”Too big to fail” or ”Too non-traditional to fail”?: The determinants of banks’ systemic importance

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"Too big to fail" or "Too non-traditional to fail"?
The determinants of banks' systemic importance*

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Abstract This paper empirically analyzes the determinants of banks' systemic importance. In constructing a measure on the systemic importance of financial institutions we find that size is a leading determinant. This confirms the usual "Too big to fail" argument. Nevertheless, banks with size above a sufficiently high level have equal systemic importance. In addition to size, we find that the extent to which banks engage in non-traditional banking activities is also positively related to banks' systemic importance. Therefore, in addition to "Too big to fail", systemically important financial institutions can also be identified by a "Too non-traditional to fail" principle.

Keywords: Too-big-to-fail, systemic importance, systemic risk, non-traditional banking, extreme value theory

JEL Classification Numbers: G01, G21, G28

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1 Introduction

The failure of a single financial institution has the potential to spark catastrophic losses in local, regional, and global financial systems. The global financial crisis which unfolded in 2008 has provided an example. In order to prevent a potential meltdown of the financial system, the US government was prompted to save large financial institutions in the onset of this crisis. The intervention activities have lead to debates in support and objection of rescuing certain distressed financial institutions. Arguments in favor stress that financial institutions receiving government support are systemically important. That is, their failure may trigger a relatively large number of simultaneous failures within the financial sector. Nevertheless, the institutions that in practice receive most, if not all, the "bailout" attention are large firms. In other words, although bailouts should be conducted for "systemically important financial institutions" (SIFIs), the practical principle is simply to rescue firms that are "Too big to fail" (TBTF). This suggests that large financial institutions are automatically SIFIs. However, such an assertion requires a careful empirical examination. This is the first question this paper addresses: Is size fundamental in characterizing the systemic importance of a financial institution? If size is not the sole determinant in differentiating banks' systemic importance, the consequent question is then: what are the other major bank-level characteristics that determine the systemic importance of a financial institution? To answer these questions, this paper empirically analyzes potential determinants of banks' systemic importance.

In our framework, we distinguish the concept of *systemic importance* from "systemic risk contribution". The term "systemic risk" has been used in a number of different contexts, and does not yet have a rigorous singular definition. It sometimes refers to the system-wide risk in the financial sector[1] and sometimes refers to the contribution to the system-wide risk by one single institution.[2] The former can be regarded as the aggregation of the latter across all institutions in the system. Conceptually, systemic

[1]Acharya et al. (2009) define systemic risk as "*the risk of a crisis in the financial sector and its spill-over to the economy*".

[2]De Bandt and Hartmann (2000) define systemic risk contribution as "*the risk of experiencing an event such that the release of bad information on, or failure of, one institution propagates across the system resulting in further failures of other institutions*".

risk contribution has two major components: the *individual riskiness* of the institution and the *spill-over effect* to the rest of the system given its failure. Our definition of the term systemic importance refers to the spill-over effect only. In this way, it reflects the interconnectedness of the underlying institution to the rest of the system without considering its own riskiness. This definition is consistent with the view of the Basel Committee on Banking Supervision (BCBS) which stresses that "*systemic importance should be measured in terms of the impact that a failure of a bank can have on the global financial system and wider economy rather than the risk that a failure can occur.*"[3]

Our first major finding is that size is, to a large extent, able to differentiate systemic importance; however, banks' systemic importance is increasing in size only up to a certain limit. For US banks during the crisis period (2007-2010), there is an increasing relation between systemic importance and size only among those having total assets, at the end of 2006, below 30 billion USD.[4] After this size "threshold" is surpassed, systemic importance of banks remains stable. Hence, differentiating the systemic importance of banks by only analyzing size is no longer possible. Furthermore, the cross-sectional dispersion on systemic importance is also larger for smaller banks. Thus, it is necessary to investigate other potential determinants for both large and small banks. With a close examination of indicators on banks' business models, our second major finding is that, in addition to size, systemic importance is also determined by how much a bank relies on money market funding to fund its projects and the amount of non-traditional income generating activities a bank involves itself in. On the time dimension, our analysis on a selection of US banks from the beginning of 1999 to the end of 2010 show that the determinants of systemic importance are not invariant over time, but depend on changing macroeconomic conditions. Lastly, we provide evidence that certain bank activities that serve to drive systemic importance have an opposite effect on banks' individual riskiness. Specifically, banks that search out more non-traditional sources of funding and income generating activities, generally have a lower individual risk at the expense of a greater systemic

[3]See BCBS press release, "Global systemically important banks: Assessment methodology and the additional loss absorbency requirement", November 2011.

[4]According to the Statistical Releases of the Board of Governors of the Federal Reserve System, 40 US commercial banks had assets totaling more than 30 billion USD as of December 31, 2006.

importance.

One potential theoretical argument that supports "TBTF" is through bank diversification. Large banks are usually better diversified compared to smaller banks. As discussed in Wagner (2010), a well diversified bank bears less individual risks, while at the same time, due to large common exposure, it is more systemically connected to the rest of the system. Therefore, larger banks can be more systemically important. Such a diversification argument can be well applied to other bank characteristics that are potentially associated to systemic diversification. Particularly, engaging in non-traditional banking activities such as generating non-interest profit and accessing interbank market funding can be regarded as alternative methods for diversifying asset and funding risks, thus may well be potential determinants of systemic importance.

Traditional banking that focuses on loan issuance and monitoring with interest income are rather specialized. Although traditional banking may bear higher individual risk, since different banks expose to different risk factors, the systemic linkage within the system is low. With financial innovation, financial conglomerates engage in other non-interest profit generating processes such as securitization or derivative trading. Such banking activities increase diversification; at the same time, this diversification leads to banks holding similar portfolios that are highly correlated. Consequently, this enhances the possibility that financial institutions will suffer from common shocks to the asset side of their balance sheets. This creates an indirect linkage in the event of a crisis, see, e.g. de Vries (2005) and Acharya (2009). One step further, an initial shock on bank asset value is likely to be amplified throughout the system as firms de-lever their positions to meet margin calls and capital requirements (Brunnermeier and Pedersen (2009)). Therefore, banks that engage more in activities generating non-interest profit will be more systemically important. Two papers, De Jonghe (2010) and Knaup and Wagner (2010), provide empirical evidence on the relation between non-interest income and systemic risk. In De Jonghe (2010), the author finds that banks operating non-traditional banking practices, such as reliance on commission and trading income, have a greater impact on the systemic stability than those engaging in more traditional forms

of funding. Knaup and Wagner (2010), while focusing on the asset decomposition on banks balance sheets, find that non-traditional banking is more hazardous to the system in terms of banks' tail risk.

Another potential channel of systemic importance comes via non-traditional funding such as interbank loans that take place in the money market. A great deal of the literature models systemic risk through the direct links banks expose themselves to each other via the interbank markets, see, e.g. Rochet and Tirole (1996), Allen and Gale (2000), and Freixas et al. (2000). The banking system is wired together as a network supported by the interbank market. When banks have the ability and means to lend to each other, it can be viewed as a diversified position to protect against liquidity risk: liquidity constraints within the financial sector are reduced by introducing the interbank market. Consequently, the financial system is able to absorb small to medium size liquidity shocks. The downside of the interbank network is that banks open themselves up in the event of a large liquidity shock which causes severe bank failure. The magnitude of a banks exposure to the interbank market can therefore reflect the bank's level of systemic importance.

To summarize, if the diversification argument supports the statement of "TBTF", it should also support the statement that engaging in non-traditional banking activities towards a more diversified position will enhance the systemic importance of a financial institution. In other words, banks may well be "Too non-traditional to fail" (TNTTF). As an empirical exercise, we test whether large bank size or high levels of engagement in non-traditional banking are associated with high level of systemic importance. This helps clarify whether TBTF or TNTTF should be the principle in identifying SIFIs.

For our empirical purpose, it is necessary to construct a measure on banks' systemic importance. Our proposed measure on systemic importance is based on the theoretical interpretation that it pertains to the spill-over effect only. More specifically, it is defined as the expected loss to the financial system given that one institution has failed. Thus, we call our measure the "systemic loss given default" (SLGD). Given the failure of the underlying institution, the expected loss to the financial system is measured by the sum

of expected losses of other institutions in the system. The systemic importance measures derived thereof gives insight on the social welfare effects of a particular bank failure: it is the liability the central authority faces if a particular bank fails and the other distressed banks are not recapitalized. To measure these losses, we consider the potential loss on insured deposits in the system given the failure of a specific financial institution. This measure contributes to the literature on measuring systemic risk or systemic importance of financial institutions.[5] We differ from previous measures of systemic risk in two ways: first, ours is a measure of systemic importance which does not contain information on the individual riskiness of the underlying institution. Second, we consider a different empirical strategy in estimating our proposed measure by implementing a multivariate extreme value theory (EVT) approach.

As for measures on systemic importance, few studies have focused solely on the spill-over effect. One candidate is the Shapley value, conceptualized in Tarashev et al. (2009). Tarashev et al. (2010) applies the Shapley value concept to construct empirical measures on systemic importance of individual institutions. Although intuitive in its interpretation, the potential downside of the Shapley value is that it requires a large amount of calculation which prohibits its empirical application to a large financial system. The other candidate for measuring systemic importance is the Systemic Impact Index (SII) of Zhou (2010). As we shall discuss in Section 2, our proposed SLGD measure is a generalization of the SII measure which considers the economic impact to the system given the failure of one single institution.

[5]For measures on systemic risk, four prominent candidates are the conditional Value-at-Risk (Adrian and Brunnermeier (2011), otherwise known as CoVaR), the marginal expected shortfall of Acharya, Brownlees, Engle, Farazmand and Richardson (2010) (MES), the probability of at least one extra failure (PAO) given a failure in the system (Segoviano and Goodhart (2009)) and the Distress Insurance Premium of Huang et al. (2010) (DIP). The CoVaR captures the Value-at-Risk (VaR) of each individual bank conditional on an adverse state of the financial system by quantile regression. Similarly, the marginal expected shortfall measures the expected capital shortfall of each individual bank given the occurrence of a systemic crisis. These two measures both require an indicator of the state of the system and are inferred from a bivariate analysis. Different from them, the PAO has the advantage of being able to move from a bivariate to a multivariate analysis by utilizing a conditional probability approach, without imposing a system indicator. The drawback of the PAO measure is that given the failure of one institution, it gives an indication on the probability of some spill-over effect without having additional information as to the level of the impact. The DIP, based on the Credit Default Swap (CDS) prices, overcomes the aforementioned drawbacks by measuring the expected loss to the other institutions in the system given the failure of a particular one.

The paper proceeds as follows. We first propose a measure of systemic importance in Section 2. Section 3 describes data and our empirical strategy on how we estimate the systemic importance measure along with how we analyze the potential determinants of systemic importance. The empirical results are reported in Section 4. Section 5 compares the determinants of systemic importance with that of individual risk. Section 6 concludes the paper and provides a discussion on possible policy implications.

2 Measuring Systemic Importance

Our measure on the systemic importance of one financial institution can be viewed as a generalization of the systemic importance measure proposed by Zhou (2010), the systemic impact index (SII). We start with reviewing the SII measure and discussing its shortcoming.

The SII measure considers the expected number of simultaneous failures in the system given the failure of one institution. Consequently, it is an aggregation of the conditional probabilities of other banks' failure given the failure of a specific bank. A direct estimation of the probability of joint failure is difficult due to the scarcity of actual "bank failures". This issue has been resolved empirically by applying multivariate EVT.[6] Instead of estimating the conditional probability of joint failures, the EVT approach proxies that by estimating conditional probability of joint bank *distresses*. A distress event is described as the market price of a bank's equity experiences a large loss. Evidence suggests that financial market data, such as a bank's market price of equity, can serve as an early warning indicator of ratings changes for publicly traded bank holding companies (BHCs), see, e.g. Krainer and Lopez (2003). Therefore, by considering the co-movement of distress events, it provides a good proxy for the conditional probability of joint failure.

Consider a banking system consisting of N banks. Denote their equity returns as $X_1, \ldots, X_N$. A distress, or tail event, is defined as an event with a low probability p.[7] In other words, values of X_i below a certain threshold level are assumed to trigger a

[6] See De Haan and Ferreira (2006) for an overview of multivariate EVT.

[7] For instance, a p of 0.001, using daily data, corresponds to a tail event once per $1/p = 1000$ days, or about once per 4 years.

tail event for bank i with probability p. Thus, this threshold level corresponds to the Value-at-Risk (VaR) of the bank

$$Pr(X_i < -VaR_i(p)) = p, \tag{2.1}$$

for some (tail) probability level p. While the choice of p is of concern for regulators and the internal risk management of the firm, we do not impose a specific p level here. Instead, we consider an equivalent p level across firms. Notice that this does not imply that the threshold levels are identical across firms, but rather that the probability of a tail event is invariant. Certain firms have a greater loss tolerance than others can thus enjoy a lower threshold for defining a tail event. Such a description allows for heterogeneity in banks' individual risk taking activities.

The SII is then defined as

$$\begin{aligned} SII_i(p) &= E(\sum_{j \neq i} I_{X_j < -VaR_j(p)} | X_i < -VaR_i(p)) \\ &= \sum_{j \neq i} P(X_j < -VaR_j(p) | X_i < -VaR_i(p)), \end{aligned} \tag{2.2}$$

where I_A is the indicator function that is equal to 1 if A occurs and 0 otherwise. If the distress of one bank is likely to be accompanied by similar distresses in other banks, this bank is said to be systemically important.[8]

From the definition, this measure is able to capture the general instability of the system associated with the failure of a single institution. Although regulators may be concerned with the number of failures in the system stemming from a single failure (Acharya and Yorulmazer (2007)), such a measure lacks information on the exact economic impact a failure would create. A distress in a bank which is accompanied by distress or failure in other small banks, or a similar impact to large banks, are indistinguishable under this

[8]This measure cannot discern any causality. For instance, a system consisting of only two banks has a corresponding $SII_1 = SII_2$. Acharya (2009) argues that causality is not necessary in determining systemic importance. If a bank's failure is often associated with other's failure, it ultimately enjoys a high chance of being bailed out. Such a bank should be regarded as systemically important from a social welfare point-of-view.

measure. Hence, it is necessary to extend this measure to account for the economic size of the impact.

Our proposed measure overcomes the shortcoming of the SII measure by considering the real economic impact to the rest of the system given the failure of one bank. We consider a measure of social welfare loss given distress to capture the systemic importance of a bank as follows,

$$SLGD(p) = \sum_{j \neq i} LGD_j \cdot P(X_j < -VaR_j(p) | X_i < -VaR_i(p)), \tag{2.3}$$

where LGD_j indicates the loss given default once bank j fails. The SII measure in Zhou (2010) is then a special case in which $LGD_j = 1$ across all firms.

Lastly, we choose a measure of loss, LGD_j. During a period of economic turmoil, when an acquisition of a failed bank by a competitor is not feasible, the government, or monetary authority, is facing a decision of whether or not to rescue the bank from bankruptcy using public funds. Considering that the authority decides, following the failure of a bank, not to provide any bailout to the other banks that fail in conjunction. As a consequence, they are responsible for the insured customer deposits held by the other failed banks. Without having data on the specific size of insured deposits held by each bank, we assume that the fraction of insured deposits against total customer deposits is comparable across banks. We therefore use the amount of total customer deposits (DEP) as a proxy for the amount of government insured deposits held by each bank. They act as the weights used in constructing the SLGD measure of systemic importance.

3 Data and Methodology

3.1 Estimating the SLGD

The key element in estimating the SLGD measure, is the estimation of the conditional probability that bank j fails given that bank i fails for each pair i and j. For that purpose, daily equity prices on US bank holding companies (BHCs) from 1999 to the end of 2010

are collected from Datastream.[9] We follow the approach in Hartmann et al. (2005) to estimate such a conditional probability by applying multivariate EVT.

The multivariate EVT approach utilized in this paper improves upon existing methodology in the following way. Most existing measure of systemic risk use a statistical methodology that assume multivariate normality. In contrast, there is a great deal of empirical evidence to suggest that financial data follow a fat-tailed distribution as opposed to the normal distribution which tends to underestimate the probability of extreme events, see, e.g. Mandelbrot (1963). Furthermore, the multivariate normal distribution is known to exhibit tail independence, see, e.g. Sibuya (1959), while financial data have non-negligible tail dependence. A methodology that incorporates a normality assumption will underestimate the tail dependence.[10] Lastly, to measure systemic risk or systemic importance, the observations in the tail region are the only important observations that should be considered in the estimation. Conversely, fitting data to the normal distribution usually results in estimates which are determined by moderate level data. An EVT approach allows for both heavy-tails and tail independence. It also focuses on the observations in the tail region only while ignoring the observations at the moderate level.

Multivariate EVT provides models such that the limit of the conditional probability is at a constant level as $p \to 0$, i.e.

$$\tau_{i,j} := \lim_{p \to 0} P(X_j < -VaR_j(p) | X_i < -VaR_i(p)). \tag{3.1}$$

Thus, the conditional probability can be approximated by its limit $\tau_{i,j}$. Suppose we have n observations on the two return series as $(X_{i,s}, X_{j,s})$ for $1 \leq s \leq n$. The limit $\tau_{i,j}$ can be estimated by taking $p = k/n$ for sample size n, where $k := k(n)$ is an intermediate

[9] Equities selected are traded on both the NYSE and the NASDAQ exchanges.

[10] As an illustration of how the techniques of EVT improve upon the methods that impose a normality assumption, we consider the analysis of two banks, Wells Fargo and Bank of America as in (3.1). We use daily returns of the two banks from the beginning of 1995 to the end of 2010 (i.e. 4175 observations). We assume that distress occurs with a probability of 1%. With such a definition the conditional probability of joint distress can be estimated non-perimetrically from the data at 59.5%. By fitting the returns of both banks to a bivariate normal distribution the conditional probability of distress is estimated to be 0.16%. By using the EVT technique the conditional probability of distress is estimated to be 51.2%. It is clear that the approach incorporating a normality assumption severely underestimates the conditional probability of joint distress, while the EVT approach provides a more reliable estimate. This result is robust to different selections of bank pairs.

sequence such that $k(n) \to \infty$ and $k(n)/n \to 0$ as $n \to \infty$. A non-parametric estimate of $\tau_{i,j}$ is then given as

$$\hat{\tau}_{i,j} := \frac{1}{k} \sum_{s=1}^{n} 1_{X_{j,s} < X_{j,(n-k)}, X_{i,s} < X_{i,(n-k)}}, \tag{3.2}$$

where $X_{i,(n-k)}$ is the $(k+1)$th lowest return among $X_{i,1}, \ldots, X_{i,n}$.[11]

When estimating the conditional probabilities in the SII measure, Zhou (2010) uses the raw equity returns to form the data set on $(X_{i,s}, X_{j,s})$. Such an approach does not take into account the fact that the co-movement among bank equity returns can be due to a common market factor. This may lead to an overestimation of the conditional probabilities. In order to remove the dependence imposed by a common market factor, we make correction by analyzing the banks excess returns over the market. We calculate the residual equity returns over the market return[12] by estimating the single-factor market model in each estimation period as

$$R_{i,s} = \alpha_i + \beta_i R_{m,s} + \epsilon_{i,s}. \tag{3.3}$$

The error term, $\epsilon_{i,s}$, is assumed to follow the standard assumptions of Ordinary Least Squared (OLS) regression. The excess returns are calculated by

$$\hat{\epsilon}_{i,s} = R_{i,s} - \hat{\alpha}_i - \hat{\beta}_i R_{m,s}. \tag{3.4}$$

We use the estimated excess returns $(\hat{\epsilon}_{i,s}, \hat{\epsilon}_{j,s})$ instead of raw returns as the data set on $(X_{i,s}, X_{j,s})$ in the estimation of the conditional probabilities.

Another technical issue in the estimation is the sequence choice of the intermediate k in (3.2). The theoretical conditions on k are not relevant for a finite sample analysis. Instead of taking an arbitrary k, a usual procedure is to calculate the estimator of $\tau_{i,j}$ under different k values and draw a line-plot of the estimates against the k values. With

[11] For the estimator of $\tau_{i,j}$, usual statistical properties, such as consistency and asymptotic normality, has been proved, see, e.g. De Haan and Ferreira (2006).

[12] The market returns for the period 1999 - 2010 refers to the returns of the SP500 index.

a low k value, the estimation exhibits a large variance, while for a high k value, since the estimation uses too many observations from the moderate level, it bears a potential bias. Therefore, k is usually chosen by picking the first stable part of the line-plot starting from low k, which balances the tradeoff between the variance and the bias. The estimates then follow from such a choice of k. Because k is chosen from a stable part of the line-plot, a small variation of the k value does not change the estimated value. Thus, the exact k value is not sensitive for the estimation of $\tau_{i,j}$. In our empirical application, the chosen k value differs for different pairs of banks, because the sample size n, the number of available excess returns in a given period, differs for different pairs of banks. Nevertheless, we keep the ration k/n constant across different samples at a level of 3%.

We also impose a cutoff value, 0.10, in the estimation of τ-measure, such that values of the estimated τ below the cutoff level are set to zero. This is to avoid the potential positive bias in the estimation of τ: when the actual τ value is zero, the estimation usually yields a small positive value. Our regression results are robust for different selection of cutoff values.

In addition to the conditional probabilities, the other element in the SLGD measure is the calculation of loss given default. For that purpose we collect annual balance sheet data on total customer deposits for each bank from the Bankscope database.[13] Since each estimation period covers four years, we use average total customer deposits over the same period as the weights. With estimating the conditional probability for each pair of banks i and j, the SLGD measure for bank i is then calculated as the sum of the product of the conditional probabilities across all other banks, $j \neq i$, and bank j's total customer deposits.

3.2 Analyzing Potential Determinants

To analyze the potential determinants of systemic importance, we collect bank balance sheet data, construct indicators reflecting their business models and perform regression analysis between the SLGD measure and the indicators. The size of the bank, our primary

[13]Equity and balance sheet accounting data are matched between the BvD Bankscope and Datastream by using the corresponding Bankscope number for each firm

focus, is measured as the logarithm of total assets in millions of USD. To capture a possible non-linear property of the size, we also consider its quadratic form in regressions. In order to avoid a potential multi-collinearity issue, the size is first standardized by its cross-sectional mean and standard deviation and then squared.

The focus on non-traditional banking activities is implemented by considering the following variables: money market funding as a ratio of total funding and non-interest income as a ratio of total income. The latter variable is further decomposed into two variables representing trading income and fee and commission income both as a ratio of total income.

Five control variables based on the CAMEL rating system[14] are included in the regressions as follows:

- **C**apital adequacy: Tier 1 Capital Ratio
- **A**sset quality: Gross Loans/ Total Assets
- **M**anagement: Problem Loans/ Total Loans
- **E**arnings: Return on Average Assets
- **L**iquidity: Liquid Assets/ Short-term Funding

We conduct our regression analysis in two ways. First, we analyze only the period between 2007 and 2010 which encapsulates the financial crisis. The choice of having a four year period for our analysis is to ensure a sufficient number of observations for the estimation of the conditional probabilities used in the SLGD measure. We filter out any institution that is not traded on at least 80% of the days within this period. We match the estimated SLGD measure with the annual balance sheet data recorded at the end of the year in 2006. After this filtering procedure, 311 BHCs are included in our regression analysis. Since the business model indicators are ahead of the SLGD measure in time,

[14]The acronym "CAMEL" refers to five components used in order to assess the overall condition and supervisory rating of a bank: Capital adequacy, Asset quality, Management, Earnings, and Liquidity. Private supervisory ratings are assigned for each of the five components. Hirtle and Lopez (1999) find that past CAMEL ratings contain useful information on the future performance and condition of a bank.

our regression analysis forms an out-of-sample, or forward-looking approach. This allows analyzing the relation between the business model of a bank before the financial crisis and its systemic importance during the crisis.

Second, in order to see whether the drivers of systemic importance stand over a longer time horizon, we extend our analysis to cover a period from the beginning of 1999 to the end of 2010. Under this approach, the SLGD measure is estimated in the same way over each four-year period that is rolled forward year by year in the sample, i.e. the SLGD measures are estimated for the periods 1999-2002, 2000-2003, ..., 2007-2010. We removed any bank that was not traded on at least 90% of the days covering the whole period and did not have end-of-year balance sheet data from 1998 to 2007. This filtering process results in a panel data set consisting of 143 banks over 8 estimation periods. With the 1125 firm-period observations in total, we perform a panel regression with time fixed effects while clustering at the bank level.

Lastly, we split the panel data set to perform eight separate OLS regressions, one for each period, in the same way as for the crisis period. This allows us to check how the determinants have emerged over the entire time horizon.

4 Empirical Results

4.1 Financial Crisis: 2007-2010

Our main result is conducted over the most recent period in our data set (2007-2010), which manifests the time surrounding the financial crisis. Table 1 provides descriptive statistics of the SLGD and potential determinants. Table 2 shows the correlation among the potential determinants. Table 3 reports the regression results.

The first regression (column 1) only contains one independent variable: the size of banks. It is positive and significant at the 99% confidence level. This result gives support to the TBTF argument that larger banks are more systemically important. We then take a close look at size in the second regression (column 2) by adding the quadratic form of the size variable. While the level of the size variable remains positive and significant at

the 99% level, the quadratic term is negative and significant at the same confidence level. Hence, the relation between the SLGD and size is non-linear.

In order to have a better insight on the non-linearity, we further analyze the quadratic relation between SLGD and $Size$ as

$$SLGD = aSize^2 + bSize + c.$$

By taking the first-order derivative, we get that $\frac{\partial SLGD}{\partial Size} = 2aSize + b$. Hence, for $Size = -\frac{b}{2a}$, the partial derivative turns to be zero. In other words, the SLGD is neither increasing nor decreasing with respect to the variation of $Size$ at such a level. With the estimation of the coefficients a and b as in Table 3 (column 2), we find that this occurs at $Size = 11.5$.[15] By partitioning the sample into two groups at $Size = 11.5$, we find a significantly positive relationship for banks with $Size < 11.5$, while for $Size \geq 11.5$ we find a slope coefficient that is indistinguishable from zero at the 95% confidence level. In other words, the SLGD of banks increase with respect to the size up to a certain threshold and then no further. This observation implies that for large banks with $Size \geq 11.5$ the TBTF principle does not hold. Since the cutoff point 11.5 is rather close to the maximum size in the sample, the quadratic relation, in fact, would be better characterized as a "kink" relation. We attempt to identify the size level where the insignificance of the $SLGD - Size$ relation starts.

Starting at 11.5 and decreasing the threshold, the regression based on large banks remains insignificant until the threshold level reaches 10.3. When splitting the sample at $Size = 10.3$, the SLGD is strictly increasing in size when $Size < 10.3$ and the regression coefficient for size is insignificant at the 95% confidence level for $Size \geq 10.3$. Below this size threshold the $SLGD - Size$ relation is positive. This relation is shown graphically in a scatter plot of SLGD against $Size$ in Figure 1.[16]

[15] The $Size$ and $Size^2$ term are constructed from standardized variables in order to remove the potential multi-collinearity problem. as a result, the solution to the above equation had to be transformed back to the original size using the transformation $Size\sigma + \mu$.

[16] Alternatively, we can run a threshold regression to search for a breakpoint that partitions the sample of banks into two segments. We utilize a test from Hansen (1999) and find a breakpoint, significant at the 95% confidence level, to be at $Size = 9.4$. This is close to the 10.3 cutoff point of the $SLGD - Size$ significance relation we found. We again partition the sample into two groups at the breakpoint predicted

Our empirical analysis confirms that large banks are systemically important, but only after a certain size level is reached. This level corresponds to a bank with total assets equaling or exceeding roughly 30 billion USD. After this threshold is surpassed, size alone cannot differentiate between the degree of systemic importance among those large US banks. This finding partially supports the validity of the TBTF argument.

To further analyze determinants of systemic importance, we add other control variables, i.e. the CAMEL ratios, to the regression alongside $Size$. The regression results on $Size$ and its quadratic term remain unchanged. This remains the case when the variables representing non-traditional banking are added to the regression. Hence the non-linear size-systemic importance relation is rather robust.

We further test the TNTTF argument by performing regressions with the variables indicating non-traditional banking. In the regression including the level and quadratic size variables (column 4) none of the variables on non-traditional banking are significant at even the 90% confidence level. This may well be a consequence of a potential endogeneity problem. When considering both size and other variables indicating a bank's business model, size is endogenous if the strategies and activities a bank chooses to undertake have direct impact on how large the bank becomes. Thus, the bank size is endogenously related with other variables including the variables describing non-traditional banking activities. Table 2 shows the correlation matrix among the size variable and other variables used in the analysis. A high correlation is observed, especially between size and variables on non-traditional banking. This could potentially overwhelm the size effect or shield any possible effects that other variables may contribute in determining a bank's systemic importance. In order to avoid such a problem, we orthogonalize the size variable by first regressing it against the other variables in the regression and then taking the residual term as a "purified size" variable. By including the purified size variable, the estimated coefficients on other variables in the regression will indicate their own contribution towards systemic importance independent of the bank size.

by the threshold test at $Size = 9.4$. In this case we find that for $Size < 9.4$ a significantly positive relationship exists, and for banks with $Size \geq 9.4$ a positive and significant relationship also exists, yet to a lesser extent.

When we replace the size variable and its quadratic form with the purified size in the regression, the purified size variable is positive and significant, while the non-interest income variable is also positive and significant at the 99% level. Therefore, we conclude that the non-interest income activities of a bank play a role in determining a bank's systemic importance. This supports the theoretical argument that as banks move from more traditional activities (e.g. deposit taking and lending) towards more non-traditional sources of income they increase their systemic connectedness (Shleifer and Vishny (2010)). This result is also consistent with the empirical finding in Brunnermeier et al. (2011). By further dividing the non-interest income variable into two variables indicating trading income and fee and commission income both as a ratio of total income, we observe that the contribution of non-interest income to systemic importance is determined by the amount of fee and commission income that a bank undertakes while the amount of trading income does not appear to be significant. For the funding side, we find the money market funding variable to be positive, yet insignificant at the 90% confidence level.

In addition to the positive effect of non-interest income on systemic importance, we also find that among the CAMEL ratios, the amount of Tier 1 capital a bank holds in relation to its risk-weighted assets and the fraction of assets that are made up of loans both contribute negatively to a bank's systemic importance level. Banks with a larger capital buffer prior to the crisis and with a greater focus on more traditional banking activities (e.g. issuing loans), are less connected to the system during the crisis.

From these results, we have evidence that SIFIs, in addition to being identified by the TBTF principle, also have the potential of being TNTTF. Here non-traditional refers to relying heavily on non-interest income generating activities in the form of fee and commission income. Further, a bank operating in a more traditional manner of maintaining a healthy capital buffer and engaging in loan issuing activities corresponds to a lower level of systemic importance.

4.2 Multi-period Analysis

To check if the results of our analysis during the crisis period are robust for periods outside the crisis, we extend our sample of data to a larger horizon starting from the beginning of 1999 to the end of 2010. As depicted in Section 3.2, the data set includes eight overlapping estimation periods. Table 5 provides descriptive statistics of the SLGD and potential determinants. The results of the panel regression over this time period are shown in Table 4.

In the panel regression we again find that bank size has a non-linear effect on its systemic importance: a positive and significant coefficient on the size variable while a negative and significant coefficient on the quadratic size term. The point estimates are close to the ones found in the 2007-2010 estimation period which hints that a potential "kink" relation remains. Furthermore, the purified size also remains significant at the 99% confidence level. To summarize, the overall effect of size on systemic importance is robust over an extended time period and smaller sample of banks.

Of the variables indicating non-traditional banking, the non-interest income ratio remains significant at the 99% confidence level. However, a key difference is that the coefficient on the money market funding variable is now also significant and positive at the 99% confidence level. The new result agrees with the theoretical argument that a shift away from traditional funding (e.g. deposit taking) towards more non-traditional funding sources was instrumental in the cause of the crisis due to their susceptibility to runs, see, e.g. Acharya, Gale and Yorulmazer (2010). The fact that we did not observe such a strong significance of the money market funding variable in the regression during the crisis period is potentially due to sample selection. In the single period exercise, our sample contains a large amount of banks that actually undertook a limited amount of money market funding. By having a lower amount of banks in the panel data analysis, the sample selection procedure results in selecting more large banks that have extensively accessed the money market funding. Money market funding now appears as a strong determinant of bank systemic importance among those selected banks.

The panel regression approach has a potential drawback: we do not allow for variation

in coefficients of the determinants of systemic importance over time. We thus analyze each of the eight estimation periods separately, which allows the potential evolution of determinants across a changing macroeconomic climate.

Table 6 shows the regression results for each of the eight estimation periods. The general observation is that the determinants are varying over time. First, the purified size is a strong positive determinant of systemic importance over the first six periods, but this relation disappears in the final two periods. The result in the last period does not necessarily contrast with that in our single period analysis with the larger sample of banks. The sample selection procedure leading to this new result removed many small banks since they did not survive over the period 1999-2010. Hence, the remaining banks are, in general, large. This is confirmed in Table 5 with summary statistics. Therefore, the new results simply reflect the non-significant effect among large banks found in the previous single period regression.

Of the variables on non-traditional banking, the non-interest income is positive and significant in six of the eight periods including not only all periods covering the financial crisis and the dot-com collapse, but also one of the periods under more benign economic conditions between the two downturns. Hence, the positive relation between non-traditional sources of income and systemic importance is robust for both an extended time period and over different macroeconomic conditions. This gives support in favor of the TNTTF principle over the TBTF principle in identifying SIFIs: it holds during both positive and negative economic conditions. The money market funding variable is positive and significant at the 95% confidence level for most of the periods with the only exceptions being the two neighboring periods of 2002-2005 and 2003-2006. The two periods cover the booming macroeconomic climate between the dot-com bubble collapse and the financial crisis, whereas the other six periods contain, at least to some extent, a time during an economic downturn or crisis. Our results provide evidence that a reliance on money market funding plays a prominent role in determining the systemic importance of banks during times of economic distress. This again supports the notion that banks are TNTTF in terms of their funding choices during a crisis.

5 Determinants of Individual Risk: A Comparison

We compare the determinants of banks' systemic importance with that of a banks' individual risk. We have shown that certain banking characteristics determine banks' systemic importance, namely the size and levels of bank's non-traditional activities. As a measure of systemic importance, the SLGD measure is constructed in such a way that it is independent of bank's individual risk. Nevertheless, conceptually, the individual risk and the systemic importance are the two components of systemic risk of a financial institution. Thus, when attempting to mitigate systemic risk, in addition to identifying the determinants of systemic importance, it is necessary to check the relation between individual risk and the bank's business model.

The individual risk of a bank is measured from the same equity price data that we used in the construction of the SLGD measure. We consider the heavy-tailed feature of equity returns by employing univariate EVT to calculate each banks expected shortfall (ES) on its equity returns. The heavy-tailedness of financial returns is well-documented in literature, see e.g. Jansen and de Vries (1991) and Embrechts et al. (1997). It shows that a power law fits the downside tail distribution of the equity return X_i,

$$P(X_i < -u) \sim A_i u^{-\alpha_i} \quad \text{as} \quad u \to +\infty. \tag{5.1}$$

Here, the parameters α_i is the so-called tail index. From such a parametric expansion of the tail distribution, it follows that, if $\alpha_i > 1$,

$$ES_i(p) := -E(X_i | X_i < -VaR_i(p)) \sim \frac{\alpha_i}{\alpha_i - 1} VaR_i(p) \quad \text{as} \quad p \to 0. \tag{5.2}$$

Similar to the estimation of $\tau_{i,j}$, the $VaR_i(p)$ at the level $p = k/n$ is estimated by the $(k+1)$th highest losses, $-X_{i,(n-k)}$, where $X_{i,(n-k)}$ is the $(k+1)$ lowest return. The estimation of α_i is achieved by way of the Hill estimator from univariate EVT. With ranking the observations $X_{i,1}, \cdots, X_{i,n}$, as $X_{i,(1)} \geq X_{i,(2)} \geq \cdots \geq X_{i,(n)}$, the Hill estimator

is defined as

$$1/\hat{\alpha}_i := \frac{1}{k}\sum_{i=1}^{k}\log(-X_{i,(n-i+1)}) - \log(-X_{i,(n-k)}). \tag{5.3}$$

For the statistical properties of the Hill estimator, see Hill (1975). With the estimation of the VaR and the tail index, we obtain the estimate of the ES on the return series of each bank. In other words, we have eight overlapping periods during which the ES of each bank is measured. We use these estimates to run a panel regression against the bank business model indicators in the same way as for the SLGD measure, using time fixed effects and clustering at the bank level.

Table 7 reports the results of the regressions. First, we regress the ES against only the $Size$ variable and find it to be negative and significant at the 99% confidence level (column 1). This is consistent with theoretical literature that larger banks are less risky due to diversification. For the regressions involving the CAMEL ratios and the variables on non-traditional banking, we use the purified size variable to avoid any potential endogeniety. The variable for non-interest income is negative and significant at the 99% confidence level. By decomposing this variable into trading income and fee and commission income (column 4), we find that the coefficient for fee and commission income variable is negative and significant at the 99% confidence level while that for trading income is insignificant. In the regression where with the decomposition of the non-interest income, we also find that the variable on money market funding is negative and significant at the 90% confidence level. All of these findings provide evidence that engaging in non-traditional banking reduces the individual risk a bank faces.

Among the CAMEL ratios, the amount of Tier 1 capital and loans as a fraction of total assets are negative and significant at the 99% and 95% confidence levels, respectively. The returns on assets variable is negative but only significant at the 90% confidence level when excluding the variables on non-traditional activities (column 2). These results show that more capitalized banks have lower individual risk. Banks that engage mainly in loan issuance are also less risky. The latter a potential consequence of the fact that our data set covers the period of the housing bubble, during which traditional loan activity was considered less risky by the market.

To summarize, we find that the determinants of systemic importance, size and non-traditional banking, induce an opposite effect on the individual risk of a bank. A potential explanation is through the diversification effect. Banks can limit their own individual risk of failure by diversifying their activities. This is accomplished by extending the scope of business activities as well as engaging in non-traditional banking activities. At the same time, these actions increase commonalities between banks which lead to an increased systemic importance. Determinants of the individual risk and the systemic importance may thus work against one another. In other words, by being involved with non-traditional banking, banks shift their individual risk to the system by enhancing their systemic importance.

6 Conclusion

This paper addresses the question of whether the size of a financial institution is fundamental in characterizing its systemic importance. In other words, can we identify SIFIs following the TBTF principle? We find partial support in favor of the TBTF hypothesis; however, the relation between size and systemic importance is non-linear. More specifically, systemic importance is positively related to size only up to a certain limit. For example, as of the end of 2006, US banks with total assets exceeding 30 billion USD are equally systemically important during the crisis period (2007-2010). Hence, systemic importance cannot be differentiated by analyzing size only.

Upon further examination, we find that systemic importance is also determined by the extent to which a bank engages in non-traditional activities. The systemic importance of financial institutions is positively related to both the amount of funding from the money market and the income generated from non-interest activities, in particular, the fee and commission income. Furthermore, banks which operate under a traditional manner such as holding a high level of Tier 1 capital and relying on loan issuing activities have a lower systemic importance.

By analyzing a selection of banks over a period of time extending from 1999 to 2010,

we show that the determinants of systemic importance are not time invariant. While the size of a bank is a strong indicator of its systemic importance before the global financial crisis, non-traditional banking activities are predominant in periods of economic downturn or crisis. Finally, we find that the determinants of systemic importance may have an opposite effect on the individual riskiness of banks. In other words, banks that diversify their positions in order to reduce individual risk may at the same time increase their systemic importance.

Our empirical findings have direct policy implications for regulators. First, regulation that attempts to reduce systemic risk in a financial system must take into account the size of financial institutions, but only to a limited degree. Once banks become sufficiently large, their systemic importance can no longer be differentiated by size. In that case, the systemic impact that large banks have on the system has to be differentiated by analyzing other bank characteristics. More specifically, non-traditional banking activities such as engaging in non-interest profit generating activities or using money market funding can also lead a bank to be a SIFI. Second, macro-prudential regulation that varies according to the macroeconomic environment is necessary to maintain the stability of the system. We observe the time variation of the potential determinants for systemic importance, which indicates that regulation has to vary with the business cycle. "Flat" regulation that does not consider macroeconomic environment may provide a sub-optimal solution. Third, when attempting to mitigate the risk taking behavior of financial institutions, it is important to be aware of the potential increase in its spill-over effects to the rest of the system. The interaction between the two sources of systemic risk shows a potential trade-off between mitigating individual risk and amplifying interconnectedness. Understanding the drivers of the two components of systemic risk is the first step in designing effective regulation that may avoid such a double-side effect.

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7 Tables and Figures

Table 1: Summary Statistics: SLGD (2007-2010) and potential determinants (2006)

	Mean	**Std. Dev.**	**Min.**	**Max.**
SLGD	12.588	1.939	6.482	14.655
Size	7.842	1.396	5.464	14.449
Tier 1 Ratio	10.51	4.49	0	24.4
Loans/Assets	70.238	11.719	27.711	92.400
Problem Loans/Loans	0.502	0.589	0	5.984
ROAA	1.097	0.485	-1.54	3.87
Liquid Assets/STF	5.704	5.722	0.74	62.29
MMF/Funding	7.559	8.26	0	77.541
NonInterest/Income	23.478	12.442	-41.632	65.493

Note: This table presents summary statistics for the systemic importance measure, SLGD, and other bank business model indicators. The SLGD measures the expected loss of customer deposits in the financial system given the distress of a particular bank in (log) million USD. The SLGD measure is calculated using data in the 2007-2010 period. The other variables are calculated at the end of 2006. The size refers to the total assets of a bank in (log) million USD. The Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. The loans to asset ratio is calculated as the gross loans of a bank divided by its total assets. The problem loans ratio is the total non-performing loans divided by the gross loans of the bank. The ROAA variable is the return on average assets. The Liquid Assets/STF is calculated at the amount of liquid assets a bank holds divided by the amount of short-term funding the bank has acquired. MMF/Funding is calculated as the total money market funding divided by total funding. NonInterest/Income is calculated as the amount of non-interest income as a ratio of total income.

Table 2: Correlation: Determinants of Systemic Importance (2006)

Variables	Size	Tier 1 Ratio	Loans/Assets	Problem/Loans	ROAA	Liquid/STF	MMF	NonInterest
Size	1.000							
Tier 1 Ratio	-0.089	1.000						
Loans/Assets	-0.270	-0.206	1.000					
Problem/Loans	0.005	0.039	-0.049	1.000				
ROAA	0.181	0.160	0.172	-0.284	1.000			
Liquid/STF	0.375	-0.045	-0.335	0.069	0.108	1.000		
MMF	0.359	0.104	-0.419	0.178	-0.055	0.227	1.000	
NonInterest	0.454	-0.051	-0.184	-0.172	0.174	0.237	0.137	1.000

Note: This table presents the correlation matrix among the potential determinants of systemic importance. The size refers to the total assets of a bank in (log) million USD. The Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. The loans to asset ratio is calculated as the gross loans of a bank divided by its total assets. The problem loans ratio is the total non-performing loans divided by the gross loans of the bank. The ROAA variable is the return on average assets. The Liquid Assets/STF is calculated at the amount of liquid assets a bank holds divided by the amount of short-term funding the bank has acquired. MMF/Funding is calculated as the total money market funding divided by total funding. NonInterest/Income is calculated as the amount of non-interest income as a ratio of total income.

Table 3: The Determinants of Systemic Importance: 2007-2010

	(1)	(2)	(3)	(4)	(5)	(6)
Size	0.914***	1.367***	1.366***	1.371***		
	(9.39)	(10.09)	(9.90)	(9.46)		
Size^2		-0.256***	-0.282***	-0.290***		
		(-6.07)	(-5.09)	(-5.52)		
Purified Size					0.389***	0.361***
					(9.03)	(8.59)
Tier 1 Ratio			-0.021	-0.018	-0.117**	-0.100*
			(-0.89)	(-0.77)	(-2.10)	(-1.82)
Loans/Assets			-0.009	-0.013	-0.167**	-0.151**
			(-0.86)	(-1.09)	(-2.32)	(-2.08)
Problem Loans/Loans			-0.307*	-0.236	-0.029	-0.073
			(-1.84)	(-1.36)	(-0.53)	(-1.17)
ROAA			-0.129	-0.155	0.070	0.081
			(-0.46)	(-0.56)	(0.95)	(1.07)
Liquid Assets/STF			0.013	0.014	-0.034	-0.018
			(0.67)	(0.76)	(-0.65)	(-0.33)
MMF/Funding				-0.019	0.043	0.066
				(-1.40)	(0.85)	(1.23)
NonInterest Income/Income				0.009	0.197***	
				(0.90)	(3.12)	
Trading/Income						-0.025
						(-0.67)
Fee and Commission/Income						0.166***
						(3.35)
Observations	311	311	311	311	311	311
R^2	0.222	0.280	0.294	0.302	0.246	0.235

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents the results of the OLS regressions, where the dependent variable is the SLGD measure calculated from 2007 to 2010. The SLGD measures the expected loss of customer deposits in the financial system given the distress of a particular bank in (log) million USD. The independent variables are calculated from 2006 year-end annual bank balance sheet data. The size refers to the total assets of a bank in (log) million USD. This variable is standardized, by its mean and standard deviation, and its quadratic form is also included. The variable Purified Size is calculated as the residual after regressing size against the other determinants. The Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. The loans to asset ratio is calculated as the gross loans of a bank divided by its total assets. The problem loans ratio is the total non-performing loans divided by the gross loans of the bank. The ROAA variable is the return on average assets. The Liquid Assets/STF is calculated at the amount of liquid assets a bank holds divided by the amount of short-term funding the bank has acquired. MMF/Funding is calculated as the total money market funding divided by total funding. NonInterest/Income is calculated as the amount of non-interest income as a ratio of total income. The last regression involves two variables representing trading income and fee and commission income both as a ratio of total income.

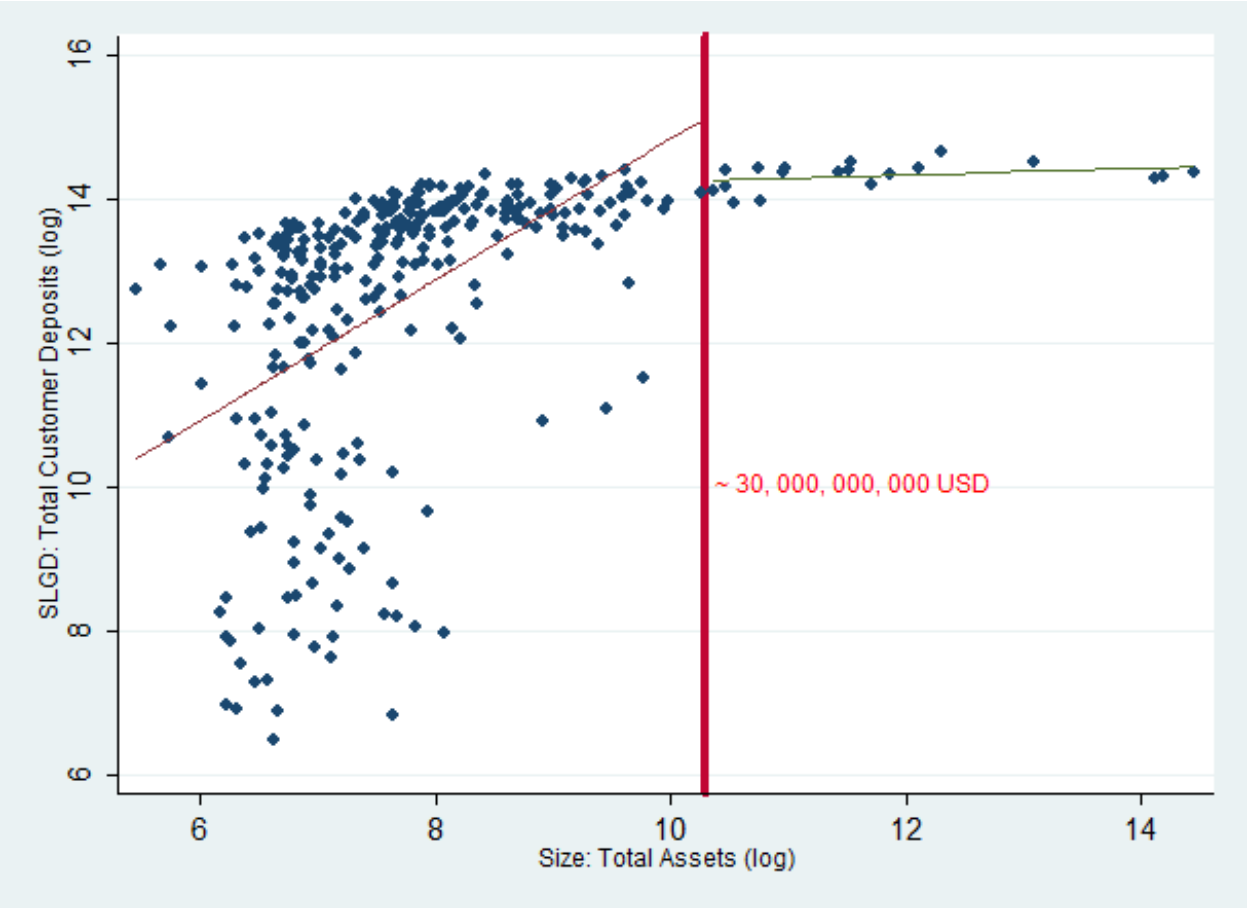

Figure 1: SLGD vs. Size: 2007-2010.
Note: The figure presents a scatter plot of the systemic importance of a bank, as measured by the logarithm of the SLGD, against the logarithm of the size of the bank (total assets in million USD). The SLGD measures the expected loss of customer deposits in the financial system given the distress of a particular bank. The vertical line indicates the estimated "breakpoint" in the regression above which the size-systemic importance relation is insignificant at the 95% confidence level.

Table 4: The Determinants of Systemic Importance: Panel Regression

	(1)	(2)	(3)	(4)	(5)	(6)
Size	0.403***	0.620***	0.610***	0.616***		
	(9.19)	(8.74)	(8.45)	(7.64)		
Size^2		-0.311***	-0.323***	-0.324***		
		(-4.85)	(-3.99)	(-4.07)		
Purified Size					0.218***	0.162***
					(6.37)	(4.87)
Tier 1 Ratio			0.065	0.065	0.040	0.037
			(1.54)	(1.55)	(0.80)	(0.77)
Loans/Assets			0.088*	0.080	0.108*	0.105*
			(1.85)	(1.51)	(1.85)	(1.86)
Problem Loans/Loans			-0.029	-0.026	0.011	-0.043
			(-0.83)	(-0.70)	(0.42)	(-1.20)
ROAA			0.072**	0.071**	0.140***	0.167***
			(2.60)	(2.42)	(3.21)	(4.96)
Liquid Assets/STF			0.052	0.048	0.006	-0.002
			(1.19)	(1.08)	(0.17)	(-0.06)
MMF/Funding				-0.021	0.150***	0.162***
				(-0.47)	(4.17)	(4.68)
NonInterest Income/Income				0.008	0.135***	
				(0.25)	(3.46)	
Trading/Income						-0.021
						(-0.72)
Fee and Commission/Income						0.158***
						(4.07)
Observations	1125	1125	1125	1125	1125	1125
R^2	0.492	0.542	0.557	0.557	0.459	0.464

Standardized beta coefficients; t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents coefficient estimates from a panel data regression using time fixed effects and clustering at the bank level. The dependent variable is the SLGD measure of systemic importance measured using a four-year rolling window from 2000 to 2010. The SLGD measures the expected loss of customer deposits in the financial system given the distress of a particular bank in (log) million USD. The independent variables are calculated from 2006 year-end annual bank balance sheet data. The size refers to the total assets of a bank in (log) million USD. This variable is standardized, by its mean and standard deviation, and its quadratic form is also included. The variable Purified Size is calculated as the residual after regressing size against the other determinants. The Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. The loans to asset ratio is calculated as the gross loans of a bank divided by its total assets. The problem loans ratio is the total non-performing loans divided by the gross loans of the bank. The ROAA variable is the return on average assets. The Liquid Assets/STF is calculated at the amount of liquid assets a bank holds divided by the amount of short-term funding the bank has acquired. MMF/Funding is calculated as the total money market funding divided by total funding. NonInterest/Income is calculated as the amount of non-interest income as a ratio of total income. The last regression involves two variables representing trading income and fee and commission income both as a ratio of total income.

Table 5: Summary statistics: SLGD (2000-2010) and potential determinants

Variable	Mean	Std. Dev.	Min.	Max.	N
SLGD	12.491	1.898	6.758	14.223	143
Size	8.129	1.774	4.758	14.449	143
Tier1 Ratio	11.38	3.634	0	27.2	143
Loans/ Assets	67.921	11.667	27.711	87.762	143
Problem Loans/ Loans	0.538	0.489	0	2.405	143
ROAA	1.084	0.475	-1.64	2.68	143
Liquid Assets / STF	6.484	7.503	0.99	62.29	143
MMF / Funding	8.386	8.321	0	66.767	143
NonInterest / Income	27.098	12.168	6.151	65.493	143

Note: This table presents summary statistics for the systemic importance measure, SLGD, and other bank business model indicators. The SLGD measures the expected loss of customer deposits in the financial system given the distress of a particular bank in (log) million USD. The SLGD measure is calculated using data in the 2007-2010 period. The other variables are calculated at the end of 2006. The size refers to the total assets of a bank in (log) million USD. The Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. The loans to asset ratio is calculated as the gross loans of a bank divided by its total assets. The problem loans ratio is the total non-performing loans divided by the gross loans of the bank. The ROAA variable is the return on average assets. The Liquid Assets/STF is calculated at the amount of liquid assets a bank holds divided by the amount of short-term funding the bank has acquired. MMF/Funding is calculated as the total money market funding divided by total funding. NonInterest/Income is calculated as the amount of non-interest income as a ratio of total income.

Table 6: The Determinants of Systemic Importance: 2000-2010

	(1) 1999	(2) 2000	(3) 2001	(4) 2002	(5) 2003	(6) 2004	(7) 2005	(8) 2006
Purified Size	0.371***	0.492***	0.462***	0.242***	0.256***	0.186***	0.049	-0.026
	(5.79)	(6.14)	(6.19)	(3.14)	(3.31)	(3.03)	(0.69)	(-0.45)
Tier 1 Ratio	0.143	0.132	0.075	0.085	-0.030	0.130	-0.222*	-0.183*
	(1.46)	(1.38)	(0.81)	(0.80)	(-0.31)	(1.10)	(-1.96)	(-1.67)
Loans/Assets	0.046	0.141	0.166*	0.162	0.153	0.034	0.035	0.018
	(0.48)	(1.34)	(1.75)	(1.50)	(1.41)	(0.36)	(0.25)	(0.13)
Problem Loans/Loans	-0.065	0.015	0.098	0.194	-0.096	0.010	0.076	-0.012
	(-0.80)	(0.23)	(1.17)	(1.11)	(-1.52)	(0.11)	(1.22)	(-0.16)
ROAA	0.008	0.195**	0.179**	0.498***	0.243***	0.145*	0.164*	0.193**
	(0.09)	(1.99)	(2.38)	(3.02)	(4.05)	(1.89)	(1.66)	(2.14)
Liquid Assets/ STF	0.010	0.021	0.085	0.116	0.017	-0.065	-0.032	-0.068
	(0.14)	(0.29)	(1.08)	(0.98)	(0.22)	(-0.81)	(-0.47)	(-0.83)
MMF/Funding	0.275***	0.329***	0.109	0.034	0.165**	0.106*	0.189**	0.185**
	(3.37)	(4.16)	(1.44)	(0.43)	(2.57)	(1.77)	(2.30)	(2.21)
NonInterest Income/Income	0.247***	0.090	0.175**	0.043	0.178**	0.227***	0.170**	0.226**
	(3.34)	(1.00)	(2.06)	(0.33)	(2.48)	(2.83)	(2.32)	(2.14)
Observations	142	139	139	136	142	142	142	143
R^2	0.303	0.343	0.329	0.210	0.269	0.152	0.183	0.203

Standardized beta coefficients; t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents coefficient estimates from a series of cross-sectional panel regressions over eight periods. The dependent variable is the SLGD measure of systemic importance measured using a four-year rolling window from 2000 to 2010. The SLGD measures the expected loss of customer deposits in the financial system given the distress of a particular bank in (log) million USD. The independent variables are calculated from 2006 year-end annual bank balance sheet data. The size refers to the total assets of a bank in (log) million USD. This variable is standardized, by its mean and standard deviation, and its quadratic form is also included. The variable Purified Size is calculated as the residual after regressing size against the other determinants. The Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. The loans to asset ratio is calculated as the gross loans of a bank divided by its total assets. The problem loans ratio is the total non-performing loans divided by the gross loans of the bank. The ROAA variable is the return on average assets. The Liquid Assets/STF is calculated at the amount of liquid assets a bank holds divided by the amount of short-term funding the bank has acquired. MMF/Funding is calculated as the total money market funding divided by total funding. NonInterest/Income is calculated as the amount of non-interest income as a ratio of total income. The last regression involves two variables representing trading income and fee and commission income both as a ratio of total income.

Table 7: The Determinants of Bank Individual Risk: Panel Regression

	(1)	(2)	(3)	(4)
Size	-0.274***			
	(-5.38)			
Purified Size		-0.222***	-0.221***	-0.167***
		(-6.98)	(-6.78)	(-4.45)
Tier 1 Ratio		-0.271***	-0.293***	-0.285***
		(-5.14)	(-5.77)	(-5.66)
Loans/Assets		-0.112**	-0.142**	-0.139**
		(-1.98)	(-2.44)	(-2.46)
Problem Loans/Loans		-0.003	-0.032	0.041
		(-0.09)	(-0.77)	(0.82)
ROAA		-0.055*	-0.007	-0.046
		(-1.68)	(-0.21)	(-1.22)
Liquid Assets/STF		-0.035	0.008	0.004
		(-0.65)	(0.16)	(0.07)
MMF/Funding			-0.059	-0.078*
			(-1.39)	(-1.97)
NonInterest Income/Income			-0.158***	
			(-3.56)	
Trading/Income				0.045
				(1.37)
Fee and Commission/Income				-0.150***
				(-3.42)
Observations	1144	1144	1144	1144
R^2	0.075	0.116	0.142	0.141

Standardized beta coefficients; t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents coefficient estimates from a panel data regression using time fixed effects and clustering at the bank level. The dependent variable is the Expected Shortfall on equity returns. This measure of individual bank risk is calculated using a four-year rolling window from 2000 to 2010. The independent variables are calculated from year-end annual bank balance sheet data from 1999 to 2006. The size refers to the total assets of a bank in (log) million USD. This variable is standardized, by its mean and standard deviation, and its quadratic form is also included. The variable Purified Size is calculated as the residual after regressing size against the other determinants. The Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. The loans to asset ratio is calculated as the gross loans of a bank divided by its total assets. The problem loans ratio is the total non-performing loans divided by the gross loans of the bank. The ROAA variable is the return on average assets. The Liquid Assets/STF is calculated at the amount of liquid assets a bank holds divided by the amount of short-term funding the bank has acquired. MMF/Funding is calculated as the total money market funding divided by total funding. NonInterest/Income is calculated as the amount of non-interest income as a ratio of total income. The last regression involves two variables representing trading income and fee and commission income both as a ratio of total income.