THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

ESRC ECONOMIC & SOCIAL RESEARCH COUNCIL

The Determinants of Systemic Importance

Kyle Moore
Chen Zhou

SRC Discussion Paper No 19

August 2014

Systemic Risk Centre

Discussion Paper Series

ISSN 2054-538X

Abstract
This paper empirically analyses the determinants of banks' systemic importance. With applying a novel measure on the systemic importance to US bank holding companies in 2000–2010, we show that size is an important determinant of systemic importance, but banks with size above a certain threshold have equal systemic importance. On top of size, engaging heavily in non-traditional banking activities, such as relying on money market fund and generating non-interest income, is also related to high 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 risk, extreme value theory

JEL classification: G01, G21, G28

This paper is published as part of the Systemic Risk Centre's Discussion Paper Series. The support of the Economic and Social Research Council (ESRC) in funding the SRC is gratefully acknowledged [grant number ES/K002309/1].

Kyle Moore, Research Officer, Systemic Risk Centre, London School of Economics
Chen Zhou, Economics and Research Division, De Nederlandsche Bank, and Erasmus School of Economics, Erasmus University Rotterdam

Published by
Systemic Risk Centre
The London School of Economics and Political Science
Houghton Street
London WC2A 2AE

Determinants of systemic importance

Kyle Moore[*†]

Systemic Risk Centre
London School of Economics

Chen Zhou[‡]

De Nederlandsche Bank and Erasmus University Rotterdam

July 31, 2014

Abstract This paper empirically analyzes the determinants of banks' systemic importance. With applying a novel measure on the systemic importance to US bank holding companies in 2000–2010, we show that size is an important determinant of systemic importance, but banks with size above a certain threshold have equal systemic importance. On top of size, engaging heavily in non-traditional banking activities, such as relying on money market fund and generating non-interest income, is also related to high 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 risk, extreme value theory

JEL Classification Numbers: G01, G21, G28

[*]The research of Kyle Moore has received funding from the European Community's Seventh Framework Programme FP7-PEOPLE-ITN-2008. The funding is gratefully acknowledged. The support of the Economic and Social Research Council (ESRC) in funding the SRC is gratefully acknowledged [grant number ES/K002309/1]. We are also grateful for the research assistance provided by Lin Zhao. Views expressed do not necessarily reflect official positions of De Nederlandsche Bank.

[†]Email: k.t.moore@lse.ac.uk

[‡]Email: c.zhou@dnb.nl, zhou@ese.eur.nl

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 at the onset of this crisis. The intervention activities lead to debates in support and objection of rescuing certain distressed financial institutions. Arguments in favour 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 is lacking 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.

We distinguish the concept of *systemic importance* from *systemic risk*. 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, a financial institution may contribute to the

[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*".

system-wide risk through their *individual riskiness* and through the potential of their own distress to inflict losses to other banks in the financial system. It is here that we delineate our separation of systemic risk from systemic importance. Our definition of the term systemic importance refers to the impact of a single bank's distress or failure to the *rest of the system*, excluding the likelihood or impact of the failure itself. 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]

With the definition of systemic importance, the TBTF refers to a positive relation between size and systemic importance. It can be supported by theoretical arguments on diversification. 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; see e.g. Wagner (2010) and Ibragimov et al. (2011). In addition, there is empirical evidence that large banks implement superior diversification strategies, see, e.g. Demsetz and Strahan (1997). Therefore, larger banks may be more systemically important due to diversification. Similarly, the diversification argument can be well applied to explain why other bank characteristics can be potentially associated with systemic importance. We consider two type of activities in this paper.

First, we argue that banking activities generating non-interest income may be associated with systemic importance. With financial innovation, financial institutions have the opportunity to participate in non-interest profit generating processes, such as securitization and derivatives trading. Such banking activities increase diversification by permitting access to different markets. As average levels of diversification rise across the financial system, banks engaging in these activities will hold increasingly similar positions. Consequently, this enhances the possibility that financial institutions will suffer from common shocks to the asset side of their balance sheets. This is in accordance with the so-called indirect linkages in the systemic risk literature, see, e.g. de Vries (2005)

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

and Acharya (2009). Therefore, banks that participate in non-interest profit generating activities have the potential to be more systemically important.

Second, increased reliance on non-core funding channels such as the money market may be associated with greater systemic importance. Traditional funding sources such as retail deposits are localized and are therefore subject to regional idiosyncratic shocks or runs, see, e.g., Diamond and Dybvig (1983). In order to mitigate such risks, banks form funding relationships with other banks through the interbank lending market. These relationships can be viewed as liability claims as insurance against uncorrelated idiosyncratic liquidity shocks.[4] However, such interbank relationships may not be able to insure against systemic shocks (Allen and Gale (2000)), and may on the contrary expose the system to possible contagion, see, e.g. Gai and Kapadia (2010). In other words, the distress of one bank leads to successive distress of other institutions, see, e.g. Brunnermeier and Pedersen (2009), Allen and Carletti (2008). Therefore, banks that are more exposed to the interbank market are potentially more systemically important.

To summarize, if the diversification argument supports the statement of "TBTF", it may also support the statement that engaging in non-interest profit generating activities and accessing interbank funding may be associated with systemic importance. These activities can be regarded as alternative methods for diversifying asset side or funding side risk. In contrast, banking activities that generate interest income or rely on retail funding sources fall into the category of specialized banking. Although engaging in specialized activities may lead to higher individual risk, such banks are less linked to the rest of the system, and are consequently less systemically important.

We label the banking activities enhancing diversification as *non-traditional* banking activities and predict that non-traditional banking activities are associated with high systemic importance. In other words, instead of being TBTF, banks may well be "Too non-traditional to fail" (TNTTF). Based on these theoretical arguments, this paper is

[4]When individual banks face privately observed liquidity shocks that are imperfectly correlated across financial institutions, these same institutions find it optimal to co-insure each other through an interbank exchange of liquidity in the form of deposits (Freixas et al. (2000)). Therefore, during benign states of the economy, the interbank payment apparatus serves to stabilize the financial system by providing and transferring liquidity across financial institutions (Goodfriend and King (1988)).

devoted to test the TBTF and TNTTF notions. More specifically, we test whether large bank size or high levels of engagement in non-interest income generating and non-traditional funding are associated with higher levels of systemic importance.

For our empirical purpose, we construct a measure on banks' systemic importance based on its theoretical interpretation. More specifically, our systemic importance measure is defined as the expected loss to the financial system given that one institution has failed. Thus, we refer to our measure as the "expected systemic loss" (ESL). 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 give insight on the potential social welfare effects of a particular bank failure without reflecting the likelihood or impact of the failure of the underlying bank.

Comparing with existing measures on systemic risk of financial institutions,[5] our measure differs in at least three aspects. First, we do not attempt to measure the system-wide risk on an aggregate level. Rather, we implement a firm-level measure in order to analyze cross-sectional differences in systemic importance. Essentially, our measure is neither a measure of current system-wide risk nor a predictor of future crisis. It serves solely as an indicator of the relative importance of each institution. Second, our measure focuses on systemic importance which does not contain information on the individual riskiness of the underlying institution. This reflects the concept of systemic importance as aforementioned. As such, the measure does not intend to be additive towards an overall level of system-wide risk. Our measure is thus distinguished from measures on systemic risk contribution.[6] Third, we implement a multivariate extreme value theory (EVT) approach in estimating our proposed measure. Multivariate EVT, as a modern statistical tool for handling tail events, has been employed for systemic risk evaluation, see, e.g. Hartmann et al. (2007) and Zhou (2010).

[5]For measures on systemic risk, various prominent candidates are present in the literature, see, e.g. Adrian and Brunnermeier (2011), Acharya et al. (2010), Segoviano and Goodhart (2009), Huang et al. (2012), and Brownlees and Engle (2012).

[6]Additivity is a usual requirement for measures on systemic risk contribution; see e.g. Tarashev et al. (2010).

Our first major finding is that size, to a large extent, is able to differentiate systemic importance. Nevertheless, banks' systemic importance is increasing in size only up to a certain limit. For US banks during the crisis period (2007–2010) large banks are more systemically important (i.e., TBTF holds), but only for banks with total assets below 100 billion USD. The systemic importance of banks with total assets exceeding this threshold are indifferent.[7] Hence, differentiating the systemic importance of banks by only analyzing size is not sufficient for large US banks. It is thus 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 non-core funding to fund its projects and the amount of non-interest income generating activities. On the time dimension, our analysis on a selection of US banks over a decade long period shows that the determinants of systemic importance vary over time.

Lastly, we provide evidence that bank activities that serve to differentiate systemic importance have an opposite effect on banks' individual riskiness. Specifically, banks that search out traditional sources of funding and income generating activities, generally have a higher individual risk with a lower systemic importance. This evidence support the diversification explanation on why banks engaging in non-traditional banking activities are associated with high systemic importance.

The paper proceeds as follows. We discuss our measure of systemic importance in Section 2. Section 3 describes data and our empirical strategy. The empirical results are reported in Section 4. Section 5 compares the determinants of systemic importance with that of individual risk. Section 6 presents the results on several robustness checks. Section 7 concludes the paper and provides a discussion on possible policy implications.

[7] According to the Statistical Releases of the Board of Governors of the Federal Reserve System, 19 US commercial banks had total assets exceeding 100 billion USD as of June 30, 2013.

2 Measuring Systemic Importance

We propose a measure on systemic importance which reflects the economic impact given the failure of a specific bank. We illustrate this idea by first recalling the expected loss in a single bank context. The expected loss (EL) of a bank given its default is measured as

$$EL = PD \cdot LGD \cdot EAD,$$

where PD is the probability of default, EAD is the exposure at default, and LGD is the loss given default, measured as the fraction of loss to EAD. The EL is used by regulators to estimate the credit risk of a bank over a specific period (usually one-year). Analogously, we intend to estimate the expected loss to the system (ESL) given the failure of bank i as

$$ESL_i = E(\text{Loss in other banks}|D_i),$$

where D_i indicates the default of bank i. More specifically, with denoting the loss to bank j as L_j, we have that

$$ESL_i = \sum_{j \neq i} E(L_j|D_i) = \sum_{j \neq i} \Pr(D_j|D_i) \cdot LGD_j \cdot EAD_j. \tag{2.1}$$

Here we assume that LGD_j is independent of the failure event D_i. We further assume that the LGD_j is constant across all banks in our sample. Therefore, for a cross-sectional comparison, we can assume $LGD_j = 1$ without loss of generality.

A direct estimation of the probability of joint failure is difficult due to the scarcity of actual "bank failures". We resolve this issue by applying multivariate EVT. Instead of estimating the conditional probability of joint failures, the EVT approach proxies that by estimating conditional probability of joint bank *distresses*. The fundamental idea behind multivariate EVT is that the dependence across extremely rare events can be represented by observed data in the tail of the distribution; see e.g. De Haan and Ferreira (2006, Chapter 6) for an overview of multivariate EVT. In this way, the conditional probability of joint default can be approximated by the conditional probability of joint distress.

We describe a distress event as occurring when 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, we analyze the co-movement of distress events in equity prices, which 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.[8] In other words, a tail event for bank i with probability p occurs if of X_i falls below the Value-at-Risk (VaR) of the bank defined by $\Pr(X_i < -VaR_i(p)) = p$. Although 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 identical. 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.

With assuming $LGD_j = 1$ and using $X_i < -VaR_i(p)$ to represent the distress event, we rewrite (2.1) as

$$ESL_i = \sum_{j \neq i} EAD_j \cdot \Pr(X_j < -VaR_j(p) | X_i < -VaR_i(p)). \tag{2.2}$$

Lastly, we use the amount of total custom deposits to proxy the EAD measure. This choice deviates from the usual practice in the literature, i.e. using bank's total liabilities,[9] because we intend to capture the social welfare loss given bank defaults. 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. If the authority decides, following the

[8]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.

[9]As a robustness check in Section 6.2, we do use total liabilities of each bank to proxy the EAD measure. In this way, we measure the expected loss to the system given a bank failure in terms of loss on all deposits, not just those insured by the central authority. The results remain qualitatively unchanged.

failure of a bank, not to provide any bailout to the other banks that fail in conjunction, they are responsible for the insured customer deposits held by the other failed banks. Without having a large cross-section of data on the size of insured deposits held by banks, we assume that the fraction of insured deposits against total customer deposits is comparable across banks. With this assumption, for a cross-sectional comparison on the ESL, we can thus use the amount of total customer deposits as the proxy of the EAD measure without loss of generality.

Different from the emerging literature on measuring systemic risk, few studies have focused solely on the systemic importance. Tarashev et al. (2010) explore a systemic importance measure with utilizing the concept of the Shapley value in game theory. Drehmann and Tarashev (2013) apply this measure to empirically assess systemic importance of individual institutions. The potential downside of the Shapley value approach is that it requires a large amount of computational effort which puts a burden on its empirical application to a large financial system. Another measure of systemic importance related to this study is the Systemic Impact Index (SII) in Zhou (2010). In fact, our proposed ESL measure can be considered as a generalization of this simple counting measure. Differently, we further account for the economic impact to the system given the failure of one single institution.

3 Data and Methodology

3.1 Estimating the ESL

The key element in estimating the ESL 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 2000 to 2010 are collected from Datastream.[10] We follow Hartmann et al. (2007) to estimate such the conditional probability by applying multivariate extreme value statistics.

Multivariate extreme value statistics improves upon existing methodology in the fol-

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

lowing way. Firstly, most existing measure of systemic risk use a statistical methodology that assumes multivariate normality. In contrast, there is a great deal of empirical evidence to suggest that financial data follow a fat-tailed distribution; see, e.g. Mandelbrot (1963). Therefore, methodologies incorporating a normality assumption tend to underestimate the probability of extreme events. Secondly, the multivariate normal distribution is known to exhibit tail independence, see, e.g. Sibuya (1959), while financial data have non-negligible tail dependence. Lastly, since systemic risk or systemic importance is about tail events, only the tail region should be considered in the estimation. Fitting data to a full parametric distribution usually results in estimates which are determined by moderate level data. Such an estimated distribution may not represent the tail co-movements. To conclude, the applying multivariate extreme value statistics allows for both heavy-tails and tail dependence, and it focuses on the observations in the tail region only while ignoring the observations at the moderate level.[11]

The maintained assumption in our multivariate EVT approach is that the limit of the conditional probability of joint distress exists, i.e. as $p \to 0$,

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

Thus, the conditional probability of joint distress 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 an intermediate sequence $k := k(n)$ 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

$$\hat{\tau}_{i,j} := \frac{1}{k} \sum_{s=1}^{n} 1_{X_{j,s} < X_{j,(n-k)}, X_{i,s} < X_{i,(n-k)}}, \tag{3.1}$$

[11] 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. 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.

where $X_{i,(n-k)}$ is the $(k+1)$th lowest return among $X_{i,1}, \ldots, X_{i,n}$.[12]

In estimating a similar conditional probability 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 is partially due to common systematic risk factors, such as the market factor. Although the systematic risk might be a source of systemic risk, we aim to measure the systemic link across banks in other channels. Therefore, using the raw returns to estimate the conditional probability may result in an upward bias.

We choose to remove the common systematic risk factors and analyze the co-movements of idiosyncratic returns. In this way, we look the potential for banks to simultaneously face distresses in the absence of large macroeconomic fluctuations. In assuming a parsimonious single market factor model, we calculate the residual equity returns over the market return[13] by estimating a single-factor market model in each estimation period as

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

where the error terms, $\epsilon_{i,s}$, are assumed to follow the standard assumptions of an Ordinary Least Squared (OLS) regression. The excess returns are then calculated from

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

We use the estimated excess returns $(\hat{\epsilon}_{i,s}, \hat{\epsilon}_{j,s})$ instead of raw returns as the dataset on $(X_{i,s}, X_{j,s})$ in the estimation of the conditional probabilities.[14]

A remaining technical issue in the estimation is the choice of the intermediate sequence k in (3.1). 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

[12] For the estimator of $\tau_{i,j}$, usual statistical properties, such as consistency and asymptotic normality, has been proved under mild conditions, see, e.g. De Haan and Ferreira (2006, Chapter 7).

[13] The market returns for the period 2000–2010 refers to the returns of the S&P 500 index.

[14] In Section 6.1, we run a robustness analysis using raw returns in our calculations. The results do not change qualitatively.

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 ratio k/n constant across different samples at a level of 3%.

The estimation of the conditional probability following (3.1) always yields a positive value even if the actual $\tau_{i,j}$ is equal to zero. This is a potential estimation bias. Ledford and Tawn (1997) provide a method to distinguish tail dependence ($\tau > 0$) from tail independence ($\tau = 0$). Bosma et al. (2012) apply a bootstrapping technique to distinguish between these two possibilities. For simplicity, we arbitrarily impose a cutoff value of 0.10 in the estimation, such that values of the estimated τ below the cutoff level are set to zero, in order to avoid the potential positive bias in the estimation of τ.

We estimate the conditional probability of joint distress in estimation windows consisting of daily observations for four years. The choice of having a four year period for our analysis is to ensure a sufficient number of observations for applying the multivariate extreme value statistics. Correspondingly, we use average total customer deposits over the same period as the EAD measure. For that purpose, we collect annual balance sheet data for each bank from the Bankscope database in 2000–2010.[15] With all the estimated components, the ESL measure for each bank is then calculated according to (2.2).

3.2 Analyzing Potential Determinants

To analyze the potential determinants of systemic importance, we collect bank balance sheet data in 1999–2006, construct indicators reflecting bank business models and perform

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

a cross-sectional regression analysis between the ESL measure and the indicators.

First, the size of a bank is measured by 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.[16]

Second, to measure non-traditional banking activities, we consider the following variables: money market funding as a ratio of total funding and non-interest income as a ratio of total income. The latter is further decomposed into two variables representing trading income and fee and commission income both as a ratio of total income.

Lastly, five control variables based on the CAMEL rating system[17] are constructed:

- **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 (RoAA)
- **L**iquidity: Liquid Assets/ Short-term Funding

We conduct our regression analysis in two ways. First, we analyse only the period between 2007 and 2010 which encapsulates the financial crisis. We filter out any institution that is not actively traded (i.e. a zero return) on at least 80% of the days within this period. We match the estimated ESL 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 ESL measure in time, our regression analysis has a "forward-looking" flavor. This allows analyzing the relation between the business model of a bank before the financial crisis and its systemic importance during the crisis.

[16]In order to avoid a potential multi-collinearity issue, the size is first standardized by its cross-sectional mean and standard deviation at end of each year and then squared.

[17]The acronym "CAMEL" refers to five components used in order to assess the overall condition and supervisory rating of a bank. Hirtle and Lopez (1999) find that past CAMEL ratings contain useful information on the future performance and condition of a bank.

Second, in order to see whether the drivers of systemic importance stand over a longer time horizon, we extend our analysis to cover a decade long period from 2000 to 2010. Under this approach, the ESL measure is estimated in the each four-year window that is rolled forward year by year in the sample, i.e. the ESL measures are estimated for the periods 2000–2003, 2001–2004, ..., 2007–2010. We remove any bank that was not traded on at least 90% of the days covering the whole period 2000–2010 and did not have end-of-year balance sheet data from 1999 to 2006. This filtering process results in a panel data set consisting of 143 banks over eight estimation periods. With the 1125 firm-period observations in total, we perform a panel regression with time fixed effects while the stardard error is calculated with clustering at the bank level.[18]

4 Empirical Results

4.1 Results in the Financial Crisis Period: 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 ESL and the potential determinants in this period. Table 2 shows the correlation among the potential determinants.

Table 3 reports our OLS regression results. The first regression (column 1) only contains one independent variable: size. 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 its quadratic form. 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 ESL and size is non-linear.

In order to have a better insight on the non-linearity, we further analyse the quadratic

[18] In the robustness check in Section 6.3, we split the panel data set to perform eight separate OLS regressions in each period. This allows us to check how the determinants have emerged over this decade.

relation between ESL and the size of a bank as

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

By taking the first-order derivative, we get that $\frac{\partial ESL}{\partial Size} = 2aSize + b$. Hence, for $Size = -\frac{b}{2a}$, the partial derivative turns to be zero. In other words, the ESL 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 $Size = 11.5$.[19]

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 ESL of banks increase with respect to the size up to a certain size threshold only. For large banks with $Size \geq 11.5$ the TBTF principle does not hold. Quantitatively, the threshold 11.5 corresponds to a total asset at roughly 100 billion USD. Since the cutoff point is rather close to the maximum size in the sample, the quadratic relation, in fact, would be better characterized as a "kink" relation as shown in Figure 1.[20]

In summary, our empirical analysis confirms that large banks are systemically important, but only up to a certain size level. 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 notion.

We further include other control variables, i.e. the CAMEL ratios, to the regression alongside $Size$. The regression results on $Size$ and its quadratic term remain unchanged in this regression and the regressions below including variables representing non-traditional banking activities. Hence, the non-linear size-systemic importance relation is rather robust.

[19]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 $\sigma Size + \mu$.

[20]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 11.5 cutoff point found. We again partition the sample into two groups at the breakpoint predicted by the threshold test at $Size = 9.4$. In this case we find that for $Size < 9.4$ a significantly positive relation exists, and for banks with $Size \geq 9.4$ a positive and significant relation also exists, albeit with a less steep upward curve.

To test the TNTTF notion, we perform regressions with the variables on money market funding and non-interest income generating activities. The initial result is shown in column 4. None of the variables on non-traditional banking are significant at the 90% confidence level. We attribute this result to a potential multicollinearity problem. When considering both size and other variables indicating a bank's business model, size is related to other variables in the regression. If the strategies and activities a bank chooses to undertake have direct impact on how large the bank becomes, the bank size will be correlated 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. 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 indicate their actual contribution to systemic importance, though the contribution is potentially via a corresponding large size. The result is shown in column 5.

Firstly, we observe that 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. 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.

Secondly, we find the money market funding variable to be positive, yet insignificant at the 90% confidence level. The fact that we did not observe a significant result on the money market funding variable is potentially due to the inactivity in the interbank payment system during the financial crisis. A key feature of the global financial crisis, and in fact, a major contributor to the instability, was the inactivity in the interbank markets. The money market funds during this time were essentially "frozen". As a result, how banks rely on the money market funds may not be sufficiently differentiated in the cross-section. Thus, it may not help to differentiate systemic importance in the cross-section. We overcome this drawback by including the period preceding the onset of the crisis in the panel regressions.

Lastly, among the CAMEL ratios, the amount of Tier 1 capital a bank holds in relation to its risk-weighted assets and total loans as a fraction of assets both negatively associate to a bank's systemic importance. Hence, 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 systemically important during the crisis.

In summary, we have evidence that SIFIs, in addition to being TBTF, also have the potential of being TNTTF. Here non-traditionality refers to relying heavily on non-interest income generating activities in the form of fee and commission income. In contrast, a bank operating in a more traditional manner, such as maintaining a healthy capital buffer and engaging in loan issuing activities, corresponds to a lower level of systemic importance.

4.2 Panel Regression Results: 2000–2010

We extend our sample of data to a larger horizon starting from the beginning of 200 to the end of 2010. The dataset include eight panels due to the eight overlapping estimation windows. Table 7 provides descriptive statistics of the ESL estimated in the eight estimation windows and the potential determinants preceding to these estimation windows.

The results of the panel regression across the eight panels are shown in Table 5. 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. A key difference in the panel regression results is that the coefficient on the money market funding variable is now also significant and positive at the 99% confidence level. This result shows that the non-traditional activities that determine bank's systemic importance also include how much banks rely on non-traditional funding sources.

5 Determinants of Individual Risk: A Comparison

The empirical findings in Section 4 shows that size and non-traditional banking activities are associated to systemic importance, i.e. TBTF and TNTTF hold. Theoretically these notations are supported by the diversification argument, see Section 1. Besides increasing systemic importance, a high level of diversification should also leads to low level of individual risks. Therefore, we expect that all determinants of systemic importance should have an opposite impact on banks' individual risk. To further support the theoretical foundation on TBTF and TNNTF, we test how bank business indicators considered in Section 4 are associated with a measure of individual risk in the cross-section of banks.

The individual risk of a bank is measured from the same equity price data that we used in the construction of the ESL 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, i.e.

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

Here, the parameters α_i is the so-called tail index. From such a parametric expansion of the tail distribution, Danielsson (2011) provides a derivation to show that if $\alpha_i > 1$

$$ES_i(p) := -E(X_i|X_i < -VaR_i(p)) \sim \frac{\alpha_i}{\alpha_i - 1} VaR_i(p)$$

Conceptually, the individual risk and the systemic importance are two separate components in the systemic risk of a financial institution. We maintain this conceptual distinction in the construction of the corresponding measures: the ES measure on bank i is solely calculated from information on bank i, whereas the ESL of bank i uses only the conditional probability of bank j's failure given the failure of bank i, with no information on the individual risk of bank i.

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 tail index α_i is estimated by the Hill estimator from; see Hill (1975). 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

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

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 for each bank.

Similar to the analysis in Section 4.2, we run a panel regression by regressing the ES estimates in eight overlapping estimation windows against the bank business model indicators using time fixed effects. Table 6 reports the results. First, in the regression with only size, the coefficient on $Size$ is negative and significant at the 99% confidence level (column 1). For the other regressions including the CAMEL ratios and the variables on non-traditional banking, we use the purified size variable to avoid potential multicollinearity. In the regression including the non-interest income variable, its coefficient is negative and significant at the 99% confidence level (column 3). By decomposing this variable into trading income and fee and commission income (column 4), we find that the coefficient on fee and commission income variable is negative and significant at the

99% confidence level while that for trading income is insignificant. In the last column, we also find that the coefficient on money market funding is negative and significant at the 90% confidence level. All these findings provide evidence that being large or engaging in non-traditional banking reduces the individual risk a bank faces.

In addition, among the CAMEL ratios, the coefficients on Tier 1 capital and loans as a fraction of total assets are negative and significant at the 99% and 95% confidence levels, respectively. The coefficient on ROAA 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 and banks that engage mainly in loan issuance are less risky. The latter might be a potential consequence of the fact that our dataset cover the period of the housing bubble, during which traditional loan activity was considered less risky by the market.

To summarize, we find that, size and non-traditional banking have an opposite impact on the individual risk of a bank, compared to that on systemic importance. The same applies to other indicators on CAMEL ratios. These results provide indirect support on the diversification theory behind the TBTF and TNTTF notation.

6 Robustness of Results

6.1 Excess Returns vesus Raw Returns

In our main results, we estimate the ESL measure using excess returns net of the market risk factor. Recall that the motivation is to avoid measuring systematic co-movement of equity returns due to the systematic market risk. Nevertheless, the systematic market risk could well be a reason for systemic risk. In order to alleviate such a concern, we reconstruct our ESL measures using the raw equity returns and preform the equivalent analysis as in Section 4.1 (in the 2007–2010 period). The results is shown in Table 7.

Comparing Table 3 with Table 7 we do not find important qualitative difference in the results. The regression coefficients and significance on the size variables do not exhibit any qualitative deviations. The same applies to the CAMEL ratios. As an exception, in column 5, we find that the negative coefficient on the Tier 1 ratio variable in the original results is no longer significant. Furthermore, the coefficient on RoAA is positive and significantly related to the ESL in this analysis at the 90% significance level.

When analyzing the variables on non-traditional banking activities, the only difference is that the positive coefficient on the non-interest to income ratio variable is no longer significant. However, when we decompose non-interest income into two variables on trading income and fee and commission income, we find that the positive coefficient on the fee and commission to income ratio variable remains significant at the 99% confidence level.

In summary, our qualitative conclusion do not depend on using raw or excess returns in the calculation of the ESL measures.

6.2 Alternative proxy of EAD: Total Liabilities

We check the robustness of our results using an alternative proxy of EAD, total liability of banks. We recalculate the ESL measures with the EAD measured by bank total liabilities. Furthermore, to check the interaction with the raw return issue raised in Section 6.1, we calculate the ESL measure using both raw and excess returns with EAD measured by bank total liabilities. We conduct regressions over the 2007–2010 period as in Section 4.1 based on all these new ESL measures.

The results can be found in Tables 8 and 9. Comparing with our original results in Table 3, the only difference we observe is that the coefficient on money market funding to total funding ratio is positive and significant result at the 95% confidence level; see Table 8, column 6. This result provides support on our conjecture that a reliance on money market funding plays a role in determining the systemic importance of banks in the cross-section. This provides further support rather than rejection to the TNTTF notion.

6.3 OLS Regressions in the Period 2000–2010

Our panel regression approach in Section 4.2 has a potential drawback: we do not allow for variation in the coefficients on the determinants of systemic importance over time. To overcome this drawback, we thus analyze the eight estimation periods in eight separate OLS regressions,

Table 10 shows the eight OLS regression results. A general observation is that the determinants of systemic importance vary over time.

The Purified Size variable is significant in six out of eight periods. It is notable that the two insignificant periods cover the recent financial crisis during which regulators are most concerned with identifying SIFIs for making potential bailout decision.

The non-interest income variable is also positive and significant in six of the eight periods. However, the six periods include all periods covering the financial crisis and the dot-com collapse. In addition, one of the six periods, 2002–2005, was under benign economic conditions between the two downturns. Hence, the positive relation between non-interest income and systemic importance is robust under different macroeconomic 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: 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.

In summary, the variation of potential determinants of systemic importance provides weak support in favor of the TNTTF principle over the TBTF principle in identifying SIFIs. The TBTF principle failed the most during the recent financial crisis while the TNTTF notion holds during both positive and negative economic conditions and was in particular successful for the recent financial crisis: the variables on non-traditional banking observed at the end of 2005 and 2006 strongly differentiate banks' systemic importance in the coming years.

7 Conclusion

This paper investigates which bank business model indicator is fundamental in determining bank's systemic importance. First, we find partial support for 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 size threshold. For example, as of the end of 2006, US banks with total assets exceeding 100 billion USD are equally systemically important during the crisis period (2007–2010). Second, we find that systemic importance is also determined by the extent to which a bank engages in non-traditional banking activities. It is positively related to both the amount of money market funding and the non-interest income, in particular, the fee and commission income. In contrast, 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 low systemic importance. Third, 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. Lastly, we observe 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.

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 the failure of a large bank have on the system has to be differentiated by analyzing other bank characteristics such as the engagement in non-traditional banking activities.

Second, if regulators attempt to mitigate the systemic risk of financial institutions by imposing policies to limit banks' incentive on risk taking, they should balance the impact on banks' individual risk taking and that on enhancing their systemic importance. The finding that determinants of the individual risk and the systemic importance may work against one another suggests that banks may shift their individual risk to the system by enhancing their systemic importance, for example, by engaging in non-traditional banking activities. Understanding the determinants of the two components of systemic risk is the first step in designing effective regulation that may avoid such a double-side effect.

Lastly, macro-prudential regulation that varies according to the macroeconomic environment is necessary to maintain the stability of the system. "Flat" regulation that does not consider macroeconomic environment may provide a sub-optimal solution.

References

V. Acharya, L. Pedersen, T. Philippon, and M. Richardson. *Regulating systemic risk*, chapter 13, pages 283–304. John Wiley & Sons, 2009.

V. Acharya, L. Pedersen, T. Philippon, and M. Richardson. Measuring systemic risk. *CEPR Discussion Paper*, DP8824, 2010.

V.V. Acharya. A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability*, 5(3):224–255, 2009.

T. Adrian and M.K. Brunnermeier. CoVaR. Technical report, National Bureau of Economic Research, 2011.

F. Allen and E. Carletti. The role of liquidity in financial crises. *Available at SSRN 1268367*, 2008.

F. Allen and D. Gale. Financial contagion. *Journal of Political Economy*, 108(1):1–33, 2000.

J. Bosma, M. Koetter, and M. Wedow. Credit risk connectivity in the financial industry and stabilization effects of government bailouts. *Deutsche Bundesbank Discussion Paper*, 16/2012, 2012.

C. Brownlees and R. Engle. Volatility, correlation and tails for systemic risk measurement. *Available at SSRN 1611229*, 2012.

M.K. Brunnermeier and L.H. Pedersen. Market liquidity and funding liquidity. *Review of Financial Studies*, 22(6):2201–2238, 2009.

J. Danielsson. *Financial risk forecasting: The theory and practice of forecasting market risk with implementation in R and Matlab*, volume 587. Wiley. com, 2011.

O. De Bandt and P. Hartmann. Systemic risk: A survey. *ECB Working Paper*, 35, 2000.

L. De Haan and A. Ferreira. *Extreme value theory: An introduction.* Springer Verlag, 2006.

C.G. de Vries. The simple economics of bank fragility. *Journal of Banking & Finance*, 29(4):803–825, 2005.

R.S. Demsetz and P.E. Strahan. Diversification, size, and risk at bank holding companies. *Journal of Money, Credit and Banking*, 29(3):300–313, 1997.

D.W. Diamond and P.H. Dybvig. Bank runs, deposit insurance, and liquidity. *The Journal of Political Economy*, 91(3):401–419, 1983.

Mathias Drehmann and Nikola Tarashev. Measuring the systemic importance of interconnected banks. *Journal of Financial Intermediation*, 22(4):586–607, 2013.

P. Embrechts, C. Klüppelberg, and T. Mikosch. *Modelling extremal events for insurance and finance*. Springer Verlag, 1997.

X. Freixas, B.M. Parigi, and J.-C. Rochet. Systemic risk, interbank relations, and liquidity provision by the central bank. *Journal of Money, Credit and Banking*, 32(3):611–38, 2000.

P. Gai and S. Kapadia. Contagion in financial networks. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Science*, 466(2120):2401–2423, 2010.

M. Goodfriend and R.G. King. Financial deregulation, monetary policy, and central banking. *FRB Richmond Economic Review*, 74(3):3–22, 1988.

B.E. Hansen. Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics*, 93(2):345–368, 1999.

P. Hartmann, S.n Straetmans, and C.G. de Vries. Banking system stability. a cross-atlantic perspective. In *The Risks of Financial Institutions*, pages 133–192. University of Chicago Press, 2007.

B.M. Hill. A simple general approach to inference about the tail of a distribution. *Annals of Statistics*, 3(5):1163–1174, 1975.

B. Hirtle and J. Lopez. Supervisory information and the frequency of bank examinations. *Economic Policy Review*, 5(1), 1999.

Xin Huang, Hao Zhou, and Haibin Zhu. Systemic risk contributions. *Journal of Financial Services Research*, 42(1):55–83, 2012.

R. Ibragimov, D. Jaffee, and J. Walden. Diversification disasters. *Journal of Financial Economics*, 99(2):333–348, 2011.

D.W. Jansen and C.G. de Vries. On the frequency of large stock returns: Putting booms and busts into perspective. *Review of Economics and Statistics*, 73(1):18–24, 1991.

J. Krainer and J.A. Lopez. How might financial market information be used for supervisory purposes? *Federal Reserve Bank of San Francisco Economic Review*, pages 29–46, 2003.

A.W. Ledford and J.A. Tawn. Modelling dependence within joint tail regions. *Journal of the Royal Statistical Society: Series B*, 59(2):475–499, 1997.

B. Mandelbrot. The variation of certain speculative prices. *The journal of business*, 36 (4):394–419, 1963.

B.M. Segoviano and C. Goodhart. Banking stability measures. *IMF Working Papers*, 09/4, 2009.

M. Sibuya. Bivariate extreme statistics, i. *Annals of the Institute of Statistical Mathematics*, 11(2):195–210, 1959.

N.A. Tarashev, C. Borio, and K. Tsatsaronis. Attributing systemic risk to individual institutions. *Bank for International Settlements Working Papers*, 308, 2010.

W. Wagner. Diversification at financial institutions and systemic crises. *Journal of Financial Intermediation*, 19(3):373–386, 2010.

C. Zhou. Are banks too big to fail? measuring systemic importance of financial institutions. *International Journal of Central Banking*, 6(4):205–250, 2010.

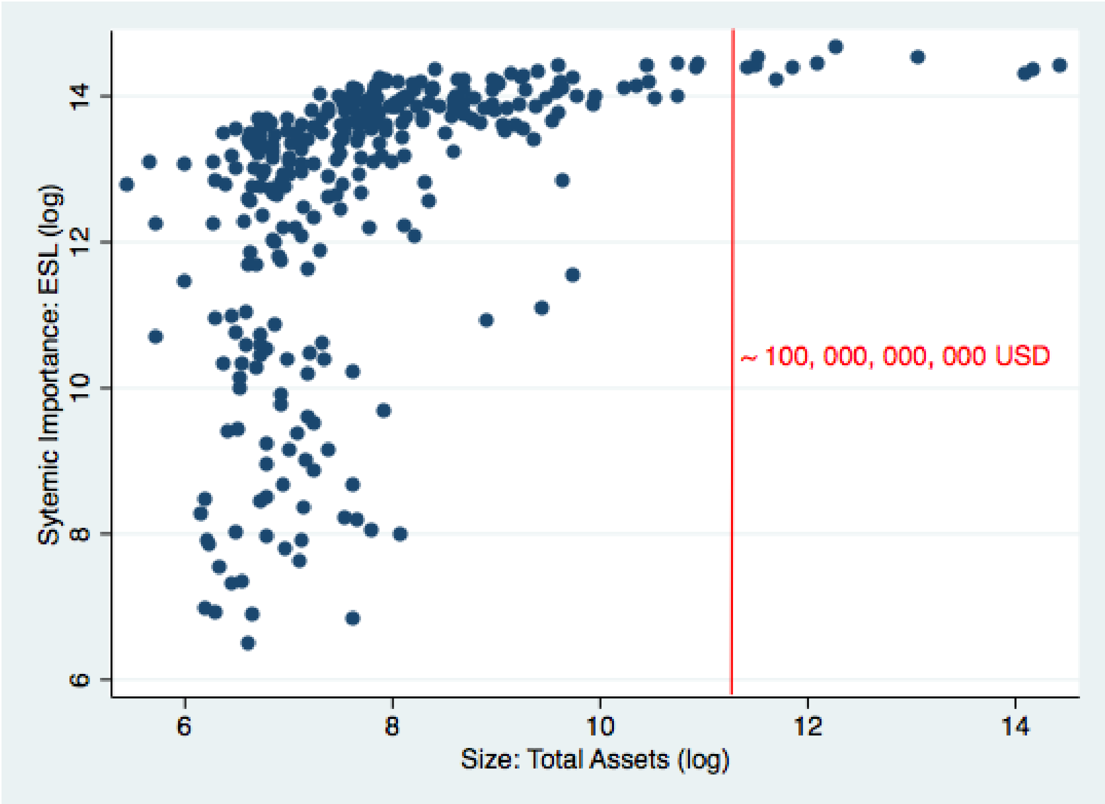
8 Tables and Figures

Table 1: Summary Statistics: ESL (2007–2010) and potential determinants (2006)

	Mean	**Std. Dev.**	**Min.**	**Max.**
ESL	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	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, ESL, and other bank business model indicators. The ESL measure is calculated from excess returns net of the market index in 2007–2010, see Section 2. The other variables are calculated from 2006 year-end annual bank balance sheet data. Size refers to the total assets of a bank in (log) million USD with standardized by its mean and standard deviation. Purified Size is calculated as the residual after regressing size against the other determinants. Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. Loans/Asset is calculated as the gross loans of a bank divided by its total assets. Problem/Loans is the total non-performing loans divided by the gross loans of the bank. ROAA is the return on average assets. 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.

Figure 1: ESL 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 ESL, against the logarithm of the size of the bank (total assets in million USD). The ESL measure is calculated from 2007 to 2010 The ESL 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 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/Income	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 variables are calculated from 2006 year-end annual bank balance sheet data. Size refers to the total assets of a bank in (log) million USD with standardized by its mean and standard deviation. Purified Size is calculated as the residual after regressing size against the other determinants. Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. Loans/Asset is calculated as the gross loans of a bank divided by its total assets. Problem/Loans is the total non-performing loans divided by the gross loans of the bank. ROAA is the return on average assets. 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			-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				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

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

Note: The dependent variable is the ESL measure calculated from excess returns net of the market index in 2007–2010, see Section 2. The independent variables are calculated from 2006 year-end annual bank balance sheet data. Size refers to the total assets of a bank in (log) million USD with standardized by its mean and standard deviation. Purified Size is calculated as the residual after regressing size against the other determinants. Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. Loans/Asset is calculated as the gross loans of a bank divided by its total assets. Problem/Loans is the total non-performing loans divided by the gross loans of the bank. ROAA is the return on average assets. 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. Trading/Income and Fee and Commission/Income are the trading income and fee and commission income both as a ratio of total income. The t-statistics are reported in parentheses.

Table 4: Summary statistics: ESL (2000–2010) and potential determinants

Variable	Mean	Std. Dev.	Min.	Max.	N
ESL	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	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, ESL, and other bank business model indicators. The ESL measure is calculated from excess returns net of the market index in 8 moving windows with yearly shifting, from 2000–2003 to 2007–2010, see Section 2. The other variables are calculated from year-end annual bank balance sheet data in 1999–2006. Size refers to the total assets of a bank in (log) million USD with standardized by its mean and standard deviation. Purified Size is calculated as the residual after regressing size against the other determinants. Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. Loans/Asset is calculated as the gross loans of a bank divided by its total assets. Problem/Loans is the total non-performing loans divided by the gross loans of the bank. ROAA is the return on average assets. 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 5: 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			-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				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

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

Note: This table presents a panel data regression with time fixed effects. The dependent variable is the ESL measure calculated from excess returns net of the market index in 8 moving windows with yearly shifting, from 2000–2003 to 2007–2010, see Section 2. The independent variables are calculated from 1999–2006 year-end annual bank balance sheet data preceding each estimation window. Size refers to the total assets of a bank in (log) million USD with standardized by its mean and standard deviation. Purified Size is calculated as the residual after regressing size against the other determinants. Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. Loans/Asset is calculated as the gross loans of a bank divided by its total assets. Problem/Loans is the total non-performing loans divided by the gross loans of the bank. ROAA is the return on average assets. 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. Trading/Income and Fee and Commission/Income are the trading income and fee and commission income both as a ratio of total income. The t-statistics reported in parentheses are calculated with standard errors clustering at the bank level.

Table 6: 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		-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			-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

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

Note: This table presents a panel data regression with time fixed effects. The dependent variable is the Expected Shortfall on equity returns in 8 moving windows with yearly shifting, from 2000–2003 to 2007–2010, see Section 2. The independent variables are calculated from 1999–2006 year-end annual bank balance sheet data preceding each estimation window. Size refers to the total assets of a bank in (log) million USD with standardized by its mean and standard deviation. Purified Size is calculated as the residual after regressing size against the other determinants. Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. Loans/Asset is calculated as the gross loans of a bank divided by its total assets. Problem/Loans is the total non-performing loans divided by the gross loans of the bank. ROAA is the return on average assets. 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. Trading/Income and Fee and Commission/Income are the trading income and fee and commission income both as a ratio of total income. The t-statistics reported in parentheses are calculated with standard errors clustering at the bank level.

Table 7: The Determinants of Systemic Importance: 2007–2010 (Raw Returns)

	(1)	(2)	(3)	(4)	(5)	(6)
Size	0.918***	1.528***	1.425***	1.464***		
	(8.10)	(11.28)	(11.12)	(11.03)		
Size^2		-0.339***	-0.363***	-0.358***		
		(-7.67)	(-7.87)	(-7.80)		
Purified Size					0.629***	0.629***
					(7.84)	(7.74)
Tier 1 Ratio			0.001	0.007	0.020	0.031
			(0.04)	(0.32)	(0.87)	(1.40)
Loans/Assets			-0.012	-0.016*	-0.030***	-0.017*
			(-1.56)	(-1.74)	(-3.04)	(-1.83)
Problem/ Loans			-0.066	-0.062	-0.086	-0.077
			(-1.11)	(-1.07)	(-1.43)	(-1.27)
ROAA			0.268**	0.275**	0.260*	0.234*
			(2.01)	(2.12)	(1.83)	(1.67)
Liquid Assets/STF			0.019	0.017	0.013	0.002
			(1.52)	(1.31)	(0.87)	(0.11)
MMF/Funding				-0.017	0.006	0.021
				(-1.27)	(0.39)	(1.39)
NonInterest/Income				-0.006*	0.001	
				(-1.69)	(0.30)	
Trading/Income						0.036
						(0.47)
Fee and Commission/Income						0.061***
						(5.07)
N	311	311	311	311	311	311
R^2	0.223	0.328	0.396	0.402	0.267	0.310

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable is the ESL measure calculated from raw returns in 2007–2010, see Section 2. The independent variables are calculated from 2006 year-end annual bank balance sheet data. Size refers to the total assets of a bank in (log) million USD with standardized by its mean and standard deviation. Purified Size is calculated as the residual after regressing size against the other determinants. Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. Loans/Asset is calculated as the gross loans of a bank divided by its total assets. Problem/Loans is the total non-performing loans divided by the gross loans of the bank. ROAA is the return on average assets. 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. Trading/Income and Fee and Commission/Income are the trading income and fee and commission income both as a ratio of total income. The t-statistics are reported in parentheses.

Table 8: The Determinants of Systemic Importance: 2007–2010 (Raw Returns with Total Liabilities)

	(1)	(2)	(3)	(4)	(5)	(6)
Size	0.926***	1.558***	1.461***	1.477***		
	(8.15)	(11.51)	(11.03)	(10.40)		
Size^2		-0.358***	-0.397***	-0.398***		
		(-7.48)	(-7.18)	(-7.38)		
Purified Size					0.670***	0.626***
					(8.23)	(8.37)
Tier 1 Ratio			-0.033	-0.032	-0.063*	-0.055*
			(-1.42)	(-1.39)	(-2.59)	(-2.21)
Loans/Assets			-0.025**	-0.027**	-0.044***	-0.040***
			(-3.15)	(-3.14)	(-4.76)	(-4.36)
Problem/Loans			-0.206	-0.189	-0.034	-0.17
			(-1.37)	(-1.18)	(-0.20)	(-0.89)
ROAA			0.376	0.373	0.827***	0.846***
			(1.77)	(1.71)	(3.45)	(3.60)
Liquid Assets/STF			0.019	0.019	-0.028	-0.023
			(1.12)	(1.17)	(-1.77)	(-1.33)
MMF/Funding				-0.007	0.022*	0.025**
				(-0.61)	(2.26)	(2.65)
NonInterest/Income				0.000	0.019*	
				(0.04)	(2.08)	
Trading/Income						-0.050
						(-1.36)
Fee and Commission/Income						0.037**
						(3.31)
N	311	311	311	311	311	311
R^2	0.228	0.339	0.373	0.374	0.278	0.282

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable is the ESL measure (using total bank liabilities as the weight) calculated from raw returns in 2007–2010, see Section 2. The independent variables are calculated from 2006 year-end annual bank balance sheet data. Size refers to the total assets of a bank in (log) million USD with standardized by its mean and standard deviation. Purified Size is calculated as the residual after regressing size against the other determinants. Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. Loans/Asset is calculated as the gross loans of a bank divided by its total assets. Problem/Loans is the total non-performing loans divided by the gross loans of the bank. ROAA is the return on average assets. 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. Trading/Income and Fee and Commission/Income are the trading income and fee and commission income both as a ratio of total income. The t-statistics are reported in parentheses.

Table 9: The Determinants of Systemic Importance: 2007–2010 (Excess Returns with Total Liabilities)

	(1)	(2)	(3)	(4)	(5)	(6)
Size	0.749***	1.125***	1.114***	1.127***		
	(9.09)	(10.17)	(9.79)	(9.06)		
Size^2		-0.213***	-0.247***	-0.250***		
		(-6.37)	(-5.61)	(-5.92)		
Purified Size					0.558***	0.524***
					(8.53)	(8.03)
Tier 1 Ratio			-0.016	-0.014	-0.040	-0.035
			(-0.77)	(-0.72)	(-1.96)	(-1.74)
Loans/Assets			-0.008	-0.010	-0.023*	-0.021
			(-0.88)	(-0.98)	(-2.08)	(-1.88)
Problem/Loans			-0.184	-0.155	-0.039	-0.140
			(-1.42)	(-1.13)	(-0.28)	(-0.83)
ROAA			-0.044	-0.053	0.304	0.330
			(-0.23)	(-0.27)	(1.46)	(1.56)
Liquid Assets/STF			0.020	0.020	-0.003	0.000
			(1.33)	(1.40)	(-0.23)	(0.02)
MMF/Funding				-0.010	0.015	0.018
				(-0.99)	(1.55)	(1.96)
NonInterest/Income				0.003	0.020*	
				(0.32)	(2.42)	
Trading/Income						-0.022
						(-0.59)
Fee and Commission/Income						0.030*
						(2.56)
N	311	311	311	311	311	311
R^2	0.210	0.266	0.278	0.280	0.224	0.219

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable is the ESL measure (using total bank liabilities as the weight) calculated from excess returns in 2007–2010, see Section 2. The independent variables are calculated from 2006 year-end annual bank balance sheet data. Size refers to the total assets of a bank in (log) million USD with standardized by its mean and standard deviation. Purified Size is calculated as the residual after regressing size against the other determinants. Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. Loans/Asset is calculated as the gross loans of a bank divided by its total assets. Problem/Loans is the total non-performing loans divided by the gross loans of the bank. ROAA is the return on average assets. 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. Trading/Income and Fee and Commission/Income are the trading income and fee and commission income both as a ratio of total income. The t-statistics are reported in parentheses.

Table 10: The Determinants of Systemic Importance: Individual Regression

	(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	-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	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

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

Note: This table presents eight cross-sectional regressions indicated by years in the column name. For each regression, the dependent variable is the ESL measure calculated from excess returns net of the market index in the four-year estimation window after the indicated year, see Section 2. The independent variables are calculated from year-end annual bank balance sheet data at the indicated year. Size refers to the total assets of a bank in (log) million USD with standardized by its mean and standard deviation. Purified Size is calculated as the residual after regressing size against the other determinants. Tier 1 Ratio is the total Tier 1 capital divided by the bank's risk-weighted assets. Loans/Asset is calculated as the gross loans of a bank divided by its total assets. Problem/Loans is the total non-performing loans divided by the gross loans of the bank. ROAA is the return on average assets. 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 t-statistics are reported in parentheses.

Systemic Risk Centre

The London School of Economics
and Political Science
Houghton Street
London WC2A 2AE
United Kingdom

Tel: +44 (0)20 7405 7686
systemicrisk.ac.uk
src@lse.ac.uk