Is Size Everything? *

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This Draft: December 31, 2017

Abstract

We comprehensively account for systemicness by constructing risk factors based on threshold size, interconnectedness (IC), complexity, leverage and liquidity. We find that, prior to 2007, our big-versus-huge threshold size factor $TSIZE$, constructed from equity returns of large financial firms, is a sufficient statistic for systemicness. The largest 10% of firms by market size load negatively on it, implying a "SIFI discount", while the remaining firms load positively on $TSIZE$, implying a "SIFI premium." The $TSIZE$ subsidy increases around Fitch Support Rating changes indicating higher probability of government support and also after the failure of Continental Illinois in 1984. However, following Lehman's failure in September 2008, IC risk becomes more significant while $TSIZE$ risk collapses, suggesting that the market starts to discriminate between these risks. Pre-2007 $TSIZE$ loadings are predictive of changes in systemic risk in the time series and the cross-section, forecasting up to 21% of the actual increase in several systemic risk measures (such as $SRISK$) in the 5 months following Lehman's failure, after accounting for size, leverage and correlation. The results, which survive a wide variety of robustness checks, indicate that while systemic risk comes in different guises, it has a broad impact on resource allocation by increasing the cost of capital of all but the largest firms.

Keywords: Too-Big-To-Fail, systemic risk, factor models, interconnectedness, complexity, financial crisis

JEL Classification:G01, G12, G21, G28

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*The views in this paper belong to the authors and do not necessarily reflect those of the Federal Reserve Bank of New York or the Federal Reserve System. We thank participants at the Bank for International Settlements, the Central Bank of Brazil Financial Stability conference, the University of San Gallen, the World Finance Conference, the Stanford Berkeley Joint Finance Seminar, and the Federal Reserve Bank of New York for comments. We also thank Viral Acharya, Tobias Adrian, Richard Crump, Fernando Duarte, Thomas Eisenbach, Zhiguo He, Benjamin Klaus, Hanno Lustig, Antoine Martin, Tyler Muir, Joao Santos, Mila Getmansky Sherman, Consuelo Silva-Buston and Annette Vissing-Jorgensen for helpful comments.

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1 Introduction

Traditionally, size has been considered the key criterion for whether a firm is deemed "too-big-to-fail" (TBTF).[1] Consistent with this notion, section 165 of the Dodd Frank Act (DFA) identifies a threshold of $50 billion of the consolidated book value of assets (BVA) for 2010, above which a bank holding company (BHC) is automatically designated as a systemically important financial institution (SIFI). Later, the same threshold was extended to determine the SIFI designation of a non-bank financial firm but, in addition to asset size, leverage and liquidity risk, interconnectedness (IC) and organizational complexity were also considered.[2] In the literature, however, size risk has received the most attention, and there is little research into the relative importance of different factors that determine systemicness.

In this paper, we comprehensively account for systemicness by constructing risk factors based on threshold size, leverage, liquidity, IC and complexity. Since market participants form expectations of government bailouts, market prices internalize systemic risk to some extent. So, we evaluate the contribution of a factor by whether it is priced in the cross-section of equity returns and whether its loading is correlated with government bailout probabilities. Further, factor loadings should predict bailouts, as implied by Gandhi and Lustig (2015), Gandhi, Lustig and Plazzi (2016) and Kelly, Lustig and Van Nieuwerburgh (2016) who show that the average risk-adjusted return of firms with high bailout probability is low during normal times in anticipation of shareholder bailouts in disaster states. Thus, we examine to what extent changes in factor loadings in normal times predict higher systemic risk in crisis.

Financial firms may benefit from size for reasons other than expected bailouts–for example, better cost efficiency (Kovner, Vickery and Zhou (2014)), market power and political influence. Moreover, perceived government support for financial firms deemed TBTF does not increase proportionately with size, but rather is viewed as an advantage accruing only to the largest firms (Basset (2014)). Motivated by these considerations, our threshold size factor

[1]Indeed, the term "TBTF" came into being after the Comptroller of Currency identified the eleven largest banks as such in September 1984.

[2] The DFA was signed into federal law on July 21, 2010 to, among other things, end TBTF and to protect American taxpayers by ending bailouts (https://www.govtrack.us/congress/bills/111/hr4173/text). Later, the Financial Stability Oversight Council (FSOC) approved using the $50 billion consolidated asset cutoff as one threshold for non-bank financial firms to be deemed SIFIs. Non-asset-size considerations (in addition to those mentioned above) are: maturity mismatch, substitutability and existing regulatory scrutiny. The latter two are applied on the basis of company-specific qualitative and quantitative anslysis as they are difficult to quantify (http://www.treasury.gov/initiatives/fsoc/Documents/Nonbank%20Designations%20-%20Final%20Rule%20and%20Guidance.pdf).

(denoted $TSIZE$) is defined as the equity returns of financial firms in the 84th to 92nd percentile of the market value of equity (MVE) minus the returns of financial firms above the 92nd percentile of MVE. The 92nd percentile threshold corresponds to the DFA cutoff of \$50 billion in the distribution of the BVA for 2010.[3] The return on $TSIZE$ is 0.62% per year and countercyclical, indicating that $TSIZE$ risk is not fully diversifiable. Notably, $TSIZE$ is minimally correlated in our sample with large-versus-small factors such as SMB (Fama and French (1993)) or the bank size factor of Gandhi and Lustig (2015) (denoted GL), indicating that it is informative even after accounting for SMB and GL.

We initially examine the pricing of $TSIZE$ in the pre-crisis sample (1963-2006) using the 3-factor model of Fama and French (1993), plus GL, momentum (Carhart (1997)) and bond market factors. In the time-series, stock returns of 26 out of 30 test portfolios sorted on size and book-to-market (BM) load significantly on $TSIZE$. Firms in the largest size decile load negatively on $TSIZE$, representing a "SIFI discount" while smaller firms load positively on the factor, representing a "SIFI premium." The advantage of firms in the largest size decile, relative to those in the next decile, amounts to 6 basis points per year or 8 million per firm per year in 2013 dollars. The price of $TSIZE$ risk is statistically significant in the cross-section, showing that it is an important determinant of average returns. In contrast, if $TSIZE$ is constructed from the largest non-financial firm returns, this alternative factor is not significantly priced in the cross-section, indicating that the common $TSIZE$ risk comes only from exposure to the largest financial firms.

Next, we construct factors based on IC, leverage and liquidity. IC is based on the principal components measure of Billio, Getmansky, Lo and Pelizzon (2012). The leverage factor is from He, Kelly and Manela (2017) which is based on innovations on capital ratios of primary dealers, and is meant to capture financial shocks to the financial intermediation sector. Finally, the market liquidity factor (expected to be correlated with funding liquidity risk) is based on the Amihud ratio (Amihud and Mendelson (1986)). When we add these factors to the model, we find that, prior to 2007, returns generally loaded insignificantly on the non-size factors which, in addition, are not priced in the cross-section. Moreover, the sign of the loadings do not switch for the largest decile of firms, as was the case for the $TSIZE$ loadings. In other words, prior to the crisis, size was a sufficient statistic for systemicness.

The largest non-financial firms may also have lower exposure to $TSIZE$ for reasons other

[3] In 2010, the firm closest to the 92nd percentile by BVA was at the 90th percentile by MVE. We use MVE cutoffs to be consistent with standard factor model methodologies but most of our results are robust to the use of cutoffs based on BVA or book value of equity BVE (see Section 4.4).

than SIFI perceptions (e.g. lower funding costs). However, we find that virtually all of the $TSIZE$ subsidies go to the largest financial firms. Moreover, when financial firms transition from the second largest size bin to the largest size bin, their $TSIZE$ loadings become negative; conversely, when the largest decile firms transition to the second largest decile, their $TSIZE$ loadings become positive (Figure 2). Thus, the $TSIZE$ tax and subsidy are linked to the position of firms in the size distribution at a point in time, likely reflecting changing market perceptions of SIFI risk. This switching behavior is only observed for financial firms.

This size threshold effect (i.e. the switch from a $TSIZE$ premium to a discount for the largest decile of firms) is not a mechanical outcome of how the $TSIZE$ factor is constructed as it holds for higher thresholds, up to a cutoff of $300 billion in consolidated BVA for 2010 (corresponding to the top 3% of financial firms by MVE). We show this by excluding the largest financial firms that are components of the $TSIZE$ factor from the largest two deciles of test assets, and find that the threshold result is qualitatively unchanged. The size threshold effect is also evident if we use book values to determine the $TSIZE$ threshold (consistent with the actual practice of regulators), instead of MVE. However, the book-value based $TSIZE$ is not priced in the cross-section of returns.

Next, we extend our sample to 2013 and examine changes in loadings around systemic events. $TSIZE$ loadings increased after the bailout of Continental Illinois in May 1984 and decreased after the bankruptcy of Lehman Brothers in September 2008 (Figure 5). More interesting, the IC loadings become more significant following Lehman and, similar to the pre-crisis pattern for $TSIZE$, they switch from positive to negative for the largest decile of firms. Thus, market participants appear to discriminate between size and IC risk following the Lehman failure, as the size subsidy falls and the IC subsidy increases. Overall, these results show that the $TSIZE$ and IC risk premia increase around systemic risk events.

$TSIZE$ subsidies for only the largest financial firms may reflect increased expectations of government support in the crisis. Indeed, we find that over 80% of banks comprising the largest size group in the $TSIZE$ factor are extremely likely to receive government support, as indicated by Fitch's Support Rating Floor, compared to less than 20% of banks with high likelihood of government support in the next largest size group. Moreover, using a panel regression, we find that $TSIZE$ subsidies increase after a Fitch Support Rating change that increases the probability of government support, afer controlling for firm characteristics.

Are pre-crisis $TSIZE$ loadings predictive of systemic risk during the crisis in the aggregate and at the firm level, after controlling for firm size, size risk, leverage and market correlation? We consider two systemic risk measures: fire-sale spillover AV (Duarte and Eisenbach (2015)) and $SRISK$, the expected capital shortfall of a firm conditional on a substantial market decline (Acharya, Pedersen, Philippon and Richardson (2010), Acharya, Engle and Richardson (2012) and Brownlees and Engle (2012)). In the aggregate analysis, impulse responses estimated from a Vector Autoregression (VAR) indicate that lower $TSIZE$ loadings of the largest financial firms predict higher systemic risk. The effect is economically meaningful as $TSIZE$ loadings from Q3 2008 forecast higher systemic risk that is between 11% and 21% (depending on the measure) of the actual increase in systemic risk following Lehman's failure. And, in the cross-section, we show that financial firms in the largest size bin with lower average $TSIZE$ loadings before the crisis had higher systemic risk in the crisis. The predictive power of $TSIZE$ remains unchanged after including the non-size factors, implying that $TSIZE$ by itself was informative of systemic risk in the economy. However, pre-crisis $TSIZE$ loadings are not predictive if the factor is constructed using book values. This is consistent with Acharya, Engle and Pierret (2014b) who find that, in contrast to market-value-based measures, regulatory risk weights do not correlate with the realized risk of banks six months hence.

Last, we add a complexity factor to the model, where complexity is measured by the number of subsidiaries of BHCs as in Cetorelli, Jacobides and Stern (2017). This factor is generally not significant except for the largest banks—the so-called GSIBs (Globally Systemically Important Banks), which experienced a sizeable increase in the number of subsidiaries from 2007. Such an increase is not observable for non-GSIBs.

The main contribution of this paper is identifying the relative importance of size and non-size related risk factors in determining the systemicness of a firm, based on whether the factor is priced, whether its loadings are correlated with expectations of government support, and whether they are predictive of systemic risk. We show that the importance of factors varies over time. Our novel "threshold risk" factor $TSIZE$, orthogonal to the usual measures of size risk, is a sufficient statistic for determining systemicness before 2007 while our IC factor is informative since Lehman's failure. While factor pricing has been previously used to study TBTF issues, a direct connection between factor loadings and government support and the evidence on predictability is new. Also new is the construction of factors based on various non-size characteristics.

An important implication of our results is that the cost of capital is higher for those firms that do not benefit from perceptions of government support. Thus, there exists a broad-based effect of SIFI risk that affect all firms due to the redistribution and repricing of risk, resulting in further misallocation of resources (i.e. both from lower cost of capital for TBTF firms and higher cost of capital for non-TBTF firms). This differs from the emphasis in the prior literature on benefits to the largest firms and not on the cost to the remaining firms.

Our factor loadings may be used as practical tools for monitoring systemic risk in the economy. These loadings predict changes in systemic risk in the time series and the cross-section, even after controlling for size, leverage and correlation. $TSIZE$ and IC are easy to construct from public data using standard asset pricing methods.

The prior literature has identified lower bond spreads for the largest firms compared to smaller firms. Our paper shows that shareholders of the largest firms also benefit from lower expected returns even when compared to shareholders of their (large) peer firms. Why are returns to equity predictive of tail risk? Government guarantees absorb risk that would be otherwise be borne by creditors and shareholders. If the value of such guarantees accrues to shareholders, Lucas and McDonald (2010) show that the ex-ante value of equity increases by the present value of being able to borrow at the risk-free rate. Banks may also over-lever in anticipation of debt guarantees, and if the higher leverage is not offset by higher debt costs, shareholder value increases at the expense of taxpayers (Acharya, Mehran and Thakor (2013)). Consistent with equity returns embodying expected bailout risk, Kelly et al. (2016) find that out-of-the-money index put options of bank stocks were relatively cheap during the recent crisis and Gandhi et al. (2016) find that an increase in small bank returns, relative to large banks, forecasts sharp declines in GDP and stock returns.

The rest of the paper is organized as follows. Section 2 describes how our paper relates to the literature. Section 3 describes the data and methodology used in the paper. Section 4 presents results from regressions of portfolio returns on SIFI factors based on size, IC, leverage and liquidity. Section 5 relates SIFI factor loadings to government guarantees for the largest financial firms, and to systemic risk events. Section 6 explores whether pre-crisis SIFI factor loadings predict systemic risk in crisis. Section 7 discusses the complexity factor in the context of financial sub-sector portfolios. Section 8 concludes.

2 Literature

The literature examines the perceived benefits of government guarantees to the largest firms, some portion of which is hypothesized as being due to TBTF risk. Benefits are generally measured by comparing bond returns or spreads (relative to Treasury securities of similar maturity) or CDS spreads of the largest financial firms with various control groups of firms. A few papers also consider a TBTF effect on equity returns. A related literature considers whether returns of the largest firms are less sensitive to risk compared to smaller firm returns.

Our analysis differs from the papers discussed below in adopting an asset pricing approach that isolates the component of expected returns due to TBTF risk. We do so by comprehensively examining the determinants of TBTF risk considered by regulators—asset size threshold, leverage, liquidity, IC, complexity—after controlling for standard risk factors. Our evidence identifies the externalities imposed on *all* firms by the threshold nature of TBTF risk, resulting in lower cost capital for the largest firms and higher cost of capital for smaller firms. The risk premia on our $TSIZE$ factor predicts changes in systemic risk.

Our paper is closest in spirit to Gandhi and Lustig (2015) who also take an asset pricing approach. After controlling for standard risk factors, they find that the largest commercial banks have lower returns than smaller banks. Their factor GL is akin to a large-versus-small size factor but using only commercial bank returns. In contrast, $TSIZE$ is a huge-versus-large size factor using the largest 16% of financial firm returns and is orthogonal to GL.[4] Since we include GL in our regressions, the effects of $TSIZE$ are in addition to those of the former. Gandhi et al. (2016) extend their analysis to financial firms in 31 countries. Different from Gandhi and Lustig (2015), we directly link the $TSIZE$ subsidy to a measure of government gurantees (i.e. Fitch Support Ratings), and show that $TSIZE$ is priced in the cross-section of returns and that it is predictive of systemic risk.

Very large firms are found to have funding cost advantages relative to other firms, although the magnitude is smaller than when comparing large firms to small firms (or the entire industry). For example, Basset (2014) finds small differences in deposit rates of very large banks and large regional banks. Santos (2014) finds that the largest banks have cost advantages (relative to their peers) in bond issues that are bigger than those enjoyed by insurance companies or non-financial corporations. Kane (2000), Schaeck, Zhou and Molyneux (2010) and Brewer and Jagtiani (2013)) find benefits for equity shareholders when their firms merge to achieve possible TBTF status. Kane (2000) finds that, while acquirer stock values generally decline in large bank mergers, they increase if the merger puts the acquirer's assets above a size threshold. Brewer and Jagtiani (2013) find at least \$15 billion in added premiums for bank mergers that brought the combined firm to over \$100 billion in assets. In contrast,

[4] Other differences with Gandhi and Lustig (2015) are: we use all financial firms rather than only banks, construct factors as in Fama and French (1993) rather than using the principal components of bank returns, and control for more risk factors such as momentum, investments and profitability.

Ahmed, Anderson and Zarutskie (2014) find that while CDS spreads are smaller for very large firms, financial firms do not enjoy a bigger advantage compared to non-financial firms.

Acharya, Anginer and Warburton (2016) find lower risk sensitivity of bond spreads for the largest financial firms but not for large non-financial firms, indicative of government guarantees. Earlier literature argue that the 11 banks deemed by the Comptroller of Currency as TBTF benefited relative to control banks either via higher abnormal equity returns (O'Hara and Shaw (1990)) or lower risk premia on their bond spreads (Morgan and Stiroh (2005)). This literature does not distinguish between the diversifiable component of risk (which should not be priced) and the systematic component (which should be), in contrast to our approach.

The cost advantage of large financial firms may have decreased after the failure of Lehman Brothers and the passage of the DFA. Barth and Schnabel (2013) find a negative relationship between a bank's systemic risk proxy and its CDS spread, which disappears after the fall of Lehman. Balasubramnian and Cyree (2014) find that the TBTF discount on yield spreads on secondary market subordinated debt transactions is reduced by 94% after the Dodd-Frank Act. GAO (2014) and IMF (2014) also show that funding advantages estimated prior to the recent financial crisis have likely reversed in recent years. Acharya et al. (2016) find that the risk sensitivity of bond spreads of the largest financial firm increased after Lehman but not after DFA. In contrast, Minton, Stulz and Taboada (2017) find that the Tobin's q of banks above the DFA threshold falls with size until 2010 and is unrelated to size after DFA.

Since the crisis of 2007-2008, a number of papers have considered the effects of interconnectedness and complexity. Firms may be connected in many ways, such as asset positions, services to clients etc. Diebold and Yilmaz (2014) study volatility connectedness of 13 major financial firms using variance decompositions and find that connectedness increased following the crisis of 2007. Papers on complexity generally find that it is imperfectly correlated with asset size as it also depends on additional factors such as the business model and geographical diversification.[5]

[5] Most papers (for example, Avraham, Selvaggi and Vickery (2012), Cetorelli and Goldberg (2014) and Laeven, Ratnovski and Tong (2014)) use the number of legal subsidiaries as a measure of complexity. One exception is Lumsdaine, Rockmore, Foti, Leibon and Farmer (2015) who use network tree analysis.

3 Construction of Factors for SIFI Risk

This section describes how we construct $TSIZE$ and factors that correspond to risks from IC, complexity, leverage and liquidity. Appendix A discusses the construction of GL and SMB' (a version of SMB that omits financial firms already in $TSIZE$).

To determine the asset size threshold for constructing the $TSIZE$ factor, it is natural to start with the DFA threshold of $50 billion of the total consolidated BVA above which financial firms are deemed to be SIFIs. To permit historical analysis, we map the dollar cutoff to a percentile number. The DFA asset size threshold corresponds to the 92nd percentile of the distribution of the BVA of financial firms in the Compustat North America Database for 2010.[6] In keeping with the asset pricing literature, we use MVE as our measure of size rather than BVA and, accordingly, the largest financial firms are those in the top 8% by MVE (denoted L8) each year. Section 4.4 describes how different choices of MVE cutoffs and constructing $TSIZE$ using book values affects our results.

For constructing the $TSIZE$ factor, we consider only the top 16% of financial firms by MVE (i.e. firms in L8 and the 8% of firms just below the SIFI threshold, denoted NL8). To identify these firms, we filter the universe of firms in Compustat to include only those with monthly returns and stock data in CRSP, and identified as finance by CRSP.[7] For firms in this sample listed on the NYSE, we calculate in December of every year the 30th and 70th percentiles of firms by BM, and in June of each year the 84th and 92nd percentiles of firms by size. We only keep observations with positive size and BM before taking the percentiles. Based on these percentiles, we assign firms in our sample to one of six portfolios for the next year: three BM bins and two size bins. We calculate size-weighted returns for each portfolio in each month, and define $TSIZE$ as the average returns of the three BM bins for firms in NL8 minus the average returns of the three BM bins for firms in L8.

Turning to the IC, complexity and illiquidity criteria, we construct the corresponding factors IC, $COMP$ and LIQ in three steps. First, we estimate measures of IC, complexity and illiquidity for the largest 16% of financial firms each year (i.e. the same group of firms

[6] We define financial firms as those considered finance by NAICS (codes beginning in 52) or by SIC (codes beginning in 6).

[7] Our CRSP sample includes only observations with share code of 10 or 11 (common stocks). We choose the CRSP rather than the Compustat classification because the latter has a large proportion of missing values in the period before 1984, whereas the CRSP classifications identify sufficiently many financial firms to construct our factor starting in 1963. To the best of our knowledge, discrepancies between CRSP and Compustat industry classifications are relatively rare for broad categorizations.

constituting the $TSIZE$ factor), as described below. Next, we sort firms into five groups based on the measure. Finally, the factor is defined as the excess returns on the lowest quintile minus excess returns on the highest quintile. If firms with greater IC, complexity and illiquidity are associated with greater expected bailout benefits, then the factor should have positive returns on average.

IC is measured using the principal component (PC) based measure of Billio et al. (2012). Consider the first n PCs of the variance-covariance matrix of standardized firm returns that explain 95% or more of total variance σ_S^2. In periods of high IC, a few PCs explain most of the system variance (n is small). Let λ_k be the k-th eigenvalue, L_{ik} the loading of firm i returns on factor k and σ_i^2 the return variance. Then firm i's exposure to IC risk is the weighted average of its squared loadings on the first n PCs, with the eigenvalues as weights:

$$IC_{i,n} = \sum_{k=1}^{n} \frac{\sigma_i^2}{\sigma_S^2} L_{ik}^2 \lambda_k \tag{1}$$

We estimate equation (1) for rolling 3-year windows for the largest 16% of financial firms.

SIFI designation requires an assessment of the complexity of the firm's legal, funding and operational structure. Complex banks may be less sensitive to funding shocks, reducing its systemic risk premium (Cetorelli and Goldberg (2016)). Our complexity measure, $COMP$, is the number of subsidiaries of BHCs.[8]

The illiquidity measure is the innovation in the Amihud ratio, or the absolute value of monthly returns divided by the monthly volume, scaled by 10^6 (Amihud and Mendelson (1986)). The innovations are residuals from an AR(5) model for the Amihud ratio. We use a market liquidity measure since the leverage factor (discussed below) is expected to correlate with funding liquidity shocks.

Data for the leverage factor LEV is from He et al. (2017), who construct it based on innovations on capital ratios of primary dealers, defined as MVE over (MVE+BVD).[9]

Data for the book-to-market (HML), Market minus risk free rate ($Mktrf$) and momentum

[8] We thank Nicola Cetorelli for the data.

[9] The source is `http://apps.olin.wustl.edu/faculty/manela/hkm/intermediarycapitalrisk/He_Kelly_Manela_Factors.zip`. We have also used the leverage factor of Adrian, Etula and Muir (2014) based on shocks to the leverage of securities broker-dealers, indicating states of the world associated with deteriorating funding conditions. As data for the series were not available for our full sample, the results are included in the online appendix.

(MOM) factors are from Kenneth French's website.[10] To isolate SIFI effects separately from SMB , we create a SMB' factor that is orthogonal to $TSIZE$ by construction (see Appendix A for further details). The bond market factors $CORP$ and GOV are corporate and government bond returns, respectively, obtained from the Global Financial Database.

Finally, we construct 30 portfolios, whose size-weighted returns we use as dependent variables in regressions, from the intersection of six size and five BM groups. We use the 20th, 40th, 60th, 80th and 90th percentiles of MVE in June of each year to make six size groups; the largest decile contains the firms expected to be benefit from the TBTF perception (see Appendix A for further details).

4 Results

This section present results on the pricing and of the size and non-size SIFI factors, except for $COMP$. As the data for $COMP$ starts only in 1986, and the measure relates only to banks, we discuss it when describing the results for financial sub-sectors in Section 7. Section 4.1 shows results from time series regressions of portfolio returns on SIFI factors. Section 4.2 reports results on factor pricing in the cross section of returns. Section 4.3 compares the effects for financial versus non-financial firms in the $TSIZE$ factor and in the test assets. It further considers firm transitions between the two largest size deciles. Section 4.4 conducts robustness checks. It considers alternative MVE and book value cutoffs and examines whether the results are due to a mechanical effect from having the same firms in the factor and the test assets.

4.1 Loadings on $TSIZE$ Factor

Figure 1 shows the value of one dollar invested in the long-short factor portfolios in 1963, and its behavior in business cycles. We do not show LEV since it is not a return and we cannot construct factor-mimicking portfolio returns as we do not have the firm-level data. $TSIZE$ and IC returns are generally countercyclical in nature.[11] This pattern is consistent

[10] See `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html`. We thank Kenneth French for use of the data.

[11] For $TSIZE$, we calculate cumulative returns by recession and expansion and find that the cumulated return over all recessions (expansions) is almost 9% (-31%). The return per month of recession is 0.11% whereas the return per month of expansion -0.02%.

with the argument that relative returns of firms with high bailout probabilities should be low in normal times in anticipation of bailouts in disaster states (Gandhi and Lustig (2015) and Kelly et al. (2016)). LIQ and $COMP$, by contrast, do not appear to vary systematically with business cycles. In unreported results, only $TSIZE$ has positive mean returns of 0.62% per year; returns for other factors are close to zero.

The countercyclical variation in $TSIZE$ returns suggests that $TSIZE$ risk is not fully diversifiable. To isolate the effect of $TSIZE$ risk, we add $TSIZE$ to the Fama and French (1993) factors, the Carhart momentum factor (Carhart (1997)) and bond market factors. We also include the bank-specific large-versus-small factor GL (Gandhi and Lustig (2015)) in order to separate its effect from the big-versus-huge $TSIZE$ effects. In unreported results, we used the 5-factor model of (Fama and French (2015)) that includes profitability and investments, and found the results essentially unchanged. The regression specification is:

$$R_t^i - R_t^f = \alpha + \beta X_t + \delta TSIZE_t + \epsilon_t \tag{2}$$

Where $\beta = [\beta_1 \;\; \beta_2 \;\; \beta_3 \;\; \beta_4 \;\; \beta_5 \;\; \beta_6 \;\; \beta_7]$ is a vector of loadings, R_t^i is the monthly return of portfolio i in month t, R_t^f is the monthly risk free rate in month t, and

$$X_t = [SMB_t' \;\; HML_t \;\; Mktrf_t \;\; CORP_t \;\; GOV_t \;\; MOM_t \;\; GL_t]' \tag{3}$$

is the vector of standard risk factors. We estimate these regressions by OLS for each of the 30 size and BM sorted test portfolios from 1970 to 2006. The start date is determined by the availability of GL. The crisis period is considered in section 5. We adjust standard errors for heteroskedasticity and autocorrelation using Newey-West standard errors (Newey and West (1987)) with a maximum of three lags.[12]

Results from estimating (2) are in Panel A of Table 1. Each row shows a successively larger size bin reading from top to bottom, while each column shows a higher BM bin reading from left to right. Excepting for the largest size portfolios *Largest*, the loadings are positive with few exceptions and highly statistically significant, indicating that smaller firm returns contained additional risk-premia due to $TSIZE$. For the largest portfolios, we find that the coefficients are mostly negative, and statistically significant for three of five portfolios. In other words, the largest firms obtained a $TSIZE$ discount before 2007 in that their returns were lower when exposed to $TSIZE$ risk. Strikingly, the sign of the $TSIZE$ loadings

[12]Our results are robust to different choices of bandwidth length.

abruptly changes from positive to negative when going from size bin five (denoted $S5$) to six (denoted $S6$); for example, for BM bin three, the estimates change from 0.06 to -0.09 and both are significant. Further, the relationship between $TSIZE$ loadings and size or BM is non-monotonic for size bins below $S6$, indicating that $TSIZE$ risk is borne similarly by firms below $S6$. These results clearly bring out the "threshold" nature of $TSIZE$ risk. Further, the $TSIZE$ effect is orthogonal to the small-versus-large GL size effects.

We now add the non-size SIFI factors IC, LIQ and LEV to the regressions:

$$R_t^i - R_t^f = \alpha + \sum_{j=1}^{7} \beta_j X_{jt} + \delta_1 TSIZE_t + \delta_2 IC_t + +\delta_3 LEV_t + +\delta_4 LIQ_t + \epsilon_t \tag{4}$$

The coefficients on $TSIZE$ after adding the non-size factors to the regression are reported in Panel B of Table 1. Comparing Panels A and B of Table 1, we find that the magnitude and significance of $TSIZE$ loadings are little changed. Panels C-E of Table 1) show that the loadings on the non-size SIFI factors are generally insignificant. Thus, prior to 2007, the market appears to have only paid attention to threshold size-related systemic risk.

Table 2 reports $TSIZE$ premium and discounts for 1970 to 2006. In Panel A of Table 2, the implied $TSIZE$ discount or premium charged to shareholders is given by the loadings on $TSIZE$ times the average return of the $TSIZE$ factor. We find that firms in all portfolios except the largest suffer a $TSIZE$ premium of up to 0.06% per annum and there is little variation in the $TSIZE$ premium within these firms. In contrast, the largest firms in four of five portfolios receive a $TSIZE$ discount of up to 0.05% per annum. Averaging (market-weighted) across BM bins, the $TSIZE$ premium is 0.04% per annum for firms in size bin five while the $TSIZE$ discount is 0.02% per annum for firms in the largest size bin. Panel B of Table 2 shows the per firm value in 2013 dollars of the $TSIZE$ premium or discount, obtained by multiplying the numbers in Panel A by the average market capitalization of firms in each portfolio. Averaging (market-weighted) across BM bins, the $TSIZE$ premium is 2.29 million per year per firm in 2013 dollars for firms in size bin five while the $TSIZE$ discount is 6.09 million per year per firm in 2013 dollars for firms in the largest size bin, or a difference of over $8 million per year per firm. In section 4.3 we show this discount accrues almost entirely to financial firms. Summarizing, the largest firms get a $TSIZE$ discount whereas smaller firms pay a $TSIZE$ premium that does not vary with size, and this discontinuity speaks to the economic significance of the threshold effect.

4.2 Price of SIFI Risk in the Cross-Section of Returns

To estimate the price of SIFI risk, we follow the two stage procedure of Fama and MacBeth (1973). For each of the 30 test portfolios, we estimate (2) using 60 month rolling windows, producing an estimate of α, β, δ in each month t. We then estimate the following cross sectional regression for each month t:

$$R_{it} = \alpha_t + \sum_{j=1}^{7} \gamma_{jt}\beta_{jit} + \sum_{j=1}^{4} \mu_{jt}\delta_{jit} + \epsilon_{it} \tag{5}$$

where i indexes portfolios and j indexes factors, β is the loading on each of the seven non-SIFI factors and δ is the loading on each of the four SIFI factors from the time-series regressions.

Table 3 presents time-series averages of the estimates of the prices of risk γ_j and μ_j. We estimate the first and second stage by OLS, but correct the final t-statistic following Shanken (1992) to address the errors-in-variables problem in the second stage. The first 3 rows show that $TSIZE$ is priced in the cross section with a positive price of risk, and it is significant with or without the Shanken (1992) correction, with an OLS (Shanken) T-statistic of 2.9 (2.43). In the next rows, we include pair-wise the other 3 SIFI factors. None are significant and $TSIZE$ remains significant with a Shanken T-statistic exceeding 2 in all cases except when paired with IC, when it drops to 1.81. Next, we include all SIFI factors. $TSIZE$ remains (weakly) significant with a Shanken T-statistic of 1.74 These results are robust to different imputation methods for filling in endogenously missing observations in some portfolios.[13] We conclude that the $TSIZE$ factor is an important determinant of the cross-section of returns.

4.3 Finance Versus Non-Finance Firms

Large non-finance firms may also have advantages from funding and economies of scope (Antill, Hou and Sarkar (2014)). To consider whether $TSIZE$ risk originates from exposure to large financial firms only, we construct $TSIZE^{NF}$ identically to $TSIZE$ but based only on non-financial firm returns—i.e. we use the 84th and 92nd percentiles of the size distribution of only non-financial firm returns (defined as those that neither SIC nor NAICS codes consider to be finance). The Fama-Macbeth regression results show that $TSIZE^{NF}$ is *not*

[13] In particular, the S6BM5 portfolio (i.e. the sixth size and fifth BM portfolio) is empty in 1975. In the reported table, we run the cross sectional regression only over the 29 nonmissing test portfolios for the 12 months in which the S6BM5 portfolio is empty.

significantly priced in the cross section of returns (last 3 rows of Table 3). Thus, the largest non-financial firms do not represent a common risk in the economy.

Next, we consider the test assets, and construct test portfolios separately for non-financial and financial firms and find that financial firms in $S6$ mostly load negatively and significantly on $TSIZE$ (Panel A of Table 4). Non-financial firms in $S6$ also load negatively but the magnitudes of the loadings are weaker (Panel A of Table 4). Benefits to the largest non-financial firms may be due to non-TBTF related advantages, such as operational, political and scale advantages. Consistent with the lower magnitudes of non-financial firm loadings, Table 5 shows that $TSIZE$ discounts accrue mostly to the largest financial firms, amounting to 9 basis points per year versus 1 basis point per year for the largest nonfinancials.[14] The SIFI advantage of financials versus non-financials (i.e. the additional subsidy of frms in $S6$ compared to those in $S5$) was 26 basis points per year versus 3 basis points.

To further examine the threshold nature of $TSIZE$ discounts to the largest financial firms, we evaluate the $TSIZE$ loadings of firms moving between $S6$ and $S5$. If negative $TSIZE$ loadings accrue on average only to the largest financial firms, then moving to $S5$ from $S6$ should decrease loadings and vice versa. For each 5 year period, we sort firms into 6 size bins (following the procedure described in section 3) and form 4 disjoint groups based on transitions in consecutive 5-year periods: firms that remained in $S5$ or $S6$ and transitioning firms that switched between $S5$ and $S6$. We average the loadings in each month by group, and for financial firms and non-financial firms separately. Histograms of the average loadings (top left panel of Figure 2) indicate that the distribution of $TSIZE$ loadings shifts to the left of zero for finance firms that move from $S5$ to $S6$ (58% of probability mass to left of zero), compared to financial firms that remain in $S5$ (only 3% of mass to left of zero). In contrast, the distribution of $TSIZE$ loadings shifts to the right of zero for financial firms that move from $S6$ to $S5$ (82% of mass to right of zero), compared to financial firms that remain in $S6$ (14% of mass to right of zero) (bottom left panel of Figure 2). In both cases, one-sided Kolmogorov Smirnov tests strongly reject the equality of distributions of transitioning versus remaining firms. For non-finance firms, the distributions are bunched around zero and we cannot reject that they are equal by the Kolmogorov Smirnov tests. These results indicate that the $TSIZE$ subsidy and tax accrues solely due to the financial firm's position in the size distribution rather than any non-size characteristics.

[14] We multiply the loadings on $TSIZE$ by the average annualized return of the $TSIZE$ factor (equal to 0.45% per year over this period), treating statistically insignificant loadings as 0.

4.4 Robustness: Testing for Mechanical Effects, and Using Alternative Market and Book Value Size Thresholds

The threshold nature of $TSIZE$ loadings for the S5 and S6 deciles of financial firms might indicate a mechanical effect as the $TSIZE$ factor is based on the largest 16% of financial firm returns. We address this issue by using higher MVE and book value thresholds. Second, we omit financial firms in the $TSIZE$ factor from the test asset portfolios.

We find that we obtain similar results when the $TSIZE$ factor is constructed using higher MVE cutoffs, up until a cutoff of 300 billion in 2010 assets (corresponding to the top 3 % of financial firms).[15] Since most firms in the top decile $S6$ are not part of the top 3% size group, they are less likely to have a negative $TSIZE$ loading for mechanical reasons. To formally show the lack of a mechanical effect, we exclude from the test portfolios, the largest 8% of financial firms that are constituents $TSIZE$ factor. Table 6 shows the estimates for $TSIZE$ with and without the non-size SIFI factors. The results continue to provide evidence of threshold effect for $TSIZE$, showing the robustness of the results to a mechanical effect.

The DFA size threshold is based on book values and regulators determine the $TSIZE$ designation based on book values. We construct $TSIZE^{BV}$ in the same manner as $TSIZE$ by sorting on BVE[16] and MB with the same cutoffs. In unreported results, we show that the majority of portfolios still load significantly on $TSIZE^{BV}$ and the threshold effect is also present (i.e. the loadings are positive and of similar magnitude for the smallest 5 size bins, while they are negative for the largest size decile). However, in the cross-section, $TSIZE^{BV}$ is not priced.

In summary, we conclude that prior to 2007, threshold size risk was a sufficient statistic for systemicness. Exposure to this factor resulted in lower return premia for the largest financial firms and higher return premia for all other firms. As financial firms become bigger and transition to the largest decile, they obtain this advantage; conversely, if they fall below the largest decile, they give up this advantage. These results are not due to a mechanical effect, they are insensitive to the particular size thresholds, and they hold for the book value version of $TSIZE$. The largest financial firms may pose a common risk due to a high probability of government support, an issue we turn to next.

[15] Conversely, when the cutoff is relaxed, we get qualitatively similar results for cutoffs that include the top 18 % or 20 % of firms. Lower cutoffs entail more firms with low bailout risk that are wrongly deemed SIFI, leading to weaker results.

[16] BVE is measured at the same time and by the same definition as the denominator of market-to-book.

5 SIFI Factor Loadings and Too-Big-To-Fail Risk

In this section, we extend our sample to 2013 which allows us to examine crisis effects. In particular, we directly link $TSIZE$ loadings to the probability of government support for the largest financial firms. In section 5.1, we report that the largest financial firms that constitute $TSIZE$ have the highest probability of government support, as indicated by Fitch's Support Rating floors, whereas the next-to-largest financial firms in $TSIZE$ do not. Subsidies, as implied by $TSIZE$ loadings, for the largest financial firms increase when the probability of government support increases. In section 5.2, we find that $TSIZE$ subsidies increase after the failure of Continental and decrease after the failure of Lehman. Conversely, IC loadings become significant after Lehman's failure and implied IC subsidies increase.

5.1 $TSIZE$ and Implicit Government Support

The largest financial firms are expected to have a higher probability of government bailout in the event of bankruptcy, relative to non-financial firms, potentially creating greater risk for the economy. We use Fitch's Support Rating Floors (SRF) as a measure of the likelihood of receiving government guarantees. As described by Fitch, it issues support rating floors based on its opinion of potential sovereign support *only* (including a government's ability to support a bank).[17] Thus, unlike other government support ratings, the SRF has nothing to do with the credit worthiness of a particular bank, or of its parent companies. Instead, this rating is Fitch's opinion on which US banks enjoy implicit government guarantees.

The SRF data is available starting on March 16th, 2007 for a subsample of banks (which include commercial banks, bank holding companies, and savings banks), of which, we keep those banks that are US publicly traded companies.[18] We focus on SRFs of A- or higher, described by Fitch as indicating an extremely high probability that the firm will receive extraordinary government support to prevent it from defaulting on its senior obligations.[19]

Panel A of Table 7 examines the share of firms constituting $TSIZE$ that have the highest government support, separately for the largest 8% of firms in $TSIZE$ (denoted $L8$) and the

[17] See `https://www.fitchratings.com/site/definitions/bankratings.html`.

[18] When both a bank and its parent holding company received a rating, we only keep the rating of the holding company. For example, we include Citigroup but not Citibank, N.A

[19] See `https://www.fitchratings.com/jsp/general/RatingsDefinitions.faces?context=5&detail=505&context_ln=5&detail_ln=500)`.

next-largest 8% of firms in $TSIZE$ (denoted $NL8$). The first row of the panel shows that the mean share of commercial banks[20] in these two size bins are similar at 25% and 24%, respectively. This difference is not statistically significant after accounting for time fixed effects (last two columns of Panel A of Table 7). Thus, differences in the share of banks with A- ratings are not due to different shares of banks in $NL8$ and $L8$. The second row of the panel indicates that 84% of banks in $L8$ have SRFs of at least A- at some point in time as compared with 19% of banks that have this rating in $NL8$, and this difference is highly statistically significant. Thus, firms in $L8$ are significantly more likely to receive future government support than firms in $NL8$.

Next, we evaluate whether firms in $L8$ have a higher probability of government support than those in $NL8$, after controlling for market capitalization. To do so, we estimate the following linear probability model by pooled OLS, with standard errors clustered by firm:

$$TBTF_{it} = \alpha + \beta_t + \delta L8_{it} + \gamma MarketCap_{it} + \epsilon_{it} \tag{6}$$

where, for month t, $TBTF$ is a dummy variable equal to 1 if bank i ever had a rating of A- or higher, β_t is the time fixed effect, $L8$ is a dummy variable equal to one if bank i is above the 92nd percentile of size among all financial firms, and $MarketCap$ is the market capitalization of bank i. The results, reported in Panel B of Table 7, show that the coefficient on $L8$ is positive and significant, even after controlling for market capitalization. Thus, large banks in $L8$ have a higher probability of government support than banks in $NL8$.

Do changes in $TSIZE$ loadings correlate with the probability of government support? We consider changes in $TSIZE$ loadings from 10 months before to 10 months after the month that firms receive an A- rating from Fitch. For the sample of banks that ever received a Fitch SRF of at least A-, we calculate 60 month rolling $TSIZE$ loadings. We find in Figure 3 that loadings on average become more negative from about four months prior to the event month (denoted as 0) and continue to decline for four months after the ratings change before reverting partially, but staying below its pre-event peak. The decline in $TSIZE$ loadings from four months before to four months after the Fitch ratings changes imply an additional subsidy of almost 11 basis points on an annualized basis, consistent with an increase in bailout expectations in anticipation of and following the Fitch ratings changes.

We estimate panel regressions to show the correlation of $TSIZE$ loadings and Fitch SR

[20]Commercial banks are defined as those with SIC codes starting with 60.

changes more formally:

$$\Delta TSIZE_{it} = \alpha + \beta_i + \gamma_1 t\epsilon[0,4]_{it} + \gamma_2 t\epsilon(4,10]_{it} + \gamma_3 t\epsilon[-4,0]_{it} + \gamma_4 BM_{it} + \gamma_5 LogMarketCap_{it} + \mu_{it} \tag{7}$$

where, for month t, the dependent variable is the change in $TSIZE$ loadings, β_i is the bank fixed effect, $t\epsilon[0,4]$ is a dummy variable equal to one for the 4 days after the event, $t\epsilon(4,10]$ is a dummy variable equal to one from 5 to 10 days after the event, $t\epsilon[-4,0]$ is a dummy variable equal to one for the 4 days before the event, BM is the book-to-market ratio and $MarketCap$ is the market capitalization of bank i. In some specifications, we use $[t >= 0]$ which is a dummy variable equal to one for 10 days after the event. If SIFI subsidies increase with greater expectation of government support, then $TSIZE$ loadings should decrease. Table 8 show results for the full sample of banks without BM and size. The results show that, after controlling for bank fixed effects, $TSIZE$ decreased on average, as hypothesized, as indicated by the negative and significant coefficient on $[t >= 0]$. This decrease mostly occurs in the first 4 days after the event, as shown by the negative and significant estimate of γ_1. Table 9 show results for US banks with BM and size data. We obtain a similar result, with higher SIFI subsidies following the ratings change, with or without fixed effects, and even after controlling for BM and size.

We have shown that the largest financial firms have a substantially higher probability of government support, even relative to the next-largest financial firms. And the SIFI subsidies to the largest financial firms correlate with the probability of government support, implying that risk events triggering government support may change the SIFI loadings.

5.2 SIFI Loadings Around TBTF Events

We examine changes in the loadings on the SIFI factors to three events that potentially changed the perception of TBTF risk in the economy: the bailout of Continental Illinois, the failure of Lehman Brothers and the passage of the DFA. The bailout of Continental Illinois, often cited as the start of TBTF perceptions, may be expected to have increased the $TSIZE$ premium and discount. As Lehman was allowed to fail, this event may have changed the $TSIZE$ premium and discount depending on how it was perceived to have changed the probability of future bailouts. The passage of the DFA in 2010 instituted an asset threshold above which firms are subject to additional regulatory costs. Some firms had incentives to grow large enough to offset these costs while other firms petitioned regulators to seek exemption from SIFI status.[21] Therefore, the expected net benefit of being above the DFA threshold may have changed, affecting our estimates of the $TSIZE$ premium.

A concern with the Lehman analysis is that risky TBTF firms may have disproportionately left the largest size group as their equity returns fell.[22] To examine this issue, we plot the share of firms in $L8$ ($NL8$), the largest (next largest) 8% of firms in $SIFI$, that transition to lower size bins every year.[23] We find, in the top panel of Figure 4, that transition rates were high prior to 1980 but have occurred at a steady rate since then with (as expected) a surge in transitions around Lehman's failure. To mitigate the effect of transitions, we rebalance the $TSIZE$ factor every 5-years rather than annually starting from 1970, thus keeping the composition of $TSIZE$ constant between 2005 and 2010, bookending Lehman's failure in 2008. The bottom panel of Figure 4 indicates that the longer rebalancing period reduces the time-variation in transition rates, as required, especially around the Lehman event.

Figure 5 shows 60-month rolling regressions for $TSIZE$ and IC for the full sample (the remaining SIFI factor charts are in the appendix). Two versions are shown, one with yearly rebalancing as previously, and another with 5-year rebalancing to account for changes in firm composition around the financial crisis of 2007-2008 (with the 5-year rebalancing, the composition of firms is frozen from 2005 to 2010). The loadings are averaged over all firms in the largest size group $S6$ and, separately, the next largest size group $S5$. For both rebalancing frequencies, we find that $TSIZE$ loadings of firms in $S5$ increase after Continental and decrease around Lehman, with no further changes around the DFA implementation. Moreover, the $TSIZE$ loadings of firms in $S6$ change in the reverse direction, decreasing post-Continental and increasing around Lehman. In other words, the $TSIZE$ tax and subsidy increased post-Continental and decreased around Lehman. By contrast, the subsidies

[21] After CIT Group Inc. agreed to buy OneWest Bank NA's parent company for \$3.4 billion, its assets increased to \$67 billion, above the DFA threshold of \$50 billion. CIT Chief Executive John Thain had been looking for a deal that would allow his firm to be substantially larger than the DFA threshold, saying in an interview: "If we had grown to just \$52 billion we would be in the worst spot." See *Wall Street Journal* July 22, 2014, http://online.wsj.com/articles/cit-group-to-buy-onewest-profit-tops-estimates-1406025881. Other investors have exhorted management to remain below the \$50 billion cutoff, even in the case of CITI (see "The heavy burden of being labelled systemically important," Robert Pozen, *Financial Times* March 27, 2016). Metlife legally contested its $TSIZE$ status, which the court rescinded on March 30, 2016.

[22] An additional concern may be shifts in the share of financial firms in the test portfolios. In the internet Appendix, we report the share of finance in the 30 test portfolios in the years before and after the Continental bailout and the Lehman bankruptcy. These indicate no major shift in the share of financial firms.

[23] Specifically, in each year t, we find the percent of firms in $L8$ or $NL8$ in year $t-1$ that are no longer in $L8$ or $NL8$ in year t.

implied by IC increase after Lehman as its loadings for firms in $S5$ and $S6$ diverge following Lehman's failure. These results are shown more formally in Table 10. The average difference in loadings between $S6$ and $S5$ firms increase after Continental and decrease after Lehman for $TSIZE$ and these changes are statistically significant. The opposite is true for IC loadings. Further changes following DFA are small.

As an alternative to rolling regressions, we re-estimate equation (2) with two additional regressors: a dummy variable $Post - Continental$ equal to one after May 1984 (when Continental was bailed out) and an interaction of SIFI factors with this dummy. In unreported results, we find that the threshold size effect increases after Continental, with no effect on non-size SIFI factors. Next, we examine how SIFI loadings changed after the bankruptcy of Lehman Brothers and the passage of the DFA. We estimate regression (2) from June 1984 (after the Continental bailout) to 2013 with four additional regressors: a dummy for the period after the Lehman bankruptcy and before the DFA (September 2008-June 2010), a dummy for the period after the DFA (from July 2010), and the interactions between SIFI factors and each of these dummies. These results show that following the Lehman bankruptcy there was a significant decrease in $TSIZE$ risk exposure for the bottom 90% of firms in $S5$ and below. Further, there was no change in loadings for the largest size group except in one case. Thus, the results indicate a reduced perception of size-related risk since the crisis of 2007. The opposite is true for IC.

6 Do Pre-Crisis SIFI Loadings Predict Systemic Risk During Crisis?

While changes in $TSIZE$ loadings occur following systemic events, do pre-event changes in the loadings predict subsequent changes in systemic risk? Such an implication follows from the time varying financial disaster risk model of Gandhi and Lustig (2015), Gandhi et al (2016).[24] In section 6.1, we describe our systemic risk measures. In section 6.2, we examine the predictive power of aggregate $TSIZE$ loadings in the time-series. In section 6.3, we investigate whether, at the firm level, pre-crisis values of $TSIZE$ loadings predict systemic

[24]See Gandhi et al (2016), proposition 2. The authors show the spread in dividend yields between stocks is related to the difference of their log resiliences (performance in disasters). In their model the dynamics of these resiliences are driven by time varying disaster risk, but if time series variation in $TSIZE$ loadings relates to bailout protection as we have shown then the time series variation in loadings should also have predictive power.

risk changes since the crisis in the cross-section. In this section, we also discuss whether the book-value based $TSIZE$ factor has predictive power.

6.1 Measures of Systemic Risk

The DFA designates a firm as SIFI if, among other standards, it rapidly liquidates assets that cause significant losses to other firms with similar holdings.[25] Our first systemic risk measure is AV, a measure constructed by Duarte and Eisenbach (2015) to capture this fire-sale spillover to financial institutions. Our second measure of systemic risk is SRISK, or expected capital shortage of a firm in case of a systemic event.[26]

Extending the "vulnerable banks" framework of Greenwood, Landier and Thesmar (2015), Duarte and Eisenbach (2015) measure the decline in asset values of financial institutions holding the same assets that banks sell after a negative shock to assets or equity capital that increases leverage. The bank is then assumed to deleverage by selling assets on its book which lowers their prices, the amount of losses depending on their illiquidity and amounts sold. This results in "second-round losses" to financial institutions holding these assets. The systemic measure AV is the sum of all such second-round spillover losses as a share of the total broker-dealer capital in the system. Empirically, Duarte and Eisenbach (2015) use quarterly regulatory balance sheet of bank holding companies (BHCs) to estimate AV for the largest 100 firms. Separately, they also use triparty repo data of broker-dealers to construct a monthly measure of AV from July 2008 (when the repo data became available).[27]

Acharya et al. (2010) and Acharya et al. (2012) provide theoretical motivation for SRISK. In Acharya et al. (2010), financial institutions pick a capital structure and a level of riskiness for their assets. A systemic crisis is assumed to occur when the aggregate bank capital falls below a certain threshold, and the associated costs of financial distress impose an externality on the economy. The socially optimal tax policy depends on a firm's default risk and its

[25]See "Final rule and interpretive guidance to Section 113 of the Dodd-Frank Wall Street Reform and Consumer Protection Act."

[26]We are grateful to the authors for providing the AV data. The $SRISK$ data is obtained from the NYU Volatility Lab website `http://vlab.stern.nyu.edu/`.

[27]The authors assume that the initial shock is a uniform decline of 1% in prices of all assets in the bank's portfolio. To deleverage, the bank is then assumed to sell all of their assets in proportion to their initial portfolio weights. Finally, it is assumed that there is one round of firesales (i.e. the second-round losses do not lead to further firesales by the impacted banks). These assumptions mostly do not impact the dynamics of AV qualitatively, as discussed extensively by Duarte and Eisenbach (2015).

systemic risk contribution which is proportional to the firm's expected capital shortfall (losses beyond some threshold) in the event of a crisis, denoted SRISK. Acharya et al. (2010) and Acharya et al. (2012) describe a procedure for empirically estimating SRISK. We obtained estimates of SRISK (in billions of dollars) starting in 2000 for firms exceeding \$ 5 billion in market capitalization as of the end of June 2007 (Brownlees and Engle (2012)).

6.2 Predicting Systemic Risk in the Time Series With Aggregate SIFI Loadings

In this section, we explore the dynamic interactions of $TSIZE$ loadings of financial firms with the two systemic risk measures, AV and $SRISK$, at the aggregate level. Since the vast majority of firms with systemic risk measures are in the largest size group S6 and in the next-to-largest size group S5, we aggregate over financial firms in these two groups with non-missing estimates of $TSIZE$ loadings. We then calculate $Loading6$ and $Loading5$, the average $TSIZE$ loadings for financial firms in S6 and S5, respectively. We also average $SRISK$ and AV for firms in S5 (denoted $SRISK5$ and $AV5$, respectively) and in S6 (denoted $SRISK6$ and $AV6$, respectively). Since lower (higher) $TSIZE$ loadings for firms in S6 (S5) imply higher SIFI discounts (tax), our hypothesis is that decreases in $Loading6$ and increases in $Loading5$ predict greater systemic risk in the time series.

To formally describe the dynamic interactions between $TSIZE$ loadings and systemic risk measures, we estimate a Vector Autoregression (VAR). Since we cannot reject the null hypothesis of unit roots for the variables, we estimate the VAR in differences, denoting the change in X as ΔX. We include, as exogenous variables in the VAR, lagged changes in market capitalization, leverage and correlation with the MSCI World stock index, averaged over firms in S5 and S6, since they have been found to be determinants of AV and $SRISK$ (Brownlees and Engle (2012) and Duarte and Eisenbach (2015)). The number of lags is selected on the basis of information criteria. The dynamic effects are presented via accumulated impulse responses which trace the response of systemic risk changes to a one-time unit SD shock to $TSIZE$ loadings changes over 10 periods. The impulses are orthogonalized using the (inverse of the) Cholesky factor.[28]

[28] In the VAR ordering, the $TSIZE$ loadings precede the systemic risk measure. Since impulse responses are sensitive to the ordering, we have verified the robustness of our results by estimating generalized impulse responses which are robust to the ordering (Pesaran and Shin (1998)). The generalized impulses are derived, for an innovation to the j-th variable, by applying a variable specific Cholesky factor computed with the j-th

We first consider the firesale measure AV. Panel A of Figure 9 shows the $TSIZE$ loadings and monthly repo-based AV estimates for broker-dealers since July 2008, averaged over firms in S6 with both AV and SIFI loadings estimates. Firms in S5 and below are omitted as there are too few with repo data to allow for statistical inference. $AV6$ increases monotonically since July 2008 and peaks in January 2009 at 1.3% per firm. $Loading6$ decreases through 2008 and troughs in March 2009 (the end of the crisis). Panel B of Figure 9 shows quarterly BHC balance sheet-based AV estimates (multiplied by 100) averaged over firms in S5 and S6 from 2002. $AV6$ generally increases and peaks in 2007 Q4 at about 0.03% per firm, the start of the crisis. The lower per-firm share in the quarterly data reflects the larger numbers of BHCs compared to active repo participants. $Loading6$, which is the monthly loading averaged over the quarter, is generally decreasing from 2005 and bottoms out between 2006 Q4 and 2007 Q4. For firms in S5, $AV5$ peaks in 2007 Q4 while $Loading5$ spikes in 2008Q3, the quarter when Lehman failed, then falls before peaking in 2010 Q2. The dynamics of AV are qualitatively similar to those reported for the full sample of firms in Duarte and Eisenbach (2015) who find that the monthly AV peaks in November 2008 while the quarterly measure peaks in 2007Q4.

We estimate VARs with endogenous variables $\Delta Loading6$ and $\Delta AV6$ for firms in S6 and $\Delta Loading5$ and $\Delta AV5$ for firms in S5 (for the quarterly data only) over the full sample. The number of lags is 6 for the monthly data and 1 for the quarterly data. The accumulated impulse responses, along with two standard error (S.E.) bands, are shown in Figure 10. Panel A shows plots for the monthly repo-based AV and $TSIZE$ loadings of financial firms in $S6$. The left-hand chart shows that a one SD shock to $\Delta Loading6$ leads to a persistent decrease in $AV6$, as hypothesized, cumulating to almost 0.04% per firm over the first five months, after which there are no further effects. The effects are statistically significant except for the contemporaneous month (i.e. period 1). The right-hand chart in Panel A shows that shocks to $\Delta AV6$ have an insignificant effect on $\Delta Loading6$. Since $TSIZE$ loadings predict AV but the reverse is not true, $TSIZE$ loadings lead AV in an informational sense.

Panels B and C of Figure 10 show cumulated impulse responses when AV is estimated using quarterly BHC balance sheet data. A shock to $\Delta Loading6$ results in a statistically significant decrease in $\Delta AV6$, mostly occurring over the first two quarters (left-hand chart of Panel B). The right-hand chart in Panel B shows that $\Delta Loading6$ does not respond to $\Delta AV6$. Panel C of Figure 10 indicates that $\Delta AV5$ responds positively to $\Delta Loading5$, as hypothesized, but

variable at the top of the Cholesky ordering. Since the Cholesky factor is used, these innovations are also orthogonal.

the response is statistically significant only for period 1. Thus, for both the monthly and quarterly AV measures, a shock to $Loading6$ has a significant and negative effect on $AV6$ that persists for about 5 months or 2 quarters.

Next, we turn to the $SRISK$ measures. Panel A of Figure 11 shows $TSIZE$ loadings (multiplied by 100) and $SRISK$ for firms in S6. The left-hand chart plots from 2000 to June 2008, three months before Lehman's failure, while the right-panel chart shows the period since then. $SRISK6$ becomes positive in August 2007 and rises until peaking in March 2009 at $37 Billion. $Loading6$ does not have a clear trend before July 2008, from which point it is intermittently negative until troughing in March 2009. For firms in S5 (Panel B of Figure 11), $SRISK5$ is generally negative except for a brief period from July 2008 to June 2009. $Loading5$ is positive throughout and has a downward trend from 2007. Overall, $SRISK$ peaks later in the crisis as compared to the quarterly AV series; correspondingly, the $TSIZE$ loadings also respond later in the crisis.

Guided by the dynamics in Figure 11, we estimate separate VARs for the period starting just before Lehman's failure (July 2008 to November 2013) and a pre-Lehman period (June 2000 to June 2008). Impulse responses in Panel A of Figure 12 show that, during the Lehman period, a one SD shock to $\Delta Loading6$ results in a cumulated decrease in $SRISK6$ of about $2 billion mostly occurring over the initial 5 months. The responses are statistically significant except for the contemporaneous month. The right-hand chart in Panel A shows that shocks to $\Delta SRISK6$ do not have a statistically significant effect on $\Delta Loading6$.

Panel B of Figure 12 shows that a shock to $\Delta Loading5$ results leads to increased $SRISK5$ contemporaneously and in the following month but not thereafter. Thus, while the *direction* of change is as hypothesized, the effect of $Loading5$ on systemic risk is less persistent than that of $Loading6$. In the reverse direction, $\Delta Loading5$ does not respond to $\Delta SRISK5$. Finally, Panels C and D of Figure 12 indicate that impulse responses are not statistically significant before the Lehman period. This is consistent with Figure 11 which showed little evidence of co-dynamics between changes in SIFI loadings and $SRISK$ prior to July 2008.

Table 11 shows the economic significance of the impulse responses, assuming that the shock to $Loading6$ occurs on September 2008 for monthly data and 2007 Q3 for quarterly data (the "shock period"). The different shock periods reflect the different dynamics of the evolution of AV and $SRISK$. The impulse response estimates provide the predicted change in systemic risk for the current (i.e. shock) and future periods. We accumulate responses over 5 months for monthly data and 2 quarters for quarterly data (after which the responses die off).

Thus, the prediction period is September 2008 to January 2009 for monthly data and Q3 to Q4 of 2007 for quarterly data. The predicted change is the accumulated response over the prediction period times the actual change in $\Delta Loading6$ in SD units over the shock period.[29] The predicted increase in the monthly and quarterly $AV6$ is about 11% and 12%, respectively, of its actual increase over the prediction period. For $SRISK6$, the predicted increase is about 21% of its actual increase during the five months after Lehman's failure.

Overall, reductions in $TSIZE$ loadings of the largest decile of firms at the start of the financial crisis (September 2008 or Q3 2007) explain an economically meaningful share of subsequent increases in systemic risk (the 5 months since Lehman's failure or the first 2 quarters of the crisis). Further, higher $TSIZE$ loadings of firms in the second largest decile also predict higher systemic risk after Lehman's failure (but the effect is only significant for $SRISK$).

6.3 Firm-Level SIFI Loadings and Systemic Risk

We now explore whether crisis period changes in the firm's systemic risk are predicted by its pre-crisis $TSIZE$ loadings, controlling for firm characteristics. For each financial firm i in size deciles S5 or S6, and for t during the crisis period, we define $\Delta X_{i,t}$ as $X_{i,t}$ minus the average X_i before the crisis (2000-2006). Denote ΔX_i as the average of $\Delta X_{i,t}$ during the crisis period (August 2007 onwards for $SRISK$ and 2007Q4 onwards for AV). Only the quarterly AV estimates are used since the monthly repo-based estimates start during the crisis period and, moreover, the cross-section is too small for reliable statistical inference. We estimate the following cross sectional regression:

$$\begin{aligned}\Delta SysRisk_i = \alpha_0 + \alpha_1 SIFI_{i,pre-2007} * S6_{i,pre-2007} + \alpha_2 SIFI_{i,pre-2007} * S5_{i,pre-2007} + \alpha_3 S6_{i,pre-2007} \\ + \epsilon_i \qquad (8)\end{aligned}$$

Next, we decompose $TSIZE$ loadings into their negative and positive components. Since the price of $TSIZE$ risk is positive, the estimated signs of the loadings imply a negative component in the expected returns of the largest firms, and a corresponding positive component in the expected returns of smaller firms due to $TSIZE$ risk. To the extent that differences

[29]To illustrate, for the quarterly AV measure, $\Delta Loading6$ decreased 0.41 SD units in 2007 Q3 (based on the full sample SD since the VAR was estimated over the full sample), which predicts an increase in $AV6$ of about 0.04% from Q3 to Q4 2007 based on the accumulated response over the first 2 quarters, or about 12% of the actual increase in $AV6$ during this period.

in these return components are due to the greater likelihood of government interventions for the largest firms, the *sign* of the loadings of firm returns on $TSIZE$ may be related to expected bailout probabilities. The regression is:

$$\begin{aligned}\Delta SysRisk_i = {} & \alpha_0 + \alpha_1 S6_{i,pre-2007} + \alpha_2 SIFIM_{i,pre-2007} * S6_{i,pre-2007} + \alpha_3 SIFIP_{i,pre-2007} * S6_{i,pre-2007} \\ & + \alpha_4 SIFIM_{i,pre-2007} * S5_{i,pre-2007} + \alpha_5 SIFIP_{i,pre-2007} * S5_{i,pre-2007} \\ & + \alpha_6 \Delta MarketCap_i + \alpha_7 \Delta Leverage_i + \alpha_8 \Delta Correlation_i \\ & + \epsilon_i \end{aligned} \tag{9}$$

where $SysRisk = SRISK$ or AV, $SIFIP = max(SIFI, 0)$, $SIFIM = min(SIFI, 0)$ and $S6$ ($S5$) is a dummy variable equal to one for firms in the largest (second largest) size decile in a year.[30] Crisis period changes (relative to the pre-crisis average) of the firm's market capitalization, leverage and correlation with the MSCI World stock index are used as controls. The subscript $pre - 2007$ indicates an average over 2000 to 2006. We hypothesize that $S6$*$SIFIM$ is estimated as negative and statistically significant, indicating that the largest firms with negative $TSIZE$ loadings prior to the crisis had a larger post-crisis increase in systemic risk compared to other firms. The regression is estimated with OLS with robust standard errors for all firms for which we have $SRISK$ or AV data.

The results for $SRISK$ are reported in Table 12. The first column shows the results from equation 8. We find that firms in $S6$ before the crisis had higher crisis-period $SRISK$ but, of these firms, those with lower loadings before the crisis had even greater increases in $SRISK$ in the crisis. Firms in $S5$ with higher pre-crisis loadings also had higher $SRISK$ during the crisis, although the significance is only at the 10% level. In the second column, the sign of $TSIZE$ loadings is interacted with membership in $S6$ and $S5$. We find that only firms in $S6$ with lower *negative* $TSIZE$ loadings before the crisis are significantly more likely to have higher $SRISK$ after the crisis, as indicated by the negative estimate of $SIFIM * S6$, and the remaining columns show that this result is robust to the inclusion of firm characteristics and additional size factors. In contrast, $TSIZE$ loadings of firms in $S5$ are not predictive of $SRISK$ during the crisis. After accounting for the sign of the pre-crisis loadings, membership in $S6$ is no longer significant, indicating that greater size by itself is not predictive of more systemic risk. The third column predicts changes in $SRISK$ using only changes in controls. Changes in leverage are positively associated, while changes in market capitalization and correlation are negatively associated, with changes in $SRISK$,

[30] Factor loadings are estimated from a firm-level time series regression of excess returns on a 6-factor Fama-French-Carhart model, $TSIZE$ and GL.

and these effects are significant. Possibly, the largest firms before the crisis suffered the greatest declines in market value and increases in systemic risk after the crisis but their debt levels did not decline to the same extent.[31] The effect of the correlation is not robust, as it goes away in later specifications. Including both loadings and controls (column 4) results in substantially higher adjusted R-squared and lower Root Mean Squared Error (RMSE) compared to specifications with only loadings (columns 1 and 2) or only controls (column 3). The final two columns include the square of market capitalization (in order to examine returns to scale effects), the pre-2007 average loadings on the GL (Gandhi and Lustig (2015)) and SMB factors, but none are significant in the regressions.

We report the results for AV in Table 13. Although the cross-section is smaller (79 firms versus 130 firms for $SRISK$), we find similar results. In particular, firms in $S6$ with more negative $TSIZE$ loadings before the crisis have significantly higher AV after the crisis. The main difference with the $SRISK$ results is that firms in $S6$ that had on average more positive loadings before the crisis also experienced greater systemic risk after the crisis. Although firms in $S6$ with both positive and negative pre-crisis loadings suffered greater systemic risk in the crisis, $SIFI * S6_{PreCrisis}$ is not significant (column 1 of the table). In other words, conditioning on the the pre-crisis sign of $TSIZE$ loadings is required for predicting systemic risk changes. Another difference with the $SRISK$ result is that $\Delta Marketcap$ is positively, rather than negatively, associated with ΔAV but with a declining marginal effect (since $\Delta Marketcap^2$ is negative and significant). As with $SRISK$, the specification with both loadings and controls (column 4 of the table) is a better fit than those with only controls (column 3) or only loadings (columns 1 and 2).

To assess the economic significance of $TSIZE$ loadings, we compare the specification with loadings (column 4 of Tables 12 and 13) with the one without loadings but with size, leverage and correlation (column 3 of the tables). The specification with loadings has lower RMSE in both tables. We show scatter plots of the fitted values of the specifications with loadings (colored red) and without loadings (colored black) against the actual changes in systemic risk (Figure 13). The red scatters are generally closer to the 45 degree line (indicating better fit) than the black scatters for both $SRISK$ and AV. In particular, the model with loadings appear to better predict changes of firms that experienced very large increases in systemic risk during the crisis (scatters in the upper right of the plots).

[31] Government programs held up leverage during the crisis. For example, the FDICs Temporary Liquidity Guarantee Program (TLGP) program backed in full the senior unsecured debt issued by participating financial firms between October 14, 2008, and October 31, 2009 (see `https://www.fdic.gov/regulations/resources/TLGP/index.html`.

As robustness checks, we also estimated panel regressions with time fixed effects to control for aggregate trends in systemic risk. The results are similar to those reported earlier: for the largest firms, more negative pre-crisis $TSIZE$ loadings predict higher post crisis systemic risk. In additional specifications, we add the $TSIZE^{NF}$ factor, decomposed into its positive and negative components, and its interactions with $S6$. The loadings on $TSIZE^{NF}$ are not significant whereas the coefficients on $TSIZE$ remains of similar magnitude and significance as in Table 12, providing further evidence that the informativeness of $TSIZE$ derives from financial firms only. Finally, we repeat the regressions using the systemic risk measure ΔCoVaR (Adrian and Brunnermeier (2011)), or value at risk of the financial system conditional on a firm being under distress and find qualitatively similar results.[32]

We repeat the analysis with $TSIZE^{bv}$, the $TSIZE$ factor based on book-value cutoffs. We find that, unlike the MVE-based $TSIZE$ loadings, these factor loadings have no predictability in the time-series or the cross-section. Results are in the online appendix.

The results in this section provide a robust indication that the MVE-based $TSIZE$ loadings predicts systemic risk measures during the crisis of 2008. We find evidence of predictive power for multiple measures of systemic risk, and for firm-level and aggregate $TSIZE$ loadings.

7 Complexity Factor and Financial Sub-Sector Portfolios

We now explore the effect of complexity on SIFI risk. Since this factor is based on subsidiaries of BHCs, we use this opportunity to investigate whether our results differ across banks, insurance and other financial sub-sectors. First, we show the evolution of BHC subsidiaries over time. Then, we provide estimates of the loadings on the complexity factor $COMP$ and other SIFI factors for different financial sub-sectors.

Figure 6 shows the evolution of the distribution of BHC subsidiaries for globally systemic banks GSIBs and non-GSIBs since 1986 when the data becomes available. The distribution of subsidiaries of non-GSIBs do not show meaningful variation over time. Although there are outlier banks with many subsidiaries, even the upper end of the distribution does not show much variation. However, the number of GSIB subsidiaries increase sharply starting from 1998 with a further spike in 2008. Thus, any effect of complexity risk appears to be

[32] We are grateful to the authors for providing the data.

predominantly a GSIB effect.

Figure 7 shows the dynamics of loadings of banks on $TSIZE$, IC and $COMP$. Results for $TSIZE$ are similar to financial firms in general. The S6 firms have lower and negative loadings prior to the crisis of 2007-2008 while S5 firms have positive loadings; the two series have converged (albeit not fully) since the Lehman failure of 2008. The regression results show that these effects are statistically significant. We find a smaller, less persistent, threshold effect for IC. There is no evidence of a threshold effect for $COMP$ prior to 2003—in fact, the loadings are higher on average for the S6 firms. However, since that time (which coincides with the period when GSIB subsidiaries exploded), the S6 loadings turned negative and lower than the S5 loadings. However, we do not observe a statistically significant effect of $COMP$ in the regressions, consistent with the effect deriving mainly from the small number of GSIBs in the sample.

Another active policy issue is the SIFI designation of non-bank financial entities, such as insurance companies.[33] Figure 8 shows the dynamics of loadings of insurance firms on $TSIZE$, IC and $COMP$. Results for $TSIZE$ are once again similar to financial firms in general. The S6 firms have lower and negative loadings prior to the crisis of 2007-2008 while S5 firms have positive loadings; in contrast to the results for financial firms generally, the two series remain divergent even after the Lehman failure of 2008. In the regressions, we find that the largest insurance firms load negatively and significantly on the $TSIZE$ factor, while smaller insurance firms load positively and significantly on $SIFI$. Thus, banks and insurance companies both contribute to systematic risk, consistent with Billio et al. (2012) who examine causal relationships between hedge funds, publicly traded banks, broker/dealers and insurance companies using monthly equity returns and find that all sectors became highly interrelated over time. We do not find significant effects of other SIFI factors on insurance company returns.

We estimated a number of additional specifications for robustness. Since the difference in loadings between the largest and the next largest firms could potentially relate to lower risk from economies of scale, we added the squared market capitalization of the portfolio as an additional regressor and found its coefficient to be intermittently significant without qualitatively affecting the estimated $TSIZE$ loadings. Our results are also robust to using SMB (Fama and French (1993)) rather than SMB'. Finally, using HSICCD rather than

[33] See "U.S. Regulators to Review 'Systemically Important' Label Process for Financial Firms," (http://online.wsj.com/articles/u-s-regulators-to-hold-hearing-on-systemically-important-label-for-metlife-1412628515).

SIC codes to determine industries in CRSP, does not affect our results.

8 Conclusion

Within the largest financial firms, we find that those firms above the size threshold associated with the SIFI designation have higher probability of government support and lower expected returns than firms just below this threshold. This difference in returns is a common risk factor, denoted $TSIZE$, that is priced in the cross-section of stock returns. In time series regressions, $TSIZE$ has significant explanatory power for stock returns of all firms from 1963 to 2006, even after controlling for standard asset pricing factors, as well as bank-size risk (Gandhi and Lustig (2015)). The largest firms (those in the top 10% of market size distribution) load negatively on it, implying a "SIFI discount," while the remaining firms load positively on it, implying a "SIFI premium." For the pre-2007 period, we estimate the discount for financial firms to be 36.43 million in 2013 dollars per firm per year.

We find evidence that $TSIZE$ was a sufficient statistic for systemicness prior the crisis of 2007 since factors related to interconnectedness, complexity, leverage and liquidity did not explain portfolio returns. As

financial fi

rms became bigger and transitioned to the largest decile, they obtained this advantage; conversely, if they fell below the largest decile, they gave up this advantage. These results are not due to a mechanical effect, they are insensitive to the particular size thresholds, and they hold for the book value version of $TSIZE$. Since the Lehman failure of September 2008, however, interconnectedness risk has instead become prominent.

The price of $TSIZE$ risk is related to TBTF perceptions as it increased after the failure of Continental Illinois. Moreover, we find that the largest 8% of financial firms have the highest probability of government support, according to Fitch's Support Rating floors. In contrast, membership in the 8% to 16% size group is negatively associated with receiving the highest rating of government support. Subsidies implied by changes in $TSIZE$ loadings increase after Fitch increases its probability of government support.

Both at the firm and aggregate level, pre-crisis market value-based $TSIZE$ loadings predict increases in systemic risk during the crisis of 2008, even after accounting for size, leverage and correlation with global market returns. We fi nd evidence of predictive power for multiple measures of systemic risk, and for rm-level and aggregate TSIZE loadings.

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Appendices

A Appendix: Methodology for Constructing GL and SMB' Factors, and Test Portfolios

Data for the SMB, book-to-market (HML), Market minus risk free rate ($Mktrf$), robust minus weak profitability ($PROF$), and momentum (MOM) factors are from Kenneth French's website.[34] Since we want to identify SIFI effects separately from the effects of standard size factors, we create a version of SMB (denoted SMB') that is orthogonal to $TSIZE$ by construction.[35] To construct SMB', we apply the Fama-French methodology to firms below the 84th percentile. In other words, small firms are those below the 42nd percentile while large firms are those between the 42nd and 84th percentiles. Creating six size-by-BM groups, as above, SMB' is the average returns of the three small size bins minus the average returns of the three large size bins. Over the full sample, SMB' has a correlation of 0.86 with SMB, and a correlation of just -.04 with $SIFI$. Additional factors used are the excess returns on a corporate bond index ($CORP$), the excess returns on 10 year USA Government bonds (GOV) and the Baa-Aaa corporate bond spread ($DISTRESS$).[36]

To construct GL, we need the portfolio returns and the weights applied to these returns. To replicate the portfolios, we follow Gandhi and Lustig (2015) and start with all firms in CRSP with SIC codes that begin with 60, value weighting returns for firms with more than one common stock issue, dropping non-US firms and suspended, inactive, or delisted stocks.[37] In January of each year, we construct ten size sorted portfolios based on deciles of market capitalization in January. We then calculate value weighted returns for each portfolio, using the size in January for value weighting in each subsequent month of the year. Finally, we apply the weights reported in Gandhi and Lustig (2015) to the value weighted returns of each portfolio to replicate GL.

The 30 test portfolios are constructed from the six size deciles (as described in the text) and

[34] See `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html`. We thank Kenneth French for use of the data.

[35] We use SAS code that replicates the Fama French factors and portfolios, obtained from WRDS.

[36] Data for $CORP$ and GOV is from Global Financial Data where $CORP$ and GOV are called the Dow Jones Corporate Bond Return Index and the USA 10-year Government Bond Total Return Index, respectively. Data for $DISTRESS$ is from the FRED database of the St. Louis Fed.

[37] We thank the authors for generously providing us with their code for creating the bank portfolios.

five BM bins, constructed following Fama and French (1993). The 30 portfolios are obtained from taking the intersection of these size and BM partitions. Within each portfolio we calculate a size-weighted return for each month, then calculate an excess return by subtracting the risk free rate.[38] We provide summary statistics on the number of firms in each portfolio and the size of the average firm in each portfolio in the online appendix.

For sector-level analysis, we create test portfolios using only non-finance firms, only finance firms or firms in particular financial sectors such as banking. As before, we define a firm to be financial if SIC or NAICS identify it as finance. To obtain disjoint partitions, we define non-financial firms to be those that neither SIC nor NAICS consider to be finance. The size and BM percentiles are calculated using these restricted samples. Banks are identified using SIC codes starting with 60, 61, or 62, or NAICS codes beginning with 522 or 523. We define nonbank financial firms as those which SIC or NAICS categorize as finance, but which neither SIC nor NAICS categorize as banks. We define insurance companies following Antill et al. (2014), as firms whose SIC codes begin with 63 or 64, or whose NAICS codes begin with 524. For each subsample, we construct 30 BM and size sorted portfolios.

[38] We use the one month Treasury bill rate from Ibbotson Associates as the risk-free rate, downloaded from Kenneth French's website.

Table 1: Loadings on $SIFI$ Factors

This table shows OLS estimates for loadings on the $TSIZE$ factor of portfolios sorted by size (reading top to bottom, rows correspond to the 20th, 40th, 60th, 80th, and 90th percentiles of the size distribution) and book-to-market (reading left to right, columns correspond to the 20th, 40th, 60th, and 80th percentiles of the book-to-market distribution).We regress monthly excess returns of each portfolio on the $TSIZE$ factor, SMB' (the Fama-French factor SMB made orthogonal to $TSIZE$), the Fama-French factors $Mktrf$ and HML , bond market factors GOV and $CORP$, the Carhart momentum factor MOM, the bank size risk factor of Gandhi and Lustig (2015) GL. In Panels B-F, we add factors based on interconnectedness IC, leverage LEV, and liquidity LIQ. *, **, *** represent statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey West (1987) with a maximum of 3 lags. The sample is from 1970 to 2006.

	Low	2	3	4	High
Panel A: Loadings on TSIZE Factor (with no other SIFI factor)					
Smallest	.00	.07**	.08***	.08***	.08***
2	.09**	.10***	.11***	.12***	.09***
3	.08**	.10***	.08**	.11***	.15***
4	.05*	.08***	.11***	.10***	.09*
5	.03	.10***	.06**	.10***	.17***
Largest	-.05**	-.03	-.09**	.01	-.22***
Panel B: Loadings on TSIZE Factor (with other SIFI factors)					
Smallest	.00	.07***	.08***	.09***	.09***
2	.08**	.10***	.11***	.12***	.09***
3	.08**	.10***	.08**	.11***	.16***
4	.05*	.08***	.11***	.10***	.09*
5	.03	.10***	.07**	.11***	.18***
Largest	-.05**	-.03	-.08**	.01	-.24***
Panel C: Loadings on Interconnectedness Factor					
Smallest	-.03	.01	.00	.00	.00
2	.01	.03*	.04**	.04***	.00
3	.01	.04**	.01	.03**	.04***
4	.00	.03**	.03	.03	-.04*
5	-.01	.01	.02	.02	.03
Largest	.01	.01	.03*	.01	-.07**

Table 1: Loadings on $SIFI$ Factors (Continued)

	Low	2	3	4	High
Panel D: Loadings on Leverage Factor					
Smallest	.01	.03	.02	.04**	.06**
2	-.03	.01	.00	.00	-.01
3	-.04	.01	.00	.02	.01
4	.00	.00	.00	.04*	.00
5	.01	.01	.06**	.05**	.07
Largest	.02	.00	.00	-.01	-.07
Panel E: Loadings on Liquidity Factor					
Smallest	.00	.00	.04*	-.01	.00
2	.02	.02	.01	.02	.01
3	-.02	-.01	.00	.02	.04
4	.01	.01	.01	.04	.05
5	-.04*	-.02	-.01	.03	-.02
Largest	.00	-.01	-.06*	-.04	.07
Panel F: Loadings on GL Factor					
Smallest	.05***	.03**	.01	.03**	.07***
2	-.02	.00	-.02	-.03**	-.01
3	-.01	-.01	-.02	.00	.01
4	.01	.01	.00	.00	.02
5	.03**	.01	.01	.01	.03*
Largest	.02	.01	-.01	-.01	.00

Table 2: Estimates of $TSIZE$ Premium and Discount Per Year, 1970-2006

This table shows estimates of the $TSIZE$ premium and discount per year for portfolios sorted by size (reading top to bottom, rows correspond to the 20th, 40th, 60th, 80th, and 90th percentiles of the size distribution) and book-to-market (reading left to right, columns correspond to the 20th, 40th, 60th, and 80th percentiles of the book-to-market distribution). The column labeled *Average* shows the average (weighted by average firm market capitalization) across book-to-market bins for each size bin. We regress monthly excess returns of each portfolio on the $TSIZE$ factor, SMB' (the Fama-French factor SMB made orthogonal to $SIFI$), the Fama-French factors $Mktrf$ and HML , bond market factors GOV and $CORP$, and the Carhart momentum factor MOM. In panel A, we multiply the loadings on $TSIZE$ by the average annualized return of the $TSIZE$ factor (equal to 0.45% per year over this period), treating statistically insignificant loadings as 0. In Panel B, we also multiply by the average market capitalization of each portfolio in millions of 2013 dollars, where the average is taken first across firms and then across months. The sample is from 1970 to 2006.

	Low	2	3	4	High	Average
Panel A: Average Annual premium and discount (%)						
Smallest	0	0.04	0.04	0.04	0.03	0.03
2	0.04	0.05	0.05	0.05	0.04	0.05
3	0.03	0.06	0.04	0.06	0.05	0.05
4	0.02	0.04	0.05	0.05	0.05	0.04
5	0	0.05	0.05	0.05	0.06	0.04
Largest	0	-0.02	-0.05	0	-0.05	-0.02
Largest -5	0	-.07	-.09	-.05	-.11	-0.06
Panel B: Average Annual premium and discount per Firm (Million$)						
Smallest	0	0.04	0.03	0.03	0.02	0.02
2	0.15	0.23	0.22	0.2	0.16	0.19
3	0.3	0.56	0.39	0.6	0.51	0.47
4	0.54	0.96	1.16	1.17	1.06	0.98
5	0	2.57	2.5	3.06	3.3	2.29
Largest	0	-5.9	-10.7	0	-10.15	-6.09
Largest-5	0	-8.48	-13.2	-3.06	-13.45	-8.38

Table 3: $SIFI$ risk in the Cross-Section of Returns

This table shows estimates of the price of risk for SIFI factors based on size $TSIZE$, interconnectedness IC, leverage LEV, and liquidity LIQ. We first estimate 60 month rolling time series regressions of 30 size and book-to-market sorted portfolio excess returns on these factors, as well as SMB' (the Fama-French factor SMB made orthogonal to $TSIZE$), the Fama-French factors $Mktrf$ and HML , bond market factors GOV and $CORP$, the Carhart momentum factor MOM, and the bank size risk factor of Gandhi and Lustig (2015) GL, in a first stage regression. Then, in each month, we regress the 30 portfolio returns on that month's estimates of factor loadings in a cross sectional regression. The first and second stages are estimated by OLS. We present the time-series averages of these coefficients, along with the standard t-statistic and the Shanken (1992) errors-in-variables corrected t-statistics. The other SIFI factor based on interconnectedness IC, leverage LEV, and liquidity LIQ are added in rows. As comparison, the final row displays results when replacing $TSIZE$ with $TSIZE^{NF}$ constructed identically to $TSIZE$ except that *only* non-financial firm returns are used. The sample is from 1970 to 2006.

	Cons	TSIZE	Liquidity	Inter	Leverage	TSIZE^{NF}
Price of Risk	1.2	0.83				
T-Stat	(5.36)	(2.9)				
Shanken T-Stat	(5.03)	(2.43)				
Price of Risk	1.11	0.7			0.13	
T-Stat	(4.86)	(2.47)			(0.34)	
Shanken T-Stat	(4.55)	(2.06)			(0.29)	
Price of Risk	1.24	0.92	-0.12			
T-Stat	(5.25)	(3.21)	(-0.23)			
Shanken T-Stat	(4.88)	(2.67)	(-0.19)			
Price of Risk	1.16	0.63		-0.03		
T-Stat	(4.83)	(2.16)		(-0.06)		
Shanken T-Stat	(4.52)	(1.81)		(-0.05)		
Price of Risk	1.17	0.61	0.81	-0.14	-0.13	
T-Stat	(4.63)	(2.1)	(1.58)	(-0.27)	(-0.35)	
Shanken T-Stat	(4.27)	(1.74)	(1.31)	(-0.22)	(-0.29)	
Price of Risk	1.38					0.13
T-Stat	(6.14)					(1.17)
Shanken T-Stat	(5.62)					(0.84)

Table 4: Loadings on $TSIZE$, Financial and Non-financial Portfolios Separately

This table shows OLS estimates for loadings on the $TSIZE$ factor of financial and non-financial portfolios sorted by size (reading top to bottom, rows correspond to the 20th, 40th, 60th, 80th, and 90th percentiles of the size distribution) and book-to-market (reading left to right, columns correspond to the 20th, 40th, 60th, and 80th percentiles of the book-to-market distribution). We construct the test portfolios using only financial firms (left), and separately using only non-financial firms (right). In each panel, we regress monthly excess returns of the finance or nonfinance portfolios on the SIFI factors (size $TSIZE$, interconnectedness IC, leverage LEV, liquidity LIQ) and, in addition, SMB' (the Fama-French factor SMB made orthogonal to $TSIZE$), the Fama-French factors $Mktrf$ and HML , bond market factors GOV and $CORP$, and the Carhart momentum factor MOM, the bank size risk factor of Gandhi and Lustig (2014) GL. *, **, *** represent statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey West (1987) with a maximum of 3 lags. The sample is from 1970 to 2006.

	Finance Portfolios					Nonfinance Portfolios				
	Low	2	3	4	High	Low	2	3	4	High
Panel A: Loadings on TSIZE Factor (controlling for SIFI factors)										
Smallest	-.09	.15***	-.02	.07	.06	.00	.07**	.09***	.09***	.10***
2	-.04	.09	.10*	.11**	.06	.09**	.12***	.11***	.12***	.07**
3	.13***	.18**	.16***	.14**	.27**	.07*	.09***	.06*	.09***	.09**
4	.03	.22***	.18***	.20***	-.07	.04	.07**	.07***	.08***	.10**
5	.19***	.29***	.32***	.45***	.65***	.04	.06*	.03	.06*	.05
Largest	-.13**	-.15*	-.13	-.28**	-.37***	-.05**	.00	-.13***	.00	-.09
Panel B: Loadings on Interconnectedness Factor										
Smallest	.00	-.01	.03	.04	.00	-.03*	.00	.00	-.01	.00
2	-.02	.05	.04	.00	.02	.01	.02	.03*	.06***	.01
3	.04*	-.03	.01	-.02	-.09**	.01	.03*	.02	.03**	.06**
4	-.01	.01	.01	-.05*	-.31***	.00	.03*	.04*	.04***	.04**
5	.02	-.02	-.06	.03	-.06	-.01	.01	.04**	.04***	.06**
Largest	.06	-.05*	-.10	-.07*	-.03	.01	.02*	.05***	.05***	.00

Table 4: Loadings on $TSIZE$, Financial and Non-financial Portfolios Separately (Continued)

Panel C: Loadings on Leverage Factor										
Smallest	.02	.04	.01	.10**	.11**	.00	.04*	.01	.02	.06*
2	.00	.07	.05	.03	.06	-.03	-.01	.00	.00	-.03
3	.08*	.07	.09	.09**	.10	-.04*	.00	-.03	.01	-.03
4	.12***	.21***	.29***	.23***	.03	-.01	-.03	-.03	-.03	-.05
5	.23***	.26***	.23***	.39***	.23**	-.01	-.02	-.03	-.02	.02
Largest	.15**	.29***	.42***	.34***	.26**	.01	-.06**	-.09***	-.12***	-.10**
Panel D: Loadings on Liquidity Factor										
Smallest	-.03	-.03	-.06	-.07	-.06	.00	.01	.05**	.02	.01
2	-.07	-.01	-.06	-.04	-.08	.03	.03	.03	.02	.02
3	.02	-.06	-.03	.01	.02	-.02	.00	.03	.01	.02
4	.01	-.07	-.12***	-.06	.01	.01	.02	.03	.06*	.09**
5	-.09	-.14**	-.04	-.07	-.10	-.03	.01	.01	.03	-.03
Largest	-.11*	.03	-.17**	-.13*	.19***	.01	-.02	-.03	.01	.10*
Panel E: Loadings on GL Factor										
Smallest	.06***	-.02	-.01	.03	.12***	.05**	.04**	.02	.02	.07***
2	.00	-.04	-.09***	-.08***	-.04	-.03	.00	-.01	-.01	.00
3	.01	-.07*	-.03	-.09***	.05	-.01	.00	-.01	.02	.00
4	-.03	-.07**	-.06***	-.09***	.01	.00	.01	.02	.02	.04**
5	-.05	-.03	-.06	-.09*	-.10**	.03***	.01	.03*	.02	.04**
Largest	-.06**	-.07*	-.08**	-.07*	-.06	.02	.02	.02	.00	.01

Table 5: Estimates of $TSIZE$ Premium and Discount per Year for Financial and Non-Financial Firms, 1970-2006

This table shows estimates of the $TSIZE$ premium and discount per year separately for financial (panel A) and non-financial (panel B) portfolios. We regress monthly excess returns of each portfolio on $SIFI$ factors (size $TSIZE$, interconnectedness IC, leverage LEV, and liquidity LIQ) as well as SMB' (the Fama-French factor SMB made orthogonal to $TSIZE$), the Fama-French factors $Mktrf$ and HML, bond market factors GOV and $CORP$, the Carhart momentum factor MOM, the bank size risk factor ofGandhi and Lustig (2015) GL. We multiply the loadings on $TSIZE$ by the average annualized return of the $TSIZE$ factor (equal to 0.45% per year over this period), treating statistically insignificant loadings as 0. The portfolios are sorted by size (reading top to bottom, rows correspond to the 20th, 40th, 60th, 80th, and 90th percentiles of the size distribution) and book-to-market (reading left to right, columns correspond to the 20th, 40th, 60th, and 80th percentiles of the book-to-market distribution). The column labeled *Average* shows the average across book-to-market bins (weighted by average firm market capitalization) for each size bin. The sample is from 1970 to 2006.

	Low	2	3	4	High	Average
Panel A: Average Annual premium and discount (%), Finance Portfolios						
Smallest	0	0.07	0	0	0	0.02
2	0	0	0.05	0.05	0	0.02
3	0.06	0.08	0.07	0.06	0.12	0.08
4	0	0.1	0.08	0.09	0	0.05
5	0.09	0.13	0.14	0.2	0.29	0.17
Largest	-0.06	-0.07	0	-0.13	-0.17	-0.09
Largest -5	-0.14	-0.2	-0.14	-0.33	-0.46	-0.26
Panel B: Average Annual premium and discount (%), Nonfinance Portfolios						
Smallest	0	0.03	0.04	0.04	0.05	0.03
2	0.04	0.05	0.05	0.05	0.03	0.05
3	0.03	0.04	0.03	0.04	0.04	0.04
4	0	0.03	0.03	0.04	0.05	0.03
5	0	0.03	0	0.03	0	0.01
Largest	-0.02	0	-0.06	0	0	-0.02
Largest -5	-0.02	-0.03	-0.06	-0.03	0	-0.03

Table 6: Time Series Loadings after Removing Top 8th Percentile of Financial Firms in Test Assets

This table shows OLS estimates for loadings on the $TSIZE$ factor of portfolios after removing the top 8th percentile of financial firms in $TSIZE$ before balancing size and book-to-market categories. The table is sorted by size (reading top to bottom, rows correspond to the 20th, 40th, 60th, 80th, and 90th percentiles of the size distribution) and book-to-market (reading left to right, columns correspond to the 20th, 40th, 60th, and 80th percentiles of the book-to-market distribution). We regress monthly excess returns of each portfolio on the $TSIZE$ factor, SMB' (the Fama-French factor SMB made orthogonal to $TSIZE$), the Fama-French factors $Mktrf$ and HML , bond market factors GOV and $CORP$, the Carhart momentum factor MOM, the bank size risk factor of Gandhi and Lustig (2014) GL. In Panels B, we add three non-size based SIFI factors based on interconnectedness IC, leverage LEV, and liquidity LIQ. *, **, *** represent statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey West (1987) with a maximum of 3 lags. The sample is from 1970 to 2006.

	Low	2	3	4	High
Panel A: Loadings on TSIZE Factor					
Smallest	.00	.06**	.07***	.08***	.08***
2	.09**	.10***	.11***	.12***	.10***
3	.09**	.10***	.07**	.11***	.15***
4	.05**	.07***	.11***	.10***	.09*
5	.03	.08***	.06**	.13***	.16***
Largest	-.04**	.01	-.08**	.06	-.04
Panel B: Loadings on TSIZE Factor (controlling for SIFI factors)					
Smallest	.00	.07**	.09***	.09***	.09***
2	.08**	.10***	.11***	.12***	.09***
3	.08**	.11***	.07**	.11***	.15***
4	.05*	.08***	.11***	.10***	.09*
5	.03	.09***	.07**	.15***	.17***
Largest	-.04**	.00	-.09**	.05	-.06

Table 7: Probability of Government Support and Funding Costs of Firms Constituting the $SIFI$ Factor

This table reports the level of extremely high government support in the largest 8% (denoted $L8$) and the next largest 8% (denoted $NL8$) of financial firms that constitute the $SIFI$ factor. Panel A of the table reports the overall share of commercial banks and the share of banks that ever had a Fitch's Support Rating floor (SRF) of at least A- (indicating a firm with extremely high probability of government support) for the $L8$ and $NL8$ groups of financial firms. The last two columns of Panel A show estimates and t-statistics from regressions on a dummy variable which equals 1 for firms in $L8$ and 0 for firms in $NL8$, with the dependent variable being either the overall share of banks or the share of banks with SRF of at least A-. The regression includes period fixed effects and standard errors clustered at the firm level. The sample is from 1963 through 2013. Panel B shows results from a linear probability model for the probability that a firm ever receives a SRF of at least A- , estimated by pooled OLS with monthly fixed effects and standard errors clustered by firm. The dependent variable is $TBTF_{i,t}$, a dummy variable equal to 1 if bank i ever had a rating of A- or higher. The regressors are, for bank i in month t: $L8_{i,t}$, a dummy variable equal to 1 if the bank is in the $L8$ group and 0 if it is in the $NL8$ group; $MarketCap_{i,t}$, the market capitalization (in trillions $). The sample consists of 163 rating observations for 21 publicly traded US banks that are in the largest 16% of financial firms and have SRFs from Fitch between March 16 2007 and 2013.

Panel A: Share of Firms that are Banks or have Highest Government Support

	In $L8$ Group		In $NL8$ Group		Regression On $L8$ Dummy	
	Mean	SD	Mean	SD	Coefficient	T-stat
Share of Banks	0.25	0.44	0.24	0.43	0.01	0.21
Ever Rated $>= A-$	0.84	0.37	0.19	0.39	0.62	4.69

Panel B: Estimating Probability of Firms with Highest Government Support

	Coefficient	Standard Error	Tstat	P
L8	0.43	0.18	2.31	0.03
MarketCap	2.32	1.21	1.91	0.07
Constant	0.05	0.14	0.34	0.74

Table 8: Changes in $SIFI$ Around Fitch Support Ratings Changes: All Firms

This table shows changes in the dependent variable, $TSIZE$ loadings on each firm that had a change in the Fitch Support Floor Rating from below A- to above A- (indicating a firm with extremely high probability of government support). The $TSIZE$ loadings in the dependent variable are estimated from 60-month rolling regressions of excess returns on the $TSIZE$ factor, SMB' (the Fama-French factor SMB made orthogonal to $TSIZE$), the Fama-French factors $Mktrf$ and HML, bond market factors GOV and $CORP$, the Carhart momentum factor MOM, the bank size risk factor of Gandhi and Lustig (2015) GL, as well as three non-size based SIFI factors based on interconnectedness IC, leverage LEV, and liquidity LIQ. A time period of $t = 0$ indicates the month of the rating change. The four months preceeding and after the change, as well as the fifth to tenth month after the change, are shown in the regressions below relative to the intial period, ten to five months before the change. 14 firms are included in the sample using rating changes from March 2007 to June 2013. *, **, *** represent statistical significance at the 10%, 5%, and 1% level, respectively. T-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
$t \geq 0$	-0.0506			-0.0506**		
	(-1.09)			(-2.12)		
$t\epsilon[-4, 0)$			0.0237			0.0237
			(0.35)			(0.68)
$t\epsilon[0, 4]$		-0.0897	-0.0802		-0.0897***	-0.0802**
		(-1.55)	(-1.25)		(-3.02)	(-2.44)
$t\epsilon(4, 10]$		-0.0180	-0.00848		-0.0180	-0.00848
		(-0.33)	(-0.14)		(-0.64)	(-0.27)
Constant	-0.236***	-0.236***	-0.245***	-0.236***	-0.236***	-0.245***
	(-7.04)	(-7.04)	(-5.66)	(-13.65)	(-13.74)	(-11.06)
PERMNO FE	None	None	None	FE	FE	FE
N	294	294	294	294	294	294

t statistics in parentheses

* p¡.10, ** p¡.05, *** p¡.01

Table 9: Changes in $SIFI$ Around Fitch Support Ratings Changes: US Firms

This table shows changes in the dependent variable, $TSIZE$ loadings on each firm that had a change in the Fitch Support Floor Rating from below A- to above A- (indicating a firm with extremely high probability of government support). The $TSIZE$ loadings in the dependent variable are estimated from 60-month rolling regressions of excess returns on the $TSIZE$ factor, SMB' (the Fama-French factor SMB made orthogonal to $TSIZE$), the Fama-French factors $Mktrf$ and HML, bond market factors GOV and $CORP$, the Carhart momentum factor MOM, and the bank size risk factor of Gandhi and Lustig (2015) GL. A time period of $t = 0$ indicates the month of the rating change. The four months preceeding and after the change, as well as the fifth to tenth month after the change, are shown in the regressions below relative to the intial period, ten to five months before the change. In this table, eight U.S. firms are included using rating changes from March 2007 to June 2013, which allows for the inclusion of additional controls, the log size and book-to-market of each firm. *, **, *** represent statistical significance at the 10%, 5%, and 1% level, respectively. T-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$t \geq 0$	-0.0992**			-0.0992***			
	(-2.25)			(-3.44)			
$t\epsilon[-4, 0)$			0.0280			0.0280	0.0379
			(0.43)			(0.65)	(0.87)
$t\epsilon[0, 4]$		-0.118**	-0.106*		-0.118***	-0.106***	-0.0966**
		(-2.12)	(-1.73)		(-3.25)	(-2.65)	(-2.37)
$t\epsilon(4, 10]$		-0.0839	-0.0727		-0.0839**	-0.0727*	-0.0557
		(-1.61)	(-1.24)		(-2.46)	(-1.90)	(-1.07)
Book-to-market							0.0189
							(0.25)
Log size							0.0819
							(1.39)
Constant	-0.0565*	-0.0565*	-0.0677	-0.0565***	-0.0565***	-0.0677**	-1.571
	(-1.77)	(-1.77)	(-1.64)	(-2.70)	(-2.70)	(-2.50)	(-1.42)
PERMNO FE	None	None	None	FE	FE	FE	FE
N	168	168	168	168	168	168	168

Table 10: Changes in $SIFI$ Risk Around Systemic Risk Events

This table shows the average differences between S5 and S6 loadings for each factor across time periods. The loading is calculated for each size and book-to-market bin separately, then averaged over size bins. We then take the difference between the loadings for the 90%-100% bin (S6) and the 80%-90% bin (S5). Finally, we take the average difference between the S6-S5 difference in each time period relative to the pre-Continental Bailout time period (pre-May 1984). That is, the first column compares May 1984-September 2008 to the previous period, the second column compares September 2008-July 2010 to the previous period, and the last column compares July 2010-November 2013 to the previous period. The last 5 rows corresponds to the lower panels in figure 5, in which $TSIZE$, LIQ, and IC are constructed with 5-year rebalancing. *, **, *** represent statistical significance at the 10%, 5%, and 1% level, respectively, for a two-sample t-test of the S6-S5 difference between the two time periods.

	Panel A: Factors Rebalanced Every Year		
	Post-Continental, Pre-Lehman - Pre-Continental	Post-Lehman, Pre-DFA - Post-Continental, Pre-Lehman	Post-DFA - Post-Lehman, Pre-DFA
TSIZE	0.077***	-0.063***	0.006***
Interconnectedness	-0.004***	0.086***	-0.016*
Liquidity	-0.083***	0.049***	-0.008*
Leverage	-0.064***	0.046***	-0.024***
	Panel B: Factors Rebalanced Every 5 Years		
	Post-Continental, Pre-Lehman - Pre-Continental	Post-Lehman, Pre-DFA - Post-Continental, Pre-Lehman	Post-DFA - Post-Lehman, Pre-DFA
TSIZE 5 Year	0.059***	-0.063***	0.014***
Interconnectedness 5 Year	0.035***	0.047***	-0.032***
Liquidity 5 Year	-0.010**	-0.085***	-0.008***
Leverage 5 Year	-0.079***	0.039**	-0.019***

Table 11: Predicting Systemic Risk Increases During Crisis with Changes in SIFI Loadings

This table shows the share of increases in systemic risk measures AV and $SRISK$ during crisis ("prediction period") due to changes in $TSIZE$ loadings of the largest decile of firms in the "shock period". The prediction period is September 2008 to January 2009 for monthly data, and Q3 to Q4 2007 for quarterly data. The shock period is September 2008 for monthly data and 2007 Q3 for quarterly data. The predicted change in systemic risk is obtained from the impulse response estimates (Figures 10 and 12). The share is the predicted change in the systemic risk measure as a percent of its actual change over the prediction period. AV is an estimate of firesale risk based on monthly broker-dealer repo data and quarterly Bank Holding Company (BHC) balance sheet data. $SRISK$ is the expected capital shortfall of a firm conditional on a substantial market decline.

Systemic risk measure	Estimation Sample	Data frequency	Shock period	Prediction period	% of systemic risk predicted
AV	2002 Q1 - 2013 Q4	Quarterly	2007 Q3	2007 Q3 - 2007 Q4	11.52
AV	July 2008 - November 2013	Monthly	September 2008	September 2008 - January 2009	10.62
SRISK	July 2008 - November 2013	Monthly	September 2008	September 2008 - January 2009	21.04

Table 12: Predicting Firm's Crisis Period Changes in SRISK Using Pre-Crisis SIFI Loadings

This table shows OLS estimates from cross sectional regressions predicting a firm's average increase in $SRISK$ (the expected capital shortage, in $Billion, of the firm in case of a systemic event) during the crisis from its pre-crisis level, using pre-crisis values of $TSIZE$ loadings. The pre-crisis period is 200-2006 and the crisis period is Q4 2007 onwards. For firm i in quarter t of the crisis period, let $\Delta X_{i,t}$ = (X_i - pre-crisis average) and ΔX_i = average of $\Delta X_{i,t}$ over the crisis period. The dependent variable is $\Delta SRISK_i$. The explanatory variables are the pre-crisis averages of $TSIZE$ loadings, $SIFIP$, the non-negative component of $TSIZE$ and $SIFIM$, the negative component of $SIFI$—all interacted with pre-crisis values of $S6$, equal to 1 for firms in the top decile in a given year and $S5$, equal to 1 for firms in the second highest decile in a given year. Also included are a firm's pre-crisis average loadings on the GL (Gandhi and Lustig (2015)) and SMB factors. The control variables are the firm's $\Delta Marketcap$, $\Delta Marketcap^2$, ΔLev and $\Delta Correlation$, or changes in the market capitalization (in $Billion), market capitalization squared, leverage, and correlation with the World MSCI stock index. Factor loadings are estimated from a firm-level time series regression of excess returns on a 6-factor Fama-French-Carhart model, bond market factors, $TSIZE$ and GL for 2000 to 2006. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. We report robust T-statistics and the Root Mean Squared Error (MSE). There are 130 observations.

	Estimate (T-stat)	Estimate (T-stat)	Estimate (T-stat)	Estimate (T-stat)	Estimate (T-stat)	Estimate (T-stat)
$SIFI_{Pre-2007} * S5_{Pre-2007}$	13.44*	—	—	—	—	—
	(1.81)	—	—	—	—	—
$SIFI_{Pre-2007} * S6_{Pre-2007}$	-57.47***	—	—	—	—	—
	(-3.15)	—	—	—	—	—
$S6_{Pre-2007}$	26.55***	14.70	—	7.26	5.23	7.31
	(3.83)	(1.12)	—	(0.97)	(0.84)	(0.98)
$SIFIM_{Pre-2007} * S6_{Pre-2007}$		-86.58**	—	-83.88***	-82.81***	-83.70***
		(-2.61)	—	(-5.19)	(-4.66)	(-5.16)
$SIFIP_{Pre-2007} * S6_{Pre-2007}$		-15.54	—	3.48	6.89	3.99
		(-0.59)	—	(0.17)	(0.37)	(0.19)
$SIFIM_{Pre-2007} * S5_{Pre-2007}$		8.31	—	-6.17	-7.35	-6.05
		(0.93)	—	(-0.79)	(-1.11)	(-0.77)
$SIFIP_{Pre-2007} * S5_{Pre-2007}$		5.04	—	3.35	3.22	3.48
		(1.13)	—	(1.26)	(1.29)	(1.36)
$\Delta MarketCap$		—	-0.53**	-0.49***	-0.46***	-0.49***
		—	(-2.58)	(-5.75)	(-3.95)	(-5.78)
$\Delta Leverage$		—	0.44***	0.19**	0.22**	0.18*
		—	(2.88)	(1.99)	(2.53)	(1.91)
$\Delta Correlation$		—	-41.97**	-4.37	-7.00	-4.46
		—	(-2.16)	(-0.60)	(-0.95)	(-0.60)
$\Delta MarketCap^2$	—	—	—	—	0.00	0.14
	—	—	—	—	(0.60)	(0.38)
$SMB_{PreCrisis}$	—	—	—	—	—	—
	—	—	—	—	—	—
$GL_{PreCrisis}$	—	—	—	—	—	-1.77
	—	—	—	—	—	(-1.04)
Intercept	0.77***	0.94***	8.17***	1.14	1.32	0.82
	(2.66)	(2.97)	(2.99)	(1.20)	(1.36)	(0.79)
Adjusted R-squared	0.56	0.60	0.47	0.87	0.87	0.87
Root MSE	13.18	12.41	13.98	7.04	6.96	7.03

Table 13: Predicting Firm's Crisis Period Changes in Fire Sale Risk Using Pre-Crisis SIFI Loadings

This table shows OLS estimates from cross sectional regressions predicting a firm's average increase in AV (the firesale risk of the firm) during the crisis from its pre-crisis level, using pre-crisis values of $TSIZE$ loadings. The pre-crisis period is 200-2006 and the crisis period is Q4 2007 onwards. For firm i in quarter t of the crisis period, let $\Delta X_{i,t} = (X_i$ - pre-crisis average) and ΔX_i = average of $\Delta X_{i,t}$ over the crisis period. The dependent variable is ΔAV_i. The explanatory variables are the pre-crisis averages of $SIFI$, the SIFI loadings, $SIFIP$, the non-negative component of $TSIZE$ and $SIFIM$, the negative component of $SIFI$—all interacted with $S6$, equal to 1 for firms in the top decile in a given year and $S5$, equal to 1 for firms in the second highest decile in a given year. Also included are a firm's pre-crisis average loadings on the GL (Gandhi and Lustig (2015)) and SMB factors. The control variables are $\Delta Marketcap$, $\Delta Marketcap^2$, ΔLev and $\Delta Correlation$, or changes in the market capitalization (in $Billion), market capitalization squared, leverage, and correlation with the World MSCI stock index. Factor loadings are estimated from a firm-level time series regression of excess returns on a 6-factor Fama-French-Carhart model, $TSIZE$ and GL for 2000 to 2006. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. We report robust T-statistics and the Root Mean Squared Error (MSE). There are 79 observations.

	Estimate (T-stat)	Estimate (T-stat)	Estimate (T-stat)	Estimate (T-stat)	Estimate (T-stat)	Estimate (T-stat)
$SIFI_{Pre-2007} * S5_{Pre-2007}$	0.10	—	—	—	—	—
	(0.56)	—	—	—	—	—
$SIFI_{Pre-2007} * S6_{Pre-2007}$	0.10	—	—	—	—	—
	(0.34)	—	—	—	—	—
$S6_{Pre-2007}$	0.15	0.05	—	-0.13	-0.01	-0.13
	(1.44)	(0.34)	—	(-1.50)	(-0.05)	(-1.41)
$SIFIM_{Pre-2007} * S6_{Pre-2007}$		-0.06	—	-0.49*	-0.60***	-0.49*
		(-0.16)	—	(-1.97)	(-3.76)	(-1.94)
$SIFIP_{Pre-2007} * S6_{Pre-2007}$		0.68**	—	1.00***	0.79**	1.03***
		(2.22)	—	(5.56)	(2.64)	(5.67)
$SIFIM_{Pre-2007} * S5_{Pre-2007}$		-0.13	—	0.17	-0.02	0.15
		(-0.46)	—	(1.03)	(-0.10)	(0.76)
$SIFIP_{Pre-2007} * S5_{Pre-2007}$		-0.03	—	-0.06	-0.04	-0.07
		(-0.29)	—	(-0.73)	(-0.40)	(-0.87)
$\Delta MarketCap$		—	0.06***	0.08***	0.04***	0.08***
		—	(4.89)	(3.61)	(2.85)	(3.57)
$\Delta Leverage$		—	0.03	0.14***	0.12***	0.15***
		—	(0.36)	(2.99)	(3.08)	(2.77)
$\Delta Correlation$		—	-0.03	-0.02	-0.01	-0.03
		—	(-0.32)	(-0.39)	(-0.44)	(-0.51)
$\Delta MarketCap^2$	—	—	—	—	-0.01***	0.01
	—	—	—	—	(-3.25)	(0.62)
$SMB_{PreCrisis}$	—	—	—	—	—	—
	—	—	—	—	—	—
$GL_{PreCrisis}$	—	—	—	—	—	-0.05
	—	—	—	—	—	(-1.39)
Intercept	-0.01	-0.01*	0.02	0.00	0.00	-0.02
	(-1.40)	(-1.75)	(1.09)	(0.02)	(-0.94)	(-1.49)
Adjusted R-squared	0.01	0.00	0.46	0.64	0.83	0.63
Root MSE	0.15	0.15	0.12	0.09	0.06	0.09

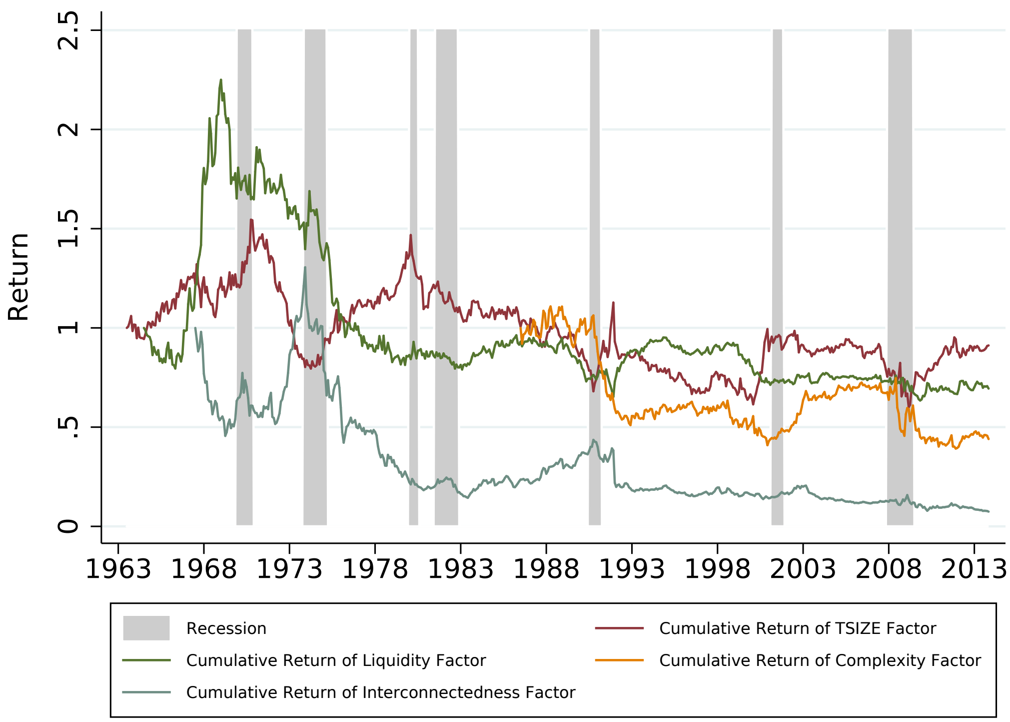


Figure 1: TSIZE Factor Returns and Business Cycles

This figure shows the cumulative return on $TSIZE$ (the value of a dollar invested in $TSIZE$ in July 1963 and rebalanced at the same frequency as the factor) with recession shading.

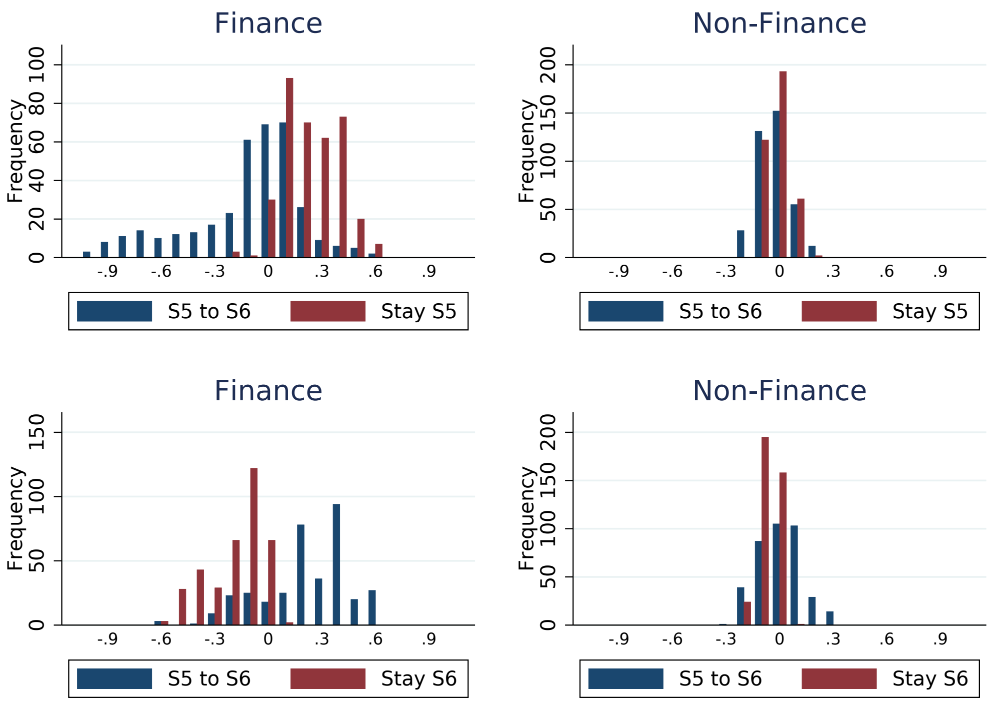
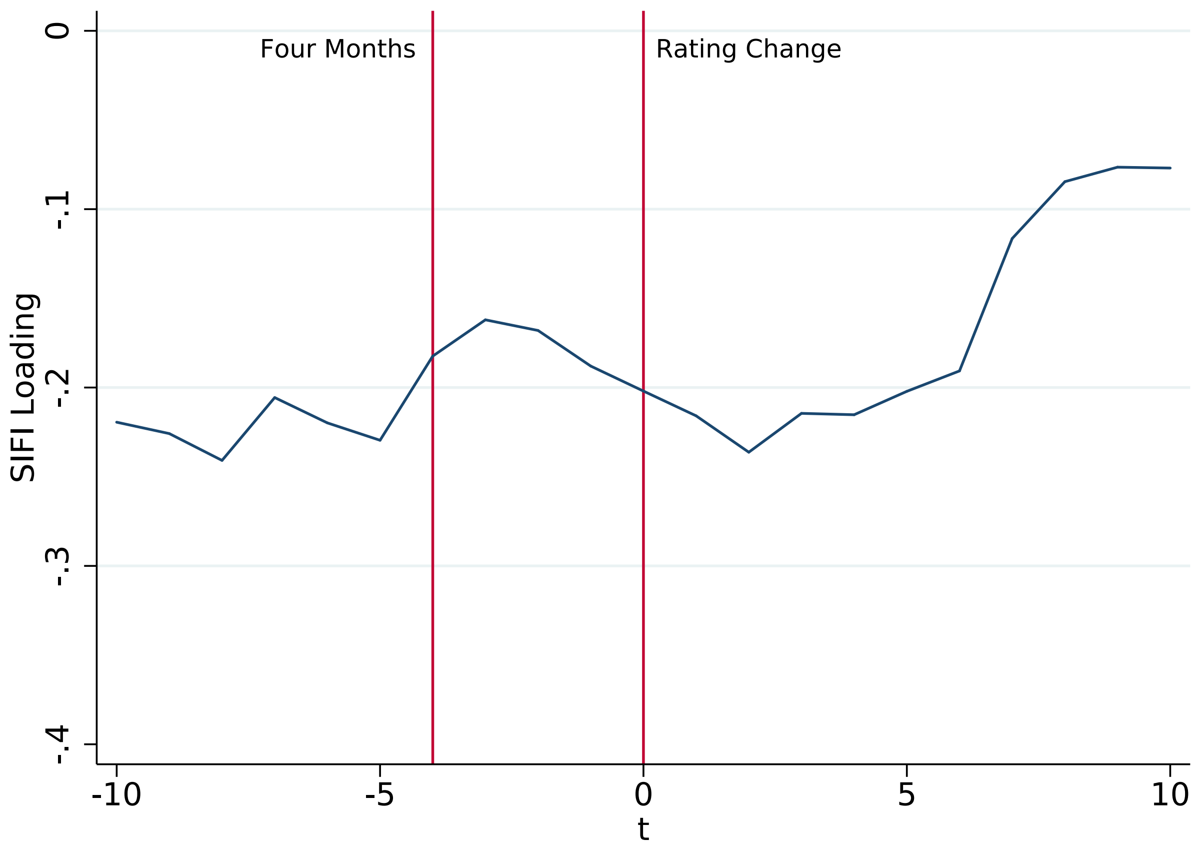


Figure 2: TSIZE Loadings of Firms That Stay In or Move Between Largest and Second Largest Size Groups

This figure shows histograms of estimates of loadings on the $TSIZE$ factor for firms that remained in the largest 10% size bin S6 and the second-largest 10% size bin S5 (denoted "stay S6" and "stay S5", respectively) and firms that switched between S5 and S6 ("S6 to S5" and "S5 to S6") in consecutive 5-year periods. The size bins are formed every 5 years corresponding to the 20th, 40th, 60th, 80th, and 90th percentiles. The loadings are calculated each month using 60 month rolling regressions of excess returns on the $TSIZE$ factor, SMB' (the Fama-French factor SMB made orthogonal to $TSIZE$), the Fama-French factors $Mktrf$ and HML , bond market factors GOV and $CORP$, the Carhart momentum factor MOM, the bank size risk factor of Gandhi and Lustig (2014) GL, as well as three non-size based SIFI factors based on interconnectedness IC, leverage LEV, and liquidity LIQ. The estimated loadings are averaged for each size group in each month, and for financial and non-financial firms separately. The sample is from 1970 to 2006.

Figure 3: Rolling $TSIZE$ Loading on Banks Leading up to Fitch SIFI Change

This figure shows the average $TSIZE$ loading of banks leading up to changes in the Fitch Support Floor Rating from below A- to above A- (indicating a firm with extremely high probability of government support). The first red line is 4 months prior to the rating change, while the second line is the month of the rating change (denoted as 0). The $TSIZE$ loadings are estimated from 60-month rolling regressions of excess returns on the $TSIZE$ factor, SMB' (the Fama-French factor SMB made orthogonal to $TSIZE$), the Fama-French factors $Mktrf$ and HML, bond market factors GOV and $CORP$, the Carhart momentum factor MOM, the bank size risk factor of Gandhi and Lustig (2014) GL, as well as three non-size based SIFI factors based on interconnectedness IC, leverage LEV, and liquidity LIQ. 14 firms are included in the sample using rating changes from March 2007 to June 2013.



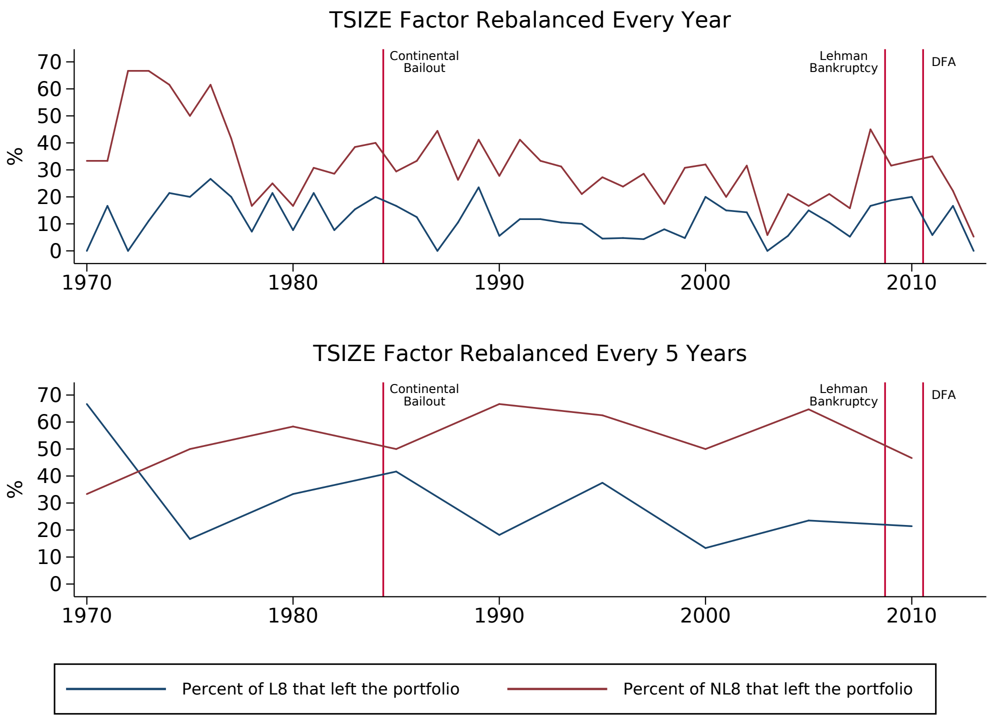


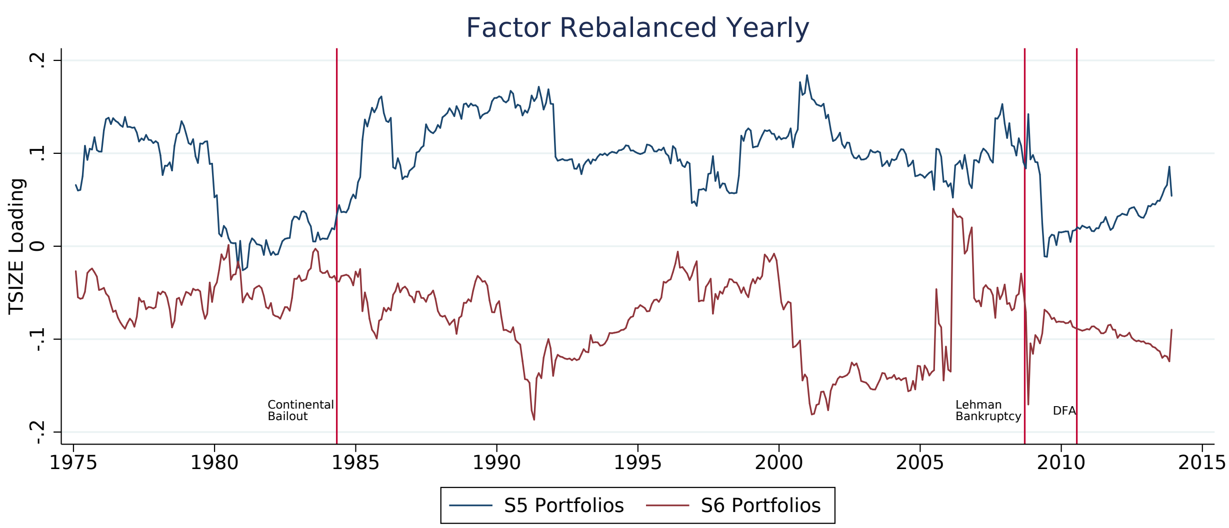
Figure 4: Share of Firms Leaving $TSIZE$ Factor: 1-Year and 5-Year Rebalancing

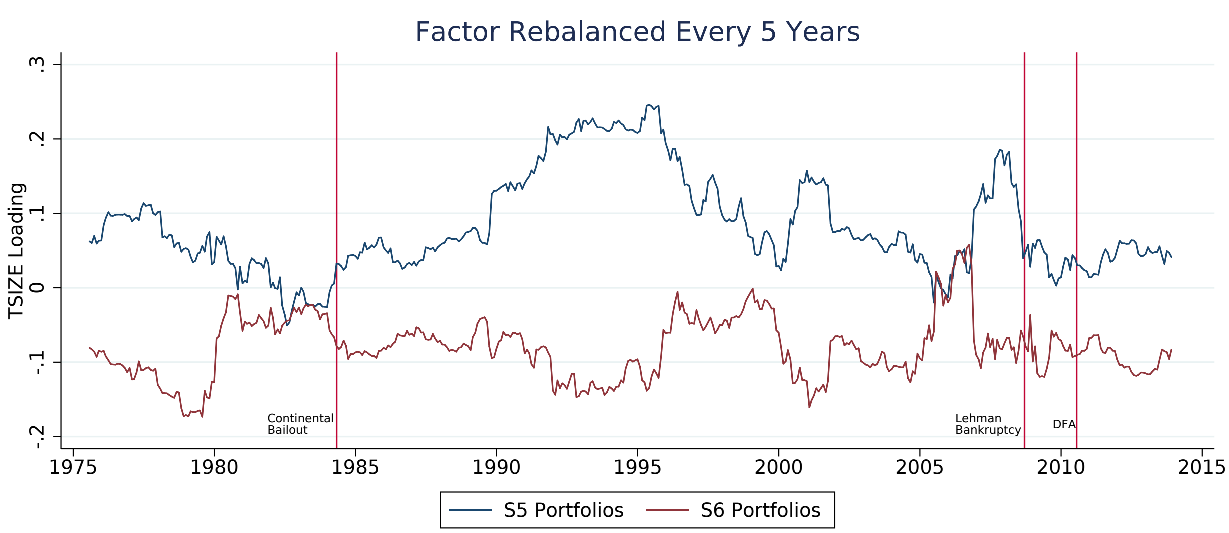
The top panel shows the percent of firms in the largest 8% size bin $L8$ and the next-largest 8% size bin $NL8$ of financial firms constituting the $TSIZE$ factor that exit from one year to the next. The bottom panel shows the percent of firms in $L8$ and $NL8$ in year $t-5$ that left in year t. The red lines correspond to the Continental Bailout (May 1984), the Lehman bankruptcy (September 2008), and the DFA implementation (July 2010).

Figure 5: Loadings on $TSIZE$ and IC from 60-month Rolling Regressions

This figure shows, at each month t, the loading on $TSIZE$ and IC from a time series regression, over the previous 60 months, of returns on the $TSIZE$ factor, SMB' (the Fama-French factor SMB made orthogonal to $TSIZE$), the Fama-French factors $Mktrf$ and HML , bond market factors GOV and $CORP$, and the Carhart momentum factor MOM, the bank size risk factor of Gandhi and Lustig (2014) GL, as well as three non-size based SIFI factors based on interconnectedness IC, leverage LEV, and liquidity LIQ. The loading is calculated for each size and book-to-market bin separately, then averaged over size bins. We present loadings for the 80%-90% bin (S5) and the 90%-100% bin (S6). The red vertical lines correspond to the Continental Bailout (May 1984), the Lehman bankruptcy (September 2008), and the DFA (July 2010). The first 60 months use the same sample as a training period. The second graph shows the same specification where $TSIZE$, IC, and LIQ are rebalanced every 5 years in its factor construction rather than yearly.

Loadings on $TSIZE$





Loadings on Interconnectedness Factor IC

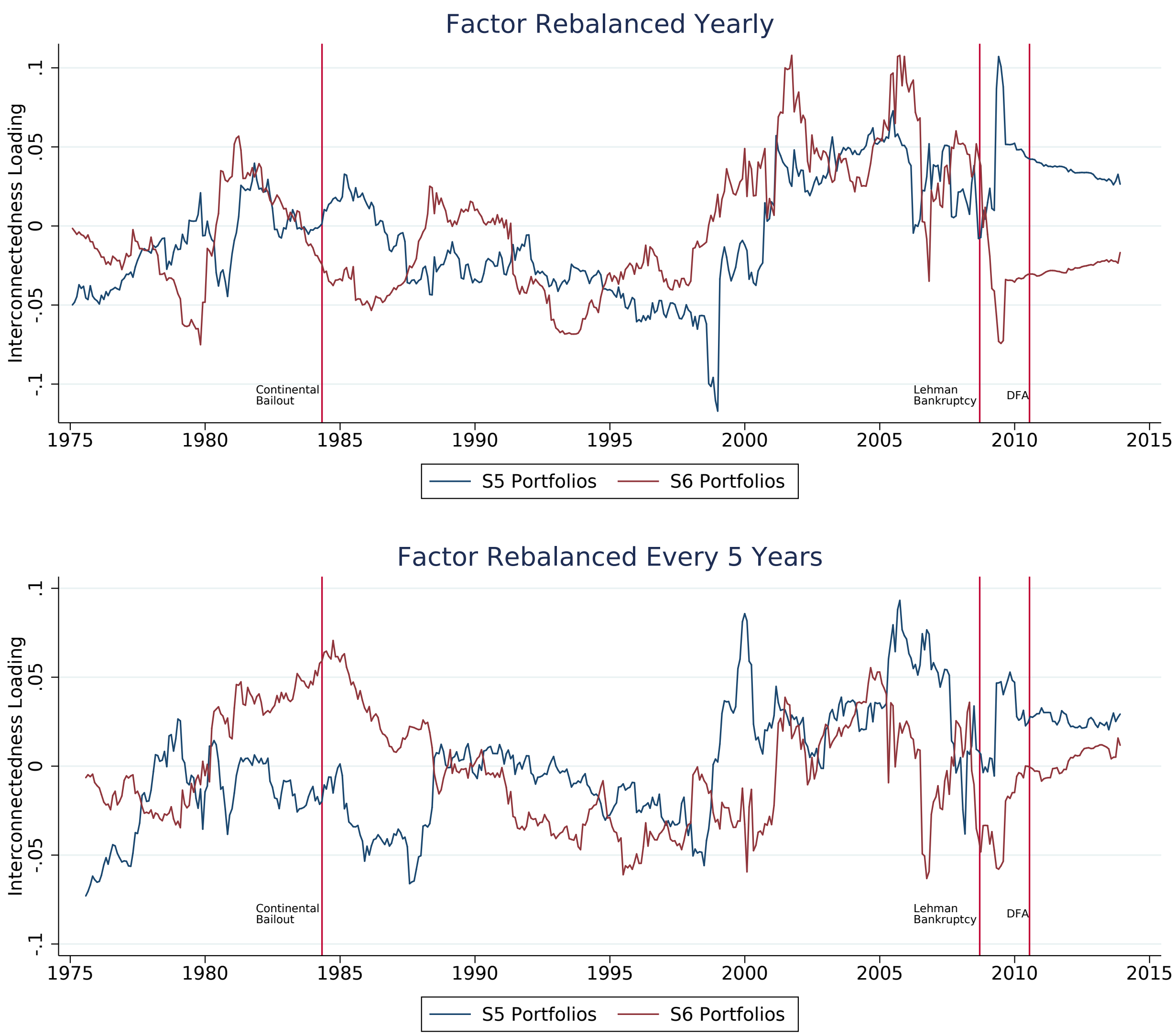


Figure 6: Subsidiaries of GSIB and non-GSIB Bank Holding Companies

This figure shows the number of subsidiaries of bank holding companies, separately for globally systemic banks (GSIBs) and non-GSIBs from 1986.

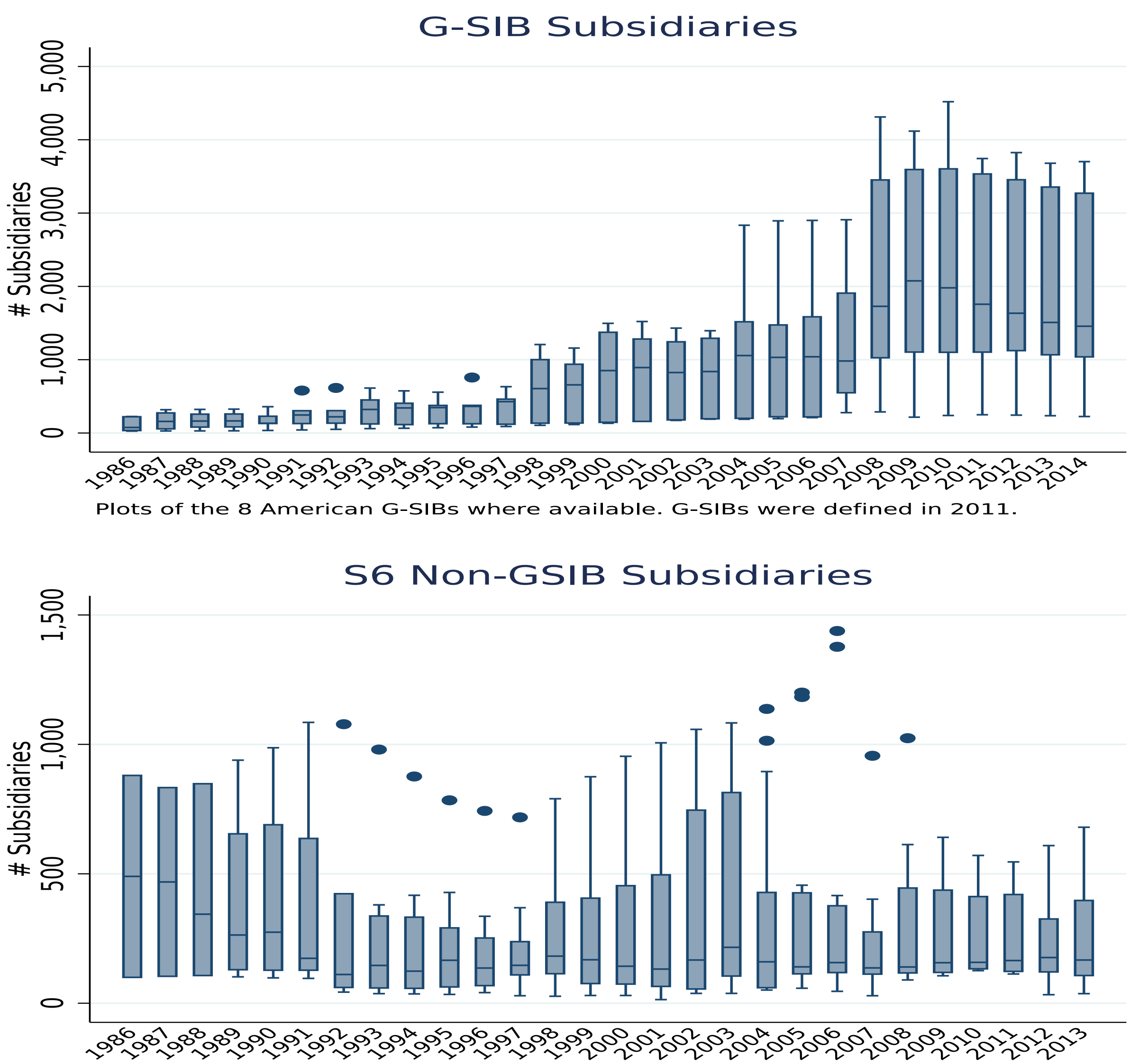
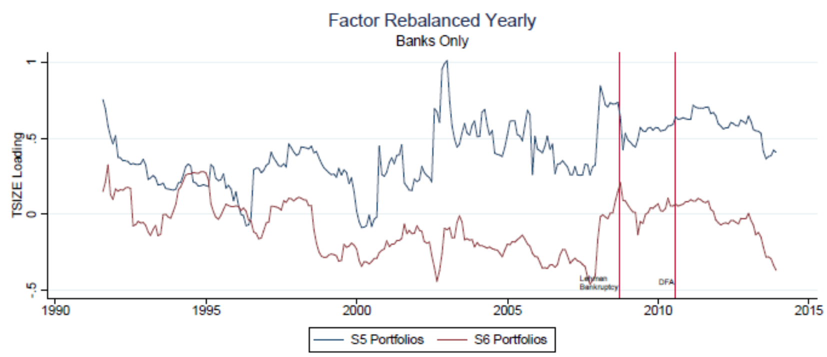


Figure 7: Loadings on Complexity, $TSIZE$ and IC from 60-month Rolling Regressions for Banks

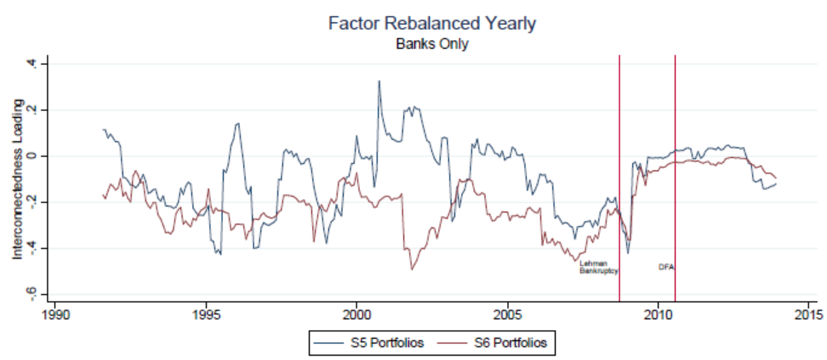
This figure shows, at each month t, the loadings on $COMP$, $TSIZE$ and IC from a time series regression, over the previous 60 months, of banking sector returns on the SIFI factors: $TSIZE$, IC, LEV, LIQ and $COMP$. The other factors are SMB' (the Fama-French factor SMB made orthogonal to $TSIZE$), the Fama-French factors $Mktrf$ and HML , bond market factors GOV and $CORP$, and the Carhart momentum factor MOM, the bank size risk factor of Gandhi and Lustig (2014) GL. The loading is calculated for each size and book-to-market bin separately, then averaged over size bins. We present loadings for the 80%-90% bin (S5) and the 90%-100% bin (S6). The red vertical lines correspond to the Continental Bailout (May 1984), the Lehman bankruptcy (September 2008), and the DFA (July 2010). The first 60 months is the training period.

Banks Only

Rolling Loadings on $TSIZE$



Rolling Loadings on IC



Rolling Loadings on $COMP$

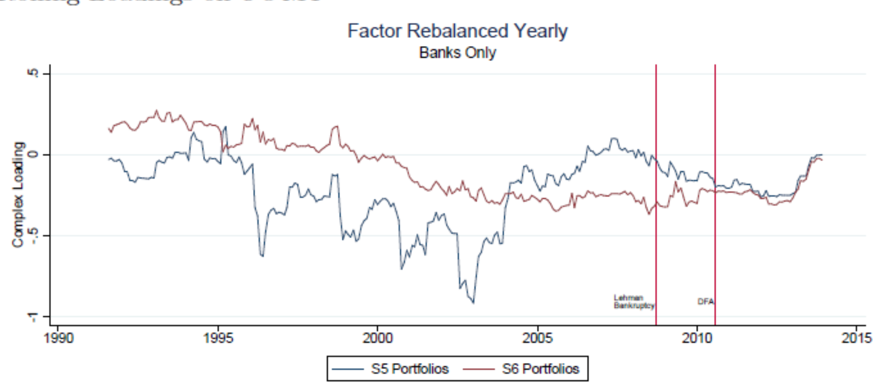
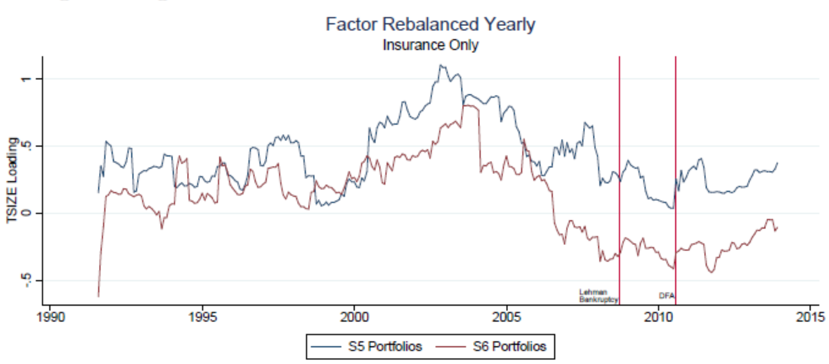


Figure 8: Loadings on Complexity, $TSIZE$ and IC from 60-month Rolling Regressions for Insurance Companies

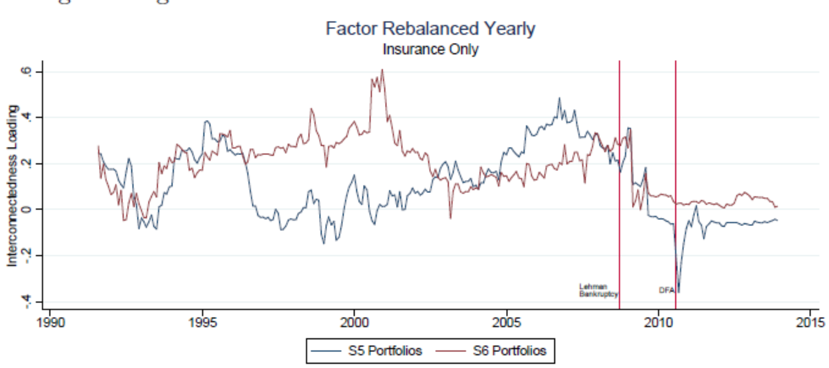
This figure shows, at each month t, the loadings on $COMP$, $TSIZE$ and IC from a time series regression, over the previous 60 months, of insurance sector returns on the SIFI factors: $TSIZE$, IC, LEV, LIQ and $COMP$. The other factors are SMB' (the Fama-French factor SMB made orthogonal to $TSIZE$), the Fama-French factors $Mktrf$ and HML , bond market factors GOV and $CORP$, and the Carhart momentum factor MOM, the bank size risk factor of Gandhi and Lustig (2014) GL. The loading is calculated for each size and book-to-market bin separately, then averaged over size bins. We present loadings for the 80%-90% bin (S5) and the 90%-100% bin (S6). The red vertical lines correspond to the Continental Bailout (May 1984), the Lehman bankruptcy (September 2008), and the DFA (July 2010). The first 60 months is the training period.

Insurance Only

Rolling Loadings on $TSIZE$



Rolling Loadings on IC



Rolling Loadings on $COMP$

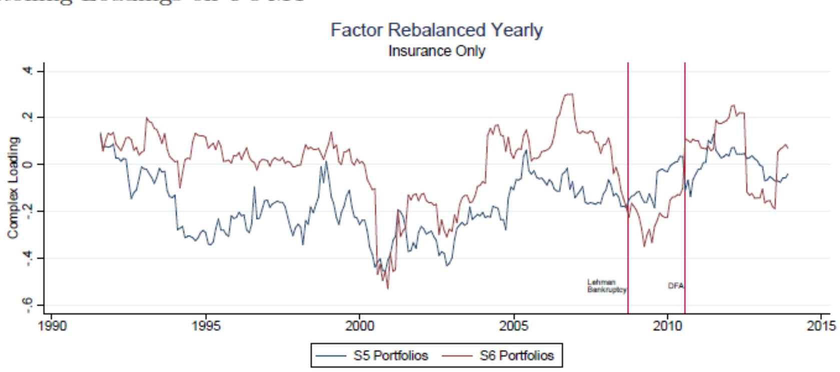
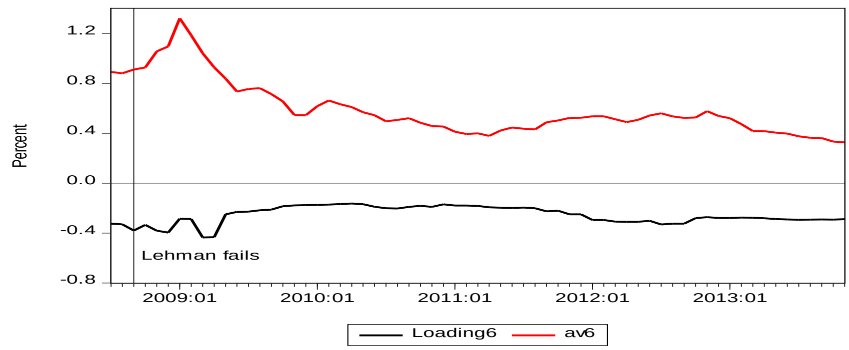


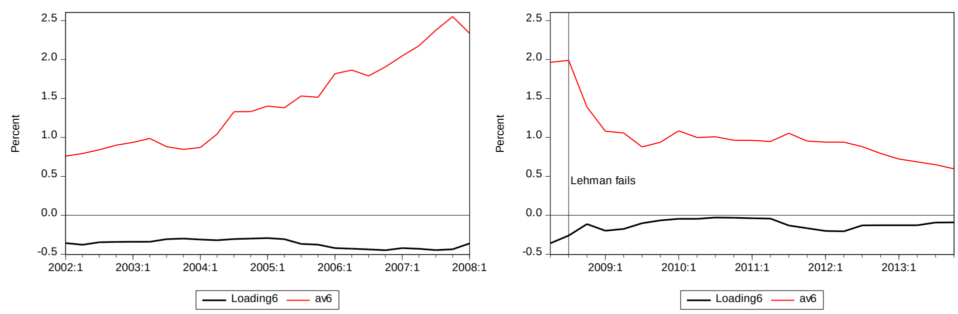
Figure 9: Firesale Risk AV and SIFI Loadings

The figure plots firesale risk AV, or spillover losses as percent of total broker-dealer capital. Panel A shows the monthly AV estimated from Triparty repo data and SIFI loadings averaged over financial firms in the largest 10% size group S6 (denoted $AV6$ and $Loading6$, respectively) with both repo and loadings data. There are no firms with repo data in the next-largest 10% size group S5. The sample is from July 2008 to December 2013. Panel B shows the quarterly AV (multiplied by 100) estimated from Bank Holding Company balance sheet data and the SIFI loadings, averaged over financial firms in S5 (denoted $AV5$ and $Loading5$, respectively) and in S6, with both repo and loadings data. The sample is from 2002 to 2013. The Lehman failure event is in September 2008 for monthly data and 2008 Q3 for quarterly data.

Panel A: AV and SIFI Loadings of Firms in Largest Size Group: Monthly Repo Data



Panel B: AV and SIFI Loadings of Firms in Largest Size Group Before and After 2008Q1: Quarterly Bank Holding Company Data



Panel C: AV and SIFI Loadings of Firms in Second Largest Size Group Before and After 2008Q1: Quarterly Bank Holding Company Data

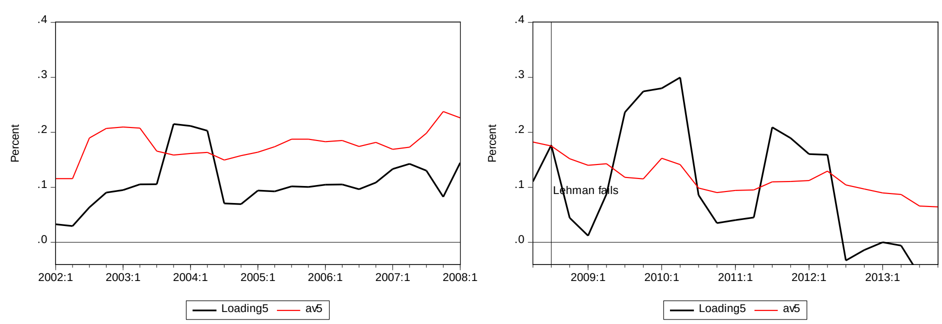
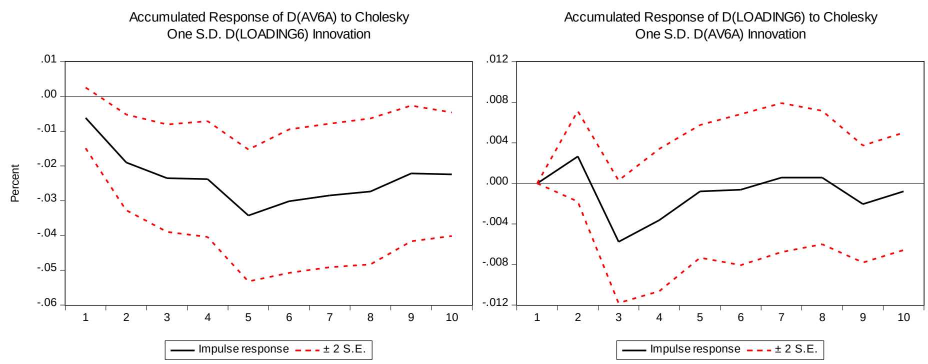


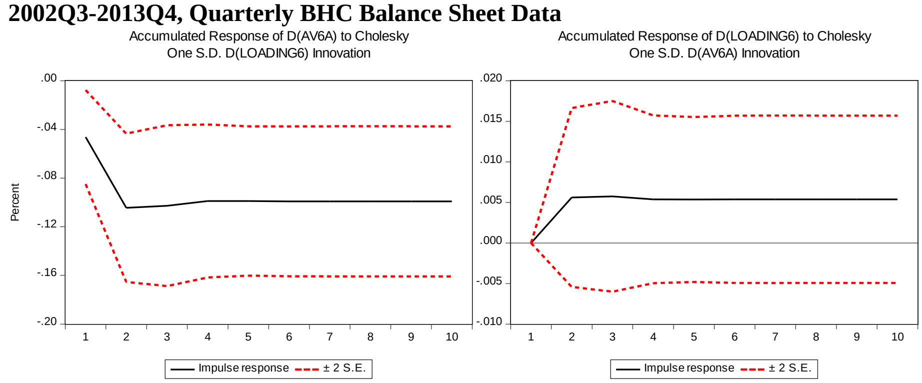
Figure 10: Impulse Responses of Firesale Spillovers AV and SIFI Loadings

The figures show impulse response functions, along with 2 standard error (S.E.) bands, estimated from a Vector Autoregression (VAR) of the change in the firesale spillover measure AV and the change in average $TSIZE$ loadings of financial firms in the largest 10% size group $S6$ (denoted $D(AV6)$ and $D(Loading6)$, respectively). Separately, the VAR is also estimated for changes in AV and $TSIZE$ loadings for financial firms in the next-to-largest 10% size group $S5$ (denoted $D(AV5)$ and $D(Loading5)$, respectively). In Panel A, AV is based on monthly triparty repo data from July 2008 to November 2013. In Panels B and C, AV is based on quarterly Bank Holding Company balance sheet data from 2002Q1 to 2013. Lagged values of average market capitalization, leverage and correlation of equity returns with the MSCI World stock index are used as exogenous variables.

Panel A: SIFI Loadings and Firesale Risk of Financial Firms in Largest Size Group: July 2008-November 2013, Monthly Repo Data



Panel B: SIFI Loadings and Firesale Risk of Financial Firms in Largest Size Group: 2002Q3-2013Q4, Quarterly BHC Balance Sheet Data



Panel C: SIFI Loadings and Firesale Risk of Financial Firms in Second Largest Size Group: 2002Q3-2013Q4, Quarterly BHC Balance Sheet Data

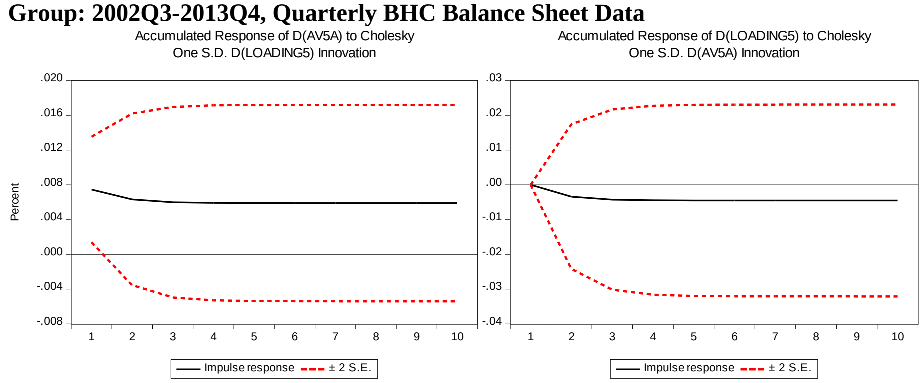
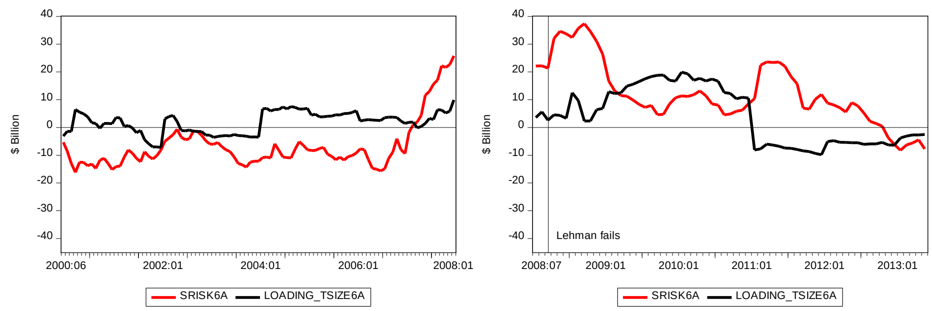


Figure 11: SRISK and SIFI Loadings

The figure shows the monthly systemic risk measure $SRISK$ (i.e. the expected capital shortfall in \$ Billion of a firm conditional on a substantial market decline) and $TSIZE$ loadings of financial firms, averaged over firms with both $SRISK$ and loadings data. $TSIZE$ loadings are multiplied by 100. The left-hand chart plots the time series till just before Lehman's failure (2000 to June 2008) and the right-hand chart shows the plot since then (July 2008 to November 2013). $SRISK$ and $TSIZE$ loadings are averaged over firms in the largest 10% size group S6 (denoted $SRISKS6$ and $Loading6$, respectively, in Panel A), and over firms in the next-largest 10% size group S5 (denoted $SRISKS5$ and $Loading5$, respectively, in Panel B). The Lehman failure event is in September 2008.

Panel A: Financial firms in Largest Size Group: Before and After July 2008



Panel B: Financial firms in Second Largest Size Group: Before and After July 2008

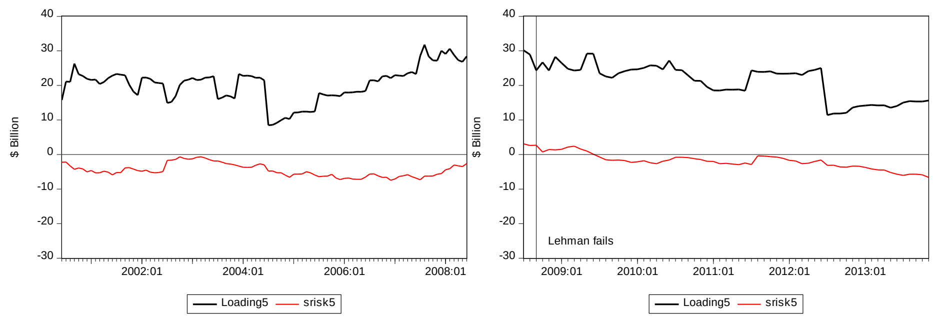
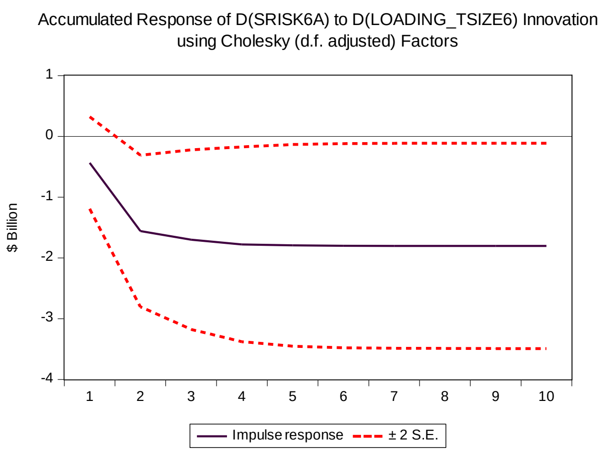
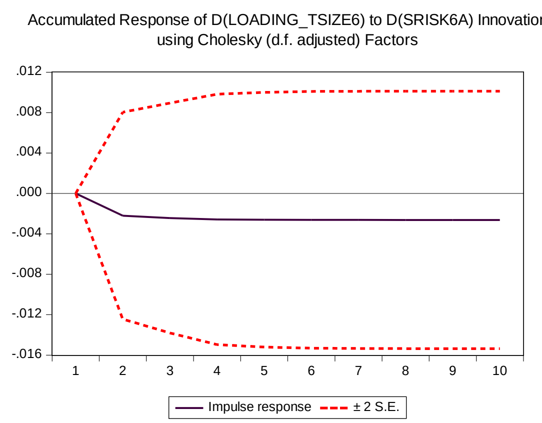


Figure 12: Impulse Responses of SRISK and SIFI Loadings

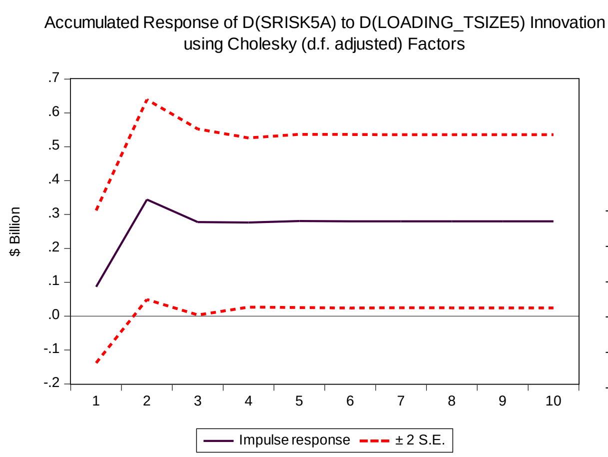
The figures show impulse response functions, along with 2 standard error (S.E.) bands, estimated from a VAR using changes in the average $SRISK$ and TSIZE loadings of financial firms in the largest 10% size group (denoted $D(SRISKS6)$ and $D(TSIZE6)$. The VAR is also estimated separately for changes in the average AV and $TSIZE$ loadings of financial firms in the next-largest 10% size group S5 (denoted $D(SRISKS5)$ and $D(TSIZE5)$). Lagged values of average market capitalization, leverage and correlation of equity returns with the MSCI World stock index are used as exogenous variables in the VAR. Panels A and B cover the period from July 2008 (just before the fall of Lehman Brothers) to November 2013 while Panels C and D cover the pre-Lehman period (June 2000 to June 2008)

Panel A: Financial firms in Largest Size Group: July 2008-November 2013





Panel B: Financial firms in Second Largest Size Group: July 2008-November 2013



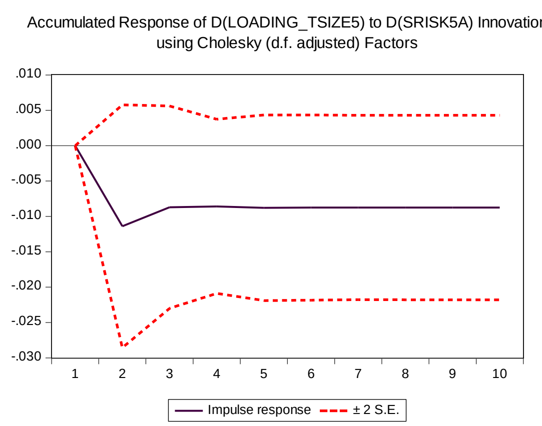


Figure 13: Predicting Firm's Systemic Risk in Crisis using Precrisis SIFI Loadings

The figure shows a scatter plot (filled red; legend FIT WITH SIFI LOADINGS) of the average actual change in the firms systemic risk during the crisis from its average pre crisis systemic risk, against the fitted change obtained from the cross-sectional regression using SIFI loadings (column 5 of Tables 12 and 13). Also shown is a scatter plot (black; legend FIT WITHOUT SIFI LOADINGS) of the average actual crisis-period change in the firms systemic risk against the fitted change obtained from the cross-sectional regression without SIFI loadings (column 3 of Tables 12 and 13). The systemic risk variables are DAV, the crisis period change in AV—the firesale risk of bank holding companies—and DSRISK, the crisis period change in SRISK—the expected capital shortage (in $Billion). The pre-crisis period is 2000 to 2006; the crisis period is August 2007 to November 2013 for DSRISK, and Q4 2007 to Q4 2013 for DAV.