean, unit variance and zero covariance under distribution F that will be specified later on. But they are not considered as independent from each other: typically when extreme values occur, it tends to happen systematically for the most risky firms.

Thus the MES can be rewritten more explicitly as a function of correlation, volatility and some tail expectations of the standardized innovations distribution:

$$\begin{aligned} MES_{i,t-1} &= E_{t-1}\left(r_{i,t} \mid r_{m,t} < C\right) && (11)\\ &= \sigma_{i,t}E_{t-1}\left(\varepsilon_{i,t} \mid \varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) && (12)\\ &= \sigma_{i,t}\rho_{i,t}E_{t-1}\left(\varepsilon_{m,t} \mid \varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) + \sigma_{i,t}\sqrt{1-\rho_{i,t}^2}E_{t-1}\left(\xi_{i,t} \mid \varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) && (13) \end{aligned}$$

Our estimation of time-varying correlations, stochastic volatilities and tail expectations follows closely on Brownlees & Engle (2010) and are reminded below. The three steps consist in estimating (i) the volatility, (ii) the correlation and (iii) the tail expectation under F.

A.1 Volatilities

The conditional volatilities are modeled with an asymmetric GARCH specification (see Rabemananjara and al. (1993)):

$$\sigma^2_{m,t} = \omega_m + \alpha_m r^2_{i,t-1} + \gamma_m r^2_{m,t-1} I_{m,t-1} + \beta_m \sigma^2_{m,t-1} \tag{14}$$

$$\sigma^2_{i,t} = \omega_i + \alpha_i r^2_{i,t-1} + \gamma_{i,} r^2_{i,t-1} I_{i,t-1} + \beta_i \sigma^2_{i,t-1} \tag{15}$$

where $I_{i,t} = \mathbf{1}_{r_{i,t}<0}$ and $I_{m,t} = \mathbf{1}_{r_{m,t}<0}$ which can capture the leverage effect. Indeed, it is generally acknowledged that volatility tends to increase more with negative shocks than positive ones. Note that in contrast with BE, we use Student-t standardized errors in order to better take into account fat tails. The degree of freedom of each Student-t distribution is part of the estimation set.

A.2 Correlation

The time-varying conditional correlations are modeled using the DCC approach introduced by Engle (2002). Actually, the DCC model we use for the MES is slightly modified since we also introduce asymmetry in its specification following Capiello et al. (2006).

The Variance covariance matrix Σ is written as follows:

$$\Sigma_t = D_t R_t D_t \tag{16}$$

where $R_t = \begin{bmatrix} 1 & \rho_{i,t} \\ \rho_{i,t} & 1 \end{bmatrix}$ is the time-varying correlation matrix of the market and firm returns and $D_t = \begin{bmatrix} \sigma_{i,t} & 0 \\ 0 & \sigma_{m,t} \end{bmatrix}$.

The standard DCC framework introduces a so-called pseudo-correlation matrix Q_t, which is a positive definite matrix, such as

$$R_t = diag\left(Q_t\right)^{-\frac{1}{2}} Q_t diag\left(Q_t\right)^{-\frac{1}{2}} \tag{17}$$

where $diag\left(Q_t\right)$ is such that $diag\left(Q_t\right)_{i,j} = \left(Q_t\right)_{i,j} 1_{i=j}$.

In the standard DCC framework, Q_t is defined as

$$Q_t = (1 - a - b)\, S + a\eta_{t-1}\eta_{t-1}^{'} + bQ_{t-1} \tag{18}$$

with S being an intercept matrix, $\eta_t = (\varepsilon_{i,t}\ \varepsilon_{m,t})^{'}$ is the vector of standardized returns. Q_t is a positive definite matrix under certain conditions which are $a > 0$, $b > 0$, $a + b < 1$ and the positive definitiveness of S. The matrix S is estimated by

$$\widehat{S} = \frac{1}{T}\sum_{t=1}^{T} \eta_t \eta_t^{'} \tag{19}$$

As explained in Brownlees & Engle (2010), jointly negative standardized returns for example have the same impact on the evolution of the future correlation matrix in the basic DCC framework. We thus consider the Asymmetric version of the DCC as in Cappiello and al. (2006). In this framework, the pseudo correlation matrix Q_t is defined as

$$Q_t = (1 - a - b)\, S - gN + a\eta_{t-1}\eta_{t-1}^{'} + gu_{t-1}u_{t-1}^{'} + bQ_{t-1} \tag{20}$$

where S and N are intercept matrices and $u_t = \eta_t.I\,[\eta_t < 0]$. To ensure the positive definitiveness of the matrix Q_t , we have a new set of constraints:

$$a > 0, b > 0, g > 0 \tag{21}$$

$$a + b + \delta g < 1 \tag{22}$$

where δ is the maximum eigenvalue of $S^{-\frac{1}{2}}NS^{-\frac{1}{2}}$ (see Engle & Sheppard (2008)) and S and N can be estimated with

$$\widehat{S} = \frac{1}{T}\sum_{t=1}^{T} \eta_t \eta_t^{'} \tag{23}$$

$$\widehat{N} = \frac{1}{T}\sum_{t=1}^{T} u_t u_t^{'} \tag{24}$$

The asymmetric DCC model is estimated via QML. The multi-step approach of the correlation estimation as in Engle and Sheppard (2002) has been compared with alternative methodologies that finally provide similar results. For comparison purposes with the Engle and Brownlees (2010) and estimation flexibility over the all set of financial institution considered, the multi-step approach has been adopted and only modified by considering Student-t distributions for the residuals.

A.3 Tail expectations

The remaining terms to be estimated in order to obtain the MES are the two tail expectations:

$$E_{t-1}\left(\varepsilon_{m,t} \mid \varepsilon_{m,t} < \kappa\right) \text{ and } E_{t-1}\left(\xi_{i,t} \mid \varepsilon_{m,t} < \kappa\right)$$

Brownlees & Engle (2010) used a non-parametric kernel estimation approach in order to estimate these tail expectations so that these estimators are not unstable when κ is large (we only have a small number of observations that satisfies the conditioning event in this case). Let

$$K_t\left(h\right) = \int_{\infty}^{\frac{t}{h}} k\left(u\right) du \tag{25}$$

where $k\left(u\right)$ is a kernel function and h a positive bandwidth.

According to Scaillet (2005), the tail expectations can be estimated via

$$E_{t-1}\left(\varepsilon_{m,t} \mid \varepsilon_{m,t} < \kappa\right) = \frac{\sum_{j=1}^{t-1} \varepsilon_{m,j} K_h\left(\varepsilon_{m,t} < \kappa\right)}{\left(t-1\right)\widehat{p_h}} \tag{26}$$

$$E_{t-1}\left(\xi_{i,t} \mid \varepsilon_{m,t} < \kappa\right) = \frac{\sum_{j=1}^{t-1} \xi_{i,j} K_h\left(\varepsilon_{m,t} < \kappa\right)}{\left(t-1\right)\widehat{p_h}} \tag{27}$$

with

$$\widehat{p_h} = \frac{\sum_{j=1}^{t-1} K_h\left(\varepsilon_{mjt} < \kappa\right)}{t-1} \tag{28}$$

From a practical point of view, we chose a Gaussian kernel and the computation of these estimators over increasing windows starts from the 100th date t onward. Otherwise the first MES we compute in the sample would be too unstable. Gaussian kernels are easier to handle because optimal bandwiths for the kernel are available. These are used in our computations. The advantage of such non-parametric defintion of F also relies on the possible instability of the distribution over time. The non-parametric set-up allows for not relying on a specific family of distribution, and potentially takes into account the mixture of distributions occuring over the sample 1996-2010.

B Appendix: List of banks in sample

Bank holding corporations (banks) considered in this study are listed below. Asset shares are in percent as of end of 2010 Q1, market capitalizations are in billion dollars as of May 3rd, 2010.

RSSD ID	name	Asset share (%)	Market Cap
1039502	JPMORGAN CHASE & CO.	12.942	183.150
1120754	WELLS FARGO & COMPANY	7.415	155.800
1951350	CITIGROUP INC.	12.133	131.620
1073757	BANK OF AMERICA CORPORATION	14.184	127.530
1119794	U.S. BANCORP	1.711	49.700
3587146	BANK OF NEW YORK MELLON CORPORATION. THE	1.339	35.940
1069778	PNC FINANCIAL SERVICES GROUP. INC.. THE	1.608	33.700
1111435	STATE STREET CORPORATION	0.926	23.540
1074156	BB&T CORPORATION	0.992	18.730
1131787	SUNTRUST BANKS, INC.	1.041	15.310
1070345	FIFTH THIRD BANCORP	0.683	12.300
1199611	NORTHERN TRUST CORPORATION	0.462	11.950
1037003	M&T BANK CORPORATION	0.415	10.690
3242838	REGIONS FINANCIAL CORPORATION	0.832	9.270
1068025	KEYCORP	0.577	8.390
2132932	NEW YORK COMMUNITY BANCORP, INC.	0.257	7.320
1245415	HARRIS FINANCIAL CORP.	0.397	6.780
1199844	COMERICA INCORPORATED	0.347	6.720
1068191	HUNTINGTON BANCSHARES INCORPORATED	0.314	5.920
1027004	ZIONS BANCORPORATION	0.313	4.470
3594612	MARSHALL & ILSLEY CORPORATION	0.343	4.280
1883693	BOK FINANCIAL CORPORATION	0.142	3.760
1049341	COMMERCE BANCSHARES, INC.	0.109	3.740
1102367	CULLEN/FROST BANKERS, INC.	0.102	3.640
1129382	POPULAR, INC.	0.205	3.270
1027518	CITY NATIONAL CORPORATION	0.122	3.060
1094640	FIRST HORIZON NATIONAL CORPORATION	0.157	2.950
1199563	ASSOCIATED BANC-CORP	0.140	2.520
2389941	TCF FINANCIAL CORPORATION	0.110	2.470
1117129	FULTON FINANCIAL CORPORATION	0.099	2.350
1025309	BANK OF HAWAII CORPORATION	0.075	2.330
1048773	VALLEY NATIONAL BANCORP	0.088	2.310
1075612	FIRST CITIZENS BANCSHARES, INC.	0.129	2.090
1078846	SYNOVUS FINANCIAL CORP.	0.197	1.950
1049828	UMB FINANCIAL CORPORATION	0.065	1.700
1079562	TRUSTMARK CORPORATION	0.056	1.510
1025541	WESTAMERICA BANCORPORATION	0.029	1.460
1086533	HANCOCK HOLDING COMPANY	0.052	1.420
1843080	CATHAY GENERAL BANCORP	0.072	1.350
1079740	WHITNEY HOLDING CORPORATION	0.070	1.300
1117026	NATIONAL PENN BANCSHARES, INC.	0.056	1.210
1117156	SUSQUEHANNA BANCSHARES, INC.	0.084	1.190
1102312	FIRST FINANCIAL BANKSHARES, INC.	0.020	1.150

RSSD ID	name	Asset share* (%)	Market Cap**
1097614	BANCORPSOUTH, INC.	0.080	1.130
1076217	UNITED BANKSHARES. INC.	0.046	1.120
2003975	GLACIER BANCORP, INC.	0.038	1.070
1142336	PARK NATIONAL CORPORATION	0.043	1.050
1029222	CVB FINANCIAL CORP.	0.041	1.010
1208184	FIRST MIDWEST BANCORP, INC.	0.046	0.968
1071276	FIRST FINANCIAL BANCORP	0.040	0.948
1105425	STERLING BANCSHARES, INC.	0.031	0.910
1048867	COMMUNITY BANK SYSTEM, INC.	0.033	0.817
1139279	NBT BANCORP INC.	0.034	0.769
2078816	COLUMBIA BANKING SYSTEM, INC.	0.025	0.746
1136803	INDEPENDENT BANK CORP.	0.028	0.623
1133286	BANCFIRST CORPORATION	0.027	0.617
1201934	CHEMICAL FINANCIAL CORPORATION	0.026	0.546
1022764	CENTRAL PACIFIC FINANCIAL CORP.	0.027	0.534
1070448	WESBANCO, INC.	0.033	0.534
1076262	CITY HOLDING COMPANY	0.016	0.513
1199602	1ST SOURCE CORPORATION	0.027	0.500
1069125	NATIONAL CITY CORPORATION	N/A	N/A
1073551	WACHOVIA CORPORATION	N/A	N/A
1117679	COMMERCE BANCORP, INC.	N/A	N/A
1378434	UNIONBANCAL CORPORATION	0.518	N/A

C Appendix: Rank tests for predictive power: robustness checks

Variable	Spearman - Big	Pearson - Big	Spearman - Small	Pearson - Small
MES	0.230	0.296	-0.039	-0.055
ROA	0.002	-0.019	-0.130	-0.212
CAR	0.143	0.137	0.036	0.161
CARTIER1	-0.440*	-0.387*	-0.341*	-0.370*
NPL	0.520*	0.434*	0.048	-0.008
WFUND	0.005	0.060	0.465*	0.338*
CIL	0.231	0.218	0.163	0.096
HOL	0.415*	0.395*	0.514*	0.518*
LIQ	-0.318*	-0.422*	-0.499*	-0.388*
SIZE	0.131	0.143	0.116	0.169

Table C.1: Spearman and Pearson correlation between pre-crisis (as of 2007 Q2) indicators and equity losses during the crisis for "big" banks (i.e. size above the median as of 2007Q2) and "small" banks. * denotes significant coefficients at the 5 percent level

D Appendix: Data construction details

Mnemonic	Definition	Call reports codes
WFUND	Short-term wholesale funding to total liabilities (%)	BHCK2309 + BHCK2332
CAR	Total equity capital to assets (%)	BHCK3210
CARTIER1	Tier-one equity capital to risk-weighted assets (%)	BHCK8274
ROA	Profitability: return on assets (%)	BHCK4340
NPL	Asset quality: non-performing loans to total loans (%)	BHCK5525 + BHCK5526
CIL	C&I loans to non-financial firms to assets (%)	BHCK1763 + BHCK1764
HOL	Mortgage loans to assets (%)	BHCK1410
LIQ	Liquid assets to total assets (%)	Cash: BHCK0081 + BHCK0395 + BHCK0397
		US Treasuries: BHCK0211 + BHCK1286
		FF sold and Sec. under repos: BHDMB987 + BHCKB989
		(previously: BHCK1350, BHCK0276 + BHCK0277)
SIZE	log(total assets)	log(BHCK2170)

Table D.1: Balance-sheet variables used in the analysis

References

[1] Acharya, V., Engle, R., Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. Unpublished manuscript, NYU Stern School of Business.

[2] Acharya, V., Pedersen, L., Philippon, T., Richardson, M. (2010). Measuring systemic risk. Technical report, Department of Finance, NYU.

[3] Adrian, T. and Brunnermeier, M. K. (2008). CoVar, Federal Reserve Bank of New York Staff Report 348.

[4] Boyd, J. H. and G. De Nicoló (2005), The Theory of Bank Risk Taking and Competition Revisited. The Journal of Finance, 60, 1329–1343.

[5] Brownlees, C. and Engle, R. (2010). Volatility, Correlation and Tails for Systemic Risk Measurement, Working Paper Series, Department of Finance, NYU.

[6] Buch, C. M., Eickmeier, S. Prieto, E. (2010). Macroeconomic factors and micro-level bank risk, Deutsche Bundesbank Discussion Paper Series 1: Economic Studies 20/2010

[7] Cappiello, L., Engle, R., Shephard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. Journal of Financial Econometrics, 4(4), 537–572.

[8] Danielsson, J., James, K. R., Valenzuela, M., Zer, I. (2012). Dealing with systemic risk when we measure it badly: a minority report, Unpublished manuscript, London School of Economics.

[9] Delis, M. D., Kouretas, G (2010). Interest rates and bank risk-taking, MPRA Paper 20132, University Library of Munich, Germany.

[10] De Jonghe, O. (2010). Back to the basics in banking? A micro analysis of banking system stability. Journal of Financial Intermediation, 19, 387-417.

[11] Demirgüc-Kunt, A., Detragiache, E., Tressel, T. (2008). Banking on the principles: compliance with Basel core principles and bank soundness. Journal of Financial Intermediation, 17, 511-542.

[12] Drehman, M., Tarashev, N. (2011). Systemic importance: some simple indicators, BIS Quarterly Review.

[13] Driscoll, J. C., Kraay A. C. (1998). Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. Review of Economics and Statistics, 80, 549-560.

[14] Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics, 20(3), 339–350.

[15] Engle,R., Sheppard, K. (2008). Evaluating the specification of covariance models for large portfolios. Unpublished manuscript.

[16] Goodhart, C., Segoviano, M.A. (2009). Banking stability measures, IMF Working Paper

[17] Gouriéroux, C., Monfort, A. (2011). Allocating Systematic and Unsystematic Risks in a Regulatory Perspective. Unpublished manuscript.

[18] Laeven, L. A., Levine, R. (2009). Bank Governance, Regulation, and Risk Taking, Journal of Financial Economics, vol. 93(2), pages 259-275.

[19] Rabemananjara, R., Zakoïan, J. M. (1993). Threshold ARCH models and asymmetries in volatility. Journal of Applied Econometrics, 8(1), 31–49.

[20] Purnanandam, A. (2007). Interest rate derivatives at commercial banks : An empirical investigation. Journal of Monetary Economics, 54, 1769-1808.

[21] Scaillet, O. (2005). Nonparametric estimation of conditional expected shortfall. Insurance and Risk Management Journal, 74, 639–660.

[22] Tasche, D. (2000). Risk Contributions and Performance Measurement, DP University of Munich.

[23] Zhang, L. (2009). Bank Capital Regulation, the Lending Channel, and Business Cycles. Deutsche Bundesbank. Discussion Paper Series 1: Economic Studies. 33/2009.

	Growth of banks assets at major M&A quarters							
Variable	Obs	Mean	Sd	Min	p25	p50	p75	Max
asset_growth (%)	60	57.02	37.97	25.16	28.88	45.62	77.36	252.64

Table 1: Growth of total bank assets at quarters whith recorded Mergers and Acquisitions.

	1996q1-2007q2					2007q3-2010q1				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
WFUND	2,959	4.21	4.31	0.00	38.17	690	4.52	4.35	0.00	25.65
CAR	2,959	8.79	1.64	4.35	17.07	690	10.09	1.93	3.88	16.68
CARTIER1	2,959	11.06	3.05	5.32	30.92	690	11.07	2.35	6.53	20.25
ROA	2,959	3.27	1.79	-5.73	12.65	690	1.32	3.90	-25.55	20.89
NPL	2,959	0.75	0.49	0.00	3.40	690	2.32	2.09	0.00	16.15
CIL	2,959	13.83	7.91	0.00	51.54	690	13.23	7.22	0.03	43.32
HOL	2,959	36.49	13.94	0.00	88.24	690	41.70	14.07	0.00	67.88
LIQ	2,959	9.14	8.65	0.64	63.90	690	6.82	7.54	0.47	44.51
SIZE	2,959	16.43	1.67	12.90	21.52	690	17.06	1.69	14.72	21.58

Table 2: Summary statistics of bank variables and the macro control variable. Outlier observations that do not correspond to Mergers and Acquisition operations are excluded. All variables in percent (except size in logs of USD thousand)

	WFUND	CAR	CARTIER1	ROA	NPL	CIL	HOL	LIQ
				1996Q1-2007Q2				
WFUND	1							
CAR	-0.23*	1						
CARTIER1	-0.30*	0.48*	1					
ROA	0.03	0.16*	-0.004	1				
NPL	0.15*	-0.08*	-0.20*	-0.11*	1			
CIL	0.11*	0.01	-0.31*	0.00	0.21*	1		
HOL	0.05*	0.28*	0.02	0.09*	-0.13*	-0.26*	1	
LIQ	-0.12*	-0.23*	0.26*	-0.14*	-0.01	-0.05*	-0.61*	1
SIZE	0.22*	-0.23*	-0.57*	0.03	0.28*	0.13*	-0.35*	0.15*
				2007Q3-2009Q2				
WFUND	1							
CAR	-0.24*	1						
CARTIER1	-0.18*	0.33*	1					
ROA	-0.12*	0.01	0.00	1				
NPL	0.21*	0.13*	0.06	-0.53*	1			
CIL	-0.02	0.07	-0.23*	-0.05	0.10*	1		
HOL	-0.03	0.25*	-0.04	-0.08	0.06	-0.10	1	
LIQ	0.01	-0.21*	0.20*	0.00	-0.08	-0.20*	-0.70*	1
SIZE	0.34*	-0.23*	-0.45*	-0.20*	0.32*	-0.00	-0.45*	0.35*

Table 3: Pooled correlation between bank balance-sheet variables, before and during the crisis. Outlier observations that do not correspond to identified Mergers and Acquisition operations are excluded. * denotes significant correlation coefficients at the 5 percent level.

1996Q1-2010Q1 MES	CAR	CARTIER1	CAR and Crisis	CARTIER1 and Crisis
WFUND	0.077***	0.062***	0.031***	0.034***
	(0.022)	(0.023)	(0.011)	(0.011)
CAR	0.199***		-0.005	
	(0.054)		(0.045)	
CARTIER1		-0.006		0.031
		(0.037)		(0.025)
ROA	−0.261***	−0.250***	−0.115***	−0.117***
	(0.069)	(0.071)	(0.029)	(0.028)
NPL	0.337***	0.417***	0.146**	0.131**
	(0.083)	(0.098)	(0.056)	(0.054)
CIL	0.086***	0.078***	0.079***	0.082***
	(0.020)	(0.022)	(0.018)	(0.018)
HOL	0.029**	0.032**	−0.019*	−0.018*
	(0.013)	(0.014)	(0.009)	(0.010)
LIQ	-0.025	−0.033**	-0.009	-0.009
	(0.016)	(0.016)	(0.011)	(0.014)
SIZE	0.957***	0.959***	0.158	0.130
	(0.169)	(0.174)	(0.155)	(0.152)
Crisis*WFUND			0.011	-0.007
			(0.047)	(0.044)
Crisis*CAR			0.162**	
			(0.075)	
Crisis*CARTIER1				0.185**
				(0.078)
Crisis*ROA			−0.169**	−0.169***
			(0.065)	(0.063)
Crisis*NPL			1.186***	1.159***
			(0.223)	(0.231)
Crisis*CIL			-0.002	0.002
			(0.021)	(0.018)
Crisis*HOL			0.016	0.016
			(0.011)	(0.011)
Crisis*LIQ			0.030	-0.004
			(0.029)	(0.034)
Crisis*SIZE			0.162	0.268**
			(0.106)	(0.124)
Observations	3582	3582	3582	3582
Adjusted R^2	0.260	0.248	0.660	0.663

Table 4: Results of regressions of bank MES (at the 5th percentile threshold of market losses) on bank characteristics over the whole period. The crisis dummy takes the value of one over the period from 2007Q3 to 2009Q2. Dummies for mergers and acquisitions and FHC status, as well as quarterly dummies and a constant are included in the regressions but not shown. OLS regression with bank fixed-effects. Standard errors are robust to intra-cluster correlation. *,**,*** denote significance at the 10, 5, 1 percent levels respectively.

Stock-taking in:	2007 Q2		2006 Q4		2006 Q2	
Variable	Spearman	Pearson	Spearman	Pearson	Spearman	Pearson
MES	0.178	0.199	-0.020	-0.034	0.124	0.056
Historical MES	0.155	0.137	0.036	-0.002	-0.022	-0.114
ROA	-0.004	-0.099	-0.042	-0.111	-0.006	-0.045
CAR	0.062	0.076	0.112	0.115	0.104	0.097
CARTIER1	-0.513***	-0.506***	-0.573***	-0.543***	-0.589***	-0.564***
NPL	0.349***	0.318**	0.363***	0.326**	0.307**	0.310**
WFUND	0.287**	0.255**	0.300**	0.245*	0.321**	0.264**
CIL	0.215*	0.155	0.239*	0.161	0.213*	0.127
HOL	0.315**	0.300**	0.301**	0.306**	0.318**	0.320**
LIQ	-0.364***	-0.255**	-0.40***	-0.292**	-0.344***	-0.261**
SIZE	0.403***	0.383***	0.392***	0.385***	0.414***	0.386***

Table 5: Spearman rank correlation and Pearson correlation coefficients between pre-crisis bank indicators and ex post equity losses through the subprime crisis. The (dynamic BE) MES are estimated using information up to 2007Q2 only (ex ante view). Historical MES are computed over a rolling window of three years. *,**,*** denote significance at the 10, 5 and 1 percent levels respectively.

Bank / Variable	Loss	MES	CARTIER1	NPL	WFUND	HOL	CIL	LIQ	SIZE
Citigroup Inc.	1	6*	7*	6*	6*	58	49	59	1*
Central Pacific Fin. Corp.	2	26	53	59	43	2*	54	9	47
Regions Fin. Corp.	3	13	8*	17	34	18	35	19	7*
Marsall & Ilsley Corp.	4	14	1*	11	5*	23	10	17	17
Popular, Inc.	5	36	41	1*	2*	30	37	33	20
Zions Bancorp.	6	48	5*	43	33	12	12	38	19
Keycorp	7	2*	11	20	17	45	7*	11	13
Fifth Third Bancorp.	8	24	10*	12	44	37	14	13	12
Huntington Bancshares Inc.	9	38	27	7*	54	27	30	40	22
Suntrust Banks, Inc.	10	5*	3*	14	35	25	28	18	6*
Success ratio		30%	50%	30%	30%	10%	10%	10%	30%

Table 6: Rankings of the worst 10 stock return performers during the crisis according to various pre-crisis indicators as measured in 2007 Q2. The (dynamic BE) MES are estimated using information up to 2007Q2 only (ex ante view). * denotes a bank correctly identified ex-ante as incurring one of the top-10 losses.

Stock-taking in:	2007 Q2		2006 Q4		2006 Q2	
Variable	Spearman	Pearson	Spearman	Pearson	Spearman	Pearson
SRISK with Simulation ($ m)	-0.032	-0.026	-0.125	-0.175	-0.039	-0.221
SRISK without Simulation ($ m)	-0.035	0.046	0.024	0.019	-0.207	0.267
LRMES	-0.011	0.001	0.074	0.053	-0.028	0.015
ROA	0.094	0.157	0.046	-0.153	0.111	0.231
CAR	0.197	0.153	0.163	0.190	0.188	0.194
CARTIER1	-0.629***	-0.544**	-0.486**	-0.528**	-0.481**	-0.509**
NPL	0.560**	0.643***	0.535**	0.534**	0.553**	0.477**
WFUND	0.201	0.237	0.077	-0.098	0.265	0.128
CIL	0.389	0.335	0.449*	0.384	0.416*	0.364
HOL	0.348	0.416*	0.421*	0.456**	0.430*	0.456**
LIQ	-0.340	-0.488**	-0.412*	-0.543**	-0.351	-0.530**
SIZE	0.193	0.153	0.116	0.148	0.107	0.132

Table 7: Spearman and Pearson correlation between pre-crisis bank indicators and ex post equity losses over the subprime crisis for a sub-sample of 19 BHCs present in both our initial sample and the VLAB website rankings. SRISK and LRMES variables are taken from the VLab website. *,**,*** denote significance at the 10, 5 and 1 percent levels respectively.

Dependent variable : SES over crisis	2007Q2			2006Q4		
	(1)	(2)	(3)	(1)	(2)	(3)
WFUND	0.723	0.918	0.905	1.412*	1.391*	1.368
CAR	1.677	1.904	1.638	2.381	2.670	2.352
CARTIER1	−4.169*	−3.839*	-3.456	−3.401*	-3.015	−3.766*
ROA	-5.956	-5.939	-5.155	-2.007	-1.988	-1.982
NPL	2.017	1.387	-0.022	0.433	1.579	1.625
CIL	0.537	0.542	0.613	0.641	0.657	0.522
HOL	1.043***	1.042***	1.102***	0.730**	0.768**	0.714**
LIQ	0.203	0.134	0.180	-0.268	-0.291	-0.285
SIZE	6.596**	6.216**	7.475**	6.716**	7.182**	6.429**
Dynamic MES		8.522			9.008	
Historical MES			6.019			-2.695
Constant	-77.277	-89.889	-118.967	-83.996	-112.175	-70.016
Nb. observations	61	61	61	61	61	61
Adjusted R^2	0.459	0.458	0.473	0.461	0.459	0.458

***, **, **denote significativity at 1, 5, 10 percent levels.

Table 8: Cross-sectional regressions of the cumulated equity loss over the crisis (SES) on bank specific characteristics and individual bank MES prior to the crisis. The (dynamic BE) MES are estimated using information up to 2007Q2 only (ex ante view). Historical MES are computed over a rolling window of three years. *,**,*** denote significativity at the 10, 5 and 1 percent levels respectively.

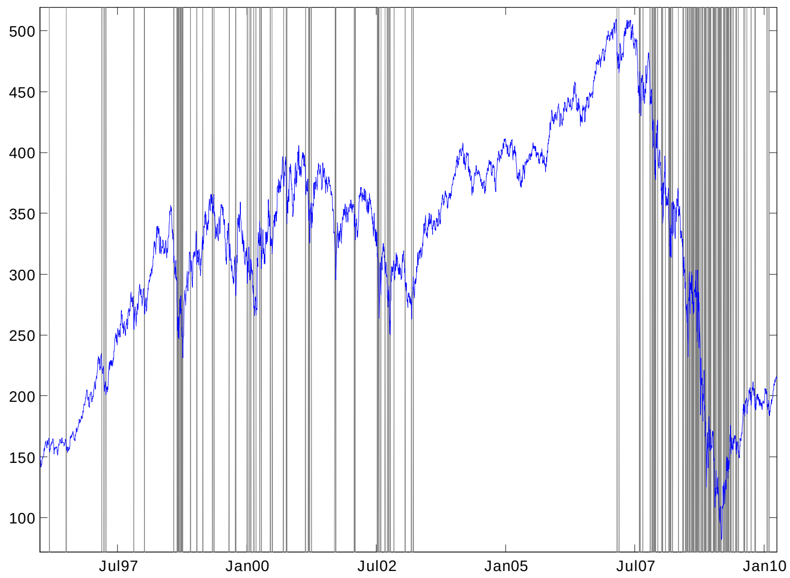

Figure 1: SP500 Financials Index from Jan 1996 to March 2010. Vertical lines correspond to dates when market losses exceeded the sample VaR of the index at 95%, or equivalently its pre-crisis VaR at 97.5% (i.e. a loss of more than 2.91 percent per day).

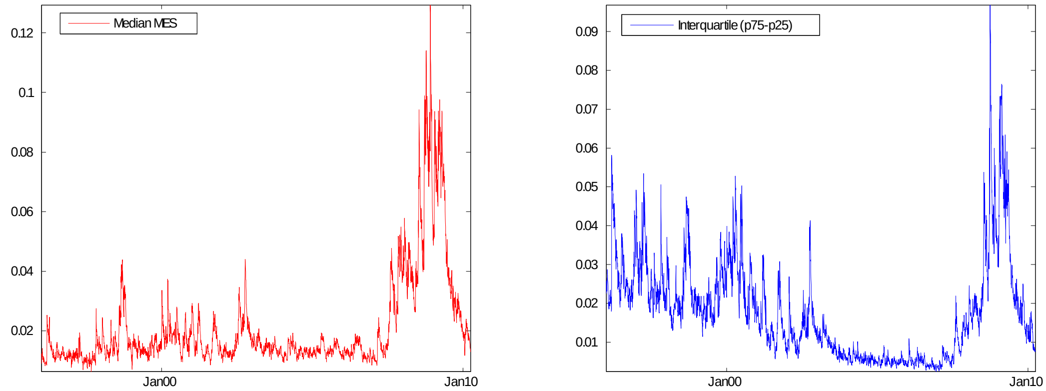

Figure 2: Median daily MES and daily MES interquartile range for 65 large US BHCs. Dynamic MES are estimated using Brownlees and Engle (2010) methodology and defining a systemic event as the 97.5% quantile of the pre-crisis empirical distribution of the SP500 Financials index.

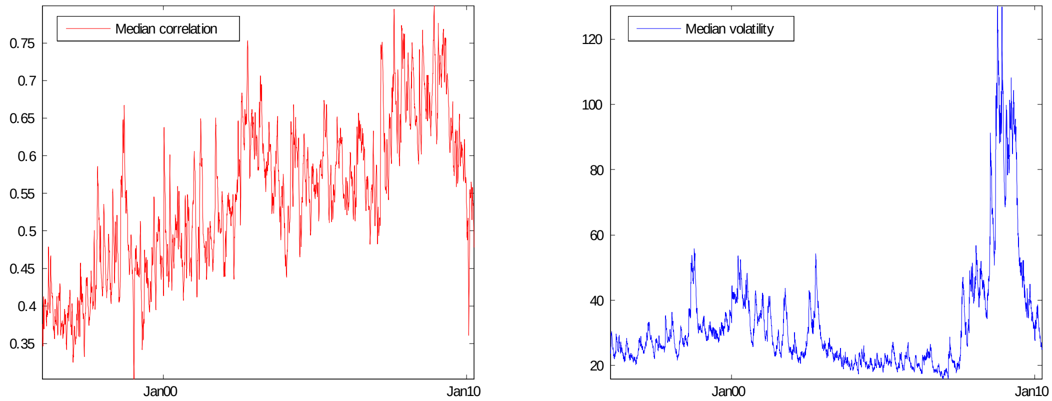

Figure 3: 5-day moving average of the estimated median dynamic correlation and median stochastic volatility of stock returns for 65 large US BHCs. The individual indicators are extracted from asymmetric GARCH models with student-t distribution for individual banks and asymmetric DCC estimated between the SP500 financial and each individual bank stock price return.

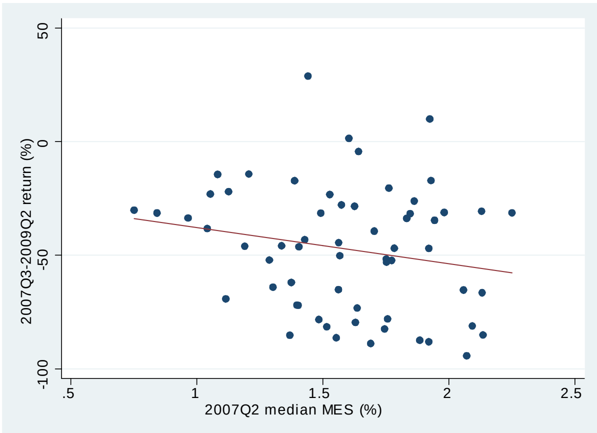

Figure 4: Cumulated bank stock returns over the crisis vs bank MES before the crisis

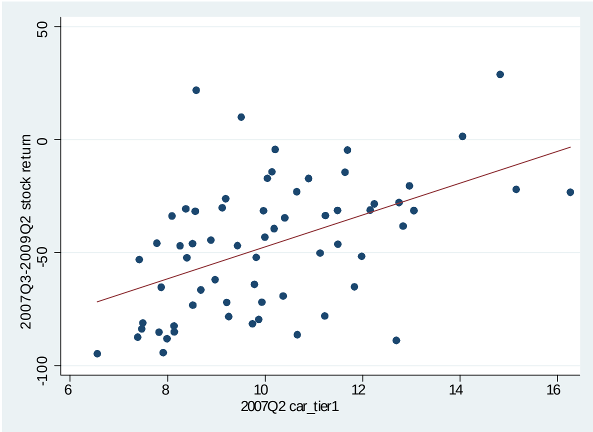

Figure 5: Cumulated bank stock returns over the crisis vs bank solvency ratio (CARTIER1) before the crisis

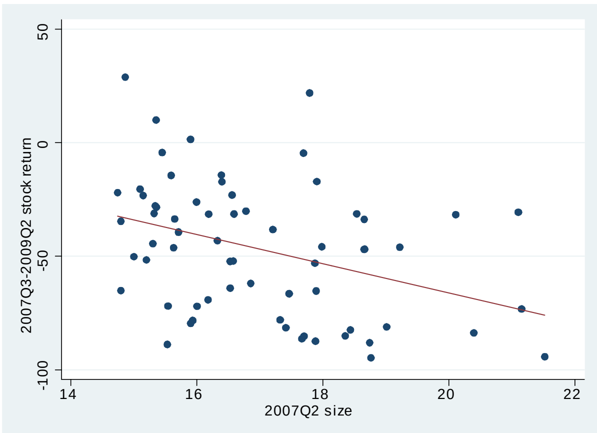

Figure 6: Cumulated bank stock returns over the crisis vs bank size before the crisis