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Discussion paper

THE TWO FACES OF INTERBANK CORRELATION

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The two faces of interbank correlation

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Abstract

We decompose the correlation of bank stock returns into a systemic risk component and a component arising from diversification activities. Estimation for U.S. Bank Holding Companies (BHCs) shows the diversification component to be large and positively related to BHC performance during the crisis of 2007-2009. This suggests that it is important to distinguish between the two sources of interbank correlations when quantifying systemic risk at banks. Our decomposition also permits us to estimate the marginal gains from diversification, which turn out to be rapidly declining with bank size. Since large banks are additionally found to display high levels of the systemic risk component, they are hence predominantly exposed to the undesirable source of interbank correlation.

Keywords: systemic risk, interbank correlation, diversification

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1 Introduction

The recent crisis has made systemic risk a priority on the agenda of policy makers. While such risk arises from a variety of sources, a common consequence is that it increases the vulnerability of the financial system to shocks. Broadly, two different channels can be distinguished. First, since financial institutions are heavily interconnected, a shock to one part of the financial system can easily spill over to other parts.[1] Second, financial institutions tend to undertake similar activities, or display homogeneity in other dimensions (such as their risk management systems), which may amplify the impact of common shocks.[2] Notably, both channels are particularly pronounced at large banks as these banks are highly connected and also tend to be a direct source of common shocks.

In order to avoid a repeat of the crisis, regulators are now redesigning financial regulation to address systemic risk.[3] A major challenge for this is the measurement of systemic risk. Since systemic risk can arise in many different ways, 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 correlations as a systemic risk indicator. Other widely-used measures of systemic risk such as the *CoVaR*, the *Marginal Expected Shortfall* or the *Distressed Insurance Premium*[4] are indirectly based on correlations of individual banks with the system.

We argue that one has to be careful in equating interbank correlations with systemic risk. The reason for this is diversification activities at banks. To see the issue, suppose that all banks in the economy are fully diversified and hence invest in the same portfolio

[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] For example, Basel III includes a capital surcharge for institutions that are deemed systemically important.

[4] Adrian and Brunnermeier (2010), Acharya et al. (2011) and Huang, Zhou, and Zhu (2009), respectively.

(the market portfolio). Interbank correlations will then obviously be one – but this is neither due to the presence of spillovers among banks nor to any banking sector-specific homogeneity. This simple example illustrates a bigger issue: interbank correlations are partly driven by the diversification characteristics of banks.

We propose a methodology that allows us to isolate the part of the interbank correlation that is not due to diversification. The method is based on the concept of *minimum commonality.* The minimum commonality is the degree of commonality at banks that is unavoidable given their degree of diversification. From this one can define a bank's *excess correlation* (the systemic part of interbank correlation) as the part of a bank's interbank correlation that exceeds the one implied by its minimum commonality.

The decomposition of interbank correlation is not only important conceptually but also from a regulatory perspective. As the components arise for very different reasons, they are expected to have different implications for financial stability. Portfolio theory suggests that diversification enhances banks' resilience to shocks. Consistent with this, subsequent Basel accords have permitted a capital relief for diversified portfolios. As a consequence, there is not necessarily a reason for regulators to be concerned about high interbank correlations if those are mainly due to diversification. By contrast, excess correlation indicates the presence of spillovers and homogeneity in the financial system not found in other sectors of the economy. It should hence be of prime concern for regulators.

We apply our methodology to U.S. BHCs. The results strengthen the view that it is important to distinguish between the different sources of bank correlations. First, we find that a large part of the (cross-sectional) variation in interbank correlations is due to diversification: about 84% of a bank's average correlation with other banks can be explained by its minimum commonality. The systemic component in interbank correlations is hence of only lesser importance. Second, the two components had different implications for the resilience of banks during the crisis of 2007-2009. While banks with a higher minimum commonality (indicating more diversification) performed better during the crisis, banks with more systemic correlation did not systematically perform differently than other banks.[5] Third, the distinction between both correlation components matters especially for large banks, which are of special importance for financial stability. These banks display very high excess correlation are hence subject to a large amount of systemic risk.

While the primary focus of this paper is the decomposition of interbank correlation, a second aim is the development of a market-based measure of diversification. Prior literature on diversification at firms (financial or non-financial) had to deal with the challenge that it is not easy to quantify a firm's overall diversification since diversification can arise from a variety of different sources.[6] In addition, construction of comprehensive diversification measures is often constrained by the fact that accounting data only provides very limited information on diversification activities.

Our diversification measure is computed from the commonality of a firm with the market portfolio. It is based on the idea that the more diversified a firm is, the closer it becomes to the market portfolio and the higher should be its correlation with the latter.[7] The advantage of this measure is that it captures overall diversification and hence encompasses a variety of sources of diversification. It is also an easily computable measure as the only (firm-specific) input is the firms' stock price.

The diversification measures computed for BHCs exhibit some interesting properties. Among others, they suggest quickly declining benefits from diversification. While at small banks increases in size are associated with substantial increases in diversification, these gains are quickly eroded. For medium-size and large banks, increases in size only lead to modest improvements in diversification. Taken together with the result that large banks display a high degree of excess correlation, this suggests that these banks have a high amount of the undesirable part of correlation, but only benefit to a lesser extent from the desirable part.

The remainder of the paper is organized as follows. Section 2 discusses the related

[5] The latter result may reflect various forms of government bailouts.

[6] Besides asset-side diversification (such as through geographical or functional diversification), diversification also arises on the liability side. For example, using different sources of funding (e.g., market-funding and bank loans) reduces exposure to funding shocks. At banks the measurement of diversification is particularly complex since banks undertake a plethora of diversifying activities, many of them also off-balance sheet (for instance, securitization and the buying and selling of credit protection).

[7] While we use correlations of market returns, an alternative is balance-sheet based correlation measures (for instance, the correlation of a firm's profits or sales with those in the economy).

literature. Section 3 explains our methodology for separating interbank correlation into a diversification and a systemic part. Section 4 presents the empirical analysis. Section 5 concludes.

2 Related Literature

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. 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 correlations that underlie them may partly be driven by diversification activities. In order to arrive at a "pure" measure of systemic risk, the measures should be alternatively computed, isolating the effect of diversification. Our approach provides a methodology for how this can be done.[8]

The second interest of our paper relates to extant work on the relationship between diversification and firm valuation and performance. The evidence pertaining to financial

[8] Applying our methodology to these systemic risk measures is relatively straightforward since in its empirical implementation it amounts to including only the part of interbank correlations that is orthogonal to the correlation with the market.

institutions is mixed.[9] Owing to data constraints, many papers focus on functional diversification, measured by the share of non-interest rate activities at banks. Baele et al. (2007) show that functional diversification increases valuation and can reduce risk at European banks. Elsas et al. (2010) find a diversification premium for a sample of developed countries. DeLong (2001) studies M&As and finds that mergers that increase focus in terms of activity and geography enhance stockholder value, whereas mergers that induce more functional diversification do not create value. In contrast, in Stiroh (2006) U.S. BHCs with higher non-interest rate income are shown to have higher risk but not to earn higher returns. Mercieca, Schaeck, and Wolfe (2007) find a negative impact of functional diversification for a sample of small European banks. Laeven and Levine (2007) find that functional diversification into non-loan activities leads to a valuation discount; a similar result is obtained in Schmid and Walter (2009). A potential explanation for the negative effects of functional diversification may be that non-interest income has an inferior risk-return trade-off than traditional lending activities. Evidence for this is provided in Stiroh and Rumble (2006) and Demirgüc-Kunt and Huizinga (2010). Acharya et al. (2006) examine Italian banks, for which detailed data on the industrial and sectorial composition of lending portfolios is available. They find mixed results for the relationship between diversification and bank return and risk.

Our study differs in two respects from prior work. First, we employ a new measure of diversification. As a market-based measure it captures *overall* diversification of a bank, including all potential on-balance sheet and off-balance sheet diversification activities. It also measures *effective* diversification in that it takes into account any correlation among activities which accounting-based measures will ignore. Second, we do not focus on bank performance in normal times, but in times of crisis. Specifically, controlling for a variety of alternative factors, we find that diversification reduces a bank's vulnerability to the crisis of 2007—2009, consistent with portfolio theory.[10] Together with some

[9] The literature on non-financials mostly arrives at a negative link between diversification and firm performance (Lang and Stulz (1994), Berger and Ofek (1995) and Servaes (1996)); however it also identifies various methodological hurdles (see Maksimovic and Phillips (2002), Campa and Kedia (2002), Graham et al. (2002)).

[10] Brunnermeier, Dong and Palia (2012) examine the non-interest income at banks. In contrast to our study they find that a higher share of such income (a proxy for functional diversification) is negatively related to performance during the crisis of 2007-2009.

evidence that diversification is efficiency-reducing in normal times, this may suggest that diversification benefits mainly materialize in downturns. This is consistent with the notion that diversification trades off loss of specialization with lower exposure to shocks.[11]

3 Methodology

In this section we describe how interbank correlation can be decomposed into a diversification part and an excess (systemic) correlation part. 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 identical 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. 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 specialize in the same asset. Interbank correlation hence consists entirely of excess 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 analyze 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 where banks

[11] An alternative explanation is that diversification benefits are specific to the type of diversification considered. For instance, while functional diversification may be detrimental to bank performance, other types of diversification may be beneficial.

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 the bank is undiversified ($w_i = 0$ or $w_i = 1$) and one if the bank 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 *minimum commonality.* For average banking sector diversification d ($d := \frac{d_A+d_B}{2}$), minimum commonality is defined as follows:

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

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

From this we can define excess commonality:

Definition 4 ***Excess commonality** $e(w_A, w_B)$ is the difference between actual and minimum 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 $w_B^{\min} = 1 - \frac{d}{2}$).[12] The resulting commonality is then $s^{\min}(d) = 1 - \left|w_A^{\min}(d) - w_B^{\min}(d)\right| =$

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

d. Thus, the minimum commonality required to achieve a certain level of diversification is given by the degree of diversification itself. It follows that

Proposition 1 *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. 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 should be one. Observing 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. In particular, a (hypothetical) bank that is fully diversified along all dimensions should have a correlation with the market portfolio of one. Second, we have to adapt the commonality measures for more than two banks. If there are at least three banks, commonality becomes bank-specific. We can then calculate the commonality of an individual bank by its average correlation with all other banks, or, alternatively, by its correlation with a banking sector index.

Third, the simple property that excess correlation equals commonality minus diversification (Proposition 1) 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.[13] In the general case, excess correlation will still be a negative 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

[13] 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 minimum 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 lower excess correlation.

diversification degree.

4 Empirical Analysis

4.1 Data

Our analysis focuses on Bank Holding Companies (BHCs) in the U.S.. We use bank-level data from the U.S. Call Reports. These reports contain quarterly data about on and off balance-sheet and income-statement information for all regulated BHCs in the U.S.. We focus our analysis on the 200 largest BHCs in 2006 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 two of our main variables, the interbank correlation and the diversification measure. 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 weekly returns (winsorized at 1% level) over the three years preceding the subprime crisis (January 2004 - December 2006).[14] 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. Similarly, the diversification component, $\rho_{i,m}$, 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 diversification component for the banks in our sample. The figure shows a clear positive relationship between these two variables. The R-squared of a regression of interbank correlation on diversification is 0.84. This strengthens the starting point of our analysis in that interbank correlations are driven by diversification activities. The figure also shows that some highly diversified banks have very high interbank correlation. Figure 2 provides a closer look at this phenomenon by depicting only banks with interbank

[14] Excluding the crisis period is warranted to avoid biases arising from calculating correlations in high volatility periods (see e.g. Forbes and Rigobon (2002)).

and diversification measures of greater than 0.5. We can see that the top three banks in terms of interbank correlation are Bank of America, Wells Fargo & Co. and Wachovia. The line in Figure 2 depicts the regression line based on the entire sample. Most banks appear clearly above the line, showing that their interbank correlation seems to be much larger than can be justified by diversification – suggesting that these banks pose excess systemic risk. Furthermore, 13 out of the 20 largest banks in the sample appear in this figure. This suggests that size plays a role in interbank correlation levels.

4.2 Decomposition of Interbank Correlation

The next step is to separate interbank correlation into the part that comes from diversification and from systemic (excess) correlation. The approach we take here is to treat systemic 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[15]:

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

where $\rho_{i,b}$ is the interbank correlation of bank i and $\rho_{i,m}$ is the diversification measure for bank i. A bank's systemic correlation is taken to be its predicted residual from this regression, $\hat{\epsilon_i}$. Systemic correlation is hence the increased interbank correlation for bank i relative to that which is predicted by bank $i's$ market correlation. Note that systemic correlation can be negative – in which case a bank has a lower correlation relative to what is predicted for its diversification measure using the entire sample of banks.

Table 1 (Panel B) presents the summary statistics of the three correlation measures. The average interbank correlation is about 27% and ranges from -19% to 83%. The diversification measure has a mean equal to 32%, with the lowest value being equal to -11% and a maximum of 69%. The mean of the systemic correlation (which is a regression residual) is zero. Systemic correlation varies between -18% and 33%. The two largest values are obtained for Bank of America and Wells Fargo & Co.

[15] We have also fitted a non-linear relationship by including the square of the diversification variable. This did not materially affect our results.

4.3 Determinants of Bank Diversification and Excess Correlation

In this section we examine how excess correlation and diversification relate to various bank characteristics. For this purpose, we estimate the following cross-section model:

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

where Y_i is either diversification $\rho_{i,m}$ or excess correlation $\hat{\epsilon}_i$ and the term B_k denotes different bank characteristics in 2006. These characteristics, first, include general bank information such as subordinated debt over assets ($Sub.\ Debt/Assets$), loans over assets ($Loans/Assets$), real estate loans over loans ($Real\ estate/Loans$) and size ($Log(Assets)$). We also allow for a non-linear relationship with size by including the square of the size variable. Second, we consider various proxies of asset quality: annual loan growth ($Loan\ growth$),[16] profitability (ROA), and interest income from loans over loans ($Interest\ from\ loans/Loans$). We also include the share of non-performing loans over loans ($NPL/Loans$) as a measure of lending quality.

Finally, we include various variables that capture credit risk transfer and derivative activities. Such activities are obvious candidates for determining bank level diversification – but they may also be drivers of excess correlation since they tend to increase interconnectedness among banks. 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 derivative activities, we include total derivatives (consisting of commodity, foreign exchange, equity and interest rate derivatives) used for hedging over assets ($Derivatives\ not\ for\ trade/Assets$).[17] We also include two variables 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, and the net position on credit derivatives over assets ($Net\ position\ CD/Assets$), which

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

[17] 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.

equals the difference between the protection bought and sold by the bank. The distinction between gross and net aims to capture the difference between a pure transfer of credit risk (net-position) and the simultaneous buying and selling of risk (gross-position). These activities are expected to have different implications for diversification and systemic risk (see Norden et. al, forthcoming).

4.3.1 Diversification

We first analyze how the diversification component, $\rho_{i,m}$, relates to various sets of bank characteristics. For this we initially investigate sets of control variables separately in order to reduce problems arising from multicollinearity. Table 2 presents the results.

Column (1) contains the estimation of the relationship between the diversification measure and general bank characteristics. The share of loans is found to be negatively and significantly related with diversification. This result implies that a higher proportion of non-traditional activities at banks (non-loan business) is associated with more diversification, consistent with previous literature that uses loan shares as an (inverse) proxy for functional diversification (see e.g. Laeven and Levine (2007)). Size is positively and significantly related to diversification, while the squared size-term is negatively and significantly related to diversification. Taken together, this indicates an inverted U-shape relationship between diversification and size. This interesting property of the data can also be directly appreciated from Figure 3, which plots diversification against size (proxied by the log of assets). The figure shows that for smaller and medium-sized banks, increases in bank size are associated with substantial improvements in diversification. However, for larger banks there is no strong increase in diversification. This picture is consistent with marginal benefits from diversification that are declining rapidly. In particular, it suggests that diversification opportunities are already reasonably well reaped at medium-sized banks.

Column (2) focuses on the relationship between asset quality and diversification. *Loan growth* is found to be positively related to diversification. Presumably, fast growing banks have to expand to new business areas, leading to higher diversification. Profitability, measured by ROA, is also positively related to diversification. This result is somewhat unexpected as one might have thought that there would be a trade-off between diversification and return.[18] It may be explained, however, if diversification into non-traditional activities (such as to fee generating income) leads to higher returns.

Column (3) reports results for the model that includes securitization proxies. It shows a positive and significant relation between securitized assets and diversification. This is explained by the fact that securitization enables banks to improve diversification by off-loading overrepresented exposures in their lending portfolios.[19]

In column (4) we analyze the role of different derivatives activities. We find a positive and significant relation for both the derivatives for hedging and the gross position held in credit derivatives. As with securitization, this result is consistent with the notion that credit risk transfer leads to more diversification (Nijskens and Wagner (2011), for example, show that credit derivative usage at banks reduces the volatility of their share prices). Notably, the net credit derivative position does not enter significantly (while the gross position does), indicating that a pure shedding of risk does not contribute to diversification.

We are also interested in studying how our market-based diversification measure relates to other diversification proxies. For this, we compare our measure with functional diversification proxies (as constructed, for instance, in Laeven and Levine (2007)). These proxies are either based on assets or revenues. Denoting with w_L the share of loans to assets, asset diversification is calculated as $Asset\ Diversity = 1 - |2w_L - 1|$. Similarly, for revenue diversity we have $Revenue\ Diversity = 1 - |2w_R - 1|$, where w_R is the share of non-interest income. In column (5) and (6) we include these proxies. As expected, both functional diversification proxies are positively related to our diversification measure.

The last column of Table 2 includes all variables jointly (except the alternative diversification proxies). Three of the bank variables become insignificant (loan growth, derivatives for hedging and the gross position held in credit derivatives). In addition, interest income becomes negatively and significantly related to diversification (consistent

[18] Consistent with such a trade-off, Stiroh and Rumble (2006) find a negative relationship between diversification and profitability using accounting data.

[19] Diversification may also be improved because following a transfer of risk, banks take on new (and possibly less correlated) risks, see Franke and Krahnen (2005) and Loutskina and Strahan (2006)).

with a diversification-specialization trade-off), while the coefficient of total securitization becomes negative and significant.

Size is an important factor in explaining variations in diversification. This can be appreciated by the fact that the R-squared in a model that only includes the two size terms is 0.56 (not reported), while the R-squared in the model that includes the full set of variables (column (7)) is only marginally higher (0.62).

4.3.2 Excess Correlation

Table 3 presents the results for various models that relate excess correlation $\hat{\epsilon_i}$ to bank characteristics. Column (1) shows the results for general bank characteristics. Bank size is negative and significant, while squared bank size relates positively to excess correlation. There is hence a U-shape relation between excess correlation and size. This relation also shows in Figure 4, which plots excess correlation against size. Medium size banks thus have the lowest excess correlation, while small and large banks display relatively large excess correlation. The result for large banks is unsurprising. Large money center banks are systemic and hence are expected to display significant comovement with the banking sector. The result for small banks is more surprising, but can be explained by the fact that small banks are very undiversified (Figure 3), hence their interbank correlation *conditional* on diversification is expected to be high. High levels of correlation among small banks may also be the result of herding incentives arising from too-many-to-fail policies (Acharya and Yorulmazer, 2007). Such incentives are expected to be more pronounced for small banks – since larger banks already enjoy bailout guarantees due to too-big-to fail policies.

Column (2), which includes the asset quality proxies, shows that the share of interest income from loans is significant and positively related to the excess correlation. This is surprising since one may have expected non-traditional activities to be perceived as more systemic by the market (and hence lending activities less). It is however consistent with the experience of the systemic crisis of 2007-2009, which was caused by common investments in subprime mortgages. Column (3), which considers securitization activities, shows that total securitization is positively related with excess correlation.

This is expected since securitization activities tend to make banks more interconnected.

Column (4) presents the results for derivatives use. As in the diversification case, only derivatives for hedging and the gross notional amount of credit derivatives have a positive and significant relation with excess interbank correlation. This finding is interesting and reaffirms the often expressed concern that financial innovation contributes to systemic risk in the financial sector. The potential for financial innovation to create system risk is especially apparent in the case of banks that build up gross-positions in derivatives, as these will result in banks being interlinked with each other through counterparty-risk without necessarily creating any benefits arising from a (net) shedding of risks out of the banking sector.

Finally, in column (5) we present the results of the estimation including all sets of controls. Although the size terms still have the same sign, all other controls are now insignificant. The U-shaped influence of size is hence a robust characteristic of excess correlation. The importance of size is also demonstrated by the fact that a regression with only the two size terms yields an R-squared of 0.33 (unreported), which is not much lower than the R-squared in column (5) that is 0.41.

Taken together, the results in this and the previous subsection show that size plays a crucial role for either component of interbank correlation. The very large banks, in particular, have high excess interbank correlation and are less diversified than their size would indicate. Our analysis thus suggests that these banks have undesirable stability characteristics in both correlation dimensions.

4.4 Interbank Correlation and Bank Performance During the Crisis

Interbank correlation is a commonly used indicator for the extent of systemic risk in the banking sector. In this section we study its impact on bank performance during the subprime crisis, separating out the diversification and the excess correlation component. For this we relate banks' overall share price returns during the subprime crisis to their pre-crisis correlation measures, controlling for other bank characteristics. We expect more diversified banks to be more resilient during the crisis, as predicted by portfolio theory. In contrast, we expect a negative relationship between the excess correlation component and bank performance, as systemic banks should have suffered more in the crisis.

Specifically, we estimate the following model:

$$SharePerf_{i,07-09} = \alpha + \beta_1 \rho_{i,m} + \beta_2 \hat{\epsilon}_i + \sum_{k=1}^{K} \phi_k B_{k,i,06} + \mu_i, \tag{7}$$

where $SharePerf_{i,07-09}$ is the share price return of bank i between January 2nd 2007 and December 31st 2009,[20] $\rho_{i,m}$ and $\hat{\epsilon}_i$ is the diversification measure and excess correlation measure of bank i computed using pre-2007 data, respectively. The terms $B_{k,i}$ are the same sets of control variables included in the previous sections, again taken from 2006.

Table 4 shows the results from various models.[21] The model in column (1) includes the two components of interbank correlation alongside general bank characteristics. The coefficient is positive for each component and significant at the 1% level. In particular, the excess correlation obtains a coefficient of 0.723; the coefficient for the diversification measure is 0.354. The sign for the latter coefficient is in line with theory that more diversified banks are likely to have better risk management and hence are better equipped to withstand crises (see e.g. Froot et al. (1993) and Silva-Buston (2012)). By contrast, the positive relation between the excess correlation and share performance is somewhat puzzling. One would have expected more correlated banks to perform worse during a systemic crisis. However, a potential explanation for the finding is that the share prices of correlated banks during crises reflect bailout expectations. We return to this issue below. The other bank controls all have the expected sign whenever significant: more leveraged banks and banks with more loans had a worse performance during the crisis period.

Column (2) shows next the results when we include the ratio of real estate loans

[20] The starting point is motivated by the fact that the banking sector price index had already began to decline in the first half of 2007.

[21] Since the focus in this table is on whether the interbank correlation measures explain subprime performance over and above other variables, we subsequently enlarge the set of control variables as we progress (this is in contrast to Tables 2 and 3 where we include separate blocks of variables each time in order to mitigate potential problems arising from multicollinearity among the bank characteristics).

over loans, loan risk controls, as well as the asset quality controls. The positive and significant relationship for both correlation components remains, but the size of the effect decreases somewhat for the diversification part. As expected, real estate loans and higher loan growth prior to the crisis lead to lower performance in 2007-2009. In addition, higher profitability in 2006 is related to higher performance during this period. This indicates that more profitable banks are more resilient to downturns. Finally, the term capturing interest income from loans is negatively related to share performance during the crisis, which is in line with the poor performance of mortgage loans during the crisis.

Regression results when securitization controls are included are contained in column (3). The coefficients for the main variables remain positive and significant at the 1% and 5% level. Among the other variables included, the term for MBS held to maturity is significant but only weakly so. In column (4) we add the derivatives controls. The coefficients of our variables of interest slightly decrease, but remain positive and significant. The derivatives controls are both insignificant.

An explanation for the positive relationship between excess correlation and bank performance is bail-out expectations. If the market perceives bail-outs to be more likely for correlated banks due to a "too-many-to-fail" policy, this may lead to a higher share price performance for correlated banks relative to their peers. To investigate this possibility, we include a dummy variable which indicates whether a given bank received TARP aid during the sample period. The results of the model are shown in column (5). The estimates for both components remain significant and positive. This potentially reflects that bailouts (actual and expected) come in a variety of forms; the TARP dummy may only very imperfectly control for them. The coefficient on the TARP dummy itself is negative and significant at 5%. This is explained by fact that banks that received TARP are banks that were especially hit by the crisis and hence also had a poor share price performance.

We account for alternative controls of bank risk in two additional regressions. In column (6), we control for systematic risk by including share price betas estimated from 2006 data. The estimate for the beta is negative and not significant. The coefficients for correlation components remain significant with the same sign. Finally, in column (7) we control for default risk by including the Z-score[22] in 2006. The excess correlation term loses its significance, while the diversification component remains positive and significant. The Z-score itself is positive and significant at the 1% level. This result suggests that the positive relationship between excess correlation and bank performance found in the previous regression is due to the omission of bank insolvency risk as a control.

The coefficient on the diversification measure is fairly stable across the various regressions and its size suggests economic significance. For example, using the coefficient from column 7 (0.304), one can calculate a standard deviation increase in bank diversification to raise share performance during 2007-2009 by 6.5 percentage points, which corresponds to an increase of 0.2 standard deviations.

In sum, in this section we have found a positive relationship between bank diversification (measured prior to the crisis) and bank performance during the crisis. In contrast, we have not found a stable relationship between excess correlation and bank performance. The results suggest that it is important to separate out the different components of interbank correlation when evaluating the systemic vulnerability of a bank. While diversification has the potential to increase resilience to crises, this is not the case for excess correlation.

5 Conclusion

Higher correlation 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 the 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

[22] The Z-score equals $\bar{R} + 1/\sigma_R$, where $\bar{R}$ is the average return and σ_R is the standard deviation of share price returns in 2006.

have high correlation in the second dimension.

We have proposed a way to conceptually disentangle both parts based on the *minimum commonality* induced by diversification. An empirical application to U.S. BHCs has shown that variation in interbank correlations comes predominantly from the diversification component; the importance of the systemic component is much smaller. In addition, banks that displayed high correlation due to diversification performed better during the subprime 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.

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Figures

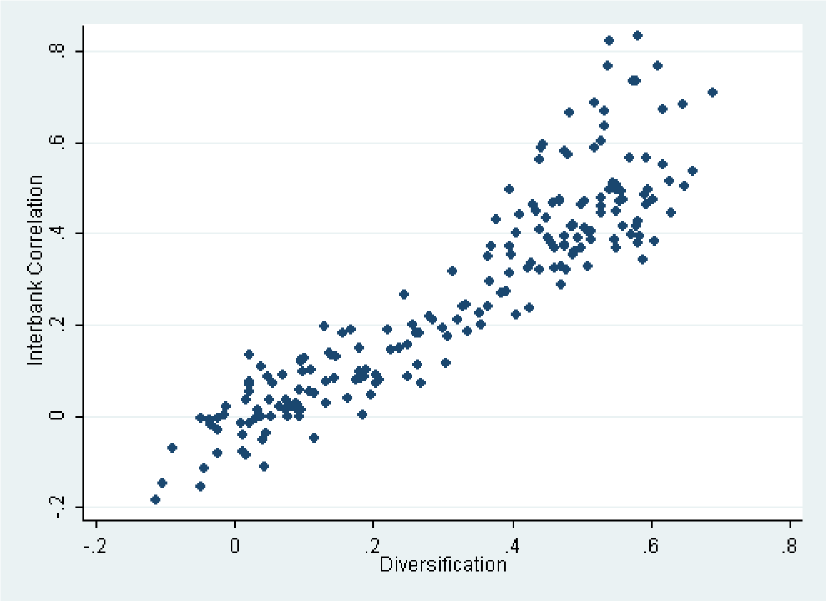

Figure 1: Interbank Correlation and Diversification

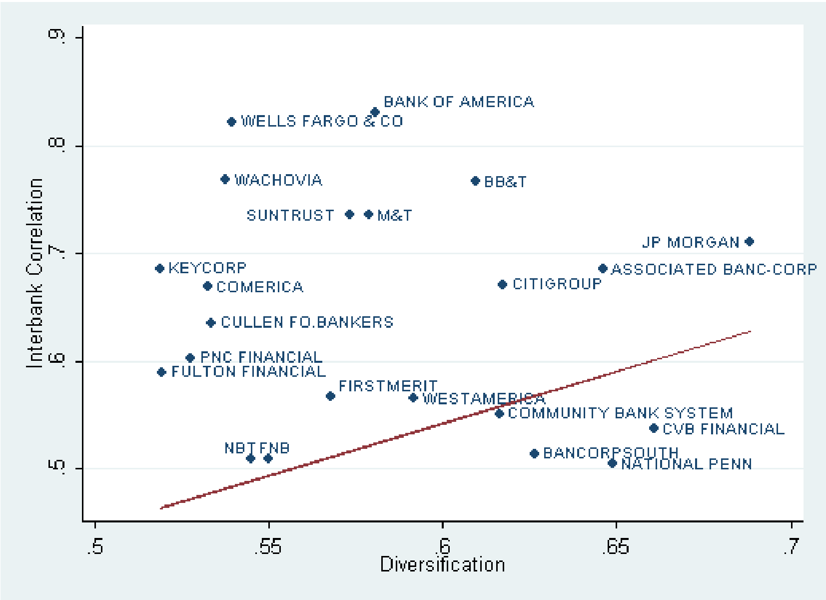

Figure 2: High Correlation Banks

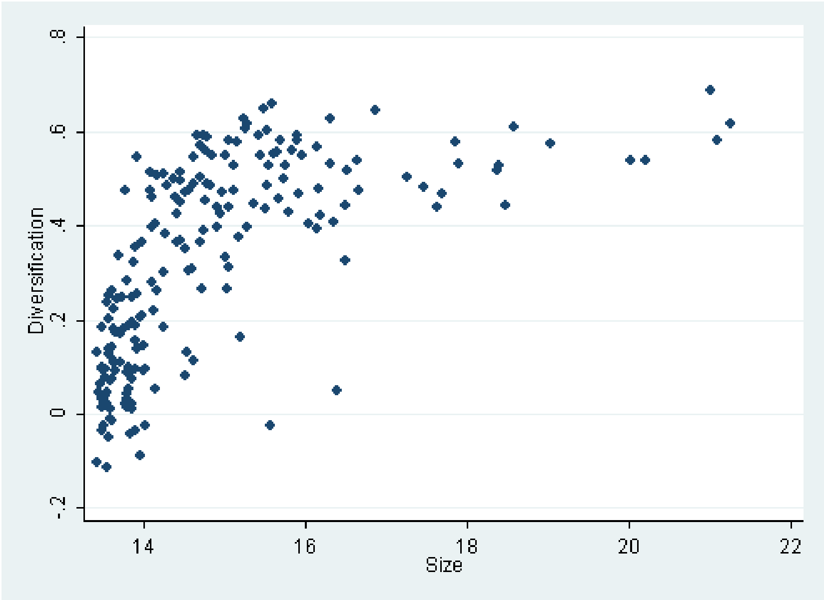

Figure 3: Diversification and Bank Size

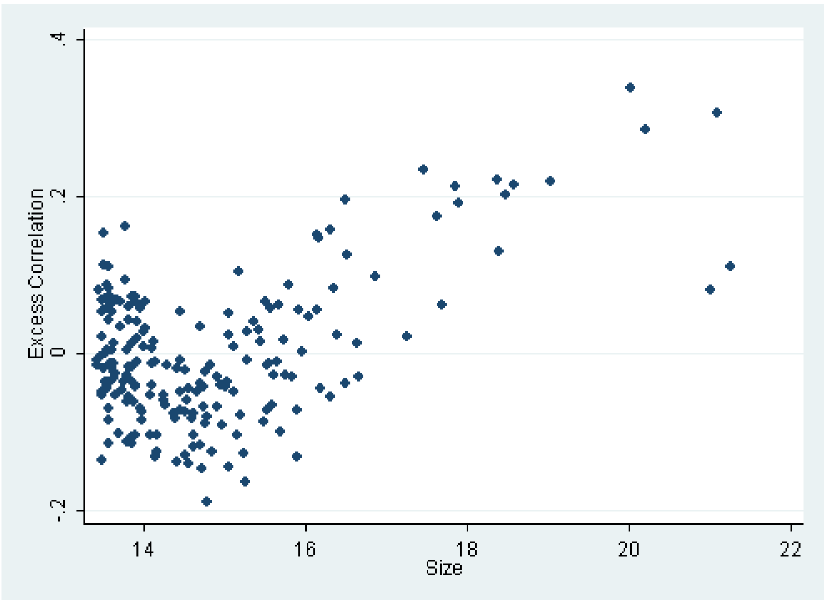

Figure 4: Excess Correlation and Bank Size

Tables

Table 1: Descriptive statistics

Variables	Mean	Std. Dev.	Min	Max
Panel A: Bank Characteristics				
Sub. debt/Assets	0.156	0.096	0.005	0.654
Loans/Assets	0.692	0.113	0.313	0.854
Log(Assets)	14.828	1.524	13.407	21.257
Real estate/Loans	0.733	0.141	0.214	0.948
Loan growth	0.026	0.051	-0.172	0.253
ROA	0.006	0.002	-0.004	0.012
Interest from loans/Loans	0.049	0.008	0.020	0.091
NPL/Loans	0.007	0.008	0.00002	0.055
MBS held to maturity/Assets	0.006	0.018	0	0.086
Securitization/Assets	0.018	0.084	0	0.743
Derivatives not for trade	0.031	0.049	0	0.147
Gross position CD/Assets	0.0004	0.002	0	0.012
Net position CD/Assets	0.0002	0.004	-0.040	0.041
Panel B: Correlation Measures				
Interbank Correlation	0.267	0.228	-0.185	0.831
Diversification	0.316	0.215	-0.112	0.688
Excess Correlation	0	0.092	-0.188	0.338

Table 2: Diversification and Bank Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sub. Debt/Assets	-0.0803						0.128
	(0.142)						(0.138)
Loans/Assets	-0.281***						-0.279**
	(0.0939)						(0.112)
Log(Assets)	0.855***						0.924***
	(0.0882)						(0.145)
Log(Assets)^2	-0.0235***						-0.0260***
	(0.00270)						(0.00469)
Real estate/Loans	0.0324						0.0431
	(0.0803)						(0.0771)
Loan growth		0.572**					0.162
		(0.274)					(0.223)
ROA		22.29***					12.54**
		(7.281)					(5.449)
Interest from loans/Loans		-1.543					-4.221**
		(2.188)					(1.880)
NPL/Loans		-1.287					-0.967
		(1.667)					(1.018)
MBS held to maturity/Assets			0.292				-1.113*
			(0.853)				(0.649)
Securitization/Assets			0.394**				-0.276***
			(0.168)				(0.0952)
Derivatives				0.888***			0.166
not for trade/Assets				(0.322)			(0.264)
Gross position				14.82***			10.26
CD/Assets				(3.958)			(11.31)
Net position				-0.238			-0.655
CD/Assets				(0.525)			(1.292)
Asset Diversity					0.308***		
					(0.0797)		
Revenue Diversity						0.453***	
						(0.0811)	
Observations	200	197	200	200	200	200	197
R-squared	0.581	0.082	0.024	0.094	0.071	0.134	0.622

The dependent variable is the correlation between the bank and S&P500 index returns. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Table 3: Excess Correlation and Bank Characteristics

	(1)	(2)	(3)	(4)	(5)
Sub. Debt/Assets	-0.0540				-0.106
	(0.0724)				(0.0787)
Loans/Assets	0.0860				0.0621
	(0.0555)				(0.0709)
Log(Assets)	-0.171**				-0.189*
	(0.0705)				(0.104)
Log(Assets)^2	0.00636***				0.00693**
	(0.00221)				(0.00341)
Real estate/Loans	0.0333				0.0277
	(0.0387)				(0.0407)
Loan growth		-0.140			-0.164
		(0.123)			(0.119)
ROA		3.051			-0.0911
		(2.754)			(2.578)
Interest from loans/Loans		2.072**			0.310
		(0.856)			(0.815)
NPL/Loans		0.807			0.273
		(0.804)			(0.813)
MBS held to maturity/Assets			-0.194		0.206
			(0.282)		(0.274)
Securitization/Assets			0.366**		0.0841
			(0.171)		(0.0863)
Derivatives				0.428***	0.195
not for trade/Assets				(0.152)	(0.150)
Gross position CD/Assets				16.28***	-3.877
				(3.091)	(7.275)
Net position CD/Assets				-1.726	-1.024
				(1.068)	(1.482)
Observations	200	197	200	200	197
R-squared	0.355	0.063	0.114	0.273	0.395

The dependent variable is the excess interbank correlation, measured as the residual of a cross section OLS regression of the interbank correlation on the correlation between the bank and S&P500 index returns. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Table 4: Share Price Performance and Interbank Correlation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Excess Correlation$_{06}$	0.723***	0.729***	0.719***	0.661***	0.656***	0.706***	0.393
	(0.257)	(0.233)	(0.233)	(0.238)	(0.236)	(0.240)	(0.254)
Diversification$_{06}$	0.354***	0.269**	0.298**	0.249**	0.261**	0.287**	0.304**
	(0.134)	(0.121)	(0.122)	(0.125)	(0.127)	(0.124)	(0.123)
Sub. Debt/Assets$_{06}$	-1.116***	-0.522**	-0.578**	-0.628**	-0.632**	-0.656***	-0.644***
	(0.253)	(0.262)	(0.250)	(0.246)	(0.249)	(0.244)	(0.244)
Loans/Assets$_{06}$	-1.465***	-1.363***	-1.244***	-1.277***	-1.224***	-1.267***	-1.247***
	(0.188)	(0.187)	(0.203)	(0.208)	(0.207)	(0.210)	(0.199)
Log(Assets)$_{06}$	-0.0398	-0.0807***	-0.0877***	-0.0803***	-0.0702**	-0.0851***	-0.0777***
	(0.0246)	(0.0249)	(0.0251)	(0.0281)	(0.0285)	(0.0285)	(0.0271)
Real estate/Loans$_{06}$		-0.583***	-0.629***	-0.640***	-0.656***	-0.667***	-0.570***
		(0.139)	(0.142)	(0.141)	(0.135)	(0.145)	(0.138)
NPL/Loans$_{06}$		-3.141	-3.584*	-3.392	-3.385	-3.265	-3.317
		(2.193)	(2.149)	(2.182)	(2.275)	(2.184)	(2.112)
Loan growth$_{06}$		-0.759**	-0.938***	-0.921**	-0.836**	-1.057***	-0.842**
		(0.354)	(0.356)	(0.360)	(0.368)	(0.392)	(0.341)
ROA$_{06}$		29.36***	27.33***	30.21***	29.91***	28.22***	29.14***
		(9.055)	(9.281)	(9.275)	(9.164)	(9.357)	(8.866)
Interest from		-6.668***	-6.210**	-7.300***	-7.335***	-8.665***	-6.669***
loans/Loans$_{06}$		(2.552)	(2.511)	(2.661)	(2.662)	(2.726)	(2.553)
MBS held			1.991*	1.872*	1.553	1.867*	1.806*
to maturity/Assets$_{06}$			(1.094)	(1.055)	(1.031)	(1.033)	(1.080)
Securitization/Assets$_{06}$			0.291	0.249	0.211	0.253	0.296
			(0.219)	(0.233)	(0.217)	(0.244)	(0.253)
Derivatives				0.621	0.606	0.734*	0.649*
not for trade/Assets$_{06}$				(0.400)	(0.415)	(0.405)	(0.392)
Gross position				-10.62	-10.54	-9.482	-10.84
CD/Assets$_{06}$				(11.05)	(11.19)	(11.49)	(10.84)
Net position				-0.494	-0.308	-0.241	-0.715
CD/Assets$_{06}$				(4.279)	(4.436)	(4.149)	(4.233)
TARP					-0.0890**		
					(0.0395)		
Betas$_{06}$						-0.0278	
						(0.0496)	
Zscore$_{06}$							0.00487***
							(0.00115)
Observations	199	196	196	196	196	194	196
R-squared	0.269	0.409	0.422	0.429	0.447	0.441	0.476

The dependent variable is the bank's share price performance over the period 2 January 2007 until 31 December 2009. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.