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Abstract

Correlations of stock returns across banks are an essential input into systemic risk measures. We demonstrate that such correlations can be decomposed into two parts: a systematic component arising from diversification activities, and a systemic component specific to banks. We find that at U.S. Banking Holding Companies correlations are to a large extent driven by the systematic component. However, applying the decomposition to the Marginal Expected Shortfall (MES), we show that it is the systemic component that predicts bank failure and risk during the Global Financial Crisis. The results suggest that it is important to distinguish between the two sources of correlations when measuring systemic risk at banks.

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The two faces of interbank correlation

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9th October 2017

Abstract

Correlations of stock returns across banks are an essential input into systemic risk measures. We demonstrate that such correlations can be decomposed into two parts: a *systematic* component arising from diversification activities, and a *systemic* component specific to banks. We find that at U.S. Banking Holding Companies correlations are to a large extent driven by the systematic component. However, applying the decomposition to the *Marginal Expected Shortfall (MES)*, we show that it is the systemic component that predicts bank failure and risk during the Global Financial Crisis. The results suggest that it is important to distinguish between the two sources of correlations when measuring systemic risk at banks.

JEL codes: G1, G2.

Keywords: systemic risk, interbank correlation, diversification

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1 Introduction

The crisis of 2007-2008 has made systemic risk a priority on the agenda of policy makers. While a multitude of factors contribute to systemic risk, broadly, two different channels can be distinguished. First, since financial institutions are heavily interconnected, a shock to one institution can easily spill over to others.[1] Second, financial institutions tend to undertake similar activities, or display homogeneity in other dimensions (such as their risk management systems), which tends to amplify the impact of common shocks.[2]

In order to avoid a repeat of the crisis, regulators are now redesigning the financial architecture to address systemic risk. A major challenge in doing this is the measurement of systemic risk. Since systemic risk can arise from a variety of sources, a popular approach is to focus on an institution's overall systemic risk, as reflected in market prices. A key input in such market-based measures is the correlation of a bank with other banks in the system. For example, in an early contribution, De Nicolò and Kwast (2002) propose to directly use pair-wise equity market correlations as a systemic risk indicator. Other widely-used measures of systemic risk such as the *CoVaR*, the *Marginal Expected Shortfall,* the *SRISK,* or the *Distressed Insurance Premium*[3] are indirectly based on correlations of individual banks with the system as they quantify covariation conditional on a large negative shock.

In this paper we show that one has to be careful when basing systemic risk measures on interbank correlations. The reason for this is diversification activities at banks. To see the issue, consider a financial system in which banks are fully diversified in that they all hold the (CAPM) market portfolio. The banks will then be fully correlated with each other – but this is neither due to the presence of spillovers among banks nor to any banking sector-specific homogeneity. This illustrates that correlations across banks are partly driven by their diversification activities, raising the question of how one can

[1] Such spillovers may arise (among others) from asset prices contagion (e.g., Allen and Gale (1998)), mutual credit exposures (e.g., Freixas, Parigi, and Rochet (2000)), interbank market contagion (e.g., Aghion, Bolton, and Dewatripont (2000)).

[2] In this context, systemic risk has been shown to result from common investments (e.g., Acharya and Yorulmazer (2007)), strategic complementarities on the liability side (e.g., Farhi and Tirole (2012)) but also from common value-at-risk constraints (Persaud (2000)) and Danielsson and Zigrand (2008)).

[3] Adrian and Brunnermeier (2010), Acharya et al. (2011), Brownlees and Engle (2015) and Huang, Zhou, and Zhu (2009), respectively.

account for this when measuring systemic risk.

We present a methodology that isolates the part of the interbank correlation that is not due to diversification. The method is based on the concept of the *systematic correlation*. Systematic correlation is the lowest possible amount of interbank correlation given the amount of diversification banks display. For example, two completely undiversified banks could in principle invest in entirely unrelated activities, resulting in no correlation among them. Their systematic correlation is thus zero. At the other extreme, two banks being fully diversified necessitates full interbank correlation, and hence a degree of systematic correlation of one. Based on this, we then define the *excess correlation* as the part of the interbank correlation that cannot be accounted for by the systematic correlation. Excess correlation is a systemic measure as it captures the part of the correlation that is specific to the banking system.[4]

The decomposition of interbank correlation is important as the two components are likely to have different consequences for financial stability, and hence have different regulatory implications. Excess correlation indicates the presence of spillovers and herding in the financial system and should hence be of prime concern for regulators. The consequences of systematic correlation are a priori unclear. Systematic correlation is essentially a measure of how much banks diversify. The traditional view based on portfolio theory is that diversification enhances banking stability by reducing their exposure to idiosyncratic shocks. This is also the view that is reflected in subsequent Basel accords, which allow for capital reliefs for banks with more diversified activities. There is hence not necessarily a reason for regulators to be concerned about high interbank correlations if those are mainly due to diversification. Recent literature, however, has emphasized that diversification activities can also result in a more fragile system (e.g., Allen et. al (2012), Ibragimov et al (2011) and Wagner (2010)).

We apply our methodology to U.S. BHCs. The results strengthen the view that it is important to distinguish between the two different sources of bank correlations. First, we find that a significant part of the (cross-sectional) variation in interbank correlations is

[4]The decomposition into systematic and excess correlation is not the same as splitting into non-diversifiable and diversifiable exposures: to the extent that systemic risk is inherent into the business of banking (arising for instance from maturity mismatch on the balance sheet) excess correlation cannot be diversified away.

due to diversification: about 79% of a bank's average correlation with other banks can be attributed to systematic variations. It is thus misleading to think of interbank correlations as predominantly capturing systemic risk. Second, we apply our decomposition to a common measure of systemic risk, the Marginal Expected Shortfall (MES). We show that only the part of the MES coming from excess correlation can identify systemically weak banks. Specifically, this part predicts bank risk and bank failures during the Global Financial Crisis, while the systematic part does not. We also show that the MES prior to decomposition is not related to a bank's realized systemic risk.[5] This is explained by this measure being a very noisy indicator of systemic risk as it confounds systemic risk with normal market risk exposure arising from diversification activities.

The literature on the measurement of systemic risk has advanced rapidly in recent years. An important strand of the literature quantifies systemic risk using information contained in the market prices of financial institutions. These measures, directly or indirectly, use interbank correlations as an input. While early work has quantified systemic risk directly through interbank correlations (e.g., De Nicolò and Kwast (2002)), recent contributions have refined measurement by looking at modifications of interbank correlations or covariates. The *CoVaR* (Adrian and Brunnermeier (2010)), for instance, estimates the covariance of a bank and the banking sector conditional on the bank experiencing a tail event. Acharya et al. (2011) propose to measure systemic risk through the *Marginal Expected Shortfall* (MES), which is the expected loss to a financial institution conditional on a set of banks performing poorly. The *SRISK* of Brownlees and Engle (2015) measures the expected capital shortfall of a financial institution conditional on a severe market decline. Huang, Zhou, and Zhu (2009) combine default probabilities from CDS with stock return correlations to calculate a *Distressed Insurance Premium* (DIP), which is the insurance premium required to cover distressed losses in the banking system. In a recent paper, Billio et al. (2012) characterize systemic risk by measuring correlation through principal components analysis. The results in our paper suggest that one has to be careful with interpreting these (and other) systemic risk measures since the correla-

[5] This echos findings in Giglio et al. (2016), who study the predictive power of a large number of (aggregate) systemic risk measures for macroeconomic downturns, and show that many systemic risk measures based on covariates with the banking sector cannot forecast tail risks in the macroeconomy.

tions that underlie them may partly be driven by diversification activities. In order to arrive at a "pure" indicator of systemic risk, the measures should be computed isolating the effect of diversification. Our paper provides a methodology for how this can be done.

The remainder of the paper is organized as follows. Section 2 explains our methodology for separating interbank correlation into a systematic and a systemic part. Section 3 presents the empirical analysis. Section 4 concludes.

2 Methodology

In this section we present a simple framework that allows us understanding how interbank correlation can be decomposed into the two parts. Suppose that there are two banks, A and B, and two assets, X and Y. The assets are identically and independently distributed and of equal supply in the economy. The economy's market portfolio hence consists of the same units of the assets.

Consider first the case where both banks are fully diversified. Denoting the share of funds bank i ($i = A, B$) invests in asset X with w_i ($w_i \in [0, 1]$), we have $w_A = w_B = \frac{1}{2}$. Banks are then fully correlated with each other – but this is entirely due to their diversification strategies. All of the interbank correlation is of systematic nature. We say that in this case there is zero *excess correlation*. Consider next a situation where banks are investing in the same asset, say, asset X ($w_A = w_B = 1$). Banks are still fully correlated with each other. However, this correlation is not due to diversification (as banks are undiversified) but to the fact that banks "herd" into the same asset. Interbank correlation hence consists entirely of excess correlation – there is no systematic correlation. Note that in this case banks are only modestly correlated with the market portfolio, while in the diversification case the correlation is one.

Let us now turn to arbitrary portfolio choices w_A and w_B. We first define a concept of commonality and diversification.

Definition 1 *The* ***degree of commonality*** *between banks A and B is given by*

$$s(w_A, w_B) = 1 - |w_A - w_B| . \tag{1}$$

Similar to interbank correlation, the degree of commonality will be zero when banks specialize in different assets (e.g., $w_A = 1$ and $w_B = 0$) and one if banks hold identical portfolios ($w_A = w_B$).

Definition 2 *The* ***degree of diversification*** *at bank i ($i \in \{A, B\}$) is given by*

$$d_i(w_i) = 1 - 2\left|w_i - \frac{1}{2}\right|. \tag{2}$$

The degree of diversification will be zero if a bank is undiversified ($w_i = 0$ or $w_i = 1$) and one if it is fully diversified ($w_i = \frac{1}{2}$).

Commonality can be decomposed as follows. We first calculate the commonality that is unavoidable to reach a degree of diversification identical to that of the banking sector, which we call *systematic commonality.* For average banking sector diversification d ($d := \frac{d_A + d_B}{2}$), systematic commonality is defined as follows:

Definition 3 *The* ***systematic commonality*** $s^{\min}(d)$ *is the lowest commonality s that can implement banking sector diversification d. Formally we have:*

$$s^{\min}(d) := \min_{w_A, w_B} s(w_A, w_B), \ s.t. \ \frac{d_A(w_A) + d_B(w_B)}{2} = d \ and \ 0 \leq w_A, w_B \leq 1. \tag{3}$$

From this we can define *excess commonality*:

Definition 4 ***Excess commonality*** $e(w_A, w_B)$ *is the difference between actual and systematic commonality:*

$$e(w_A, w_B) := s(w_A, w_B) - s^{\min}(d(w_A, w_B)). \tag{4}$$

In our simple example, excess commonality can be easily computed. For a given diversification, the smallest commonality obtains when banks specialize as much as possible in different assets. For average banking sector diversification d ($d := \frac{d_A + d_B}{2}$), it is easy to see that an allocation that minimizes commonality arises when bank A invests a fraction $\frac{d}{2}$ in asset X and bank B invests a fraction of $\frac{d}{2}$ in asset Y ($w_A^{\min} = \frac{d}{2}$ and $w_B^{\min} = 1 - \frac{d}{2}$).[6]

[6] Since the portfolio shares enter linearly into the commonality measure, there are many other portfolios that lead to the same minimum commonality.

The resulting commonality is then $s^{\min}(d) = 1 - \left|w_A^{\min}(d) - w_B^{\min}(d)\right| = d$. Thus, we have:

Proposition 1 *In the two-bank two-asset economy, systematic commonality $s^{\min}(d)$ equals the degree of diversification d.*

It then follows that

Proposition 2 *In the two-bank two-asset economy, excess commonality $e(w_A, w_B)$ is given by the difference between actual commonality $s(w_A, w_B)$ and diversification $d(w_A, w_B)$.*

In an empirical implementation we face various challenges. First, we do not have information on the bank portfolio shares w_i that are needed for calculating commonality and diversification. However, one can approximate commonality using the correlation of bank stock returns across banks. In particular, the share price correlation of two banks with zero commonality should be zero, while for banks with maximum commonality the correlation is one. Recalling that diversification is effectively a measure of commonality with the market portfolio, we can in addition approximate diversification by the correlation of a bank with the market portfolio.[7] In particular, a (hypothetical) bank that is fully diversified along all dimensions should exhibit a correlation with the market of one. Second, we have to adapt the commonality measures for more than two banks. While in the two-bank case there is a single measure of commonality, commonality becomes pair-specific when there are more banks. We can then calculate the commonality of an individual bank as the correlation of the bank with the average bank in the system, or a banking sector index.

Third, the simple property that excess correlation equals commonality minus diversification (Proposition 2) only holds for the special case of uncorrelated assets and when the number of assets is at least as large as the number of banks. If the number of assets is less than the number of banks, it is not possible for banks to all specialize in (pair-wise) different assets. As a result, the systematic commonality associated with a certain degree of diversification rises, and excess correlation falls. Similarly, when assets are (positively) correlated, banks will be correlated even if they invest in different assets, again leading to

[7] Demsetz and Strahan (1997) similarly propose a diversification measure based on a bank's goodness-of-fit in a market regression, whereas Roll (1998) explores the R-squared as a measure of diversification for publicly traded firms in general.

lower excess correlation. In the general case, excess correlation will still be a decreasing function of the diversification degree. The exact functional form, however, will depend on what is assumed about the set of investable assets in the economy. In our empirical implementation we will hence *estimate* the excess correlation. For this we will take excess correlation to be the regression residual from a regression of interbank correlation on diversification. This has the consequence that excess correlation becomes a relative concept (and can hence be negative) as it compares a bank's actual correlation to that which is predicted for its diversification degree.

3 Empirical Analysis

3.1 Data

Our analysis focuses on Bank Holding Companies (BHCs) in the U.S.. We use bank-level data from the Federal Reserve Y-9C Reports. These reports contain quarterly data about on and off balance-sheet and income-statement information for all regulated BHCs. We focus our analysis on the 250 largest BHCs in 2015 that are classified as commercial banks and are listed in the U.S.. Summary statistics of these variables are shown in Table 1 (Panel A).

We combine this data with daily share price data for BHCs – as well as for the S&P 500 price index and the S&P 500 banking sector price index – collected from Datastream. From this data we compute our main variables, the interbank correlation and the systematic correlation. Interbank correlation for bank i, denoted $\rho_{i,b}$, is taken as the correlation between bank $i's$ share price return and the return on the S&P 500 banking sector index. For this we use daily returns (winsorized at 1% level) over a one-year time period. Note that the S&P 500 banking sector price index is capitalization-weighted and hence has the desired feature of giving larger banks a larger weight in the benchmark. Next, the systematic correlation ("diversification"), $\rho_{i,m}$, is calculated as the correlation between the bank return i and the return of the S&P 500.

Figure 1 depicts the relationship between the interbank correlation and the systematic correlation for the banks in our sample. Figure 1 reveals a very positive relationship

between these two variables. The R-squared of a regression of interbank correlation on systematic correlation is 0.79. This strengthens the premise of our analysis that interbank correlations are confounded by diversification activities.

3.2 Decomposition of Interbank Correlation

The next step is to separate interbank correlation into the parts that come from diversification (the systematic part) and systemic risk (excess correlation). The approach we take here is to treat excess correlation as the part of the interbank correlation that cannot be explained by diversification, and hence has to be the result of other bank characteristics that cause correlatedness. Specifically, we run the following cross-sectional regression:

$$\rho_{i,b} = \alpha + \beta \rho_{i,m} + \epsilon_i, \tag{5}$$

where $\rho_{i,b}$ is the interbank correlation of bank i and $\rho_{i,m}$ is the systematic correlation for bank i. Excess correlation is taken to be the regression residual, $\hat{\epsilon}_i$. Excess correlation is hence the interbank correlation for bank i relative to that which is predicted by bank $i's$ market correlation. Note that excess correlation can be negative – in which case a bank has a lower correlation relative to what is predicted for its systematic correlation using the entire sample of banks.

Table 1, Panel B, presents the summary statistics for the various correlation measures. The mean interbank correlation is about 0.39. The systematic correlation obtains an average value of 0.22. Finally, the mean of excess correlations is zero as they are regression residuals.

3.3 Determinants of Systematic and Excess Correlation

In this section we examine how the components of correlation relate to various bank characteristics. For this purpose, we estimate the following cross-sectional model:

$$Y_i = \alpha + \sum_{k=1}^{K} \phi_k B_{k,i} + \epsilon_i, \tag{6}$$

where Y_i is systematic correlation $\rho_{i,m}$ or excess correlation $\hat{\epsilon}_i$. The term B_k denotes different bank characteristics, measured in 2015. These characteristics include general bank properties such as size ($Log(Assets)$), subordinated debt over assets ($Sub.\ Debt/Assets$), loans over assets ($Loans/Assets$) and profitability (ROA). We also allow for a non-linear relationship with size by including the square of the size variable. We expect size to be positively related with both systematic and excess correlation as, first, large banks will tend to be more diversified (e.g., Demsetz and Strahan (1997)), and second, because large banks are more interconnected and hence subject to more systemic risk (Leuven, Ratnovski and Tong (2016)). Subordinated debt over assets is a measure of leverage. We would not expect leverage to be related to diversification (and hence systematic correlation), however, higher leverage may cause more systemic risk as banks displaying more leverage are more fragile (Leuven et. al show that systemic risk is inversely related to bank capital). The relationship between subordinated debt and excess correlation may hence be positive. As for loans, their expected relationship with systematic correlation is ambiguous. On one hand, a larger loan portfolio allows for more diversification (Demsetz and Strahan (1997) show that banks with larger loan portfolios are more diversified), resulting in higher systematic correlation. On the other hand, more loans may imply less functional diversification (e.g., less non-traditional activities)[8], leading to lower systematic correlation. Loans may also be positively or negatively related to excess correlation, depending on whether lending activities are subject to more or less systemic risk relative to a bank's other activities.[9] Finally, more profitable banks may be considered as more resilient by the market, and hence ROA be negatively related to excess correlation.[10] The literature on specialization (e.g., Acharya, Hasan and Saunders (2006)) suggests also a possible negative link between ROA and diversification (systematic correlation), as higher diversification may result in a loss of specialization benefits.

We first analyze how the systematic correlation, $\rho_{i,m}$, relates to various bank characteristics. Table 2, Columns (1) and (2), contains the results. Column (1) considers

[8] In fact, the literature often uses share of non-lending activities as a measure of diversification, see Laeven and Levine (2007).

[9] De Jonghe (2010) finds that non-interest generating activities increase a bank's systemic risk.

[10] However, high profitability may also be a sign of risk-taking, in which case it may be associated with more systemic risk (De Jonghe (2010)).

bank size as main determinant, showing that size is positively and significantly related to diversification. This is according to our priors as larger banks will generally have their activities more spread out, and hence are expected to have higher diversification.[11] The squared size term is also significant and obtains a negative sign. This indicates declining returns from diversification, consistent with portfolio theory.[12] Overall, size is an important determinant of diversification, as the regression R-squared is 0.48. The importance of size can also be appreciated from Figure 2, which plots bank diversification against size. Especially for smaller and medium-sized banks, increases in bank size are associated with substantial improvements in diversification. The figure also confirms the idea of declining marginal benefits as the relationship seems to weaken for the very large banks. In column (2) we add the remaining bank controls. None of these additional variables enter significantly in this model. The two size terms retain their significance and sign.

Column (3) presents the results for the model that relates excess correlation, $\hat{\epsilon}_i$, to size. The coefficient for bank size is positive and significant at the 1% of significance level. The sign is again consistent with priors. The squared term is negative and also significant, indicating a weakening of the relationship for larger banks. Figure 3 depicts the relationship between size and excess correlation. It shows that for especially for smaller and medium-sized banks, increases in bank size are associated with steep increases in excess correlation. However, once a certain bank size has been reached, the excess correlation no longer increases. Column (4) shows the results when including additional bank controls. The two size terms do not change much. Profitability shows a negative relationship with excess correlation. This is consistent with theory. The potential for spillovers across banks is larger when banks are weak and hence they should comove more with other banks.

We conclude that size is a main determinant of systematic and excess correlation, explaining a significant part of the variation in both components. Large banks display a high amount of systematic correlation (indicating their diversified nature) but also excess

[11] Note that the positive relationship between bank size and diversification is not an artefact of the fact that larger banks have more weight in the S&P 500. This is because individual bank weights are fairly small (the largest weight for a bank in the index is around 1.5%).

[12] The risk reduction achieved through investing in more assets falls when the number of assets in the portfolio is already large.

correlation. The latter likely reflects higher systemic risk at such banks.

3.4 Interbank Correlation and Bank Fragility During the Global Financial Crisis

A key function of systemic risk measures is to identify banks that are particularly vulnerable to systemic events. In this section, we analyze whether taking into account the different sources of interbank correlations facilitates this task. We analyze two dimensions of systemic vulnerability: bank failure as well as bank risk during the Global Financial Crisis (GFC).

The first step is to decompose a systemic risk measure according to whether "risk" arises from excess correlation or from market dependence due to diversification. We focus on the Marginal Expected Shortfall (MES) proposed by Acharya et al. (2017). The MES represents the losses of a financial institution in the tail of the banking sector loss distribution. The MES thus measures by how much a bank's stock declines when the bank index declines by a (large) amount. It is thus similar to a beta – but measuring a bank against the bank index (and not the market). A bank's MES is hence determined by how a bank covaries with other banks (in the tail). This covariation can be split up into two parts – exactly as we have done for correlation: one part arising from common market exposures (the systematic part of the MES), and one that is specific to banking sector (the excess part of the MES).

Following Acharya et al. (2017), we compute the MES by taking average daily returns for a bank during worst days of the banking sector. Specifically, we calculate the MES using as threshold the 2.5% worst days.[13] We calculate this measure using pre-crisis information (2006) to predict systemic vulnerability during the GFC. We construct decomposed MES measures as follows. We first create a *Systematic MES* by computing a bank's average return on days with the 2.5% worst returns of the *stock market* over 2006. Second, we obtain an *Excess MES* calculating the residuals from a (cross-sectional) regression of a bank's MES on its *Systematic MES*. The residual MES represents the losses

[13] We use a more stringent cut-off than Acharya et al. (2017) (who use a 5% threshold) since we are interested in predicting bank failures – which is an extreme event. The results using the 5% cut-off are similar.

for a bank that arise independently of the market. It measures exposures that arises from dependence on fluctuations that are unique to the banking system, similar to the excess correlation. By contrast, the *Systematic MES* measures exposures to general fluctuations in the stock market index, as would arise in the case of diversification. Descriptive statistics of these measures are shown in Table 1, Panel C.

We expect the *Excess MES* to be positively related to a bank risk during the subprime crisis, as it represents pure systemic risk. The impact of the *Systematic MES* is not clear a priori. A high *Systematic MES* may indicate diversification activities that make a bank more resilient – but as previous research has shown, diversification may also contribute to systemic risk in which case *Systematic MES* would be associated with higher fragility. In addition, we would expect the *Excess MES* to be more strongly related to systemic risk than a bank's total *MES*, as the latter includes the ambivalent systematic part.

3.4.1 Predicting Bank Failures

We first consider the relationship between the decomposed measures and bank failures during the crisis. Specifically, we estimate the following probit model:

$$p(fail)_i = \alpha + \beta_1 MES_{Systematic,i} + \beta_2 MES_{Excess,i} + \sum_{k=1}^{K} \phi_k B_{k,i,06} + \mu_i, \qquad (7)$$

where $p(fail)_i$ is a dummy variable indicating whether a bank failed during the period 2007-2010, $MES_{Systematic}$ and MES_{Excess} are the *Systematic* and *Excess MES* described above, respectively. The terms $B_{k,i}$ denotes various control variables. Besides the variables considered in the previous section, they include real estate loans over loans ($Real\ estate/Loans$) to start with. We also consider various proxies of asset quality: annual loan growth ($Loan\ growth$),[14] interest income from loans over loans ($Interest\ from\ loans/Loans$) and the share of non-performing loans over loans ($NPL/Loans$) as a measure of lending quality. We also include various variables that capture credit risk transfer and derivative activities. To proxy securitization activities, we consider mortgage-backed securities ($MBS\ held\ to\ maturity/Assets$) and total securitized assets ($Securitization/Assets$) both relative to assets. To capture derivatives activities, we

[14] Loan growth has been found to reduce lending quality (see Foos, Norden, and Weber (2010)).

include total derivatives (consisting of commodity, foreign exchange, equity and interest rate derivatives) used for hedging, scaled by assets ($Derivatives\ not\ for\ trade/Assets$).[15] We also include one variable measuring the use of credit derivatives, the gross position on credit derivatives over assets held by the banks ($Gross\ position\ CD/Assets$), which equals the sum of the protection bought and sold in the credit derivatives market. All explanatory variables are taken in 2006.

Table 4 reports the marginal effects from the probit regressions. Column (1) first includes the MES measure prior to decomposition. The MES obtains a positive coefficient but is not significantly associated with bank failure. Column (2) contains the MES split-up. The *Systematic MES* obtains a positive coefficient of 0.023 that is insignificant. The *Excess MES* obtains a positive coefficient of 5.207, significant at the 5% level. The sign of the coefficient indicates that banks with a higher exposure to systemic risk prior to the crisis are more likely to fail in the crisis. We also note that the *Excess MES* has a much more positive coefficient than the total MES in column (1), suggesting that the former better captures systemic risk. As such, it seems a preferable measure for the regulatory task of identifying vulnerable banks.[16]

We consider different control variables in columns (3)-(8). In column (3) we include proxies for size, the risk of the loan portfolio and asset quality. The coefficient for the *Excess MES* decreases slightly and remains significant at the 5% level. The coefficient for the *Systematic MES* remains insignificant. Among the controls, we can see that the propensity to fail increases with a bank's real estate loans' exposure (10% significance level), consistent with the crisis being caused by subprime mortgages.

Regression results when securitization controls are included (column (4)) are similar. The coefficient for the *Excess MES* remains positive and significant. Securitized assets enter with a negative sign and are weakly significant at 10%. This may indicate that securitization of assets leaves the seller with less risk – even though risk increases for the

[15] Since a large part of bank derivative activities consists of trading activities that are unrelated to credit risk transfer, it is advisable to only include the part of derivatives that are related to hedging.

[16] Giglio et al. (2016) find that the MES (and several other common systemic risk measures based on comovement with other banks) are not a good out-of-sample predictor of aggregate systemic risk. This is consistent with our cross-sectional findings: the undecomposed MES does not predict bank failures. Only once the decomposition is done, a significant relationship arises. This suggests the possibility that the weakness of many systemic risk measures in Giglio et al. (2016) is caused by the fact that they confound systemic risk with normal market risk.

buyer. In column (5) we add controls for derivative activities. Again, the MES coefficients do not change in a noteworthy way. Credit derivatives display a positive and significant relationship with bank failure, consistent with these instruments being at the heart of the crisis.

An important, so far omitted, factor are bail-outs. Bail-outs may be more likely for correlated banks (thus banks we would expect to have a high *Excess MES*) due to a "too-many-to-fail" doctrine (Acharya and Yorulmazer, 2007), which will bias our estimates for the MES components. To investigate this possibility, we include in column (6) a dummy variable which indicates whether a given bank received TARP aid during the sample period. The results for the MES components are comparable to the previous columns. The TARP dummy obtains a negative coefficient, showing that TARP recipients are found to be less likely to fail. This may reflect the effectiveness of the TARP programme in reducing bank risk, but may also simply be driven by banks that failed before TARP subsidies become available.

Finally, in column (7) and (8) we compare our systemic risk measure with two standard measures of bank risk. These measures serve as a natural benchmark against which to evaluate the *Excess MES*. The first measure is the variance of an institution's stock return (*Volatility)*, measured as the standard deviation of daily returns. Giglio, Kelly and Pruitt (2016) assess different systemic risk measures and show that volatility outperforms other commonly used measures in terms of predicting realized systemic risk. In column (7) we compare the *Excess MES* and this measure. The coefficient of the *Excess MES* remains positive and significant. *Volatility*, on the contrary, is not significant. The second risk measure we include is the *Zscore* prior to the crisis (column (8)). The Z-score is computed as the bank's return on assets plus one divided by the standard deviation of asset returns over the pre crisis period 2006. The *Systematic MES* turns negative and remains insignificant, while the *Excess MES* remains positive and significant, although at the 10% level. The Zscore is negative and significant at 5%. Safer banks are less prone to fail, as expected.

The coefficient of the *Excess MES* is fairly stable across regressions and its size suggests economic significance. For example, considering the model in column (5), one can

calculate a standard deviation increase in the *Excess MES* to increase the probability of failure by 1.1 percentage points. This represents an increase of 24% compared to the average probability of failure in the sample.

3.4.2 Predicting Z-Scores

We next turn to the analysis of bank risk, which we approximate by the Z-Score. We run a regression similar to the previous regression model (equation (7)),

$$Z - Score_i = \alpha + \beta_1 MES_{Systematic,i} + \beta_2 MES_{Excess,i} + \sum_{k=1}^{K} \phi_k B_{k,i,06} + \mu_i, \qquad (8)$$

where the dependent variable now is the bank Z-Score calculated over the post crisis period 2007–2010.

Table 4 reports the results for these regressions. As in the failure models, the first column shows the MES measure prior to decomposition. The MES obtains a negative and significant coefficient, indicating that banks with a higher MES previous to the crisis had higher insolvency risk during crisis. Column (2) contains the MES split-up. The *Systematic MES* obtains a negative coefficient of -123.6 that is significant at the 5% level. The *Excess MES* obtains a negative coefficient of -472.3, significant at the 1% level. The sign of the coefficient indicates that banks with a higher exposure to pure systemic risk prior to the crisis display higher insolvency risk in the crisis. We also note that, as in the failure models, the *Excess MES* has a much larger coefficient in absolute value than the total MES in column (1), again suggesting that the former better captures systemic risk.

In the next columns (3)-(8) we include the same controls as in the failure models. Importantly, we also control in all of these models for the Z-Score level in 2006. The coefficients on the other variables can thus be interpreted as how they *change* the Z-score during the crisis. A good systemic risk measure should predict a worsening of bank risk during an economy-wide crisis. The regression in column (3) shows that when including these controls, the *Systematic MES* turns insignificant while the *Excess MES* remains negative and highly significant (at 1% level). Among the bank controls, the pre-crisis

Z-Score level and bank profitability are found to reduce insolvency risk during the crisis. A larger size, a higher loan share, and a higher proportion of real estate loans as well as higher interest from loans increases insolvency risk during the crisis.

Results remain similar when including securitization variables and derivatives in column (4) and (5), respectively. Securitization now enters positively – suggesting that securitization lowered bank risk during the GFC – consistent with the results from bank failures. The significance level however is only 10%. Derivatives used for hedging purposes enter with a positive and significant sign. This is consistent with hedging removing risk from the balance sheet of the bank. The gross position of credit derivatives enters with a negative sign and is significant. This confirms results from Table 4 and is consistent with the notion that trading in credit derivatives was at the heart of the crisis.

Finally, we control for TARP aid and volatility in the last two models. Results do not change when including these variables. The coefficient for the *Systematic MES* remains not significant, while the *Excess MES* remains negative and highly significant. None of the added controls show to be significant in these models.

The coefficient of the *Excess MES* does not vary much across regressions and its size suggests economic significance. Considering the model in column (5), one standard deviation increase in the *Excess MES* decreases the Z-Score by 3.482. This represents 12% of the average Z-Score in the sample.

In sum, this section has provided evidence that decomposing a systemic risk measure according to the risk source improves the ability to predict vulnerabilities, as measured by the propensity to fail and Z-Scores during the subprime crisis. The *Excess MES* displayed a much stronger association with ex-post systemic risk than the standard MES.

4 Conclusion

A high degree of comovement across banks is typically taken to imply systemic risk. In particular, interbank correlations are often used as a direct proxy of systemic risk or enter systemic risk measures indirectly, such as through a (conditional) covariance of bank returns and banking sector returns. In this paper we have argued that interbank correlations consist of two parts. One part is indeed due to systemic risk, but there is also

a second one that arises due to diversification activities. While banks that display high correlation in the first dimension should clearly alert regulators, this is not necessarily the case for banks that have high correlation in the second dimension.

We have proposed a method to disentangle both parts based on the systematic correlation induced by diversification. The empirical application to U.S. BHCs has shown that variation in interbank correlations come to a large extent from the systematic part; the importance of the systemic component is much smaller. In addition, we have shown that only the part of the MES that arises from the systemic component relates to bank fragility following the Global Financial Crisis. Taken together, this sheds doubt on the appeal of using straight correlation measures as input into systemic risk assessments and suggests that regulators should take into account the different sources of bank correlation when evaluating systemic risk at banks.

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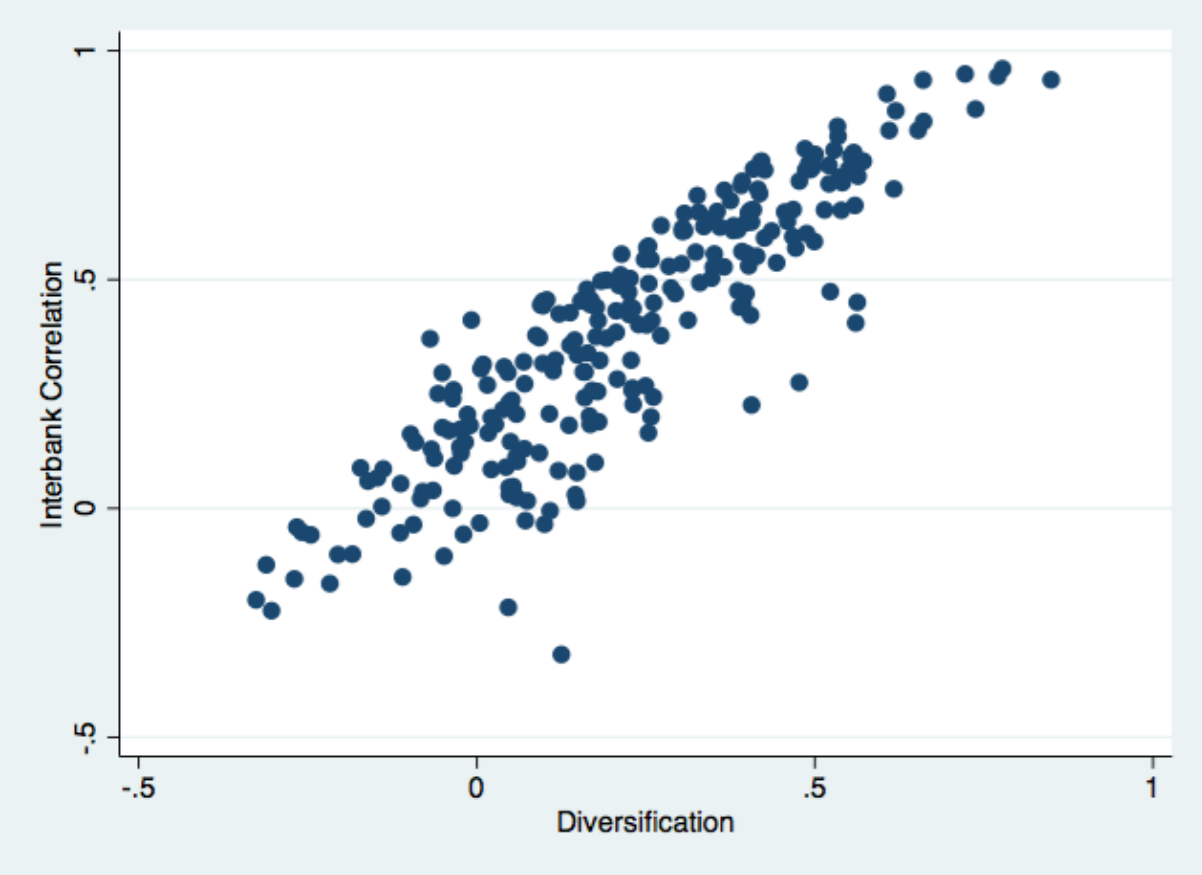
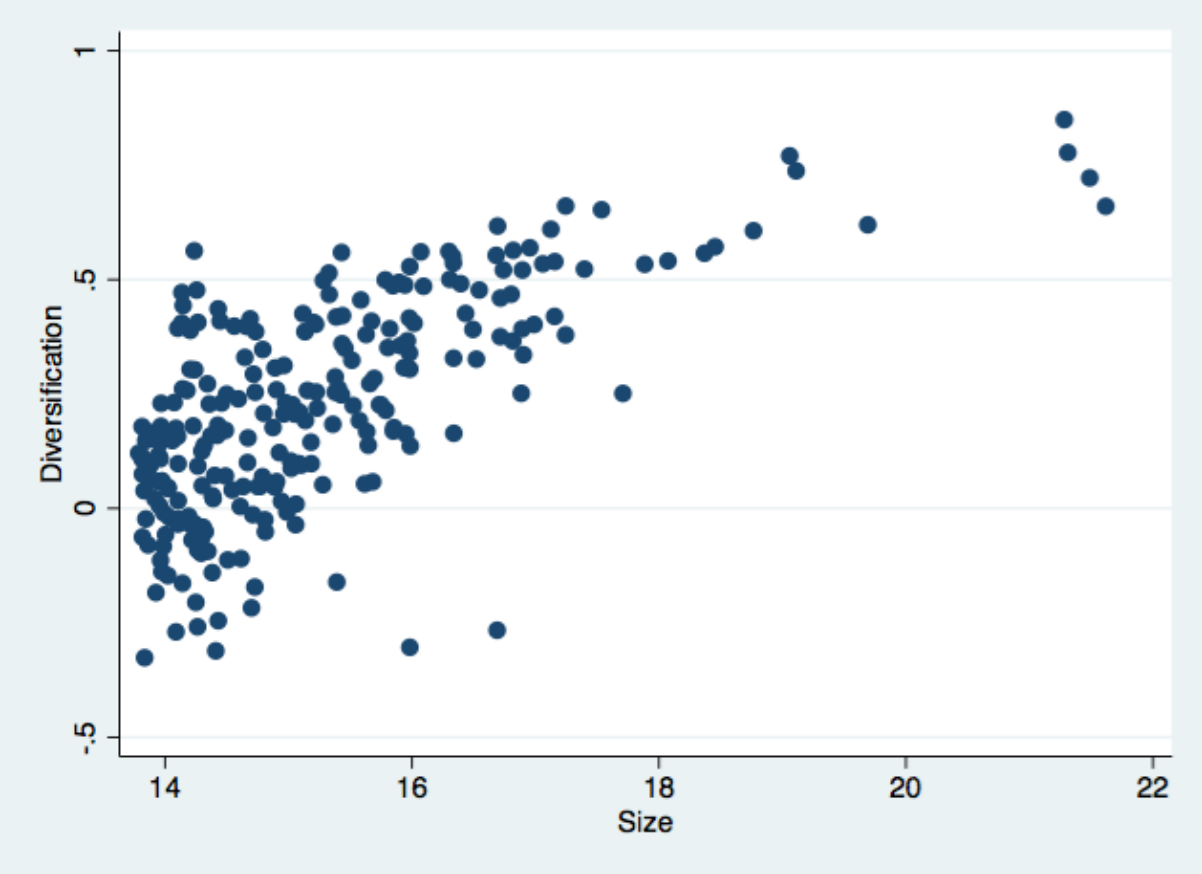
Figures

Figure 1: Interbank Correlation and Systematic Correlation



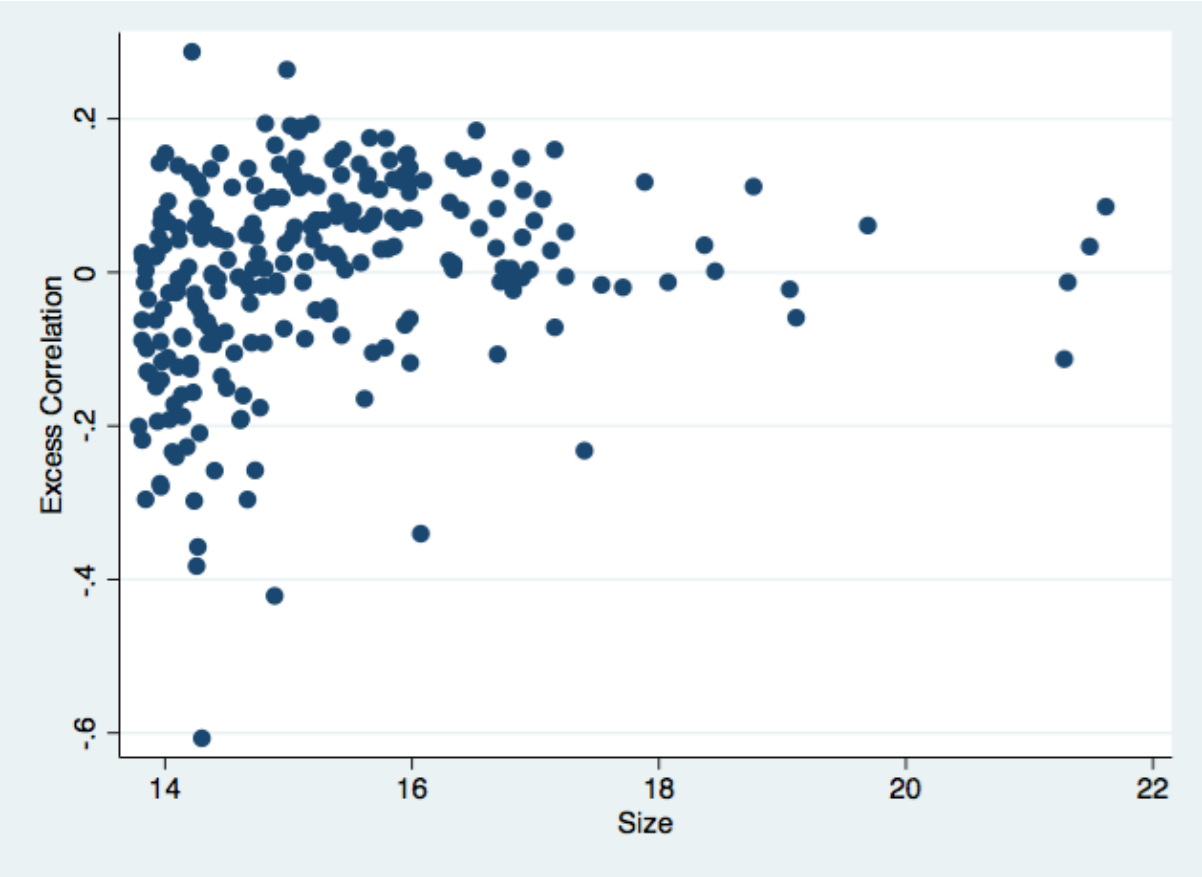
The figure depicts the relationship between the interbank correlation and the systematic correlation for the banks in our sample. Interbank correlation is taken as the correlation between bank $i's$ share price return and the return on the S&P 500 banking sector index. For this we use daily returns (winsorized at 1% level). The systematic correlation is calculated as the correlation between the bank return i and the return of the S&P 500. Both components are computed using data from 2015.

Figure 2: Systematic Correlation and Bank Size



The figure depicts the relationship between the systematic correlation and bank size in 2015. The systematic correlation is calculated as the correlation between the bank return i and the return of the S&P 500. Size is measured as the logarithm of the assets.

Figure 3: Excess correlation and Bank Size



The figure depicts the relationship between the excess correlation and bank size in 2015. A bank's excess correlation is taken to be its predicted residual from the regression of the interbank correlation on the diversification component. Size is measured as the logarithm of the assets.

Tables

Table 1: Descriptive statistics

Variables	25th perc.	50th perc.	75th perc.	Mean	Std. Dev.	Min	Max	N
Panel A: Bank Characteristics								
$\text{Log(Assets)}_{2015}$	14.250	14.903	15.853	15.258	1.392	13.787	21.618	250
$\text{Sub. debt/Assets}_{2015}$	0.057	0.092	0.138	0.106	0.070	0.001	0.368	193
$\text{Loans/Assets}_{2015}$	0.625	0.690	0.763	0.682	0.112	0.272	0.928	250
ROA_{2015}	0.004	.005	0.006	0.0059	0.005	-0.003	0.086	250
Panel B: Correlation Measures								
$\text{Interbank Correlation}_{2015}$	0.176	0.422	0.614	0.390	0.278	-0.319	0.960	250
$\text{Systematic Correlation}_{2015}$	0.049	0.213	0.402	0.223	0.235	-0.326	0.849	250
$\text{Excess Correlation}_{2015}$	-0.071	0.018	0.091	0	0.128	-0.606	0.287	250
Panel C: MES Measures								
MES_{2006}	0	0.006	0.014	0.006	0.008	-0.018	0.029	248
$\text{MES}_{Systematic,2006}$	0	0.007	0.019	0.010	0.011	-0.021	0.044	250
$\text{MES}_{Excess,2006}$	-0.003	-0.0006	0.003	0	0.005	-0.013	0.018	248

This table reports summary statistics of the main regression variables. The statistics are based on annual data for the year 2015 (Panel A and B) and 2006 (Panel C). *Sub. Debt/Assets* is the subordinated debt over assets. *Loans/Assets* is total loans over assets. *Log(Assets)* corresponds to the logarithm of total assets. *ROA* equals net income over total assets. *InterbankCorrelation* is the correlation between the bank and S&P500 banking sector index returns. *SystematicCorrelation* is the correlation between the bank and S&P500 index returns. *ExcessCorrelation* is the residual of a cross-section OLS regression of the interbank correlation on the correlation between the bank and S&P500 index returns. *MES* is the average daily returns for a bank during worst 2.5% days of the banking sector. *Systematic MES* is a bank's average return during the days of the 2.5% worst daily returns of the *stock market*. *Excess MES* are the residuals from a regression of a bank's MES on its *Systematic MES*.

Table 2: Systemic Risk Components and Bank Characteristics

	Systematic Correlation		Excess Correlation	
	(1)	(2)	(3)	(4)
Log(Assets)	0.392***	0.398***	0.330***	0.329***
	(0.0798)	(0.0911)	(0.0637)	(0.0785)
Log(Assets)^2	-0.00836***	-0.00868***	-0.00931***	-0.00916***
	(0.00230)	(0.00270)	(0.00189)	(0.00237)
Sub. Debt/Assets		0.284		-0.318
		(0.318)		(0.291)
Loan/Assets		-0.120		-0.0760
		(0.111)		(0.0803)
ROA		-1.439		-2.678***
		(0.992)		(0.936)
Observations	250	193	250	193
R-squared	0.475	0.511	0.117	0.147

This table presents regression results of the two systemic risk components on bank control variables. Sample consists of 250 largest banks in U.S. in 2015 in terms of total assets. All variables are computed using data for the year 2015. The dependent variable in models (1)-(2) is the correlation between the bank and S&P500 index returns. The dependent variable in models (3)-(4) is the excess interbank correlation, measured as the residual of a cross-section OLS regression of the correlation between the bank and S&P500 banking sector index returns on the correlation between the bank and S&P500 index returns. *Sub. Debt/Assets* is the subordinated debt over assets. *Loans/Assets* is total loans over assets. *Log(Assets)* corresponds to the logarithm of total assets. *ROA* equals net income over total assets. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Table 3: Bank failures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MES_{2006}	2.048							
	(1.435)							
$\text{MES}_{Systematic,2006}$		0.0233	0.0821	-0.0626	0.920	0.0143	0.888	-0.238
		(1.030)	(1.117)	(1.072)	(0.931)	(0.919)	(0.921)	(0.879)
$\text{MES}_{Excess,2006}$		5.207**	4.153**	4.411**	4.213**	3.236**	4.184**	3.312*
		(2.506)	(2.066)	(2.145)	(2.100)	(1.650)	(2.096)	(1.836)
$\text{Log(Assets)}_{2006}$			0.0165	0.0208	0.00757	0.0314**	0.00786	0.0192
			(0.0135)	(0.0138)	(0.0128)	(0.0145)	(0.0129)	(0.0146)
Sub. $\text{Debt/Assets}_{2006}$			0.215	0.285	0.329*	0.360**	0.341*	0.438**
			(0.183)	(0.178)	(0.177)	(0.154)	(0.183)	(0.193)
$\text{Loan/Assets}_{2006}$			0.368	0.369	0.393	0.337*	0.398	0.399*
			(0.233)	(0.228)	(0.240)	(0.193)	(0.244)	(0.232)
ROA_{2006}			-4.491	-4.623	-5.490	-1.896	-5.233	-3.427
			(6.579)	(6.398)	(6.544)	(5.127)	(6.600)	(6.074)
Real $\text{Estate/Loans}_{2006}$			0.211*	0.242*	0.309**	0.177*	0.306**	0.272**
			(0.125)	(0.124)	(0.140)	(0.102)	(0.141)	(0.125)
NPL/Loans_{2006}			0.202	0.783	1.101	0.801	1.115	1.184
			(1.946)	(1.674)	(1.560)	(1.950)	(1.573)	(1.553)
Loan growth_{2006}			-0.0318	-0.0170	-0.0891	-0.333	-0.0863	-0.0566
			(0.275)	(0.280)	(0.272)	(0.341)	(0.276)	(0.282)
Interest from			-1.560	-1.433	-1.415	-1.387	-1.426	-1.978
$\text{loans/Loans}_{2006}$			(1.751)	(1.635)	(1.649)	(1.575)	(1.670)	(1.827)
MBS held				-0.0560	0.0497	-0.311	0.0338	-0.488
to $\text{maturity/Assets}_{2006}$				(0.722)	(0.678)	(0.653)	(0.678)	(0.767)
Securitization/Assets_{2006}				-0.200*	-0.225*	-0.197*	-0.232*	-0.295**
				(0.106)	(0.115)	(0.109)	(0.119)	(0.133)
Derivatives					-0.170	-0.285	-0.167	-0.168
not for $\text{trade/Assets}_{2006}$					(0.225)	(0.256)	(0.225)	(0.228)
Gross position					12.93**	21.49***	12.84**	12.02**
CD/Assets_{2006}					(5.296)	(5.717)	(5.314)	(5.087)
TARP						-0.126***		
						(0.0226)		
Volatility_{2006}							0.309	
							(0.561)	
Zscore_{2006}								-0.00152**
								(0.000612)
Observations	248	248	245	245	245	245	245	245
Pseudo-R^2	0.02	0.05	0.21	0.23	0.27	0.48	0.27	0.31

This table presents regression results of an indicator of bank failure on the systemic risk components and bank control variables. Sample consists of 250 largest banks in U.S. in 2006 in terms of total assets. Control variables are computed using bank level data for the year 2006. The dependent variable in these models is the bank-specific failure indicator over the post crisis years, 2007-2010. *MES* is the average daily returns for a bank during worst 2.5% days of the banking sector. *Systematic MES* is a bank's average return during the days of the 2.5% worst daily returns of the *stock market*. *Excess MES* are the residuals from a regression of a bank's MES on its *Systematic MES*. *Sub. Debt/Assets* is the subordinated debt over assets. *Loans/Assets* is total loans over assets. *Real estate/Loans* are real estate loans over total loans. *Log(Assets)* corresponds to the logarithm of total assets. *Loan growth* is the annual growth of total loans. *ROA* equals net income over total assets. *Interest from loans/Loans* is the interest income from loans over total loans. *NPL/Loans* is the share of non-performing loans over loans. *MBS held to maturity/Assets* are the mortgage-backed securities over total assets. *Securitization/Assets* are the total securitized assets over total assets. *Derivatives not for trade/Assets* is total derivatives (consisting of commodity, foreign exchange, equity and interest rate derivatives) used for hedging, scaled by assets. *Gross position CD/Assets* equals the sum of the protection bought and sold in the credit derivatives market. *TARP* is a dummy variable which indicates whether a given bank received TARP aid during the crisis. *Volatility* is the annual variance of an institution's stock return. $Z-score$ is computed as $\bar{R}+1/\sigma_R$, where $\bar{R}$ is the average share price return and σ_R is the standard deviation of the returns. All regressions report marginal effects. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Table 4: Z-scores

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MES_{2006}	-299.5***						
	(76.46)						
$\text{MES}_{Systematic,2006}$		-123.6**	-9.459	-2.698	-26.31	-26.44	-25.26
		(54.38)	(60.57)	(60.34)	(63.92)	(64.13)	(64.10)
$\text{MES}_{Excess,2006}$		-472.3***	-307.6***	-310.2***	-316.6***	-313.9***	-317.2***
		(125.7)	(114.2)	(114.6)	(114.4)	(116.1)	(114.8)
Zscore_{2006}			0.163***	0.162***	0.160***	0.161***	0.168***
			(0.0298)	(0.0291)	(0.0293)	(0.0296)	(0.0328)
$\text{Log(Assets)}_{2006}$			-2.804***	-2.989***	-2.770***	-2.817***	-2.778***
			(0.549)	(0.547)	(0.705)	(0.774)	(0.707)
Sub. $\text{Debt/Assets}_{2006}$			4.875	2.580	1.377	1.347	1.640
			(9.443)	(9.452)	(9.271)	(9.264)	(9.277)
$\text{Loan/Assets}_{2006}$			-52.52***	-50.67***	-52.99***	-53.08***	-52.93***
			(6.755)	(6.889)	(6.864)	(6.952)	(6.862)
ROA_{2006}			967.1***	932.5***	985.8***	986.0***	998.8***
			(329.7)	(329.1)	(330.8)	(331.2)	(331.6)
Real $\text{Estate/Loans}_{2006}$			-16.78***	-18.07***	-19.03***	-18.97***	-19.19***
			(4.681)	(4.855)	(4.840)	(4.820)	(4.867)
NPL/Loans_{2006}			-152.4	-178.2	-174.3	-174.2	-174.4
			(136.9)	(145.3)	(147.2)	(146.8)	(147.6)
Loan growth_{2006}			-3.310	-7.841	-6.438	-6.629	-6.196
			(13.62)	(12.89)	(13.04)	(13.05)	(13.07)
Interest from			-199.2***	-203.9***	-213.6***	-213.1***	-212.9***
$\text{loans/Loans}_{2006}$			(53.85)	(52.39)	(54.65)	(54.71)	(54.66)
MBS held				55.19	51.94	52.96	51.82
to $\text{maturity/Assets}_{2006}$				(46.51)	(46.20)	(46.19)	(46.24)
$\text{Securitization/Assets}_{2006}$				11.89*	9.725	9.832	9.501
				(6.812)	(7.113)	(7.121)	(7.089)
Derivatives					18.63**	18.72**	18.64**
not for $\text{trade/Assets}_{2006}$					(9.145)	(9.242)	(9.153)
Gross position					-472.6**	-467.2*	-480.1**
CD/Assets_{2006}					(239.3)	(242.2)	(240.0)
TARP						0.290	
						(1.216)	
Volatility_{2006}							38.96
							(50.81)
Observations	247	247	244	244	244	244	244
R-squared	0.055	0.065	0.409	0.419	0.429	0.429	0.429

This table presents regression results of an indicator of bank failure on the systemic risk components and bank control variables. Sample consists of 250 largest banks in U.S. in 2006 in terms of total assets. Control variables are computed using bank level data for the year 2006. The dependent variable in these models is the bank Z-score computed as the bank's return on assets plus one divided by the standard deviation of asset returns over the post crisis period 2007–2010. *MES* is the average daily returns for a bank during worst 2.5% days of the banking sector. *Systematic MES* is a bank's average return during the days of the 2.5% worst daily returns of the *stock market*. *Excess MES* are the residuals from a regression of a bank's MES on its *Systematic MES*. *Sub. Debt/Assets* is the subordinated debt over assets. *Loans/Assets* is total loans over assets. *Real estate/Loans* are real estate loans over total loans. *Log(Assets)* corresponds to the logarithm of total assets. *Loan growth* is the annual growth of total loans. *ROA* equals net income over total assets. *Interest from loans/Loans* is the interest income from loans over total loans. *NPL/Loans* is the share of non-performing loans over loans. *MBS held to maturity/Assets* are the mortgage-backed securities over total assets. *Securitization/Assets* are the total securitized assets over total assets. *Derivatives not for trade/Assets* is total derivatives (consisting of commodity, foreign exchange, equity and interest rate derivatives) used for hedging, scaled by assets. *Gross position CD/Assets* equals the sum of the protection bought and sold in the credit derivatives market. *TARP* is a dummy variable which indicates whether a given bank received TARP aid during the crisis. *Volatility* is the annual variance of an institution's stock return. $Z-score$ is computed as $\bar{R}+1/\sigma_R$, where $\bar{R}$ is the average share price return and σ_R is the standard deviation of the returns. All regressions report marginal effects. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.