

# Identifying systemically important financial institutions: size and other determinants\*

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April 13, 2012

## Abstract

This paper analyzes the conditions under which a financial institution is systemically important. Measuring the level of systemic importance of financial institutions, we find that size is a leading determinant confirming the usual “Too Big To Fail” argument. Nevertheless, the relation is non-linear during the recent global financial crisis. Moreover, since 2003, other determinants of systemic importance emerge. For example, decisions made by financial institutions on their choice of asset holdings, methods of funding, and sources of income have had a significant effect on the level of systemic importance during the global financial crises starting in 2008. These findings help to identify systemically important financial institutions by examining their relevant banking activities and to further design macro-prudential regulation towards reducing the systemic risk in the financial system.

*JEL Classification: G01, G21, G28.*

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\*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. We are also grateful for the research assistance provided by Lin Zhao. Views expressed do not necessarily reflect official positions of De Nederlandsche Bank.

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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 initiated in 2008 has provided an example. Measures taken by the US government, in the onset of the crisis, attempted to save large financial institutions from possible default. Similarly, during the European debt crisis, the European Central Bank introduced a program designed to prop up banks struggling to raise funds. These intervention activities have led to debates in both 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, and as a result, large losses to the entire economy. Nevertheless, the institutions that in practice receive most, if not all, the “bailout” attention are the large firms that are considered “Too Big to Fail”. This raises the question as to whether size is fundamental in determining the interconnectedness of the financial system. If size is not a sufficient measure in detecting bank interconnectedness, the consequent question most regulators would ask is: Which banks are “Too Systemically Important to Fail”?

This paper aims to close this gap by empirically analyzing potential determinants of systemic importance of a financial institution. We analyze potential determinants of the systemic importance namely the size, leverage, and other components on individual institutions’ balance sheets. More specifically, we examine three categories comprising the assets composition, methods of funding, and sources of revenue. The implications of such a study will allow regulators to assess the systemic risk imposed by a single bank to the financial sector based on examining its banking activities.

Regarding size as the determinant of systemic importance, we find strong support in favor of the TBTF hypothesis. However, the relation between size of a financial institution and its systemic importance is highly non-linear and depends on macroeconomic conditions. On the cross-section dimension, increases to systemic importance in relation to size are most pronounced for medium sized banks. On the time dimension, the relation varies according to the time period being analyzed. For example, in the period surrounding the financial crisis from 2007 to 2010, we find that size can only be considered as a proxy for systemic importance if the size is below a certain threshold level

of approximately \$20 billion (USD). Banks having a size exceeding this threshold, while all highly systemically important, do not differ in the degree of their systemic importance.

In addition to size, we find other bank characteristics that significantly determine the systemic importance. The amount of short term funding a bank employs is positively related to its systemic importance. The leverage, the amount of interest income, and the volume of problem loans are all negatively related to the systemic importance. Nevertheless, on the time dimension, we observe the variation of potential determinants of systemic importance under different macroeconomic environments.

This paper also contributes to the literature on the measurement and assessment of systemic risk. The term “systemic risk” is used in a number of different contexts, and does not yet have a rigorous singular definition leaving room for various interpretations. For instance, Acharya *et al.* (2009) define systemic risk as “*the risk of a crisis in the financial sector and its spill-over to the economy*”. The definition offered by De Bandt & Hartmann (2000) is more direct. They define systemic risk 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*”. From this definition, the systemic risk imposed by each individual institution can be drawn as the marginal contribution of a particular institution to the overall systemic risk. This contribution can be further decomposed into the individual riskiness of the institution and the spill-over effect to the rest of the system conditional on its failure. We consider the second component as the institution’s systemic importance. More specifically, the systemic importance of a bank can be measured by the expected loss it imposes to the financial system given that it has failed.

We find that the two components of systemic risk may interact. Many of the drivers of systemic importance 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 failing by diversifying their activities. At the same time, this increases commonalities between banks leading to an increased systemic importance. Analogous to the notion of portfolio diversification, determinants of the individual risk and the systemic importance, may work against one another.

Our results have direct policy implications for regulators. Regulation that attempts to reduce

the systemic risk in the financial industry must take into account more than just the size of a bank. Furthermore, in order to reduce the overall risk in the system, regulators should consider a balance between the systemic importance and individual risk - the dual contributors of systemic risk induced by a bank.

The Systemic Impact Index introduced by Zhou (2010) measures the expected number of simultaneous bank failures in the system conditional on the failure of a specific individual institution. This approach is able to capture the general instability of the system associated with the failure of a single institution. The notion of too-many-to-fail may raise regulators concern on the number of failures in the system stemming from a single failure; however, such a measure lacks information on the exact economic impact a failure would create. More specifically, the deterioration of social welfare within the system such as the amount of government assistance required to maintain a healthy banking system.

We extend the definition of systemic impact to include two types of potential losses to the financial system. Conditional on a particular bank's failure, the first measures the expected capital shortfall of other failed institutions, and the second measures the expected loss on insured deposits held by other failed banks. The two measures give additional insight into the social welfare effects of a particular bank failure. The first can be viewed as the recapitalization bailout costs of other banks in the event of a particular bank failure. The second is the liability the central authority faces if the other failed banks are not recapitalized, that is the total insured creditors' demand on their guaranteed deposits.

The paper proceeds as follows. We first introduce the related literature in Section 2. Section 3 describes the construction of the three measures of systemic importance. The potential determinants of systemic importance are explored in Section 4. The data collection and empirical methodology in analyzing the determinants of systemic importance are shown in Section 5 with the results explained in Section 6. Section 7 concludes the paper.

## 2 Literature Review

This paper relates to three strands of literature on systemic risk. The first strand deals with the theoretical models on systemic risk and systemic importance. A great deal of the literature models systemic risk through the direct links banks expose themselves to each other through the interbank markets, see, e.g. Rochet & Tirole (1996), Allen & Gale (2000), and Freixas *et al.* (2000). The banking system is wired together as a network supported by the interbank market. Liquidity constraints within the financial sector are reduced when banks have the ability and means to lend to each other. The downside of this activity is that banks open themselves up in the event of a bank failure. The magnitude of the chain reaction of failures introduced by the failure of one bank reflects the bank's level of systemic importance (Furfine (2003)). This type of bank interconnectedness is derived from specific financial linkages between institutions and is referred to as direct channel linkages.

Banks may also be connected through a common funding shock to the system that affects all those exposed to it. If the shock is of a large magnitude it will cause a subset of banks to fail simultaneously. A classic example is the standard bank run model described by Bryant (1980) and Diamond & Dybvig (1983). In this literature, a shock to the confidence of deposit holders, in the absence of deposit insurance, can lead to a swift withdrawal of bank capital regardless of its solvency. This, in turn, has the potential to spark simultaneous runs on other banks, healthy or otherwise. As a result, those models provide support for the potential of funding activities in determining a bank's systemic importance.

An indirect approach in modeling systemic risk can be considered via common shocks to the asset side of a financial institution's balance sheet. Banks that hold similar portfolios, or highly correlated ones, will be indirectly linked in the event of such a shock, see, e.g. De Vries (2005) and Acharya (2009). Due to the nature of banks, the initial shock is likely to be amplified throughout the system as firms de-lever their positions to meet margin calls and capital requirements (Brunnermeier & Pedersen (2009)). Adrian & Shin (2010) provide empirical evidence for this. In this regard, the source or focus of the shock is not of primary importance since the linkages are a result of the similarities in banking characteristics. Therefore, the type and quantity of asset holdings of banks

may contribute to their systemic importance.

The second strand of literature relating to this study is on measuring systemic risk contribution of individual financial institutions. Huang *et al.* (2010) develop a measure of systemic risk based on the credit default swap (CDS) prices. Two other candidates are the conditional Value-at-Risk (Adrian & Brunnermeier (2011)), otherwise known as CoVaR, and the probability of at least one extra failure (PAO) given a failure in the system (Segoviano & Goodhart (2009)). The CoVaR is able to capture pairwise risk of each individual bank against an indicator of the state of the market by quantile regression. Unlike the CoVaR, the PAO has the advantage of being able to move from a bivariate to a multivariate analysis of systemic importance by utilizing a conditional probability. The drawback of this measure is that it does not contain any additional information as to the level of impact the failure of an institution would have on the rest of the system, but merely an indication that some spill-over effect would be observed. The Systemic Impact Index (SII) of Zhou (2010) improves on this by introducing a scale of systemic importance that ranks based on the number of simultaneous bank failures in the system.

The third strand of relevant literature deals with the determinants of systemic (or individual) risk in the financial sector. For individual risk, Demsetz & Strahan (1997) show that size is beneficial in reducing idiosyncratic risk through diversification. Moreover, Demsetz & Strahan (1997) find the leverage ratio to be a significant determinant of idiosyncratic risk. Stiroh & Rumble (2006), focusing on the operating strategies of bank holding companies (BHCs), find that, while size is negatively correlated, asset-to-equity leverage ratio, consumer lending, non-performing loan ratio, and non-interest income are positively linked to a bank's individual risk between 1997 and 2004.

The determinants of individual risk are not necessarily determinants of systemic risk. Two papers, De Jonghe (2010) and Knaup & Wagner (2010), provide empirical analysis on the drivers of tail risk of financial institutions conditional on negative shocks in the market. In De Jonghe (2010), the author finds that non-traditional banking practices, such as reliance on commission and trading income, have a greater impact on the systemic stability than more traditional forms of funding. Knaup & Wagner (2010), while focusing on the asset composition on banks balance sheets, find that non-traditional banking is more hazardous to the system in terms of the connections it

facilitates.

### 3 Systemic Importance Measures

#### 3.1 The Systemic Impact Index: SII

The systemic importance measure proposed by Zhou (2010) is based on an application of multivariate Extreme Value Theory (EVT)<sup>1</sup>. The SII measures the expected number of simultaneous failures given a single failure by measuring the conditional probability of one bank’s failure on 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”. We resolve this issue empirically by instead estimating the probability of bank *distress*. 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 & Lopez (2003). Therefore, we describe a distress event when the market price of a bank’s equity experiences a large (daily) loss.

Consider a banking system consisting of  $N$  banks. Denote their equity returns as  $X_1, \dots, X_N$ . A distress, or tail event, is defined as an event with a low probability  $p$ .<sup>2</sup> In other words, values of  $X_i$  below a certain threshold level are assumed to trigger a tail event for bank  $i$ . More explicitly, this threshold level is determined by the Value-at-Risk (VaR) of the bank and is defined as

$$Pr(X_i < -VaR_i(p)) = p, \tag{1}$$

for some sufficiently low (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 a constant  $p$  level across firms. Notice that this does not imply that the threshold levels are constant 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. Our description allows for heterogeneity in banks’ individual risk taking activities.

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<sup>1</sup>See De Haan & Ferreira (2006) for an overview of multivariate EVT.

<sup>2</sup>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.

The SII is defined as

$$\begin{aligned}
SII_i(p) &= E\left(\sum_{j \neq i} I_{X_j < -VaR_j(p)} | X_i < -VaR_i(p)\right) \\
&= \sum_{j \neq i} P(X_j < -VaR_j(p) | X_i < -VaR_i(p)),
\end{aligned} \tag{2}$$

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<sup>3</sup>.

This measure is able to capture the degree to which an individual bank distress or failure can influence the rest of the banking system, however, it is unable to distinguish the economic size of the impact. 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 measure. Hence, it is necessary to extend this measure to account for the economic size of the impact.

### 3.2 Extension to a Weighted SII: Social Welfare Measures

We propose two different weighting measures to capture the systemic importance of a bank in terms of social welfare loss given its distress. The first extension is the expected capital shortfall in the system given a particular bank is distressed. The capital shortfall ( $CS$ ) of a bank can be approximated by the product of its equity and the Expected Shortfall ( $ES$ ) of its equity return given the return falls below a certain  $VaR$  level as

$$CS_i = Equity_i \cdot ES_i, \tag{3}$$

where  $Equity_i$  is the equity for bank  $i$ , and the  $ES$  of bank  $i$  is given by

$$ES_i(p) = -E(X_i | X_i < -VaR_i(p)), \tag{4}$$

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<sup>3</sup>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.



for a given probability level  $p$ . Given a specific bank distress in the system, a calculation of the expected total capital shortfall of the system can be estimated by aggregating the individual capital shortfalls as follows:

$$\begin{aligned}
SI_i^{CS}(p) &= \sum_{j \neq i} E(CS_j | X_i < -VaR_i(p)) \\
&\approx \sum_{j \neq i} CS_j \cdot E(1_{X_j < -VaR_j(p)} | X_i < -VaR_i(p)) \\
&= \sum_{j \neq i} CS_j \cdot P(X_j < -VaR_j(p) | X_i < -VaR_i(p)). \tag{5}
\end{aligned}$$

We observe that the capital shortfall of a bank  $j$  can be used to weight the impact of bank  $i$  distress has on the distress of bank  $j$ . Thus, the systemic importance (SI) measure,  $SI^{CS}(p)$ , is a weighted version of the original  $SII$  measure.

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 tax payer funds. The capital injection required to save the bank can be approximated by the amount that can restore the firm's equity to its initial level before any shock. If bank  $i$  is allowed to reach a level of distress or to fail, then the authority will face a decision to bailout other banks that face a distressed level simultaneously. The measure  $SI^{CS}$  is therefore the expected amount of capital injection necessary to restore the system given a particular bank becomes distressed. Since we condition on the distress of a certain bank  $i$ , only the expected CS of the other banks,  $j \neq i$ , are included as weights.

The second weighting measure stems from a similar idea by 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 data on the specific size of insured deposits held by each bank, we assume that the fraction of insured deposits against total deposits is comparable across banks. We therefore use the total volume of customer demand and savings deposits as a proxy for the volume of government insured deposits held by each bank. The second weighted SI measure is given as

follows:

$$SI_i^{DEP}(p) = \sum_{j \neq i} DEP_j \cdot P(X_j < -VaR_j(p) | X_i < -VaR_i(p)), \quad (6)$$

where  $DEP_j$  is the sum of the customer demand and time deposits held by bank  $j$ .

## 4 Potential Determinants of Systemic Importance

Our systemic importance measure does not reflect the likelihood of an individual bank distress or failure, but rather the expected additional costs given such an event. The operations and features of a bank that increase its individual tail risk do not necessarily increase its interconnectedness. The two contributors to systemic risk, the individual risk and the systemic importance, can work in parallel or against one another. Consequently, certain determinants, such as size, may induce an opposite effect on systemic importance in comparison to individual risk of failure. We discuss the potential determinants of systemic importance and make hypotheses as to their impacts.

### 4.1 Size

Banks have an incentive to hold diversified portfolios. While this may be an optimal strategy in terms of lowering individual risk, it induces a negative externality on the system. The benefits of diversification, minimizing a portfolio's exposure to idiosyncratic risk, are countered by an increase to systemic connectedness when other banks hold similar portfolios. A shock to a certain class of assets will affect all banks that hold these assets. If a large fraction of banks are holding a comparable collection of assets, then a large negative shock will cause these banks to all become distressed simultaneously (Ibragimov *et al.* (2011)).

Therefore, larger banks holding more diversified portfolios are typically recognized as being more stable, whereas when one fails the probability that this shock also affects other banks is high. On the contrary, smaller banks hold a smaller set of assets, and are thus more isolated from the rest of the system. Therefore, size may be positively associated with SI, opposite the relation to individual risk.

## 4.2 Leverage

The risk taking of a bank is determined, to a large degree, by its leverage position. While taking on leverage allows for banks to increase their return on equity, excessive leveraging by financial institutions is considered as a potential cause of financial crises. Balance sheet leverage, the focus in this paper, exists whenever the value of assets exceeds the value of equity of the bank. The increase of a bank's leverage is caused by either acquiring more funding by borrowing, or by a negative shock to its asset value. As a bank's leverage ratio increases the bank is able to earn a higher return on equity, however, this is at the expense of an increasing risk to the debt holders. Due to the riskiness imparted by high leverage, banks may choose to limit their exposures to highly levered institutions, thereby isolating them in the system<sup>4</sup>. Therefore, a high leverage position may lead to a disconnected position within the financial system.

## 4.3 Funding

The funding decision of a financial institution plays an important role in determining its stability. Banks, unlike non-financial corporations, issue debt liabilities with maturities that are significantly shorter than the assets they hold. This reliance on short term funding, ranging from immediately callable retail deposits to slightly longer term money market funds, leave the bank exposed to maturity mismatch and considerable liquidity risk (Goodhart (1988)).

The maturity mismatch of the investments to the funding decision leaves even solvent banks exposed to a quick withdrawal of funds by panicked investors. Acharya *et al.* (2010) and ? find that a reliance on wholesale funding leads to an increase in the bank's downside tail risk. Guarantees on retail deposits have removed some of the liquidity risk, however, this did not stop retail depositors from initiating a bank run such as that on Northern Rock's funds in September 2007.

Runs on the short term funding of banks are the result of a lack of confidence in particular financial institutions, which is regarded as a funding shock. When a common funding shock hits the banking sector, it leads to an erosion of creditor confidence. Banks relying heavily on short term funding may simultaneously face a run on their short term funding. Even if the shock is

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<sup>4</sup>See, e.g. BCBS (1999b): Banks. Interactions with Highly Leveraged Institutions, Basel Committee on Banking Supervision, BIS, Basel, January.

specific to a particular bank, the spillover effect of the loss of confidence may result in bank runs at other institutions having high volumes of retail deposits. On the contrary, long term wholesale funding does not suffer from a maturity mismatch problem. These funds are typically regarded as more stable than short term funding. Therefore, financial institutions that hold high proportions of short term funding may bear not only higher individual risk but also a higher level of systemic importance.

#### 4.4 Assets and Income Strategy

The type of assets that banks purchase to build their portfolio, and the income generating activities they focus on, represent two other ways that banks take on different risks and may potentially determine the systemic importance.

Banks attempt to construct portfolios that maximize their profits while controlling the risk. Consequently, the portfolio structures of banks with similar risk appetites and risk management strategies are relatively similar. Among them, a shock to the assets of a particular bank is thus likely to have a similar effect on the other banks. Different risk appetite of banks can result in portfolio differences. For instance, specialized banks typically enjoy a slightly higher rate of return than more diversified banks (Kamp *et al.* (2007)), but, at the same time, have higher downside tail risk (Winton (1999)). They may not be as exposed to a general shock to the sector compared to non-specialized banks. In this way, the individual risk of such institutions is high, but the interconnectedness may be lower, while the opposite holds for well-diversified banks.

The same intuition can be extended to the income strategies of banks. Acharya *et al.* (2009) show that institutions that derive income mainly through interest related activities, contribute less to the interconnectedness of the system prior to the global financial crisis. Interest is regarded as a stable source of income. Moreover, institutions that rely heavily on interest income can be considered as more specialized than other firms that diversify into more exotic forms of non-interest income. As argued with the assets holdings of firms, the more specialized institutions are exposed to certain specific shocks to the system, but less exposed to common shocks. Therefore, we conjecture that firms which rely primarily on interest based income will be less systemically important than

banks that have decided to generate income from non-interest bearing activities.

## 5 Data and Methodology

### 5.1 Data for Constructing the Systemic Importance Measures

To construct the three systemic important measures, daily equity prices on US bank holding companies (BHCs) from 1999 to the end of 2010 are collected from Datastream<sup>5</sup>. Corresponding annual balance sheet data for the total equity and customer demand deposits for each firm is matched with the Bankscope database<sup>6</sup>.

Data are divided into three non-overlapping periods, 1999-2002, 2003-06, and 2007-10. 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 in the three SI measures. We filter out any institution not traded on at least 55% of the days within a certain period. Therefore, the minimum number of trading days for an institution within each period is 570.

When estimating the conditional probabilities in the SII measure, Zhou (2010) did not correct for the possibility that the co-movement of bank equity returns can be due to a common market factor. This may lead to an overestimation of the SI measures. 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<sup>7</sup> using the single-factor market model:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t}. \quad (7)$$

The error term,  $\epsilon_{i,t}$ , is assumed to follow the standard assumptions of Ordinary Least Squared (OLS) regression and are cross-sectionally uncorrelated. The excess returns are calculated as

$$\hat{\epsilon}_{i,t} = R_{i,t} - \hat{\alpha}_i - \hat{\beta}_i R_{m,t}, \quad (8)$$

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<sup>5</sup>Equities selected are traded on both the NYSE and the NASDAQ exchanges.

<sup>6</sup>Equity and balance sheet accounting data are matched between the BvD Bankscope and Datastream by using the corresponding Bankscope number for each firm

<sup>7</sup>The market returns for the period 1999 - 2010 refers to the returns of the SP500 index.

which are used in the construction of the three SI measures.

The scope of financial institutions included in the analysis is further filtered by the inter-period availability of balance sheet data. The yearly accounting data are smoothed by averaging over four years. We require that firms included in the regression analysis have balance sheet data for at least three out of the four years in each period. In the end the number of selected BHCs are 194 for the period of 1999-2002, 298 for 2003-2006, and 375 for the period 2007-2010.

## 5.2 Estimation of the SI measures: an EVT approach

The key element in estimating all three SI measures (see (2) (4) and (5)), is the estimation of the conditional probability that bank  $j$  fails given that bank  $i$  fails for each pair  $i$  and  $j$ . We follow the approach in de De Jonghe (2010) and Zhou (2010) which applies multivariate EVT. Multivariate EVT provides models such that the limit of the conditional probability is at a constant level as  $p \rightarrow 0$ , i.e.

$$\tau_{i,j} := \lim_{p \rightarrow 0} P(X_j < -VaR_j(p) | X_i < -VaR_i(p)). \quad (9)$$

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

$$\hat{\tau}_{i,j} := \frac{1}{k} \sum_{s=1}^n 1_{X_{j,s} < X_{j,(n-k)}, X_{i,s} < X_{i,(n-k)}}, \quad (10)$$

where  $X_{i,(n-k)}$  is the  $(k+1)$ th lowest return among  $X_{i,1}, \dots, X_{i,n}$ .<sup>8</sup>

Practically, the theoretical conditions on  $k$  is not relevant for a finite sample analysis. Thus, how to choose a proper  $k$  in the estimator is a major issue in estimation. 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 against the  $k$  values. With 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

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<sup>8</sup>For the estimator of  $\tau_{i,j}$ , usual statistical properties, such as consistency and asymptotic normality, has been proved, see, e.g. De Haan & Ferreira (2006).

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 follow from the  $k$  choice. 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 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 4%.

We also impose a cutoff value, 0.15, in the estimation of  $\tau$ -measure, such that values of the estimated  $\tau$  below the cutoff level are set to zero. This is to avoid the potential positive bias in the estimation of  $\tau$  when the actual  $\tau$  value is zero, the estimation usually yields a small positive value. Our regression results are robust for different selection of cutoff values.

When estimating the SI measure weighted by the expected capital shortfall, it is necessary to estimate the ES of equity returns for each bank. We consider heavy-tailed feature in estimating the expected shortfall as in univariate EVT. The heavy-tailedness of financial returns is well-documented in literature, see e.g. Jansen & De Vries (1991) and Embrechts *et al.* (1997). It assumes a power law of the downside tail distribution of the return  $X_i$ ,

$$P(X_i < -u) \sim A_i u^{-\alpha_i} \quad \text{as } u \rightarrow +\infty. \quad (11)$$

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

$$ES_i(p) = -E(X_i | X_i < -VaR_i(p)) \sim \frac{\alpha_i}{\alpha_i - 1} VaR_i(p) \quad \text{as } p \rightarrow 0. \quad (12)$$

Similar to the estimation of  $\tau_{i,j}$ , the  $VaR_i(p)$  is estimated at the level  $p = k/n$  by the  $(k+1)$ th highest loss among  $-X_{i,s}$  (i.e. the  $(k+1)$ th lowest return multiplied by -1),  $-X_{i,(n-k)}$ . The estimation of  $\alpha_i$  is by the Hill estimator in univariate EVT. With the observations  $X_{i,1}, \dots, X_{i,n}$ ,

by ranking them as  $X_{i,(1)} \geq X_{i,(2)} \geq \dots \geq X_{i,(n)}$ , the Hill estimator is defined as

$$1/\hat{\alpha}_i := \frac{1}{k} \sum_{i=1}^k \log(-X_{i,(n-i+1)}) - \log(-X_{i,(n-k)}). \quad (13)$$

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 expected shortfall on the return series of each bank. Together with the market capitalization, they can be used in weighing the conditional probabilities which yield the estimate of the SI measure in terms of expected capital shortfall. The other SI measure,  $SI^{DEP}$ , is formed in a similar way by using the bank's total deposits to weigh the conditional probabilities.

### 5.3 Data for Potential Determinants

Two variables applied in the empirical analysis, size (*Size*) and leverage (*Leverage*), are defined by the logarithm of total assets and the ratio of total liability to total equity, respectively. To capture a non-linear property of the size of the institution, we also consider its quadratic form  $Size^2$ . The analysis of the remainder of the balance sheet items considered in the regression analysis are separated into three categories, funding sources, assets holdings, and income strategy.

The funding sources of banks is dissected into short-term and long-term components as a ratio of the total funding. Including both variables introduces a multi-collinearity problem. Thus we choose to include the short-term component (*STF*) in the regression. The short-term funding is then sub-divided into three variables: money market funding, demand deposits (*Demand*), and saving deposits (*Savings*) as a ratio of the total short-term funding. Again, to avoid any multi-collinearity, only *Savings* and *Demand* are included in the regression along with *STF*.

In order to analyze the asset structure of the bank we look at the fraction of total assets that are held as loans (*Loans*) versus those held as securities. We omit the variable for securities, to avoid multi-collinearity. *Loans* is then divided into two non-disjoint variables, the fraction of loans that are mortgages (*Mortgage*), and the fraction of loans that are non-performing (*Problem*).

For the third category, the total gross income of each financial institution is divided into interest



or non-interest bearing activities. The total gross interest income of the firm as a fraction of the total gross income (*Interest*) is included in the regression.

## 6 Empirical Results

We conduct our empirical analysis in three disjoint periods between 1999 and 2010. Each captures a different and unique economic climate. The most recent period (2007-2010) manifest the time surrounding the financial crisis which is in direct contrast to the previous period (2003-2006) when the economy was experiencing a boom. These two periods allow for a comparison of determinants of systemic importance under different economic conditions. The earliest period (1999-2002) covers the time surrounding the bursting of the dot-com bubble and its subsequent deflation. Moreover, it also contains the introduction of bill that repealed, in part, the Glass-Steagall Act and began a wave of consolidation in the financial sector.

Table 1 provides the summary statistics of our SI measures in each period. We observe that the interconnectedness within the system in 2007-2010 is in general higher than that in the previous two periods. Table 2 lists the most systemic banks by each measure for 2007-2010 period. These three lists differ from each other, while the “big banks” (Bank of America, Wells Fargo, Citigroup, etc.) appear only when the weighted measure is applied<sup>9</sup>. We observe that our weighted measures report different systemically important financial institutions (SIFIs) compared to that identified by the unweighted SII measure. Therefore it is necessary to take the exact economic impact into account when measuring banks systemic importance.

Table 3 shows the correlation matrix among the measures for each of the three periods. The correlation between the non-weighted SII and the two SI measures weighted by social welfare losses vary between periods, whereas the correlation of the two social welfare measures are close to 1. The low correlations between the two weighted measures and the SII measure may be a result of the different methods to account the impact to the system. On the contrary the high correlation

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<sup>9</sup>If the expected shortfall on equity and the loss to customer deposits for the conditionally failed bank were also included as weights, then the list would essentially represent the 15 largest banks. This is partly due to the fact that the the probability of simultaneous failure conditional on the failure of a certain bank is relatively low. Therefore, the weight placed on the conditional bank dominates the measure.

between the two weighted measures shows that they provide similar information in terms of ranking systemic importance. For this reason, our regression analyses focus on only the  $SI^{CS}$  measure. Similar results on the  $SI^{DEP}$  measures are obtained. Although the result for the SII measure deviate, it is of less interest due to aforementioned drawback of this measure<sup>10</sup>.

## 6.1 Financial Crisis and Great Recession: 2007-2010

During this period, the most significant determinant of systemic importance is size of the institution. We report a strong positive relationship that is significant at the 99% confidence level. This result holds in all regressions performed, giving support to the “Too Big to Fail” (TBTF) argument.

Figure 1 provides a scatter plot between the  $SI^{CS}$  measure and the size measure. It illustrates that  $SI^{CS}$  is increasing with respect to the size of the institution. However, it also depicts a non-linear relation. This shows up as a negative and significant coefficient on the  $Size^2$  variable. The analysis suggests that the relation between size and systemic importance is diminished for firms with size above and below certain threshold levels. The convexity shown in Figure 1 indicates that the marginal increase in SI as size increases is most pronounced for medium sized banks.

The size of the banks can be split roughly into three regions. With a threshold regression (Hansen (1999)) we find evidence of two breakpoints in the regression against the size. Figure 2 reports the F-test from the threshold regression analyses. The test statistics reach “spikes” at the  $Size$  levels 7.5 and 9.9, indicating two potential “breaks” in this neighborhood. We divide the sample of banks into regions where the “small” banks have less than roughly 2 billion USD ( $Size < 7.6$ ) and the “large” banks greater than 20 billion USD ( $Size > 9.9$ ) in total assets. We form a regression with dummy variables interacting with the size of the firm. The relative size of the firm is used to form three interaction terms where the small firms are categorized as having  $Size < 7.6$ , the large firms having  $Size > 9.9$ , and the medium sized firms in between these two threshold levels. We run a regression of the weighted systemic importance measure against the size as well as two interaction terms, *Small* and *Large*, omitting the medium sized firms to avoid multicollinearity. The results of this regression are found in Table 5.

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<sup>10</sup>The results for the  $SI^{DEP}$  and the SII measure can be made available upon request.

From this regression we observe that above and below these two thresholds, increasing or decreasing the size of the bank has less impact to its systemic importance. We conclude that for this period size is only a determinant of systemic importance for medium sized firms. When firms become too large, or small, the SI ceases to increase with size. Banks that grow larger increase their systemic importance, but only up to a limit. Above this limit threshold, large banks have a similar level of systemic importance. Zhou (2010) provides empirical evidence that size is not necessarily a determinant of systemic importance. However, the analysis was based only on data from 28 large US banks. Interestingly, we find also find that the 30 largest banks in our sample do not significantly differ in systemic importance giving support to this result. Our sample covers also medium and small banks, and thus provides a more complete picture on testing TBTF.

Our results have direct policy implications. The Obama administration in early 2010 announced their intention that the implementation of policy based on the concept of TBTF would cease. At the same time, the governor of the Bank of England has publicly stated his desire to limit the size of banks. In either case, it is necessary to know if and when size is an important determinant of systemic importance. Based on our findings, a regulator imposing a TBTF policy should consider not the relative size of large banks, but rather a frontier size, above which all institutions become TBTF. The analysis shows that limiting the size of banks, is only effective if the appropriate size limit is imposed.

While the relation between the systemic importance of a bank and its leverage is negative, it is not significant for the weighted measure. As aforementioned, a bank's leverage ratio may increase in two ways: increasing the debt level or decreasing the asset value. Given the negative market conditions in this period, it is more likely that leverage increases as a result of depressed asset values. Leverage increasing in this way would have a similar effect on all banks in the system and can be regarded as being "involuntary". Therefore, the argument on the potential negative impact of leverage discussed in Section 4.2 may not apply during the global financial crisis. This partially explains the insignificant result during this period.

The hypothesis that traditional banking practices are less risky, not only to the idiosyncratic risk, but also to the systemic risk is confirmed in our analysis: the coefficient on the fraction of

income generated by interest is negative with a significance at the 95% level. Our finding supports regulating non-traditional banking activities since they help to mitigate both individual risk as well as the interconnectedness of the system.

## 6.2 Economic Boom and US Housing Bubble: 2003-2006

When conducting analysis in the 2003-2006 period which corresponds to the rapid expansion in the US, the impact of asset holdings and income strategy has on the systemic importance of institutions is essentially unchanged. However, three differences are observed.

First, the partial linear effect of size on the bank's SI weighted by capital shortfall is apparent in Figure 3, however, with only single breakpoint for this period. This occurs in the neighborhood around the point where  $Size = 7.4$  (see Figure 4). We find that when  $Size < 7.2$  the coefficient on the size is no longer significant. Conversely, it is highly significant in the positive direction when  $Size$  is greater than 7.2. This gives strong support for the TBTF hypothesis.

Second, the coefficient on the leverage variable is highly significant in this period in the negative direction. In this period the economy is booming. Increased leverage positions are not due to a common negative shock on asset prices, as during the crisis, but rather a choice by the bank to increase its level of debt. We have conjectured that banks choosing to increase their leverage have a lower SI because of taking on a more isolated position. In addition, as these highly levered banks sought out more risky investment opportunities their operations and asset holdings became increasingly unique and less susceptible to common shocks. De Jonghe (2010) finds that leverage contributes positively to the systemic importance of financial institutions, which is opposite to what we find. The difference in our findings may be attributed to the different SI measures employed. The systemic risk of a bank in De Jonghe (2010) is defined as the probability that a bank receives an extreme negative return on its equity at the same time that the banking index suffers from an extreme drop in value. This measure is similar to the PAO of Segoviano & Goodhart (2009), in the sense that it only reports the probability of a spillover effect, and not the expected losses to the system as in our paper.

Moreover, we find that the ratio of problem loans to total loans is significant in determining

the systemic importance of a financial institution. The relation is negative and significant for the weighted  $SI^{CS}$  measure at the 10% level in this period. The data suggests that the more non-performing loans a bank has on its book the less systemically important it is. Banks with poor lending practices that result in many problematic loans do not mitigate risk across the financial system. A potential explanation is that banks can become systemically linked through the issuance of consolidated loans. Since these loans are monitored very closely, their failure is less likely. Banks engaging in consolidated loans are less risky while at the same time become systemically important due to the fact that such loans are held by more banks compared to the non-consolidated loans. We conclude that the types of loan activity banks are engaging in, consolidated or not, may be an important factor for regulators to monitor.

Determinants such as the leverage and the fraction of problem loans seem to demonstrate an opposite impact on the systemic importance compared to that on the individual risk. We further analyzing this by regressing individual risk measure on the same variables. As a proxy for the individual risk, we use the VaR of a bank at the 1% probability level. We report the regression result in Table 7. We find that a number of determinants have an opposite relation. First, size is negatively related to the individual risk. Moreover, we also find that the leverage and the fraction of problem loans are positively related to the individual risk. This is an indication that a tradeoff exists between the two ways a bank may contribute to the overall systemic risk in the financial sector: by increasing (decreasing) leverage the bank can increase (decrease) its individual risk while decreasing (increasing) its connections with the rest of the system. A similar impact exists for the amount of risky loans that it pursues. To summarize, any policy that attempts to limit systemic risk through regulating banks individual risk taking, such as risky loans or excessive leverage, should consider such a tradeoff.

Finally, the third difference in this period is that funding activities now play a significant role in determining a firm's systemic importance. Our analysis shows that a bank that relies more heavily on short term funding, and therefore bearing a high maturity mismatch, is more systemically important. Furthermore, the type of short term funding it utilizes also plays an important role. A breakdown of the composition of the funding methods shows demand and saving deposits are

positive and significant at the 95% level.

Funding in the form of retail deposits is regarded as a traditional approach to bank operations. The use of short term wholesale funding grew during this period as the economy boomed and banks struggled to attract additional customer deposits. Our results suggest that the failure of a bank with a large reliance on money market funding is less systemically important than banks with more traditional funding sources. The increase in money market funding is often cited as a cause of the global financial crisis. Again, this might be a result of the risk tradeoff. On the contrary, when analyzing the individual risk in Table 7, the fraction of funding that is short-term is still positively related to the individual risk. In general, different from the risk tradeoff we find for other determinants, banks relying on short-term funding not only correspond to higher individual risk such as bank runs, but also are more exposed to common funding shocks and thus bear a higher systemic importance.

We also find that although the probability of failure may be greater for a firm that relies on wholesale funding, simultaneous failures do not accompany it. Traditional retail deposits have shorter maturities than money market funds. Banks that rely heavily on demand and savings deposits are more susceptible to bank runs caused by a common funding shock than banks heavily exposed to the wholesale money market. When regulating money market funding, the two-fold impact of tail risk and interconnectedness should be acknowledged.

### **6.3 GLB Act and the Dot-Com Deflation: 1999-2002**

When analyzing the period 1999-2002, since non-traditional banking activity, such as non-interest income and wholesale money market funding, were less common during this period, it is not surprising that we do not find significance on the variables for funding and income strategies. The only significant variable in the regressions for the weighted SI measure is the size of the institution. Moreover, the non-linear relationship between size and SI is not significant in this period in any of the regressions.

Using the threshold regression for this period, we find no breakpoint in the regressions, as shown in Figure 5. The size of a bank is directly proportional to its SI. Therefore, not only is

TBTF fundamental in determining systemic importance in this period, SI is also a simple linear relation with respect to systemic importance, unlike in the other two periods.

The complexity of the multiple determinants of systemic importance in the other two periods diminish in this period. This difference might be a consequence of the sophisticated financial innovations in more recent years. Expansion of financial products, such as asset backed securities, allowed banks to increase their diversification in order to decrease their individual risk. However, as bank's increased their diversification they, in fact, increased their risk exposures in a number of ways. While possibly decreasing their individual risk, they in fact become more systematically important. Before the era during which financial institutions increase their scope through diversifying on more elaborate financial products, funding and income generation, the only determinant of systemic importance, in terms of social welfare, is the size of the institution under the weighted measure for expected capital shortfall.

Financial innovations, while on the one hand, weaken the TBTF feature for large banks allowing banks to grow larger without increasing systemic linkage, on the other hand, they eliminate the isolated position that small banks enjoy. This creates a more interconnected system. Therefore, regulators should consider other determinants other than size in identifying the SIFIs in recent periods.

## 7 Conclusion

This paper extends an existing measure of systemic importance that captures the simultaneous number of bank failures, into two other measures so that each capture a type of social welfare loss to the system given a single bank failure. We then investigate the relation between these measures and a selection of potential determinants of systemic importance from bank balance sheet items.

We find strong support in favor of the TBTF hypothesis; however, the relationship between the size of a financial institution and its systemic importance can be highly non-linear. This result is dependent on the macro-economic conditions analyzed. We find that in two of three periods, non-linearity exists. For example, in the 2007-2010 period any bank with assets exceeding 20 billion USD does not significantly increase its systemic importance with an increase in its size.

The exception is the period spanning 1999-2002 where the systemic importance grows linearly with size. Moreover, size is the only determinant of systemic importance in this period. In the other two periods additional determinants emerge. We find that the amount of short term funding the bank employs is positively related to the SI. In general, the leverage, amount of interest income, and the volume of problem loans are all negatively related to the SI. However, the degree to which these variables are significant depends largely on the macroeconomic conditions of the period analyzed.

Our result has direct policy implications for regulators. Regulation that attempts to reduce the systemic risk in the financial industry must take into account more than just the size or leverage of a bank. Instead, it is necessary to separate banking activities that have influence over individual tail risk from those that create interconnectedness. We find that some drivers of systemic importance have the opposite effect on the individual risk of a bank. To reduce the overall risk in the system, regulators should consider a balance between these two contributors of systemic risk.

Moreover, the variation of potential determinants of systemic importance under different macroeconomic environments indicate that regulation towards controlling systemic risk has to vary according to the business cycle. A flat regulation may provide a suboptimal solution. Therefore, a macro-prudential regulation that addresses macro-conditions is necessary in maintaining stability of the financial sector in its entirety.



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## 8 Appendix

**Table 1:** Summary Statistics

	2007-2010			2003-2006			1999-2002		
	Mean	StDev	Max	Mean	StDev	Max	Mean	StDev	Max
$SII$	14.45	15.69	51.08	5.28	3.97	17.53	2.95	1.84	9.69
$SI^{CS}$	6.62	3.33	10.94	3.81	1.92	7.57	3.89	2.20	8.10
$SI^{DEP}$	9.03	3.65	13.10	7.26	2.17	11.42	6.94	2.42	11.70

This table presents summary statistics for the three estimated measures of systemic importance. The  $SII$  measure estimates the expected number of simultaneous bank distresses given the distress of a particular bank. The  $SI^{CS}$  and the  $SI^{DEP}$  measure the expected capital shortfall and loss of customer deposits in the financial system, respectively, given the distress of a particular bank. The units for both weighted SI measures are in the log of million USD.

**Table 2:** Most Systemically Important Banks by Measure: 2007-2010

$SII$	$SI^{CS}$	$SI^{DEP}$
City National	<b>Fifth Third Bancorp</b>	<b>US Bancorp</b>
Valley National	<b>Citigroup</b>	<b>Wells Fargo</b>
Chemical Financial	Huntington Bancshares	Zions Financial
City Holding	<b>US Bancorp</b>	<b>PNC Financial</b>
Wintrust Financial	<b>Regions Financial</b>	Comerica
<b>US Bancorp</b>	Zions Bancorp	M&T Bank
Dime Community	<b>Keycorp</b>	<b>SunTrust Banks</b>
Independent Bank	<b>Suntrust Banks</b>	City National
Zions Bancorp	<b>Bank of America</b>	<b>CitiGroup</b>
Prosperity Bancshares	<b>Wells Fargo</b>	<b>KeyCorp</b>

This table presents the list of the top ten most systemically important banks based on each of our three estimated systemic importance measures: the expected number of simultaneous bank distresses ( $SII$ ), the expected loss of bank capital ( $SI^{CS}$ ) in the system, and the expected loss to customer deposits ( $SI^{DEP}$ ) in the system given a specific bank distress or default. Banks in bold typeface represent those in the top 15 of US BHCs in terms of total deposits as of June 30, 2010 (source [www.fdic.gov](http://www.fdic.gov)).

**Table 3:** Correlation of SI Measures

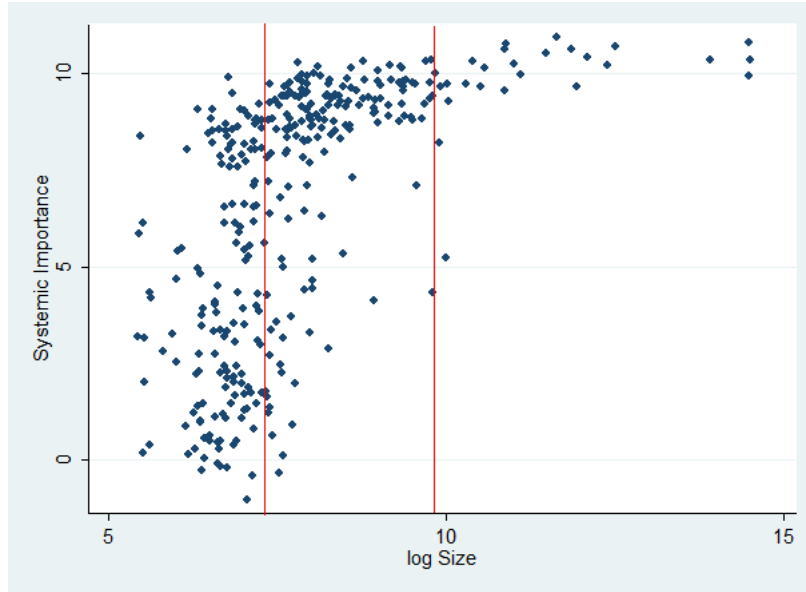
	2007-2010			2003-2006			1999-2002		
	<i>SII</i>	<i>SI<sup>CS</sup></i>	<i>SI<sup>DEP</sup></i>	<i>SII</i>	<i>SI<sup>CS</sup></i>	<i>SI<sup>DEP</sup></i>	<i>SII</i>	<i>SI<sup>CS</sup></i>	<i>SI<sup>DEP</sup></i>
<i>SII</i>	1			1			1		
<i>SI<sup>CS</sup></i>	0.729	1		0.567	1		0.721	1	
<i>SI<sup>DEP</sup></i>	0.758	0.983	1	0.557	0.972	1	0.743	0.984	1

This table presents the Pearson correlation coefficients between each of the three estimated systemic importance measures: the expected number of simultaneous bank distresses (*SII*), the expected loss of bank capital (*SI<sup>CS</sup>*) in the system, and the expected loss to customer deposits (*SI<sup>DEP</sup>*) in the system given a specific bank distress or default.

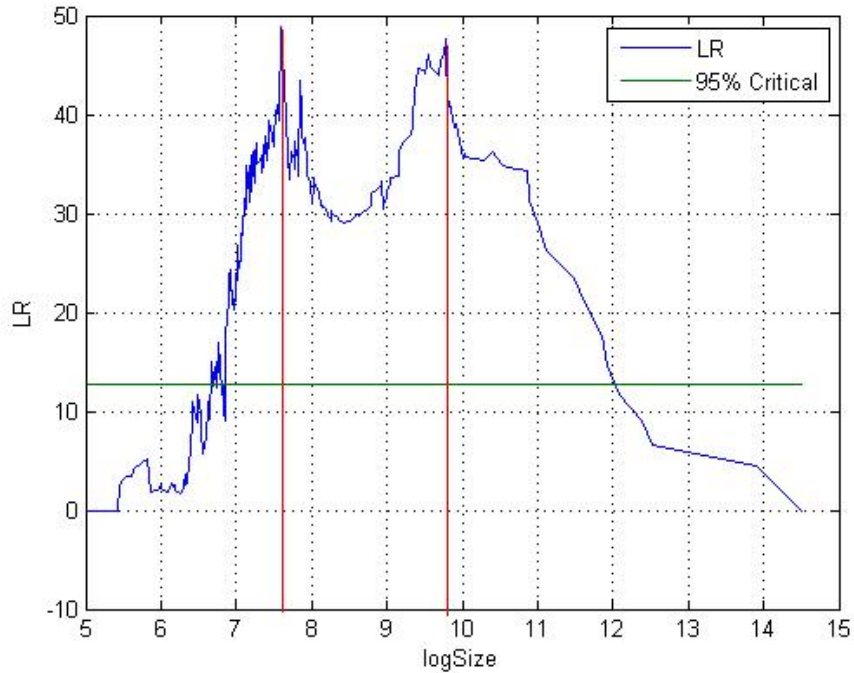
**Table 4:** *SI<sup>CS</sup>*: 2007-2010

	(1)	(2)	(3)	(4)	(5)	(6)
Size	1.876*** [14.56]	1.886*** [14.54]	1.919*** [13.63]	1.886*** [14.57]	1.889*** [14.11]	1.845*** [14.16]
Size2	-0.453*** [-8.36]	-0.425*** [-7.53]	-0.423*** [-7.36]	-0.448*** [-8.12]	-0.448*** [-8.05]	-0.449*** [-8.26]
Leverage	-0.0154 [-0.33]	-0.00790 [-0.17]	-0.00249 [-0.05]	-0.0151 [-0.32]	-0.00242 [-0.05]	-0.00484 [-0.10]
STF		3.113 [1.53]	3.278 [1.58]			
Demand			2.150 [0.83]			
Savings			1.992 [0.95]			
Loans				1.007 [0.82]	1.232 [0.98]	
Mortgage					0.0566 [0.10]	
Problem					-5.526 [-0.78]	
Interest						-0.331** [-2.48]
_cons	-7.427*** [-6.17]	-10.39*** [-4.36]	-12.71*** [-3.85]	-8.276*** [-5.28]	-8.458*** [-5.03]	-6.846*** [-5.41]
<i>N</i>	342	342	342	342	342	342
adj. <i>R</i> <sup>2</sup>	0.398	0.400	0.398	0.397	0.395	0.400
<i>BIC</i>	1639.0	1642.6	1653.2	1644.2	1655.2	1642.5

*t* statistics in brackets  
\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$



**Figure 1:**  $SI^{CS}$  vs. Size: 2007-2010. The figure presents a scatter plot of the systemic importance of a bank, as measured by the  $SI^{CS}$ , against the log of the size of the bank (total assets in million USD). The vertical lines indicate the estimated “breakpoints” in the regression.



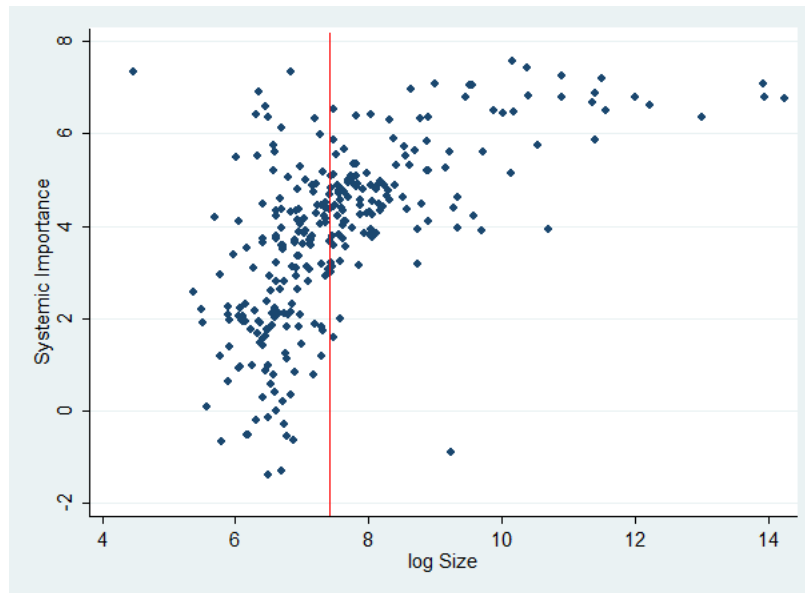
**Figure 2:** F-test for the Breakpoint Test: 2007-2010. The figure shows the results of a series of likelihood ratio tests under the null hypothesis of no breakpoint on the estimated regression coefficient for  $Size$ . The critical value of the test is constructed from a bootstrap procedure (?).

**Table 5:**  $SI^{CS}$ : 2007-2010 with Dummies

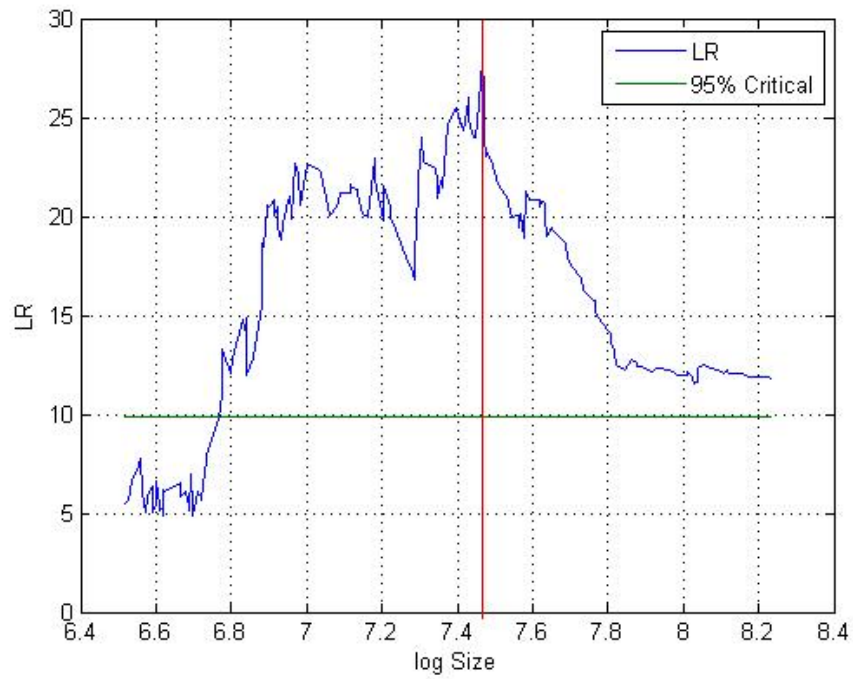
	(1) $SI^{CS}$
Size	1.528*** (5.96)
Leverage	-0.0214 (-0.45)
Small	-1.104* (-1.93)
Big	-1.030** (-2.14)
Observations	342

*t* statistics in parentheses

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



**Figure 3:**  $SI^{CS}$  vs. Size: 2003-2006. The figure presents a scatter plot of the systemic importance of a bank, as measured by the  $SI^{CS}$ , against the log of the size of the bank (total assets in million USD). The vertical line indicates the estimated “breakpoint” in the regression.



**Figure 4:** F-test for the Breakpoint Test: 2003-2006. The figure shows the results of a series of likelihood ratio tests under the null hypothesis of no breakpoint on the estimated regression coefficient for *Size*. The critical value of the test is constructed from a bootstrap procedure (?).



**Table 6:**  $ST^{CS}$ : 2003-2006

	(1)	(2)	(3)	(4)	(5)	(6)
Size	1.029*** [8.00]	1.041*** [8.33]	1.135*** [8.31]	1.024*** [7.98]	1.029*** [7.26]	1.011*** [7.85]
Size2	-0.184*** [-3.04]	-0.177*** [-2.90]	-0.184*** [-3.09]	-0.186*** [-3.08]	-0.178*** [-3.09]	-0.193*** [-3.19]
Leverage	-0.113*** [-2.94]	-0.107*** [-2.79]	-0.105*** [-2.64]	-0.113*** [-2.93]	-0.115*** [-3.06]	-0.104*** [-2.70]
STF		1.704* [1.83]	1.110 [1.16]			
Demand			4.482** [2.41]			
Savings			3.250** [1.98]			
Loans				-0.459 [-0.77]	-0.631 [-1.09]	
Mortgage					0.256 [0.48]	
Problem					-34.29* [-1.96]	
Interest						-0.660** [-2.23]
_cons	-2.639** [-2.40]	-4.299*** [-3.65]	-7.657*** [-3.23]	-2.258* [-1.85]	-2.124 [-1.30]	-1.771 [-1.50]
$N$	292	292	292	292	292	292
adj. $R^2$	0.390	0.393	0.418	0.389	0.401	0.397
$BIC$	1083.8	1087.0	1084.1	1089.0	1092.7	1085.4

$t$  statistics in brackets

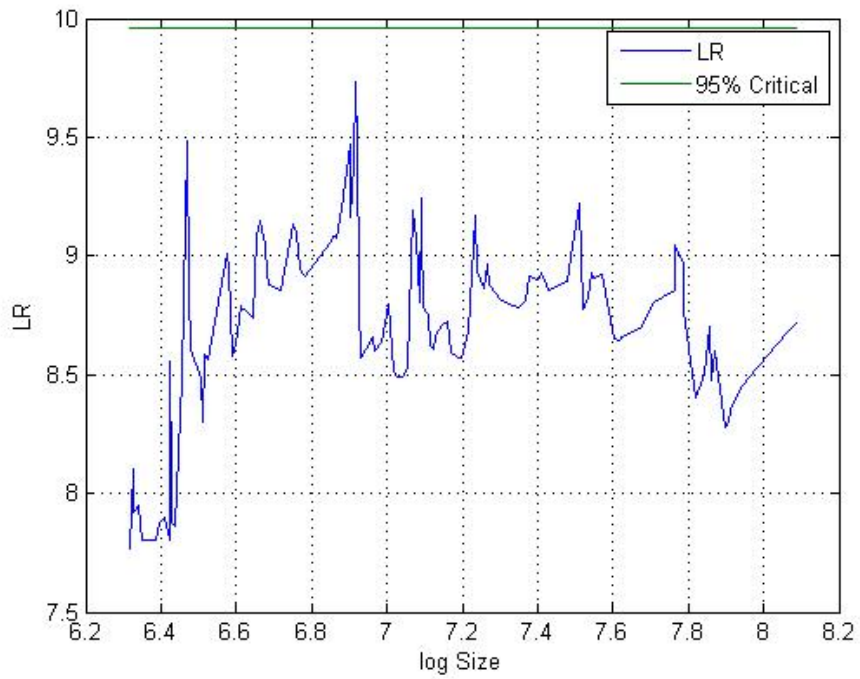
\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table 7:**  $VaR_{1\%}$ : 2003-2006

	(1)	(2)	(3)	(4)	(5)
Size	-0.00666*** (-7.10)	-0.00736*** (-8.45)	-0.00684*** (-7.57)	-0.00661*** (-8.44)	-0.00673*** (-7.15)
size_2	0.00109*** (3.01)	0.00111*** (3.00)	0.00101*** (2.70)	0.000905** (2.55)	0.00103*** (2.75)
Leverage	0.000448* (1.66)	0.000409 (1.50)	0.000436 (1.57)	0.000441* (1.69)	0.000421 (1.54)
STF	0.00647 (0.74)	0.00911 (1.02)			
Demand		-0.0241* (-1.89)			
Savings		-0.0223** (-2.09)			
Loans			-0.0106* (-1.93)	-0.00672 (-1.21)	
Mortgage				-0.000410 (-0.15)	
Problem				0.590** (2.33)	
Interest					-0.00227 (-0.35)
Observations	294	294	294	294	294

$t$  statistics in parentheses

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



**Figure 5:** F-test for the Breakpoint Test: 1999-2002. The figure shows the results of a series of likelihood ratio tests under the null hypothesis of no breakpoint on the estimated regression coefficient for *Size*. The critical value of the test is constructed from a bootstrap procedure (?).

**Table 8:**  $SI^{CS}$ : 1999-2002

	(1)	(2)	(3)	(4)	(5)	(6)
Size	0.695*** [4.64]	0.695*** [4.63]	0.658*** [4.23]	0.702*** [4.71]	0.686*** [4.36]	0.692*** [4.60]
Size2	0.0827 [0.91]	0.0813 [0.90]	0.0658 [0.74]	0.0826 [0.93]	0.0833 [0.94]	0.0773 [0.85]
Leverage	-0.0351 [-0.64]	-0.0378 [-0.63]	-0.0494 [-0.76]	-0.0331 [-0.61]	-0.0323 [-0.56]	-0.0325 [-0.60]
STF		-0.199 [-0.13]	-1.036 [-0.62]			
Demand			3.468 [1.30]			
Savings			-0.498 [-0.22]			
Loans				0.849 [0.81]	0.770 [0.73]	
Mortgage					-0.259 [-0.34]	
Problem					-8.992 [-0.27]	
Interest						-0.165 [-0.47]
_cons	-1.042 [-0.89]	-0.835 [-0.39]	0.264 [0.08]	-1.730 [-1.27]	-1.333 [-0.79]	-0.811 [-0.63]
$N$	190	190	190	190	190	190
adj. $R^2$	0.293	0.289	0.292	0.292	0.285	0.290
$BIC$	790.6	795.8	803.5	795.2	805.4	795.7

$t$  statistics in brackets

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