Is Size Everything? *

Samuel Antill[†] Asani Sarkar [‡]

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Abstract

We examine sources of systemic risk (threshold size, complexity, and interconnectedness) with factors constructed from equity returns of large financial firms, after accounting for standard risk factors. From the factor loadings and factor returns, we estimate the implicit government subsidy for each systemic risk measure, and find that, from 1963 to 2006, only our big-versus-huge threshold size factor $TSIZE$ implies a positive implicit subsidy on average. Further, pre-2007 $TSIZE$-implied subsidies predict the Fed's liquidity facility loans and the Treasury's TARP loans during the crisis both in the time series and the cross section. $TSIZE$-implied subsidies increase around the bailout of Continental Illinois in 1984 and the Gramm-Leach-Bliley Act of 1999, as well as around changes in Fitch Support Ratings indicating higher probability of government support. Since 2007, however, the relative share of $TSIZE$-implied subsidies falls, especially after Lehman's failure, whereas complexity and interconnectedness-implied subsidies are substantial, resulting in an almost seven-fold increase in total implicit subsidies. The results, which survive a variety of robustness checks, indicate that the market's perception of the sources of systemic risk changes over time.

Keywords: Too big to fail, systemic risk, implicit subsidies, interconnectedness, complexity, financial crisis, bailout, TARP, Fed, GSIB

JEL Classification:G01, G12, G21, G28

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[†]Stanford Graduate School of Business, 655 Knight Way, Stanford, CA, 94305.

[‡]Federal Reserve Bank of New York, 33 Liberty Street, New York, NY 10045.

1 Introduction

As implied by the term "too-big-to-fail" (TBTF), size has traditionally been the key criterion for whether a firm is deemed systemic. 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, interconnectedness (IC) and organizational complexity were also considered.[1] This increased recognition of non-size risk, however, is not fully reflected in the literature. Most papers focus on specific sources of systemic risk (such as size or IC) but not on the relative importance of the different sources. The latter is important for guiding policy debates, such as whether the size threshold for SIFI designation should be increased, as was done in Senate Bill 2155.[2]

In this paper, we comprehensively account for systemic risk by constructing factors for complexity, IC, and threshold size, while also accounting for leverage and liquidity risk.[3] As traders form expectations of government support, market prices internalize non-diversifiable systemic risk. Thus, we evaluate the contribution of a factor by whether it is priced in the cross-section of equity returns and its loading is correlated with bailout probabilities and systemic risk events. Further, since the average risk-adjusted return of firms with high bailout probability is low during normal times in anticipation of shareholder bailouts in crisis (Gandhi and Lustig (2015), Gandhi, Lustig and Plazzi (2016) and Kelly, Lustig and Van Nieuwerburgh (2016)), we examine to what extent factor loadings in normal times predict government support and systemic risk in crisis. We show that the market's view of the sources of systemic risk has evolved from an exclusive focus on size prior to the crisis of 2007, to viewing complexity and interconnectedness risk as its main concerns since then.

Financial firms may benefit from size for reasons other than expected bailouts–for example,

[1] The DFA was signed into law on July 21, 2010 to, among other things, end TBTF and bailouts (`https://www.govtrack.us/congress/bills/111/hr4173/text`). Later, the Financial Stability Oversight Council (FSOC) approved using the $50 billion asset cutoff as a criterion to deem non-bank financial firms as SIFIs.

[2] The bill, enacted in 2018, increased the size threshold for prudential regulation to $250 billion (`https://www.congress.gov/bill/115th-congress/senate-bill/2155`).

[3] FSOC considers leverage and liquidity in its SIFI designation. Other considerations are: maturity mismatch, substitutability and existing regulatory scrutiny. The latter two are applied on the basis of company-specific qualitative and quantitative analysis as they are difficult to quantify (`http://www.treasury.gov/initiatives/fsoc/Documents/Nonbank%20Designations%20-%20Final%20Rule%20and%20Guidance.pdf`).

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)). Accordingly, our threshold size factor (denoted $TSIZE$) is the equity return on a portfolio that is short financial firms in the top 8 percentile by market value of equity (MVE) and long financial firms in the 84th to 92nd percentile of the MVE distribution. The 92nd percentile threshold corresponds to the DFA cutoff of $50 billion in the distribution of the BVA for 2010.[4] If the largest firms are TBTF then their expected returns should be lower, implying a positive return for $TSIZE$ on average. We find that the $TSIZE$ return is positive and varies with business cycles, implying that $TSIZE$ risk is not 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 has information beyond SMB and GL.

For the pre-crisis sample (1963-2006), we add $TSIZE$ to the 3-factor model of Fama and French (1993), plus momentum (Carhart (1997)) and bond market factors (denoted the SIFI1 model).[5] We find that $TSIZE$ is priced, and so it is a determinant of average returns. 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 $TSIZE$ (a "SIFI discount") while all other firms load positively on it (a "SIFI premium"). We call the switch from a premium for the second-largest decile of firms to a discount for the largest decile, the "threshold effect." Then, we define the implicit subsidy *Sub_size* to the largest decile firms as the difference in the average loadings of the two deciles, scaled by the average return of the $TSIZE$ factor. *Sub_size* is 6 basis points per year on average or 10 million per firm per year in 2013 dollars, most of which accrue to financial firms. As financial firms become bigger and move to the largest decile, they obtained this advantage; conversely, if they fall below the largest decile, they give up this advantage (Figure 2).

The threshold effect is not a mechanical outcome of the fact that the $TSIZE$ factor is short the largest financial firms – the same ones also in the top decile of test assets. First, the $TSIZE$ loadings switch signs when firms switch size deciles in consecutive 5-year periods, even though the $TSIZE$ factor is only rebalanced annually. Second, results are similar when we exclude from the largest quintile of test assets those financial firm months shorted in the

[4] 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).

[5] Our results are robust to using the 5-factor model of Fama and French (2015). See section 7.2.

$TSIZE$ factor. Also, the results are robust to a higher asset cutoff, up to $300 billion in consolidated BVA for 2010 (or the top 3% of financial firms by MVE), in constructing $TSIZE$. Finally, the threshold effects are robust to using BVE to determine the size threshold for $TSIZE$, and the BVE-based $TSIZE$ factor is priced in the cross-section of returns.

Next, for the top 16% of financial firms, we construct factors for complexity $COMP$ and interconnectedness IC. Complexity is measured by the number of subsidiaries of BHCs (Cetorelli, Jacobides and Stern (2017)), using data from 1986. Global banks operating in multiple legal jurisdictions with many subsidiaries are harder to resolve when they fail (Bright, Glasserman, Gregg and Hamandi (2016)), increasing the likelihood of government support. Alternatively, complex banks may be less sensitive to funding shocks, reducing their systemic risk premium (Cetorelli and Goldberg (2016)). IC is based on the principal components measure of Billio, Getmansky, Lo and Pelizzon (2012). The factors are formed from long-short portfolios after projecting the measures onto the returns space (Section 3).

If more complex and interconnected firms are more likely to be bailed out, then the factor returns should be positive on average. We find that prior to 2007, average returns of $COMP$ and IC are negative and, when we add these factors and GL to the SIFI1 model, the test assets generally load insignificantly on them, they do not display a threshold effect and are not priced in the cross-section. Thus, $TSIZE$ alone explains returns in the pre-crisis period.

We examine whether Sub_size is sensitive to systemic risk events using 60-month rolling regressions. $TSIZE$-implied subsidies increase around the bailout of Continental Illinois in May 1984 (that gave rise to the term "TBTF"), the Gramm-Leach-Bliley Act of 1999 (that facilitated bank consolidation) and in September and October of 2008 (the first two months of Lehman's failure; see Figure 3). However, it decreases after October 2008. In contrast, the $COMP$ and IC-implied subsidies increase consistently during and following Lehman's failure. Overall, total implicit subsidies increase 7-fold since the crisis, and the share of $TSIZE$ in the total fall from 100% before 2007 (when $TSIZE$ is the only factor with positive returns on average) to less than 15% since then, with $COMP$ and IC-implied subsidies making up most of the total. Thus, market perception of the sources of systemic risk changes, especially following Lehman's failure, whether due to changes in fundamentals or beliefs (Gennaioli and Shleifer (2018)).

$TSIZE$-implied subsidies for the largest financial firms reflect expectations of government support during crises. We find that over 80% of banks in the short portfolio of the $TSIZE$ factor have the highest probability of government support, as indicated by Fitch's Support

Rating Floor, as compared to less than 20% of banks in the long $TSIZE$ portfolio. Further, regression results show that $TSIZE$-implied subsidies increase significantly around Fitch Support Rating changes that increase the probability of government support.

Pre-crisis $TSIZE$ loadings are predictive of government assistance (i.e. the Fed's loans to critical institutions and via liquidity facilities and the Treasury's TARP loans) during the crisis in the aggregate (Figure 8) and at the firm level (Figure 9), even after controlling for firm size, leverage and market correlation. In addition, the loadings are informative of 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)). The predictive power of $TSIZE$ is lost, however, if the factor is constructed using book values. This is consistent with Acharya, Engle and Pierret (2014) 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.

Since 2007, the complexity factor accounts for more than half of total implicit SIFI subsidies. We examine whether complexity risk mostly resides in the very largest banks, designated as Globally Systemically Important Banks (GSIBs) since 2011. We find that the number of subsidiaries of GSIBs increases sharply from the early 2000s, even relative to other large banks. For banks, we find that, since Lehman's failure, most implicit subsidies are expected to accrue to GSIBs rather than large non-GSIB banks. This result is consistent with the aim of increasing the size threshold for prudential regulation, as in Senate Bill 2155.

The main contribution of this paper is using equity prices to identify the relative importance of size and non-size risk factors in determining the systemic risk of a firm, based on whether the factor is priced, and whether its loadings predict government support and systemic risk. We show meaningful time-variation in the market's evaluation of the sources of systemic risk. While the use of factor pricing to study TBTF is not new, our $TSIZE$, IC and $COMP$ factors are novel. Also new is the direct connection between factor loadings and government support and the evidence on predictability.

An important result is the "threshold" nature of the exposure to SIFI risk, indicating a double misallocation of resources from lower cost of capital for SIFI firms and higher cost of capital for non-SIFI firms. This implies that there exists a broad-based effect of SIFI risk that affects all firms due to the redistribution and repricing of risk in the market. This differs from the prior emphasis on redistribution from households to large financial firms.

Our factor loadings may be used as practical tools for monitoring and predicting systemic risk as they are easily constructed from public data using standard asset pricing methods.

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 discusses 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 government support and systemic risk in crisis. Section 7 discusses GSIBs and additional results. Section 8 concludes. Unreported results discussed in the paper are available in the internet appendix.[6]

2 Literature

In this section, we discuss the literature that examines the perceived benefits of government guarantees to the largest firms. Then, we review the IC literature that focuses on indirect connections between firms from exposure to common factors or asset prices (as compared to direct effects via contractual obligations). Finally, we review the effects of organizational complexity on systemic risk. A literature review of intermediary asset pricing is provided in He and Krishnamurthy (2018) and of liquidity risk in Amihud, Mendelson and Pedersen (2012). Our analysis differs from the papers discussed below in adopting a factor pricing approach that isolates components of expected returns from threshold size, complexity, IC, leverage, and liquidity, after controlling for standard risk factors.

[6] https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr864Appendix.pdf

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 its effects are orthogonal to those of GL.[7] Different from Gandhi and Lustig (2015), we directly link $TSIZE$ loadings to a measure of government support (i.e. Fitch Support Ratings), show that $TSIZE$ is priced in the cross-section of returns and that its loadings are predictive of systemic risk and government support. Gandhi et al. (2016) further examine TBTF risk in 31 countries.

TBTF 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. Large firms are found to have funding cost advantages relative to small firms, although the magnitude is reduced when comparing the largest firms to other large 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. In contrast, 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.

Are large firm returns less sensitive to risk than returns of smaller 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 papers 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 and systematic components of risk.

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

[7] 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.

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 firms 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.

Turning to IC risk, Allen, Babus and Carletti (2012), Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) and Greenwood, Landier and Thesmar (2015) theoretically study the vulnerability of financial networks. Empirically, firesale spillovers are found from connectedness via bank balance sheets (Duarte and Eisenbach (2015)), debt flows of mutual funds (Falato, Hortacsu, Li and Shin (2016)), equity returns (Billio et al. (2012)) and equity volatility (Diebold and Yilmaz (2014)). IC measures have been based on network topology, variance decomposition (Diebold and Yilmaz (2014)) and Granger Causality (Billio et al. (2012)). Our IC measure is based on the principal components of equity returns, as in Billio et al. (2012), but we construct an IC factor rather than use the measure directly. This approach has two benefits. Typically, IC measures are either bivariate which fail to fully account for network effects (Basu, Das, Michailidis and Purnanandam (2017)) or are VAR-based estimates of small panels (due to the dimensionality problem). By comparison, we estimate the exposure to an IC common risk for all US-listed firms and for a long time-series. Second, if the market is efficient, then price-based measures may underestimate spillovers (Falato et al. (2016)). By comparison, market efficiency increases the accuracy of our estimations.

Complexity may arise from business activities, geographical diversification and organizational structure. Many papers focus on organizational complexity, using the number of legal subsidiaries as a measure, and find it imperfectly correlated with size (Avraham, Selvaggi and Vickery (2012), Cetorelli and Goldberg (2014) and Laeven, Ratnovski and Tong (2014)).[8] Carmassi and Herring (2016) show that this measure is correlated with the complexity factors considered by the Basel Committee.[9] Nevertheless, the demand for subsidiaries likely reflects diverse factors, such as set up costs, the business model, and the tax, regulatory and reporting environment (Carmassi and Herring (2016)). By mapping the measure to returns of the long-short portfolio of the largest financial firms, we extract its systemic component.

[8] One exception is Lumsdaine, Rockmore, Foti, Leibon and Farmer (2015) who use network tree analysis.

[9] The Basel factors (i.e. the amount of over-the-counter derivatives, the quantity of trading and available for sale securities and the amount of Level 3 assets) are typically unavailable from standard data sources.

3 Construction of Factors for SIFI Risk

Our SIFI factors are those corresponding to risks from size, IC and complexity. In addition, we account for leverage and liquidity risk. This section describes how we construct these factors. The internet appendix A discusses the construction of GL and SMB' (a version of SMB that omits firms already in the size factor $TSIZE$).

To determine the asset size threshold for constructing $TSIZE$, 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.[10] In keeping with the asset pricing literature, the largest financial firms are defined as those in the top 8% (denoted L8) by MVE each year. Section 4.4 describes how different cutoff choices (e.g. different MVE cutoffs and using book values) affect our results.

For constructing $TSIZE$, we consider only the top 16% of financial firms by MVE (i.e. firms in L8 and the next largest 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.[11] For firms in this sample listed on the NYSE, we sort by MVE in June of year t, and then by BM calculated as BVE for the fiscal year ending in year $t-1$ divided by MVE for end-December of year $t-1$.[12] 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.

We construct factors for interconnectedness, IC and complexity, $COMP$ in three steps.

[10] Financial firms are those with NAICS codes beginning in 52 or SIC codes beginning in 6.

[11] 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 industry categories.

[12] We follow Fama and French (1993) in forming portfolios at the PERMNO level. To the extent that firms have multiple common stocks, this should bias against our results. This concern is also ameliorated by the robustness of our results to the use of BVE, which is measured at the PERMCO level.

First, we estimate measures of IC and complexity for the largest 16% of financial firms each year (i.e. the same firms constituting the $TSIZE$ factor), as described below. Next, we sort firms into five groups based on the measure. Finally, the factors are defined as the returns on the lowest quintile (by the respective measure) minus returns on the highest quintile. If firms with greater IC and complexity are more likely to be bailed out, and so have lower expected returns, then the factors should have positive returns on average.

Our complexity measure, $COMP$, is the number of subsidiaries of BHCs.[13] IC is measured using the principal components (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.

Data for the leverage factor LEV is from He, Kelly and Manela (2017), who construct it based on innovations in capital ratios of primary dealers, defined as MVE over (MVE+BVD).[14]

The illiquidity factor LIQ is defined as the highest quintile of firm returns minus the lowest quintile by illiquidity, since firms with more illiquidity risk are expected to have higher returns. Illiquidity 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 to complement the leverage factor which is a funding liquidity measure.

Data for the book-to-market (HML), Market minus risk free rate ($Mktrf$) and momentum (MOM) factors and the risk free rate are from Kenneth French's website.[15] To orthogonalize threshold size effects from SMB, we create a SMB' factor that is orthogonal to $TSIZE$ by construction. The bond market factors $CORP$ and GOV are corporate and government

[13]We thank Nicola Cetorelli for the data.

[14]The source is `http://apps.olin.wustl.edu/faculty/manela/hkm/intermediarycapitalrisk/He_Kelly_Manela_Factors.zip`. We thank the authors for the data.

[15]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.

bond returns, respectively, obtained from the Global Financial Database. We subtract the risk free rate from these bond returns to create an excess return.

Finally, we construct 30 test 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 benefit from SIFI perceptions (see internet appendix A for how we construct the sectoral portfolios and additional details).

4 SIFI Factor Pricing

This section presents results on the pricing of SIFI factors. Section 4.1 shows estimates of $TSIZE$ factor loadings and implicit subsidies from time-series regressions. Section 4.2 considers time-series estimates of implicit subsidies from $COMP$ and IC factor loadings. Section 4.3 reports on factor pricing using Fama and MacBeth (1973) regressions. Section 4.4 examines a possible mechanical effect from having the same financial firms in the $TSIZE$ factor and the largest size quintile of the test portfolios.

4.1 Loadings on the $TSIZE$ Factor

Figure 1 shows that the cumulated return of the $TSIZE$ factor returns (blue line) vary with business cycles, suggesting that $TSIZE$ risk is not fully diversifiable.[16] In the pre-crisis period (Panel A), $TSIZE$ has consistently positive returns. However, in the crisis (Panel B), $TSIZE$ returns turn negative as bailouts actually occur before becoming positive again after June 2009. Our baseline SIFI1 model is:

$$R_t^i - R_t^f = \alpha + \sum_{j=1}^{6} \beta_j X_{jt} + \delta_1 TSIZE_t + \epsilon_t \tag{2}$$

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 β_j are loadings on the standard risk factors:

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

[16]The average annualized $TSIZE$ returns from 1963 to 2013 is about 2.8% (0.3%) per month in NBER recessions (expansions). As there more months of expansions than recessions, the cumulated return over all recessions (expansions) is 141% (233%) per annum during this same period, and the difference is significant.

We estimate these regressions by OLS for each of the 30 size and BM sorted test portfolios from July 1963 to 2006. 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.[17]

Results from estimating δ_1 in (2) are in Panel A of Table 1. Each row shows size bins in ascending order reading from top to bottom, while each column shows a higher BM bin reading from left to right. Excepting for the largest size decile 6 ($S6$ from now on), the loadings are positive with few exceptions and highly statistically significant, indicating that returns of firms below $S6$ contain additional risk-premia due to $TSIZE$. For $S6$ portfolios, we find that the coefficients are mostly negative, and statistically significant for 3 of 5 portfolios. In other words, the largest firms obtained a $TSIZE$ discount before 2007. Strikingly, the sign of the $TSIZE$ loadings abruptly changes from positive to negative when going from size decile 5 ($S5$ from now on) to $S6$; for example, for BM bin three, the estimates change from 0.10 to -0.10 and both are significant. Further, $TSIZE$ loadings do not vary with size or BM for size bins below $S6$, clearly bringing out the "threshold" nature of $TSIZE$ risk.

The results imply that the implicit subsidy may be defined as the difference in average SIFI factor loadings of portfolios in $S5$ (denoted $Loading5$) and $S6$ (denoted $Loading6$):

$$\begin{aligned} Sub\_size_{factor} =& 100 * AvgReturn(Factor) * (Loading5 - Loading6), \\ & given\, AvgReturn(Factor) > 0 \end{aligned} \tag{4}$$

We condition on positive average returns because, otherwise, estimated subsidies could be positive even with $Loading6 > Loading5$ (i.e., the largest firms losing from TBTF risk). We only compare firms in $S5$ and $S6$ since smaller firm returns are subject to operational, funding and other risks that would be mismeasured as SIFI premia.

Table 2 reports $TSIZE$ premia and discounts for 1963 to 2006. In Panel A, the $TSIZE$ discount or premium is the $TSIZE$ loading (with non-significant loadings estimates assumed to be 0) times 45 basis points, the average annual return of the $TSIZE$ factor from 1963 to 2006. We find that returns for all portfolios except those in $S6$ have a $TSIZE$ premium of up to 6 basis points per annum with little variation between portfolios. In contrast, 3 of 5 portfolios in $S6$ receive a $TSIZE$ discount of up to 5 basis points per annum. Averaging across BM bins, the $TSIZE$ premium (discount) is 4 (2) basis points per annum for firms in $S5$ ($S6$). Thus, Sub_size is 6 basis points per annum. Panel B of Table 2 shows the per firm value in 2013 dollars of the $TSIZE$ premium or discount, given by multiplying Sub_size by

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

the average market capitalization of firms in each portfolio. Averaging across BM bins, the $TSIZE$ premium (discount) is 2.66 (7.24) million per year per firm in 2013 dollars for firms in $S5$ ($S6$), and so the implicit subsidy is about 10 million per year per firm in 2013 dollars.

Similar to large financial firms, large non-finance firms may also have advantages from funding and economies of scope (Antill, Hou and Sarkar (2014)).[18] We construct non-financial and financial test portfolios and find that financial firms in $S6$ mostly load negatively and significantly on $TSIZE$ (Panel A of Table 3). Of non-financial firms in $S6$, 4 of 5 BM portfolios also load negatively but only one portfolio is significant and the magnitudes are smaller (Panel B of Table 3).[19] Sub_size is 30 basis points per year for financial firms versus 3 basis points for nonfinancials. Thus, $TSIZE$ subsidies accrue mostly to the largest financial firms.

4.2 Loadings on $COMP$ and IC Factors

Figure 1 shows the cumulated returns of IC and LIQ factors since 1970 and $COMP$ since 1986. LEV is not shown as it is not in returns space. In the pre-crisis period, all factors have zero or negative cumulated returns, except $TSIZE$. In contrast, $COMP$ and IC have consistently positive returns in the crisis period, unlike $TSIZE$ returns, suggesting a shift in market perceptions of sources a systemic risk, as we show later in this paper. Cumulated returns of $COMP$ and IC are higher in recessions, indicating business cycle variation. We estimate the SIFI4 model by adding IC, LEV and LIQ to the SIFI1 model. To allow for bank size effects separate from $TSIZE$, we add the GL factor (Gandhi and Lustig (2015)):

$$R_t^i - R_t^f = \alpha + \sum_{j=1}^{6} \beta_j X_{jt} + \delta_1 TSIZE_t + \delta_2 IC_t + \delta_3 LEV_t + \delta_4 LIQ_t + \delta_5 GL_t + \epsilon_t \quad (5)$$

We estimate the regression from 1970 (when data for all regressors in (5) first become available) to 2006. The coefficients on $TSIZE$ are reported in Panel B of Table 1. Comparing with Panel A of the table, we find that the magnitude and significance of $TSIZE$ loadings are little changed. Thus, the $TSIZE$ effect remains even after including non-size SIFI and GL factors. Panels C-E of Table 1 show that non-size SIFI factor loadings are generally insignificant and they do not exhibit a size threshold effect.

[18] Non-financial firms are defined as those considered as non-finance in both SIC and NAICS codes.

[19] Smaller non-financial firms generally load positively on $TSIZE$, similar to Demirer, Gokcen and Yilmaz (2018) who find that small non-financial firm returns covary negatively with their IC measure but have higher expected returns. This result underscores why we omit firms below $S5$ when measuring implicit subsidies.

We add $COMP$ to equation 5 and report results in Panel F of Table 1. No portfolio has significant loadings and there is no threshold effect. As average returns of $COMP$ and IC are negative pre-crisis, their factor loadings do not imply any implicit subsidies to $S6$ firms.[20]

4.3 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) and estimate the following cross-sectional regression for each month t:

$$R_{it} = \alpha_t + \sum_{j=1}^{n} \gamma_{jt}\beta_{jit} + \sum_{j=1}^{m} \mu_{jt}\delta_{jit} + \epsilon_{it} \tag{6}$$

where i indexes portfolios and j indexes factors, β is the loading on the Fama-French, momentum and bond market factors and δ is the loading on the SIFI and GL factors. β and δ are estimated from first-stage 60-month rolling window regressions.

Table 4 presents time-series averages of the estimates of the price of SIFI risk μ_{jt}. We estimate the first and second stage by OLS, but correct the t-statistic following Shanken (1992) to address the errors-in-variables problem in the second stage. The first 3 rows show results from the SIFI1 model. $TSIZE$ has 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 (2.4). Next, we pair $TSIZE$ with a non-size SIFI factor and also add GL. $TSIZE$ remains significant with a Shanken T-statistic exceeding 2 in all cases except when paired with $COMP$ (likely due to the shorter sample starting 1986), whereas the non-size SIFI factors are all insignificant. The results are robust to estimating all non-$COMP$ SIFI factors simultaneously (Internet appendix B).[21] We conclude that $TSIZE$ is priced and thus a determinant of the cross-section of returns, except in the short time-series.

Does $TSIZE$ risk originate only from financial firms? We construct $TSIZE^{NF}$ identically to $TSIZE$ but based on non-financial firm returns and find that $TSIZE^{NF}$ is not significantly

[20] Results are similar when the test assets are split into financial and non-financial sectors (Internet Appendix B). LEV loadings are positive and significant for the largest 40% of financial firms, consistent with a positive exposure to leverage risk for these firms. However, they do not exhibit a threshold effect.

[21] These results are also robust to different imputation methods for filling in endogenously missing observations in some portfolios. In particular, the S6BM5 portfolio (i.e. the sixth size decile 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.

priced in the cross-section of returns (last 3 rows of Table 4). Thus, the largest non-financial firms are not sources of common risk in the economy.

4.4 Firm Transitions Between Size Deciles and Alternative Size Thresholds

The threshold nature of $TSIZE$ loadings for financial firms might be a mechanical effect as the $TSIZE$ factor is based on a long-short portfolio of the largest 16% of financial firms that are also included in the top quintile of test assets. However, firms smaller than those in $S5$ load positively on $TSIZE$, even though these firms are not included in the long portfolio. Second, the IC, $COMP$ and LIQ factors are also constructed from the largest 16% of financial firms and these loadings do not exhibit the threshold pattern. Nevertheless, we further address this issue by examining firm transitions between size deciles, by removing from $S6$ the firm-months in the short portfolio, and by changing the size cut-off to vary the mix of long-short $TSIZE$ portfolio firms in $S6$.

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 those 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 $S6$ (60% of probability mass to left of zero), compared to financial firms that remain in $S5$ (only 2% 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 $S6$ (13% 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. These results show that the sign of loadings change with firm transitions consistent with the threshold effect, even though the $TSIZE$ factor is rebalanced annually while the test assets are rebalanced every 5 years. For non-finance firms, the distributions are bunched around zero, consistent with the weak threshold effects for non-finance firms.

Next, we reconstitute the $S6$ portfolios to make them orthogonal to the short portfolio $L8$. Specifically, we exclude $9,000$ financial firm months from $S6$, about 66% of the total, that were also in $L8$ and recalculate the value-weighted returns in each BM bin of $S6$. $TSIZE$

loadings for the new $S6$ portfolios are shown in Table 5. Loadings for firms in $S6$ continue to be negative for 4 of 5 $S6$ portfolios, although with reduced significance. For the SIFI1 (Panel A) and the SIFI4 specifications (Panel B), 1 of 5 BM portfolios in $S6$ is significant. For the SIFI4+$COMP$ specification (Panel C), 3 of 5 BM portfolios in $S6$ are significant. These results provide further evidence against a mechanical effect.

Our results are similar when we use higher MVE cutoffs for the long-short portfolio (Internet appendix B), up to a cutoff of $300 billion in 2010 assets (comprising the top 3 % of financial firms). Since most financial 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.[22]

The DFA size threshold and the $SIFI$ designation are based on book values. We construct $TSIZE^{BVE}$ analogous to $TSIZE$ by sorting on BVE and BM, with the same size cutoffs. We find that the majority of portfolios load significantly on $TSIZE^{BVE}$ and the threshold effect is also present (Internet appendix B). In the cross-section, $TSIZE^{BVE}$ is priced when paired with another non-size factor such as IC (Internet appendix B).

We conclude that, prior to 2007, exposure to threshold size risk resulted in lower return premia for the largest decile of financial firms and higher return premia for smaller firms. These results are not due to a mechanical effect, and hold for a range of size thresholds and for the book value version of $TSIZE$. Non-size SIFI factors do not exhibit a threshold size effect, suggesting that before the crisis, markets did not view complexity and interconnectedness risk as systemic (or, alternatively, did not discriminate between the various sources of risk).

5 SIFI Factor Loadings and Systemic Risk

In this section, we extend our sample to 2013 and relate $TSIZE$ loadings directly to the probability of government support. In section 5.1, we examine changes in implicit subsidies, as implied by SIFI factor loadings, around systemic events such as the bailout of Continental Illinois and Lehman's failure. In section 5.2, we assess how the implicit subsidies change with the probability of government support, as indicated by changes in Fitch Support Ratings.

[22] With lower cutoffs, there is evidence of positive implicit subsidies up to the top 10% of financial firms in the short portfolio. Lower cutoffs allow more non-SIFI firms to be categorized as SIFI, diluting the evidence.

5.1 SIFI Loadings Around Systemic Events

We examine changes in the loadings on the SIFI factors due to four events that potentially changed the perception of systemic risk: the bailout of Continental Illinois, often cited as the start of TBTF perceptions, the Gramm-Leach-Bliley (GLB) Act that facilitated consolidation of financial firms, the failure of Lehman Brothers and the passage of the DFA. The bailout of Continental and the GLB Act are expected to have increased the implicit SIFI subsidies. As Lehman was allowed to fail, this event may have changed the implicit SIFI subsidies depending on its effect on the perception of future bailouts. The DFA instituted an asset threshold above which firms face enhanced regulation, affecting the net benefits of remaining above or below the DFA threshold and thereby the implicit SIFI subsidies.[23]

We estimate 60-month rolling regressions using the SIFI4 model to obtain monthly loadings for the 30 BM x Size portfolios and then average over size deciles 5 and 6 to obtain $Loading5$ and $Loading6$. We apply equation 4 to obtain the implicit subsidies Sub_size. Figure 3 plots Sub_size for the $SIFI$ factors. For the pre-crisis period (Panel A), only $TSIZE$ had positive average returns (LHS chart). The $TSIZE$-implied subsidy increases following the Continental bailout of May 1984, and peaks after the GLB Act is enacted in November 1999, as hypothesized. IC and $COMP$-implied subsidies are intermittently positive (RHS chart in Panel A) but this is a mechanical effect of negative factor returns and negative threshold effects. For 2007-2013 (Panel B), all factors have positive average returns. $TSIZE$-implied subsidies jump in October 2008, but then fall through June 2009 (LHS chart). $COMP$ and IC-implied subsidies turn positive in April 2007 and October 2008, respectively, and in contrast to $TSIZE$-implied subsidies, continue to increase after October 2008. Thus, the plots show time-variation in the market's perception of the sources of systemic risk.[24]

[23]Some firms wanted to grow large enough to offset the regulatory costs while other firms petitioned regulators to seek exemption from SIFI status. After CIT Group Inc. agreed to buy OneWest Bank NA's parent company, its assets increased to \$67 billion, above the DFA threshold of \$50 billion. CIT Chief Executive John Thain said in an interview: "If we had grown to just \$52 billion we would be in the worst spot" (*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 labeled systemically important," Robert Pozen, *Financial Times* March 27, 2016). Metlife legally contested its SIFI status, which the court rescinded on March 30, 2016.

[24]LEV subsidies, defined as $Loading5$-$Loading6$ without scaling (since it is not in return space) is positive on average before the crisis, and increases after the Continental bailout. LIQ has negative average returns both pre- and post-crisis. See Internet appendix C.

When average factor returns are positive ($TSIZE$ for the full sample, IC and $COMP$ for the crisis sample), Table 6 reports results from a regression of the change in *Sub_size* on dummy variables that equal 1 as follows: between July 1983 and June 1985 when *Continental*-related events occurred (Swary (1986)); between November 1999 and August 2001 when *GLB Act* legislations were enacted[25]; from August 2007 to August 2008 for *Crisis*; from September to October 2008 for *Lehman*; between November 2008 to June 2009 for $Post-Lehman$; and, for $DoddFrank$, from June 2009 (when it was proposed) to July 2010 (when it was enacted).[26] We control for a broad range of financial variables with the National Financial Conditions Index $NFCI$.[27] In the pre-crisis period, the $TSIZE$ subsidy increases significantly around the Continental bailout and enactment of the GLB Act. All implicit subsidies show significant increases in the month of and after Lehman's failure but, in the post-Lehman period, $TSIZE$ subsidies decrease while IC and $COMP$ subsidies increase (but insignificantly for $COMP$). Around the passage of DFA, $TSIZE$ subsidies increase while IC and $COMP$ subsidies decrease but the changes are not significant at the 5% level.

We summarize the share of each SIFI factor in overall systemic risk in Table 7 by pre-crisis (1963-2006) and crisis (2007-2013) periods, conditional on the factor having a positive average return in the period. $TSIZE$ subsidies vary between 7 and 10 bp in 1963-1979, 1980-1989, 1990-1999 and 2000-2006. While total implicit subsidies grow from 25 bp in 2000-2006 to more than 170 bp since, the share of $TSIZE$ subsidies in the total fall to less than 15% while that of IC and $COMP$ subsidies are around 30% and 57%, respectively.

Since risky firms may have disproportionately left the largest size decile in the crisis, we repeated the analysis with 5-year factor rebalancing, thereby keeping the composition of firms fixed from 2005 to 2010, and found similar results.[28] Hence, prior to the crisis, either size risk was the only source of systemic risk or the market neglected some types of systemic risk (Gennaioli and Shleifer (2018)). However, after Lehman failed, equity prices indicate substantial $COMP$ and IC risk, while size risk becomes *relatively* less prominent.

[25] See `https://en.wikipedia.org/wiki/Gramm%E2%80%93Leach%E2%80%93Bliley_Act`

[26] See `https://en.wikipedia.org/wiki/Dodd%E2%80%93Frank_Wall_Street_Reform_and_Consumer_Protection_Act#Origins_and_proposal`

[27] Higher (lower) values of NFCI indicate tighter (looser) than average conditions. The data is from `https://fred.stlouisfed.org/series/NFCI`.

[28] See Internet Appendix C. With yearly rebalancing, transition rates of firms in and out of $L8$ and $NL8$ were high prior to 1980, occurred at a steady rate since, and then surged around Lehman's failure. With 5-year rebalancing, the time-variation in transition rates is reduced, especially around the Lehman event. Shares of financial firms in the test portfolios may also shift in the crisis, but we do not find this to be the case before and after the Continental and Lehman events.

5.2 SIFI Loadings 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 smaller 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).[29] 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.

We include 14 publicly traded US banks (having SIC codes starting with 60) from the SRF data that are a subset of firms in the $TSIZE$ factor.[30] 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.[31] We have 163 ratings observations in our sample, starting from March 16th, 2007.

We find that of banks with SRFs of at least A- at some time, 84% are in $L8$, the largest 8 percentile of financial firms, and just 19% in $NL8$, the next largest 8 percentile. This difference is statistically significant and is not driven by different shares of banks in the groups (which are 25% for $L8$ and 24% for $NL8$; see Internet appendix C). Moreover, being in $L8$ is a strong predictor of high support ratings, even after controlling for market capitalization (Internet appendix C). Thus, the largest banks have a substantially higher probability of government support, even relative to other large banks.

Do changes in $TSIZE$ loadings correlate with the probability of government support? We consider changes in $TSIZE$ loadings from 6 months before to 6 months from the month that firms receive an A- rating from Fitch. For banks that ever received a Fitch SRF of at least A-, we estimate $TSIZE$ loadings for each firm using 60-month rolling regressions. We find in Figure 4 that loadings on average become more negative from about 3 months prior to the event month (denoted as 0) and continue to decline for 4 months afterwards before partially

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

[30]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.

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

reverting. To show these results more formally, we estimate the following panel regression:

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

where $\Delta TSIZE$ is the change in $TSIZE$ loadings, β_i is the bank fixed effect, and $t\epsilon[a,b]$ is a dummy variable that equals 1 from a months to b months relative to the event month. In some specifications, we use $[t \geq 0]$ which equals 1 for ten months after the event. If $TSIZE$ subsidies increase with greater expectation of government support, then $TSIZE$ loadings should decrease around the rating change (i.e. the estimated γ_i <0).

Table 8 shows results from estimating (7). We find that, after controlling for bank fixed effects, $TSIZE$ loadings decreased from the event month to 10 months after, as indicated by the negative and significant γ_1 and γ_2. The estimated decline in $TSIZE$ loadings implies an additional implicit subsidy of about 27 basis points per bank on an annualized basis, consistent with an increase in bailout expectations following the Fitch ratings changes.[32] We also estimate equation (7) after including book-to-market and size data, and obtain a similar result (Internet appendix C).[33] We conclude that implicit $TSIZE$ subsidies to the largest banks increase with the probability of government support.

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

While changes in SIFI loadings occur around systemic events, do pre-event changes in subsidies implied by these loadings predict subsequent changes in systemic risk, as follows from the time varying financial disaster risk model of Gandhi and Lustig (2015) and Gandhi et al (2016)?[34] We examine this issue in two ways. First, are the loadings informative of systematic risk measures such as $SRISK$ that predict government support (Brownlees and Engle (2012))? Second, do pre-crisis loadings predict government assistance in the crisis (e.g. the

[32] We multiply the estimated coefficient by 12 and by the $TSIZE$ yearly return to arrive at this number.

[33] Regarding non-$TSIZE$ factors, IC loadings are lower prior to the event month with weak significance and insignificant following the event month (Internet appendix C). $COMP$ loadings, by comparison, increases following the event (Internet appendix C).

[34] Gandhi et al (2016), proposition 2, 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.

Fed's liquidity facilities loans and the Treasury's Tarp loans)? In section 6.1, we describe the systemic risk measures. In section 6.2, we examine the predictive power of $TSIZE$ loadings in the time-series. In section 6.3, we investigate whether, at the firm level, pre-crisis $TSIZE$ loadings predict systemic risk and government assistance in the crisis. In section 6.4, we explore the predictability of non-$TSIZE$ factors.

6.1 Measures of Systemic Risk

We use two systemic risk measures that utilize diverse data sources (equity prices, repo haircuts, and bank balance sheets). Our first measure is AV that captures fire-sale spillover to financial firms (Duarte and Eisenbach (2015)).[35] Extending the "vulnerable banks" framework of Greenwood et al. (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. Their measure AV is the sum of all such second-round spillover losses as a share of the total broker-dealer capital in the system.[36] Empirically, Duarte and Eisenbach (2015) use quarterly regulatory balance sheets of BHCs to estimate AV for the largest 100 firms. Separately, they also use triparty repo data of broker-dealers to construct a monthly measure AVM from July 2008 (when the repo data became available).[37]

Our second measure is $SRISK$, or expected capital shortage of a firm in case of a systemic event (Acharya et al. (2010) and Acharya et al. (2012)). 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 systemic risk contribution which

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

[36] The initial shock is a uniform decline of 1% in prices of all assets in the bank's portfolio. To deleverage, the bank sells all of their assets in proportion to their initial portfolio weights. Finally, there is assumed to be 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 (Duarte and Eisenbach (2015)).

[37] We are grateful to the authors for providing the AV and AVM data.

is proportional to the firm's expected capital shortfall (losses beyond some threshold) in the event of a crisis, denoted $SRISK$. We obtained firm-level 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)).[38]

6.2 Predicting Systemic Risk and Government Assistance With $TSIZE$ Loadings: Time Series Evidence

As most financial firms with systemic risk data are in the largest quintile $S5$ and $S6$, we explore the dynamic interaction of their average implicit subsidies Sub_size and average systemic risk. We first estimate firm-level $TSIZE$ loadings from 60-day rolling regressions using the SIFI1 model, use equation (4) to obtain Sub_size, and then average it over firms in $S5$ and $S6$. The average systemic risk of these firms is denoted $Y56$, where Y=($SRISK, AV, AVM$). Our hypothesis is that higher Sub_size predicts greater $Y56$ and higher government support.

The dynamic interactions are estimated using a VAR in differences, with ΔSub_size and $\Delta Y56$ as the endogenous variables, as we cannot reject the null hypothesis of unit roots in the levels. We include, as exogenous variables in the VAR, lagged changes in market capitalization, leverage and correlation with the MSCI World stock index, that are determinants of $SRISK$ (Brownlees and Engle (2012)) and AV (Duarte and Eisenbach (2015)), averaged over firms in S5 and S6. The number of lags is based on the 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 implicit subsidies over 10 periods. The impulses are orthogonalized using the (inverse of the) Cholesky factor.[39]

We first consider the firesale measures AV and AVM. Panel A of Figure 5 shows the $TSIZE$ loadings and AVM estimates for broker-dealers since July 2008, averaged over firms in $S6$ with both AVM and $TSIZE$ loadings estimates. We cannot calculate Sub_size as there are no firms in $S5$ with repo data. $AVM6$ increases monotonically from July 2008 and peaks in January 2009 at 1.3% per firm. $Loading6$ is always negative and troughs in December 2008, then rises steadily from March 2009 before leveling off in 2010. Panel B shows quarterly BHC balance sheet-based AV estimates (multiplied by 100) from 2002. $AV56$ peaks in 2007 Q4,

[38] We thank the NYU Volatility Lab (`http://vlab.stern.nyu.edu/`) for the data.

[39] In the VAR ordering, the implicit subsidies precede the systemic risk measure. Since impulse responses are sensitive to the ordering, we have switched the order and found qualitatively similar results.

the start of the crisis, at about 0.03% per firm.[40] Sub_size generally co-moves with $AV56$, peaking one quarter earlier in 2007Q3 and then trending down except for short periods.

We estimate a VAR with ΔSub_size and $\Delta AV56$ (or $\Delta Loading6$ and $\Delta AVM6$) over the full sample. The number of lags is 1 for the quarterly data and 6 for the monthly data. The accumulated impulse responses, along with two standard error (S.E.) bands, are shown in Figure 6. Panel A shows plots for AVM and $TSIZE$ loadings of firms in $S6$. The left-hand chart shows that a one SD shock to $\Delta Loading6$ leads to a persistent decrease in $AVM6$, implying higher implicit subsidies, cumulating to almost 0.04% of bank capital over the first 5 months. The right-hand chart shows that shocks to $\Delta AVM6$ have an insignificant effect on $\Delta Loading6$. Panel B of Figure 6 shows results when AV is estimated using quarterly BHC balance sheet data. A shock to ΔSub_size results in higher $\Delta AV56$ (left-hand chart) that is statistically significant after quarter 1 (when the shock hits). The effect accumulates to 0.04% of bank capital two quarters after the shock. The right-hand chart shows that ΔSub_size does not respond to $\Delta AV56$. Thus, for both the monthly and quarterly AV measures, a shock to Sub_size has a significant and positive effect on AV, as hypothesized, that persists for about 5 months or 2 quarters, and the effects are statistically significant for all 10 quarters. Further, Sub_size leads AV in an informational sense.

Turning to $SRISK$, Panel C of Figure 5 shows $TSIZE$ subsidies (scaled by 30) and $SRISK$ for firms in $S5$ and $S6$. The sample is from 2000 to June 2008 (LHS chart) and since July 2008 (RHS chart). $SRISK56$ becomes positive in October 2007 and peaks in March 2009, as does Sub_size. All series co-move from just before Lehman's failure.

We estimate the VAR with ΔSub_size and $\Delta SRISK56$ from July 2008 to November 2013. Impulse responses in Panel C of Figure 6 show that a one SD shock to ΔSub_size results in a statistically significant cumulative increase in $SRISK56$ of about \$1 billion, mostly occurring over the initial 4 months. The right-hand chart shows that shocks to $\Delta SRISK56$ do not have a statistically significant effect on ΔSub_size. When the VAR is estimated for the pre-July 2008 sample, the impulse responses are not significant (Internet appendix D).

Given that $TSIZE$ subsidies are informative of AV and $SRISK$, we assess their economic significance by predicting government support during the crisis with out-of-sample forecasts of the subsidies. The prediction period is December 2007 to September 2011 for the Fed's loans to critical institutions $CritInst$ and via liquidity facilities $LiqFac$, and November 2008

[40] The lower per-firm share in the quarterly data reflects the larger numbers of BHCs compared to active repo participants. The dynamics of $AV56$ are qualitatively similar to those reported for the full sample of firms in Duarte and Eisenbach (2015) who find that AVM peaks in November 2008 and AV in 2007 Q4.

to December 2009 for TARP loans $Tarp$.[41] We estimate VARs from June 2000 to November 2007 with $\Delta SRISK$ and $\Delta Loading5(6)$, where $SRISK5(6)$ and $Loading5(6)$ are $SRISK$ and $TSIZE$ loadings, respectively, averaged over firms in S5(S6). Then, we dynamically forecast the loadings $Loading5f$ and $Loading6f$ for December 2007 to September 2011. Applying equation 4, and using the fact that the average annualized pre-crisis returns of $TSIZE$ is 45 bp, we obtain the predicted subsidy Sub_sizef in bp for month t:

$$Sub\_sizef_t = 45 * (Loading5f_t - Loading6f_t) \tag{8}$$

The VARs are repeated from 2002 to 2007Q4 using $\Delta AV5(6)$ to obtain another set of Sub_size forecasts. The prediction period is 2008Q1 to 2011Q3 for the Fed's loans to critical institutions $CritInst$ and via liquidity facilities $LiqFac$. Panel A of Figure 7 shows that Sub_sizef track the dynamics of government support when Fed liquidity support was decreasing. However, relative to the peak of Fed support in December 2008, the subsidy forecasts peak later when using AV and earlier when using $SRISK$. The figure also shows Yf, the forecasts of AV and $SRISK$ from the VAR. AVf tracks liquidity support when it's rising but peaks in 2010 whereas $SRISKf$ has a similar dynamic to Sub_sizef.

To assess how Sub_sizef correlates with government support, we estimate this regression:

$$\begin{aligned}\Delta G_t = a_0 + a_1 Lag(G) + a_2 Dumdown_t + a_3 \Delta Sub\_sizef + a_4 Dumdown_t * \Delta Sub\_sizef \\ + a_5 \Delta Yf + a_6 Dumdown_t * \Delta Yf + \epsilon_t\end{aligned} \tag{9}$$

$G = \{Liqfac, CritInst, Tarp\}$ is in changes as we cannot reject the hypothesis of unit roots in G. We include the lag of G since the amount of new loans (ΔG) depends in part on the amount rolling over, which is a function of prior outstanding loans. We include $Yf = \{AVf, SRISKf\}$ to see whether Sub_sizef has independent predictive power.[42] $DumDown$=1 for the wind-down period (January 2009 to November 2011). The regression is estimated for the prediction period except for $CritInst$ where we exclude the first 6 months of 2008 when $\Delta CritInst$ was zero.

Table 9 shows that changes in forecasted subsidies are positively and significantly correlated with changes in $LiqFac$ and $CritInst$ in the wind-down period but not during the peak

[41] Fed loans data are from `https://www.federalreserve.gov/regreform/reform-transaction.htm`. The critical institutions are Bear Sterns, JPMorgan Chase, AIG, Bank of America, and Citigroup. TARP data is from `https://www.treasury.gov/initiatives/financial-stability/reports/Pages/TARP-Investment-Program-Transaction-Reports.aspx`.

[42] This is a concern since Sub_sizef is estimated from VARs that include Y. In particular, in the VAR with $SRISK$, pre-crisis $TSIZE$ loadings are not informative of $SRISK$.

support period. This reflects the fact that the subsidy forecasts do not peak at the same time as the Fed's support (Figure 7). For $Tarp$ loans, we find a positive and significant correlation in the full sample.[43] Forecasts of $SRISK$ are positively associated with the Fed's liquidity support, consistent with Brownlees and Engle (2012), but do not detract from the significance of Sub_sizef. Figure 8 shows the fitted values closely track actual changes in government assistance, even when Yf is excluded. This is particularly true for the quarterly data (Panel B) which washes out the month to month volatility. We have checked that the close fit is not due to the inclusion of lag G in the regression. In 2008Q4, the period with the largest increase in Fed liquidity facility loans, the fitted values excluding (including) AV forecasts are about 24% (40%) of actual increases in the loans. The corresponding numbers excluding (including) $SRISK$ forecasts are 78% (82%). Hence, we conclude that forecasts of $TSIZE$ subsidies using pre-crisis data provide meaningful information about actual government support during the crisis.

6.3 SIFI Loadings, Systemic Risk and Government Assistance: Cross-Section Evidence

We now explore whether, in the cross-section, subsidies forecasted by pre-crisis $TSIZE$ loadings predict crisis-period changes in firm-level systemic risk measures and government assistance, controlling for firm characteristics. Let the suffix $pre-2007$ denote an average in the pre-crisis period (2000-2006). We define the implicit subsidy to firm i (multiplied by 45 to convert to bp units), as implied by its average pre-crisis $TSIZE$ loadings, as follows:

$$Sub\_size_{i,pre-2007} = 45 * (Loading5 * MS5 - Loading6 * MS6)_{i,pre-2007} \qquad (10)$$

$Loading5$ ($Loading6$) is the average pre-crisis $TSIZE$ loading of firm i in S5 (S6), and $MS5$ ($MS6$) is the fraction of months in a year that firm i was in S5 (S6) before the crisis.[44] We scale Loading5(6) by $MS5(6)$ as firms may move between $S5$ and $S6$ (see Figure 2).

Denote $Y = AV, SRISK$. Let $\Delta Y_{i.t} = Y_{i,t} - Y_{i,pre-2007}$ be the crisis-period change for firm i and for t between August 2007 and 2013. Denoting ΔY_i as the crisis-period average of $\Delta Y_{i.t}$,

[43] We omit the regression of $\Delta Tarp$ when forecasting from the VAR with AV as it has only 4 observations.

[44] Specifically, $MS5$ ($MS6$) is the pre-crisis average of $S6$ ($S5$), a dummy variable equal to one if firm i was in the $S6$ ($S5$) size decile during the year.

we estimate the following regression:

$$\Delta Y_i = \alpha_0 + \alpha_1 \Delta MarketCap_i + \alpha_2 \Delta Leverage_i + \alpha_3 \Delta Correlation_i + \alpha_4 Sub\_size_{i,pre-2007} + \epsilon_i \tag{11}$$

As controls, we include the average *crisis-period* changes in the firm's market cap, leverage and correlation with the MSCI World stock index. We expect that $\alpha_4 > 0$: firms with higher pre-crisis implicit subsidy $Sub\_size_{i,pre-2007}$ have larger increases in systemic risk Y in crisis.

If a firm's $TSIZE$ loadings change from negative to positive when it moves from $S6$ to $S5$ (Figure 2), does it become less systemic? And, in the reverse case, more systemic? To address this question, we decompose a firm's $TSIZE$ loading into its negative $NegLoading = min(Loading, 0)$ and positive $PosLoading = max(Loading, 0)$ components. Let $PosLoading5(6)$ and $NegLoading5(6)$ be the averages of the positive and negative components, respectively, over firms in size decile 5(6). We define two more implicit subsidy measures:

$$Sub\_size\_sign_{i,pre-2007} = 45 * (PosLoading5 * MS5 - NegLoading6 * MS6)_{i,pre-2007} \tag{12}$$
$$Sub\_sign_{i,pre-2007} = 45 * (PosLoading6 * MS6 - NegLoading5 * MS5)_{i,pre-2007}$$

Sub_size_sign conditions on both the size decile and the sign of the loadings, whereas $Sub\_sign_{i,pre-2007}$ conditions only on the sign of the loadings. The new specification is:

$$\Delta Y_i = \alpha_0 + \alpha_1 \Delta MarketCap_i + \alpha_2 \Delta Leverage_i + \alpha_3 \Delta Correlation_i + \alpha_4 Sub\_size\_sign_{i,pre-2007} + \alpha_5 Sub\_sign_{i,pre-2007} + \epsilon_i \tag{13}$$

We expect $\alpha_4 > 0$, given the size threshold effect (Table 1). The expected sign of α_5 is ambiguous. If firms with negative (positive) loadings are TBTF (not TBTF), independent of size, then $\alpha_5 > 0$. If, instead, the size decile is the sole determinant of TBTF, then $\alpha_5 \leq 0$.

The results for AV and $SRISK$ are reported in Table 10. Considering AV first, column (1) shows that $\Delta Marketcap$ is positively correlated with changes in AV. Column (2) shows that *Sub_size* positively predict ΔAV but it is not significant. However, the adjusted R-squared improves and so does forecasting accuracy, as shown by the lower Root Mean Squared Error (RMSE). When we decompose the loadings (column 3), we find that a 10 bp increase in *Sub_size_sign* significantly predicts a rise in AV of 7 bp. *Sub_sign* also predicts AV, indicating that the sign of loadings are informative of firesale risk, whether the firm was in $S5$ or $S6$. For $\Delta SRISK$, all firm characteristics are significant (column 1) and a 1 bp increase in *Sub_size* significantly predicts higher $SRISK$ of \$0.99 trillion (column 2). Including the implicit subsidy measure strongly improves the fit and RMSE. While Sub_size_sign significantly predicts increased $SRISK$ (column 3), as expected, Sub_sign is not significant, different from the AV result.

Denote $G = Liqfac, Tarp$.[45] We re-estimate regressions (11) and (13) using G as the dependent variable (by definition, G=0 before the crisis) and with Tobit, since we include firms that were eligible but did not borrow. The results are in Table 11. Firm characteristics are not significant in any case. Sub_size positively and significantly predicts $LiqFac$ and $Tarp$ (column 2), with a one bp increase in subsidies predicting an increase of \$6 billion in $Liqfac$ and \$300 million in $Tarp$. Sub_size_sign also positively predicts government support (column 3), as hypothesized. In contrast, Sub_sign is either negatively or insignificantly related to government assistance. In all cases, including the implicit subsidy measures improves the fit and the forecast RMSE of the regressions.

To evaluate how much better $TSIZE$ subsidies predict government support relative to firm characteristics, we compare the specification with loadings (column 3 in Tables 10 and 11) with the one with only size, leverage and correlation (column 1 of the tables). We show scatter plots of the fitted values with loadings (colored red) and without loadings (colored black) against the actual changes in systemic risk and government assistance (Figure 9). The red scatters are generally closer to the 45 degree line than the black scatters in all cases, as also indicated by the lower RMSE of regressions with loadings. However, the prediction for outlier firms – those with very large increases in systemic risk and government assistance during the crisis – is generally rather poor (i.e. scatters in the upper-right corner of the plots are below the 45 degree line). This is consistent with our prior result that, in the time series, forecasted subsidies correlate poorly with the Fed's loans during the ramp-up period, when support to the outlier firms occurred.

6.4 Predictability of Non-Size SIFI Factors

Panel B of Figure 7 shows that forecasted subsidies based on pre-crisis non-size SIFI factor loadings are generally negative and do not co-move with government support. Consistent with this observation, $COMP$ and IC have no independent predictive power for government support (Internet appendix D).[46]

[45] We do not use the AVM measure since the sample only starts in the crisis period.

[46] IC forecasts predict $Liqfac$ by itself, but not when paired with $TSIZE$ forecasts (which are significant).

Loadings on $TSIZE^{BVE}$, the $TSIZE$ factor based on BVE cutoffs, have no predictability in the time-series or the cross-section (Internet appendix D). These results suggest that market prices are needed for predicting systemic risk and government support. Nor do $TSIZE^{NF}$ factor loadings have predictive power, further evidence that the informativeness of $TSIZE$ derives from large financial firm returns only.

The results in this section provide a robust indication that pre-crisis $TSIZE$ loadings, both at the aggregate and the firm-level, are predictive of government assistance during the crisis of 2007-2009. This predictive power obtains even after accounting for the informativeness of other systemic risk measures, such as AV and $SRISK$.

7 Globally Systemic Banks and Additional Results

Since the complexity factor is based on subsidiaries of BHCs, is the growth in implicit subsidies from complexity risk since 2007 concentrated in a few very large banks? We explore the role of globally systemic banks or GSIBs in the evolution of the complexity factor (section 7.1). Additional investigations and robustness checks are in 7.2.

7.1 Globally Systemically Important Banks

Figure 10 shows the yearly distribution of BHC subsidiaries for GSIBs and non-GSIBs in $S5$ and $S6$ since 1986. The median number of GSIB subsidiaries increases sharply starting from 1998 with a further spike in 2008, consistent with Avraham et al. (2012) and Carmassi and Herring (2016). Non-GSIBs in $S6$ have more subsidiaries than those in $S5$ but the distribution of non-GSIB subsidiaries does not show a secular trend. Thus, the recent growth in bank complexity (at least by this measure) appears to be concentrated among GSIBs.

Motivated by Figure 10, we carve out a GSIB portfolio out of $S5$ and $S6$ and estimate the SIFI4+COMP model for 1986-2006.[47] If markets expect most subsidies to accrue to GSIBs, then the GSIB (and not $S6$) portfolios should load negatively on SIFI factors. The results are in Table 12. GSIB portfolio loadings on $TSIZE$ (Panel A) are intermittently significant with mixed signs, whereas $S6$ ($S5$) loadings are generally negative (positive). Thus, $TSIZE$-

[47] We take out GSIBs from the $S5$ and $S6$ portfolios and form a $GSIB$ portfolio. Then we reform the BM groups for these 3 new portfolios (i.e. GSIB, non-GSIB S5 and non-GISB S6) using the methodology described in Section 3. The list of GSIBs is in internet appendix E.

implied subsidies accrue to $S6$ firms, as before, even with GSIBs taken out. In contrast, 3 of 5 GSIB portfolio loadings on $COMP$ are negative and significant (Panel B), and no $S6$ or $S5$ portfolio has significant loadings. Similarly, 2 of 3 GSIB portfolios load negatively on IC and other portfolio loadings are positive (Panel C).[48] Thus, for complexity and IC risks, subsidies are expected to accrue to $GSIBs$ at the expense of *non-GSIBs*, different from $TSIZE$ risk. Conversely, since non-GSIB $S6$ portfolios load insignificantly on $COMP$ and positively on IC, non-GSIB top-decile firms do not benefit from complexity and IC risk.

To further examine the role of GSIBs, we estimate 60-month rolling regressions of bank excess returns using the SIFI4+$COMP$ model. Figure 11 shows subsidies implied by $TSIZE$, IC and $COMP$ loadings for banks.[49] The test portfolios are GSIBs and non-GSIB $S5$ and $S6$ banks. The implicit subsidy measure is *Subsidy-S5-S6* — the same as *Sub_size* but with GSIBs omitted from $S5$ and $S6$. A new measure indicates the SIFI discount for GSIBs relative to the largest decile of banks $S6$:

$$\textit{Subsidy-S6-Gsib}_{factor} = 100 * AvgReturn(Factor) * (Loading6 - Loading\text{-}GSIB) \quad (14)$$

Loading-$GSIB$ is the average loading of GSIBs.The average factor return is for the pre-crisis period (LHS chart) or 2007-2013 (RHS chart). The LHS chart of Panel A shows that before 2007 $TSIZE$ subsidies are similar for GSIBs and the largest decile banks $S6$. Following Lehman's failure, however, implicit subsidies to $S6$ banks plunge (consistent with results in section 4.2), while implicit GSIB subsidies increase sharply and remain high (RHS chart). In other words, since the crisis, equity markets expect subsidies from TBTF risk to mainly benefit GSIBs, rather than large banks generally. Turning to $COMP$ and IC implicit subsidies (Panels B and C), their pre-crisis subsidies are not shown as both factors had negative average returns during this time. In the crisis period, *Subsidy-S6-Gsib* becomes consistently positive while *Subsidy-S5-S6* is generally negative shortly during (for $COMP$) or shortly after (for IC) Lehman's failure. Thus, for all 3 SIFI factors, a consistent pattern emerges: since Lehman's failure, most implicit subsidies are expected to accrue to GSIBs rather than large non-GSIB banks. This results supports the idea of focusing prudential regulation on the largest banks.

[48] GSIB portfolios also load positively on LEV (Panel D), and insignificantly on LIQ (Panel E).

[49] The estimated portfolio loadings are shown in Internet appendix E.

7.2 Additional Investigations and Robustness Checks

We estimated additional specifications for robustness. We used the 5-factor model of Fama and French (2015) that includes profitability and investments, and found the results essentially unchanged (Internet appendix E). 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 (Internet appendix E).[50]

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

8 Conclusion

While firm size has traditionally been viewed as the main source of systemic risk, since the crisis of 2007-2008 there has been increased focus on complexity and interconnectedness risk, both by regulators and market participants. In this paper, we construct factors based on these 3 criteria, while also accounting for leverage and liquidity risk, and estimate the implicit subsidies implied by the factor loadings and factor returns.

Our factors are long-short portfolios based on equity returns of the largest 16% of financial firms, with the Dodd-Frank size threshold of $50 billion dollars corresponding to the 8th percentile of BVA distribution in 2010. Our size factor $TSIZE$ is short the largest 8% of financial firms and long the next largest 8%. Our complexity $COMP$ and interconnectedness IC factors are constructed after projecting the measures (subsidiaries of BHCs for $COMP$ and a PCA-based metric for IC) onto the returns space. In all cases, firms with the greatest size, complexity or interconnectedness (i.e. the short portfolio) are expected to have lower returns on average due to lower tail risk, implying positive average returns for the factors.

We add the factors to the 3-factor and 5-factor models of Fama and French (1993) and Fama and French (2015), and assess whether they are priced in the cross-section of equity returns and their loadings are correlated with government bailout probabilities and systemic risk

[50] We thank the authors for the use of their data which was not available for our full sample.

events. Further, we examine if factor loadings in normal times predict systemic risk and government support in crisis.

In the pre-crisis period, from 1963-2006, only $TSIZE$ has positive average returns and it is the only factor priced in the cross-section of returns. In the time-series, we identify a "threshold effect" for $TSIZE$ loadings: they switch from negative for the largest decile of firms to positive for the second-largest decile of firms. This difference in the average loadings of the two deciles, scaled by the average return of $TSIZE$, is our implicit subsidy measure Sub_size, estimated as 6 basis points per year on average, most of which accrue to financial 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 $TSIZE$.

Implicit subsidies implied by pre-crisis $TSIZE$ loadings predict systemic risk and government support in the crisis both at the firm and aggregate levels, even after accounting for size, leverage and correlation with global market returns. The implicit subsidies are correlated with the probability of government support, as given by Fitch Support ratings.

In the pre-crisis era, $TSIZE$-implied subsidies increase around bailout events and regulations facilitating bank consolidation while $COMP$ and IC subsidies are effectively zero. By comparison, since 2007, and especially during and after Lehman's failure, the $COMP$ and IC implied subsidies increase consistently while the share of $TSIZE$ in total implicit subsidies fall to less than 15%. Thus, market participants' perception of the sources of systemic risk changes dramatically in the crisis. Whether the evolution in the market's perception of SIFI factors is due to changes in the financial system, or due to collective learning about neglected risks (Gennaioli and Shleifer (2018)), is a subject for future research.

References

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, "Systemic Risk and Stability in Financial Networks," *American Economic Review*, 2015, *105*, 564–608.

Acharya, Viral, Deniz Anginer, and A. Joseph Warburton, "The End of Market Discipline? Investor Expectations of Implicit State Guarantees," *Working Paper*, 2016.

– , Hamid Mehran, and Anjan Thakor, "Caught Between Scylla and Charybdis? Regulating Bank Leverage When There Is Rent Seeking and Risk Shifting," *FRBNY Staff Report No. 469*, 2013.

– , Lasse Pedersen, Thomas Philippon, and Matthew Richardson, "Measuring Systemic Risk," *Technical Report*, 2010.

– , Robert Engle, and Diane Pierret, "Testing Macroprudential Stress Tests: The Risk of Regulatory Risk Weights," *Journal of Monetary Economics*, 2014, *65*, 36–53.

– , – , and Matthew Richardson, "Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks," *American Economic Review*, 2012, *102* (3), 59–64.

Adrian, Tobias, Erkko Etula, and Tyler Muir, "Financial Intermediaries and the Cross-Section of Asset Returns," *The Journal of Finance, Forthcoming*, 2014.

Ahmed, Javed, Christopher Anderson, and Rebecca Zarutskie, "Are Borrowing Costs of Large Financial Firms Unusual?," *Working Paper*, 2014.

Allen, Franklin, Anna Babus, and Elena Carletti, "Financial Connections and Systemic Risk," *Journal of Financial Economics*, 2012, *104*, 519–534.

Amihud, Yakov and Haim Mendelson, "Asset Pricing And the Bid-Ask Spread," *Journal of Financial Economics*, 1986, *17* (2), pp. 223–249.

– , – , and Lasse Heje Pedersen, "Asset Pricing And the Bid-Ask Spread," *Cambridge University Press*, 2012.

Antill, Samuel, David Hou, and Asani Sarkar, "Components of U.S. Financial Sector Growth: 1950-2013," *Economic Policy Review*, 2014, *20* (2).

Avraham, D., P. Selvaggi, and J.I. Vickery, "A structural view of U.S. Bank holding companies," *Economic Policy Review*, 2012, *18*, 65–81.

Balasubramnian, Bhanu and Ken B. Cyree, "Has market discipline on banks improved after the Dodd-Frank Act?," *Journal of Banking and Finance*, 2014, *41*, pp. 155–166.

Barth, A. and I. Schnabel, "Why Banks Are Not Too Big to Fail–Evidence from the CDS Market," *Economic Policy*, 2013, *28* (74), pp. 335–369.

Basset, W.F., "Using insured deposits to refine estimates of the large bank funding advantage," *Working Paper*, 2014.

Basu, Sumanta, Sreyoshi Das, George Michailidis, and Amiyatosh Purnanandam, "A System-wide Approach to Measure Connectivity in the Financial Sector," *Working Paper*, 2017.

Billio, Monica, Mila Getmansky, Andrew W. Lo, and Loriana Pelizzon, "Econometric measures of connectedness and systemic risk in the finance and insurance sectors," *Journal of Financial Economics*, 2012, *104* (3), pp. 535–559.

Brewer, Elijah and Julapa Jagtiani, "How Much Did Banks Pay to Become Too-Big-To-Fail and to Become Systemically Important?," *Journal of Financial Services Research*, 2013, *43* (1), pp. 1–35.

Bright, Steve, Paul Glasserman, Christopher Gregg, and Hashim Hamandi, "What Can We Learn from Publicly Available Data in Banks Living Wills?," *Office of Financial Research Brief Series 16-05*, 2016.

Brownlees, Christian T. and Robert F. Engle, "Volatility, Correlation and Tails for Systemic Risk Measurement," *Working Paper*, 2012.

Carhart, Mark M., "On Persistence in Mutual Fund Performance," *The Journal of Finance*, 1997, *52* (1), pp. 57–82.

Carmassi, Jacopo and Richard Herring, "The Corporate Complexity of Global Systemically Important Banks," *Journal of Financial Services Research*, 2016, *49*, 175–201.

Cetorelli, Nicola and Linda S. Goldberg, "Measures of Complexity of Global Banks," *Economic Policy Review*, 2014, *20.*

– **and** – , "Organizational Complexity and Balance Sheet Management in Global Banks," *Working Paper*, 2016.

– **, Michael G. Jacobides, and Samuel Stern**, "Transformation of Corporate Scope in U.S. Banks: Patterns and Performance Implications," *Federal Reserve Bank of New York Staff Reports No. 813*, 2017.

Demirer, Mert, Umut Gokcen, and Kamil Yilmaz, "Financial Sector Volatility Connectedness and Equity Returns," *Working Paper*, 2018.

Diebold, Francis X. and Kamil Yilmaz, "On the network topology of variance decompositions: Measuring the connectedness of financial firms," *Journal of Econometrics*, 2014, *182*, 119–134.

Duarte, Fernando and Thomas Eisenbach, "Fire-Sale Spillovers and Systemic Risk," *Federal Reserve Bank of New York Staff Reports 645*, 2015.

Falato, Antonio, Ali Hortacsu, Dan Li, and Chaehee Shin, "Fire-Sale Spillovers in

Debt Markets," *Working Paper*, 2016.

Fama, Eugene F. and James D. MacBeth, "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy*, 1973, *81* (3), pp. 607–636.

– **and Kenneth R. French**, "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics*, 1993, *33* (1), pp. 3–56.

– **and** – , "A five-factor asset pricing model," *Journal of Financial Economics*, 2015, *116* (1), pp. 1–22.

Gandhi, Priyank and Hanno Lustig, "Size Anomalies in U.S. Bank Stock Returns," *The Journal of Finance, Forthcoming*, 2015, *70* (2), 1540–6261.

– **,** – **, and Alberto Plazzi**, "Equity is cheap for large financial institutions: The international evidence," Technical Report, National Bureau of Economic Research 2016.

GAO, "Large Bank Holding Companies: Expectations of Government Support," 2014. Gao-14-621, United States General Accounting Office.

Gennaioli, Nicola and Andrei Shleifer, "A Crisis of Beliefs: Investor Psychology and Financial Fragility," *Forthcoming, Princeton University Press*, 2018.

Greenwood, R., A. Landier, and D. Thesmar, "Vulnerable Banks," *Journal of Financial Economics*, 2015, *115* (3), 471–485.

He, Zhiguo and Arvind Krishnamurthy, "Intermediary Asset Pricing and the Financial Crisis," Technical Report, Working Paper 24415, National Bureau of Economic Research 2018.

– **, Bryan Kelly, and Asaf Manela**, "Intermediary Asset Pricing: New Evidence from Many Asset Classes," *Journal of Financial Economics*, 2017, *126*, pp. 1–35.

IMF, "How Big is the Implicit Subsidy for Banks Considered Too Important to Fail?," 2014. Global Financial Stability Report, International Monetary Fund.

Kane, Edward J., "Incentives for Banking Megamergers: What Motives Might Regulators Infer from Event-Study Evidence?," *Journal of Money, Credit, and Banking*, 2000, *32* (3), pp. 671–701.

Kelly, Bryan, Hanno Lustig, and Stijn Van Nieuwerburgh, "Too-Systemic-to-Fail: What Option Markets Imply about Sector-Wide Government Guarantees," *American Economic Review*, 2016, *106* (6), 1278–1319.

Kovner, Anna, James Vickery, and Lily Zhou, "Do big banks have lower operating costs?," *Economic Policy Review*, 2014, *20* (2).

Laeven, L, L Ratnovski, and H Tong, "Bank Size and Systemic Risk," *IMF Staff Discussion Note SDN/14/04*, 2014.

Lucas, Deborah and Robert McDonald, "Valuing Government Guarantees: Fannie and Freddie Revisited," *in Measuring and Managing Federal Financial Risk, ed. Deborah Lucas, University of Chicago Press*, 2010, pp. 131–54.

Lumsdaine, R.L., D.N. Rockmore, N. Foti, G. Leibon, and J.D. Farmer, "The Intrafirm Complexity of Systemically Important Financial Institutions," *Working Paper*, 2015.

Minton, Bernadette A., René M. Stulz, and Alvaro G. Taboada, "Are Larger Banks Valued More Highly?," Technical Report, National Bureau of Economic Research 2017.

Morgan, Donald P. and Kevin J. Stiroh, "Too Big To Fail After All These Years," *FRBNY Staff Report No. 220*, 2005.

Newey, Whitney K. and Kenneth D. West, "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 1987, *55* (3), pp. 703–708.

O'Hara, Maureen and Wayne Shaw, "Deposit Insurance and Wealth Effects: The Value of Being "Too Big to Fail"," *The Journal of Finance*, 1990, *45* (5), pp. 1587–1600.

Santos, Joao, "Evidence From the Bond Market on Banks' "Too-Big-To-Fail" Subsidy," *Economic Policy Review*, 2014, *20* (2).

Schaeck, Klaus, Tim Mi Zhou, and Philip Molyneux, "'Too-Big-To-Fail' and its Impact on Safety Net Subsidies and Systemic Risk," *CAREFIN Research Paper No. 09/2010*, 2010. available at SSRN: https://ssrn.com/abstract=1798633.

Shanken, J., "On the Estimation of Beta-Pricing Models," *The Review of Financial Studies*, 1992, *5* (1), pp. 1–33.

Swary, Itzhak, "Stock Market Reaction to Regulatory Action in the Continental Illinois Crisis," *Journal of Business*, 1986, *59* (3), 451–476.

Table 1: Loadings on $SIFI$ Factors: 1963-2006

This table shows OLS estimates for loadings on $SIFI$ factors relating to complexity $COMP$, interconnectedness IC and threshold size $TSIZE$ 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 BM (reading left to right, columns correspond from lowest to highest quintiles of the BM distribution). Also shown are loadings on the leverage LEV and liquidity LIQ factors. In Panel A, we report estimates from regressions using the SIFI1 specification. In Panel B-E, the estimates are based on the SIFI4 model. In Panel F, we add $COMP$ to the SIFI4 model. *, **, *** 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 July 1963 to 2006 in Panel A, 1970 to 2006 in Panels B-E and 1986 to 2006 in Panel F.

	Low	2	3	4	High
Panel A: Loadings on TSIZE Factor (excluding IC, LIQ, LEV, GL)					
Smallest	.00	.09***	.08***	.09***	.06**
2	.08**	.12***	.12***	.11***	.09***
3	.07*	.13***	.09***	.14***	.12***
4	.05*	.09***	.11***	.11***	.10***
5	.02	.10***	.10***	.12***	.13***
Largest	-.03	-.05*	-.10**	.02	-.12*
Panel B: Loadings on TSIZE Factor (including IC, LIQ, LEV, GL)					
Smallest	-.02	.10***	.10***	.12***	.07**
2	.07	.14***	.14***	.13***	.10***
3	.06	.14***	.10***	.15***	.16***
4	.05	.11***	.12***	.13***	.11**
5	.02	.13***	.12***	.13***	.17***
Largest	-.04	-.04	-.13***	.04	-.15*
Panel C: Loadings on Interconnectedness Factor IC					
Smallest	-.02	.00	.00	-.01	.00
2	.01	.02	.02	.03**	.02
3	.02	.02	.01	.02	.03
4	.00	.02	.02	.00	.00
5	-.01	.00	.00	.01	-.01
Largest	.03*	.00	.05**	.02	-.11**

Table 1: Loadings on $SIFI$ Factors: 1963-2006 (Continued)

	Low	2	3	4	High
Panel D: Loadings on Liquidity Factor LIQ					
Smallest	.00	.00	.05**	.00	-.01
2	.01	.04	.03	.01	.05*
3	-.01	.01	.02	.03	.02
4	.01	.01	.01	.04	.09***
5	-.02	-.02	-.01	.03	.02
Largest	.01	-.05*	-.09**	-.04	.08
Panel E: Loadings on Leverage Factor LEV					
Smallest	.00	.03	.02	.04**	.06***
2	-.03	-.02	.00	.00	-.01
3	-.05	.00	.00	.01	.04
4	-.01	.01	.01	.03	.01
5	-.02	.03	.08***	.04*	.05
Largest	.02	.03	.01	.01	-.08
Panel F: Loadings on Complex Factor $COMP$					
Smallest	.06	-.02	.00	-.02	-.03
2	.06	-.06	-.04	-.03	-.02
3	.03	-.04	.01	-.02	-.04
4	.02	-.01	.01	-.01	-.06
5	-.04	.01	-.04	-.03	-.04
Largest	.02	.01	.02	-.01	-.01

Table 2: Estimates of $TSIZE$ Premium and Discount per Year, 1963-2006

This table shows estimates of the $TSIZE$ premium and discount per year from regressions using the SIFI1 specification. 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 multiply the numbers in Panel A 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 column labeled *Average* shows the average across book-to-market bins (weighted by average firm market capitalization) for each size bin. 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 sample is from July 1963 to 2006.

	Low	2	3	4	High	Average
Panel A: Average Annual premium and discount (Basis points)						
Smallest	0	4.05	3.6	4.05	2.7	2.86
2	3.6	5.4	5.4	4.95	4.05	4.69
3	3.15	5.85	4.05	6.3	5.4	4.95
4	2.25	4.05	4.95	4.95	4.5	4.13
5	0	4.5	4.5	5.4	5.85	4.05
Largest	0	-2.25	-4.5	0	-5.4	-2.3
Largest -5	0	-6.75	-9.01	-5.4	-11.26	-6.36
Panel B: Average Annual premium and discount per Firm (Millions)						
Smallest	0	0.05	0.04	0.04	0.02	0.03
2	0.17	0.26	0.26	0.23	0.19	0.22
3	0.35	0.64	0.45	0.69	0.59	0.54
4	0.62	1.09	1.32	1.33	1.21	1.12
5	0	2.99	2.9	3.57	3.87	2.66
Largest	0	-6.97	-12.96	0	-12.74	-7.24
Largest -5	0	-9.96	-15.86	-3.57	-16.61	-9.9

Table 3: Estimates of $TSIZE$ Premium and Discount per Year for Financial and Non-Financial Firms, 1963-2006

This table shows estimates of the $TSIZE$ premium and discount per year separately for financial (panel A) and non-financial (panel B) test portfolios from regressions using the SIFI1 specification. 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 July 1963 to 2006.

	Low	2	3	4	High	Average
Panel A: Average Annual premium and discount (Basis points), Finance Portfolios						
Smallest	0	10.81	0	4.95	0	3.4
2	0	6.3	6.75	5.85	0	3.78
3	6.75	0	8.56	6.75	9.01	6.25
4	0	8.56	6.75	0	0	3.07
5	6.75	17.11	12.16	15.76	21.16	14.72
Largest	-13.06	-14.86	-9.91	-13.96	-22.97	-15.18
Largest -5	-19.81	-31.97	-22.06	-29.72	-44.13	-29.9
Panel B: Average Annual premium and discount (Basis points), Nonfinance Portfolios						
Smallest	0	3.15	4.05	4.05	2.25	2.69
2	4.5	5.85	5.85	4.5	3.15	4.79
3	0	4.5	4.05	5.85	4.5	3.78
4	0	3.6	4.05	3.15	6.3	3.41
5	0	3.6	3.15	4.05	0	2.16
Largest	0	0	-4.95	0	0	-0.99
Largest -5	0	-3.6	-8.11	-4.05	0	-3.14

Table 4: $SIFI$ risk in the Cross-Section of Returns: 1963-2006

This table shows estimates of the price of risk of SIFI factors related to threshold size $TSIZE$, complexity $COMP$ and interconnectedness IC. α is the intercept. Also shown are estimates for leverage LEV and liquidity LIQ factors. In the first and last 3 rows, the first-stage regressions use the SIFI1 specification. In the last 3 rows, $TSIZE^{NF}$ (a threshold size factor using non-financial instead of financial firm returns) is used instead of $TSIZE$. In the remaining rows, the first-stage regression pairs $TSIZE$ with a non-size factor and adds the GL factor of Gandhi and Lustig (2015). We present the time-series averages of the coefficients of the second-stage cross-sectional regressions, along with the standard t-statistic and the Shanken (1992) errors-in-variables corrected t-statistics. The sample is from July 1963 to 2006 for the first and last 3 rows, 1986 to 2006 for $COMP$ and 1970 to 2006 for the remaining rows. The first and second stages are both estimated by OLS.

	α	TSIZE	Liquidity	Inter	Leverage	Complex	TSIZE^{NF}
Price of Risk	0.99	0.82					
T-Stat	(4.61)	(2.86)					
Shanken T-Stat	(4.36)	(2.43)					
Price of Risk	1.06	0.73	-0.1				
T-Stat	(4.28)	(2.55)	(-0.27)				
Shanken T-Stat	(3.95)	(2.11)	(-0.22)				
Price of Risk	1.05	0.81		0.55			
T-Stat	(4.18)	(2.82)		(1.08)			
Shanken T-Stat	(3.9)	(2.35)		(0.9)			
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	1.48	0.19				-1.05	
T-Stat	(5.27)	(0.53)				(-1.81)	
Shanken T-Stat	(4.84)	(0.43)				(-1.48)	
Price of Risk	1.09						0.12
T-Stat	(5.09)						(1.24)
Shanken T-Stat	(4.84)						(0.92)

Table 5: $TSIZE$ Loadings after Removing from Test Assets the Financial Firm Months in Short Portfolio of $TSIZE$ Factor

This table shows OLS estimates for $TSIZE$ loadings after removing firm-months in the top 8th percentile of financial firms (i.e. the short portfolio in the $TSIZE$ factor). 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 BM (reading left to right, columns correspond from the lowest to highest quintiles of the BM distribution). The regressions use the SIFI1 (Panel A) or SIFI4 (Panel B) or SIFI4 + complexity factor $COMP$ (Panel C) specifications. *, **, *** 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 starts from July 1963 (Panel A), 1970 (Panel B) or 1986 (Panel C), ending in 2006 in all cases.

	Low	2	3	4	High
Panel A: Loadings on TSIZE Factor, SIFI1 Model					
Smallest	.00	.09***	.08***	.09***	.06*
2	.08**	.12***	.12***	.11***	.09***
3	.07*	.13***	.09***	.14***	.12***
4	.05*	.09***	.11***	.12***	.10***
5	.02	.11***	.11***	.12***	.14***
Largest	-.03	-.02	-.08*	.05	-.08
Panel B: Loadings on TSIZE Factor, SIFI4 Model					
Smallest	-.02	.10***	.10***	.12***	.07**
2	.07*	.14***	.14***	.13***	.10***
3	.06	.14***	.10***	.14***	.16***
4	.05	.11***	.12***	.13***	.11**
5	.02	.13***	.12***	.13***	.17***
Largest	-.04	-.01	-.11**	.06	-.10
Loadings on TSIZE Factor, SIFI4+Complex Model					
Smallest	-.02	.12***	.13***	.15***	.09**
2	.04	.19***	.21***	.19***	.16***
3	.07	.17***	.14***	.19***	.21***
4	.04	.13***	.14***	.22***	.15**
5	.02	.15***	.16***	.17***	.32***
Largest	-.06*	-.07*	-.13**	.10	-.21**

Table 6: Changes in SIFI Implicit Subsidies Around Systemic Risk Events

This table shows a regression of the change in implicit subsidies Sub_size implied by SIFI factors (equation 4) on systemic risk events. The regression is estimated over the sample for which the factor has positive average returns: $TSIZE$ for the full sample (1963-2013), and IC and $COMP$ in the crisis sample (2007-2013). Dummy variables are defined equal to 1 as follows: *Continental* between July 1983 and June 1985; Gramm-Leach-Bliley or *GLB Act* between November 2009 and August 2001; *Crisis* from August 2007 to October 2008; *Lehman* from September 2008 to October 2008; $Post - Lehman$ from November 2008 to June 2009; *Dodd Frank* from June 2009 to July 2010. $NFCI$ is the Chicago Fed's National Financial Conditions Index. *, **, *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable:		
	Δ Sub_$size_{Tsize}$	Δ Sub_$size_{IC}$	Δ Sub_$size_{Comp}$
	Estimate (T-Stat)	Estimate (T-Stat)	Estimate (T-Stat)
Continental	0.58***	—	—
	(2.68)	—	—
GLB Act	0.54*	—	—
	(1.91)	—	—
Crisis	0.03	-2.86	6.39
	(0.10)	(-0.47)	(1.56)
Lehman	5.43***	65.81***	23.45**
	(4.03)	(2.80)	(2.48)
Post-Lehman	-1.96***	16.67**	1.41
	(-4.59)	(2.11)	(0.34)
Dodd-Frank	0.42*	-11.42	-2.32
	(1.84)	(-1.49)	(-1.01)
Δ NFCI	0.00	-35.28	-15.32
	(-0.01)	(-1.58)	(-1.48)
Adjusted R-squared	0.10	0.23	0.03

Table 7: Components of Implicit SIFI Subsidies: 1963-2013

This table shows implicit subsidies implied by the loadings on $SIFI$ factors (see equation 4) relating to complexity $COMP$, interconnectedness IC and threshold size $TSIZE$, as a share of total implicit subsidies. The shares are reported by time period, and conditional on the factor having a positive average return in the pre-crisis (1963-2006) and crisis (2007-2013) periods. Only $TSIZE$ has positive average returns in the pre-crisis period and $COMP$, IC and $TSIZE$ all have positive average returns in the crisis period. The pre-crisis period is further divided into: 1963-1979, 1980-1989, 1990-1999, 2000-2006.

	1963-1979	1980-1989	1990-1999	2000-2006	2007-2013
Total (bp)	6.98	5.43	8.13	9.92	172.30
Tsize (bp)	6.98	5.43	8.13	9.92	23.43
Tsize share	100.00%	100.00%	100.00%	100.00%	13.60%
IC (bp)	—	—	—	—	50.07
IC share	—	—	—	—	29.06%
COMP (bp)	—	—	—	—	98.79
COMP share	—	—	—	—	57.34%

Table 8: Changes in $TSIZE$ Loadings Around Fitch Support Ratings Changes

This table shows changes in $TSIZE$ loadings around changes in the Fitch Support Floor Rating from below A- to above A- (indicating a firm with extremely high probability of government support). $TSIZE$ loadings are estimated from firm-level 60-month rolling regressions using the SIFI1 specification. $t = 0$ is the month of the rating change. $t\epsilon[a, b]$ is a dummy variable equal to one from a to b months relative to the event. 14 banks and 294 bank months 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)
FIRM FE	None	None	None	FE	FE	FE
N	294	294	294	294	294	294

Table 9: Predicting Government Support in Crisis with Forecasts of $TSIZE$ Loadings: Time-Series Results

This table shows a regression of changes in crisis-period government support ΔG on changes in out-of-sample forecasts of subsidies implied by pre-crisis $TSIZE$ loadings $Subsizef$ and of systemic risk measure Yf, where $Y = AV, SRISK$. The forecasts are obtained from estimating over a pre-crisis period a VAR that includes changes in $Loading6(5)$ and $Y6(5)$, where $Loading5(6)$ and $Y5(6)$ are the average $TSIZE$ loadings and Y, respectively, of firms in size decile 5(6), and 5(6) is the second-largest (largest) size decile. $Subsizef$ is obtained by applying equation 4 to the forecasts of $Loading5$ and $Loading6$. The pre-crisis period is from June 2000 to November 2007 for $SRISK$ and 2002 to Q4 2007 for AV. The prediction period is December 2007 to September 2011 for the Fed's liquidity facilities loans $LiqFac$, July 2008 to September 2011 for loans to critical institutions $CritInst$ and November 2008 to December 2009 for Tarp loans $Tarp$. $DumDown$ is a dummy variable equal to 1 from January 2009 to November 2011, when the Fed's liquidity support was decreasing.

	Dep. Var. $\Delta G : \Delta Liqfac$				Dep. Var. $\Delta G : \Delta CritInst$				Dep. Var. $\Delta G : \Delta Tarp$	
	$Y = AV$		$Y = SRISK$		$Y = AV$		$Y = SRISK$		$Y = SRISK$	
	Estimate (T-Stat)	Estimate (T-Stat)	Estimate (T-Stat)	Estimate (T-Stat)	Estimate (T-Stat)	Estimate (T-Stat)	Estimate (T-Stat)	Estimate (T-Stat)	Estimate (T-Stat)	Estimate (T-Stat)
Lag G	-0.25***	-0.23**	-0.04	-0.06	0.11	0.12	-0.25**	-0.26**	-0.54***	-0.52***
	(-3.40)	(-2.73)	(-0.97)	(-1.66)	(0.86)	(0.92)	(-2.37)	(-2.07)	(-18.13)	(-20.24)
Dumdown	-8.68***	20.55	-0.83**	-0.63**	-1.06***	-1.08***	-0.05	-0.01	—	—
	(-3.19)	(0.87)	(-2.16)	(-2.36)	(-11.71)	(-10.55)	(-1.36)	(-0.35)		
$\Delta Subsizef$	-146.72***	99.01	-0.83	-3.67	-6.06***	-6.22***	-0.02	-0.33	0.07***	0.09***
	(-3.95)	(0.51)	(-0.20)	(-1.18)	(-9.66)	(-9.13)	(-0.07)	(-1.67)	(3.85)	(4.78)
Dumdown*$\Delta Subsizef$	150.07***	-95.45	12.87***	13.83***	6.13***	6.33***	0.94*	1.16**	—	—
	(4.05)	(-0.49)	(3.03)	(2.95)	(8.62)	(8.65)	(1.86)	(2.09)		
ΔYf	—	146.38	—	0.13*	—	-0.12	—	0.02***	—	-0.00*
		(1.30)		(1.91)		(-0.62)		(3.33)		(-2.08)
Dumdown*ΔYf	—	-147.81	—	-0.12	—	—	—	-0.01**	—	—
		(-1.31)		(-1.63)				(-2.68)		
Adjusted R^2	0.76	0.77	0.34	0.45	0.73	0.70	0.21	0.25	0.97	0.98

Table 10: Predicting Crisis Period Systemic Risk With Pre-Crisis $TSIZE$ Loadings: Cross-Section Results

This table shows results from cross-sectional regressions predicting a firm's average crisis-period change in systemic risk Y with subsidies implied by pre-crisis average $TSIZE$ loadings, where Y={AV, $SRISK$}. $SRISK$ (in $ trillion) is the expected capital shortage in case of a systemic event and AV (in bp) is the firesale risk measure. For a financial firm i in the largest size quintile, the crisis-period change in Y is defined as $Y_{i,t}$ for t in the crisis period (August 2007 to 2013), minus $Y_{i,pre-2007}$, its average before the crisis (2000-2006). The dependent variable is ΔY_i, the average crisis-period change for firm i. The main predictor is the implicit subsidy to firm i implied by pre-crisis $Tsize$ loadings Sub_size, which is only based on the firm's size decile (equation 10). Alternative implicit subsidy definitions used are Sub_size_sign, based on both firm size and the sign of loadings and Sub_sign, only based on the sign of loadings (equation 12). The control variables are the firm's $\Delta Marketcap$, ΔLev and $\Delta Correlation$, or crisis-period changes in the market cap, leverage, and correlation with the World MSCI stock index. Factor loadings are estimated from firm-level 60-month rolling regressions using the SIFI1 specification from 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 (RMSE). There are 75 (106) firms in the AV ($SRISK$) regression.

	Dependent Variable: ΔAV			Dependent Variable: $\Delta SRISK$		
	Estimate (T-stat) (1)	Estimate (T-stat) (2)	Estimate (T-stat) (3)	Estimate (T-stat) (1)	Estimate (T-stat) (2)	Estimate (T-stat) (3)
$\Delta MarketCap$	0.06***	0.07***	0.07***	-0.53***	-0.54***	-0.53***
	(4.89)	(4.05)	(3.74)	(-2.66)	(-4.07)	(-4.23)
ΔLev	0.04	0.14	0.24**	0.44**	0.34***	0.29**
	(0.36)	(1.59)	(2.46)	(2.32)	(2.72)	(2.27)
$\Delta Corr$	-2.64	1.45	-0.07	-39.82*	-20.33	-27.38*
	(-0.32)	(0.24)	(-0.01)	(-1.71)	(-1.23)	(-1.78)
$Sub\_size_{Pre2007}$	—	0.57	—	—	0.99***	—
	—	(1.62)	—	—	(2.97)	—
$Sub\_size\_sign_{Pre2007}$	—	—	0.67*	—	—	1.18***
	—	—	(1.87)	—	—	(3.32)
$Sub\_sign_{Pre2007}$	—	—	0.84***	—	—	0.21
	—	—	(3.27)	—	—	(1.56)
Adjusted R^2	0.46	0.55	0.62	0.47	0.64	0.67
Forecast RMSE	11.57	10.46	9.65	15.62	12.76	12.09

Table 11: Predicting Crisis Period Government Support With Pre-Crisis $TSIZE$ Loadings: Cross-Section Results

This table shows results from cross-sectional regressions predicting a firm's average crisis-period government support G with subsidies implied by its pre-crisis average $TSIZE$ loadings, where G={$Lfac$, $Tarp$}. $Lfac$ is the Fed's loans via liquidity facilities and $Tarp$ is the Treasury's TARP loans (both in $ billion). For a financial firm i in the largest size quintile, the dependent variable is G_i, the average of $G_{i,t}$ for t in the crisis period (August 2007 to 2013). The main predictor is the implicit subsidy to firm i implied by pre-crisis $TSIZE$ loadings Sub_size, only based on the firm's size decile (equation 10). Alternative implicit subsidy definitions used are Sub_size_sign, based on both firm size and the sign of loadings and Sub_sign, only based on the sign of loadings (equation 12). The control variables are the firm's $\Delta Marketcap$, ΔLev and $\Delta Correlation$, or crisis-period changes in the market cap, leverage, and correlation with the World MSCI stock index. Factor loadings are estimated from a firm-level 60-month rolling regressions using the SIFI1 specification from 2000 to 2006. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. We report robust T-statistics, the log likelihood and the Root Mean Squared Error (RMSE) from forecasting G in-sample. The regressions are estimated with Tobit and uses 142 observations. The sample period is December 2007 to November 2011 for $LiqFac$, and November 2008 to December 2009 for $Tarp$.

	Dependent Variable: $Lfac$			Dependent Variable: $Tarp$		
	Estimate (Z-stat) (1)	Estimate (Z-stat) (2)	Estimate (Z-stat) (3)	Estimate (Z-stat) (1)	Estimate (Z-stat) (2)	Estimate (Z-stat) (3)
$\Delta MarketCap$	-0.03	-0.02	-0.02	-0.00	-0.00	-0.00
	(-1.53)	(-1.61)	(-1.59)	(-0.47)	(-0.33)	(-0.32)
ΔLev	0.36	0.34	0.38	-0.01	-0.01	-0.01
	(0.33)	(0.32)	(0.36)	(-0.25)	(-0.26)	(-0.26)
$\Delta Corr$	-0.42*	-0.38	-0.41*	-0.01**	-0.01**	-0.01**
	(-1.71)	(-1.61)	(-1.69)	(-2.35)	(-2.31)	(-2.34)
$Sub\_size_{Pre2007}$	—	5.99**	—	—	0.30***	—
	—	(2.46)	—	—	(3.22)	—
$Sub\_size\_sign_{Pre2007}$	—	—	6.84***	—	—	0.31***
	—	—	(2.75)	—	—	(3.15)
$Sub\_sign_{Pre2007}$	—	—	1.27	—	—	-0.22
	—	—	(0.20)	—	—	(-1.14)
Log Likelihood	-442.43	-439.27	-438.52	-230.10	-221.17	-221.11
Forecast RMSE	309.52	301.98	300.88	4.22	3.35	3.33

Table 12: Loadings on Complexity Factor for GSIBs and Non-GSIBs

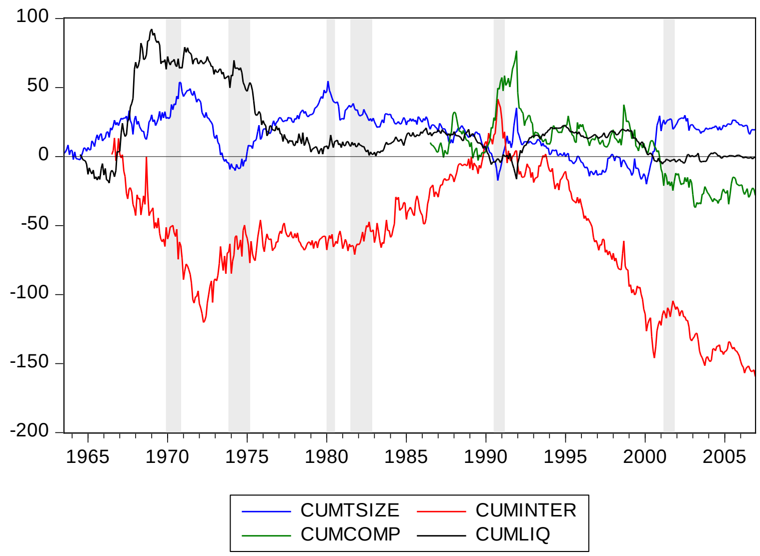
This table shows OLS estimates for loadings on $SIFI$ factors (relating to size $TSIZE$, complexity $COMP$ and interconnectedness IC), estimated using the SIFI4+$COMP$ model, for portfolios sorted by size and book-to-market (BM). A separate portfolio of Globally Systemic Banks (GSIBs) is carved out of the second largest size decile $S5$ and the largest size decile $S6$. S6 and S5 Non-GSIB are the top two size decile portfolios after excluding GSIBs. The remaining size groups are not shown. Also shown are loadings on the leverage LEV and liquidity LIQ factors. For BM groups, reading left to right, columns correspond from the lowest to highest quintiles of the BM distribution. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey West (1987) with a maximum of 3 lags. The sample is from July 1986 to 2006.

	Low	2	3	4	High
Panel A: Loadings on TSIZE Factor					
S5 Non-GSIB	.02	.15***	.14***	.16***	.31***
S6 Non-GSIB	-.06*	-.09**	-.11**	.07	-.24***
GSIB	-.43*	.11	.21	.31***	.30
Panel B: Loadings on Complexity Factor					
S5 Non-GSIB	-.04	.01	-.03	-.02	-.03
S6 Non-GSIB	.02	.03	.05	-.01	-.02
GSIB	.02	-.15*	-.30**	-.09	-.31*
Panel C: Loadings on Interconnectedness Factor					
S5 Non-GSIB	-.03	.08**	.04	.01	-.03
S6 Non-GSIB	.00	.08**	.07*	.10**	-.11
GSIB	.03	.03	-.11	-.23**	-.31**
Panel D: Loadings on Leverage Factor					
S5 Non-GSIB	-.05*	.08*	.08**	.00	-.01
S6 Non-GSIB	.00	.09***	.02	.08	-.10
GSIB	-.02	.70***	.42***	.53***	.82***
Panel E: Loadings on Liquidity Factor					
S5 Non-GSIB	-.04	-.02	-.03	-.06*	-.02
S6 Non-GSIB	-.01	.00	-.03	-.04	.18**
GSIB	-.44***	.15	.00	-.03	.03

Figure 1: SIFI Factor Returns and Business Cycles

This figure shows the cumulated returns on SIFI factors: size $TSIZE$, complexity $COMP$ and interconnectedness IC. Also shown are cumulated returns on the liquidity factor LIQ. The leverage factor is not shown as it is not in returns space. Panel A shows the pre-crisis period (1963-2006) and Panel B shows the crisis period (2007-2013). Shaded areas correspond to NBER-dated recessions.

Panel A: Cumulated SIFI Factor Returns: 1963-2006



Panel B: Cumulated SIFI Factor Returns: 2007-2013

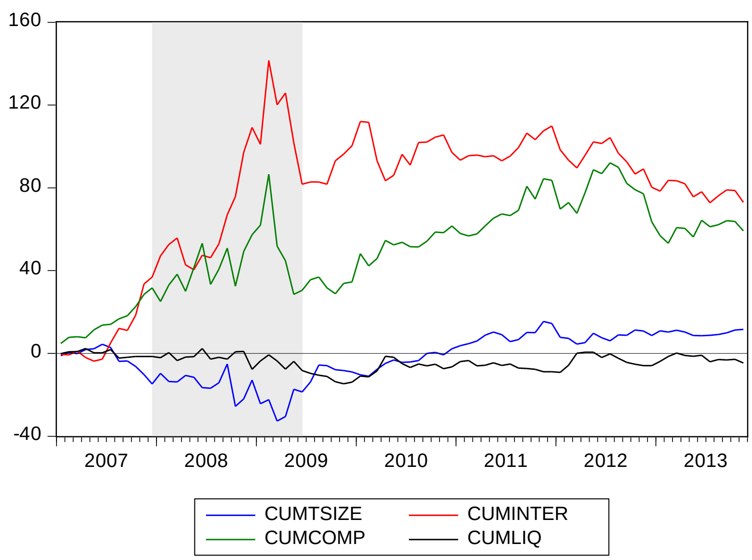


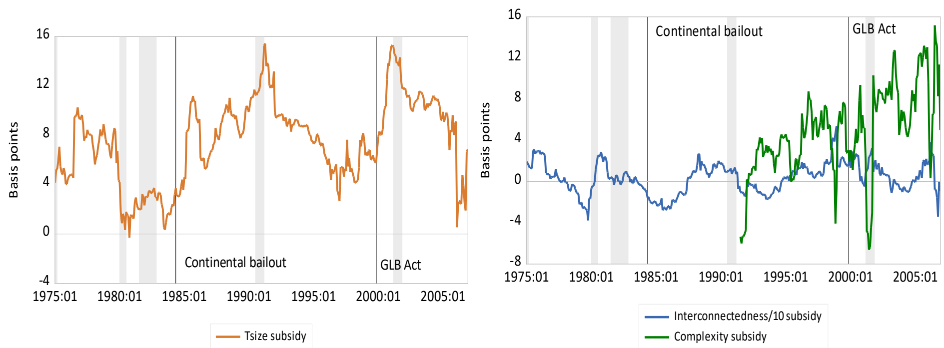
Figure 2: TSIZE Loadings of Firms That Remain in or Move Between Largest and Second Largest Size Deciles

This figure shows histograms of estimates of $TSIZE$ factor loadings for firms that remained in the largest size decile $S6$ and the second-largest size decile S5 (denoted "stay S6" and "stay S5", respectively) and firms that moved between S5 and S6 (denoted "S6 to S5" and "S5 to S6") in consecutive 5-year periods. The size bins are formed every 5 years corresponding to quintiles of the size distribution. The loadings are estimated monthly from 60-month rolling regressions using the SIFI1 specification, then averaged for each size decile, for financial and non-financial firms separately. The sample is from 1963 to 2006.

Figure 3: Implicit Subsidies Implied by $SIFI$ Factor Loadings

The figure shows implicit subsidies implied by SIFI factor loadings for 1975-2006 (Panel A) and 2007-2013 (Panel B) estimated from rolling 60-month regressions using the SIFI4 specification for the size $TSIZE$ (LHS chart) and interconnectedness IC (RHS chart) factors and SIFI4+$COMP$ for the complexity factor (RHS chart). The red vertical lines correspond to the Continental Bailout (May 1984), the Gramm-Leach-Bliley Act (Novermber 1999), the Lehman bankruptcy (September 2008), and the Dodd Frank Act (July 2010). The grey shaded areas are NBER recession periods.

Panel A: Implicit Subsidies Implied by SIFI Loadings: 1975-2006



Panel B: Implicit Subsidies Implied by SIFI Loadings: 2007-2013

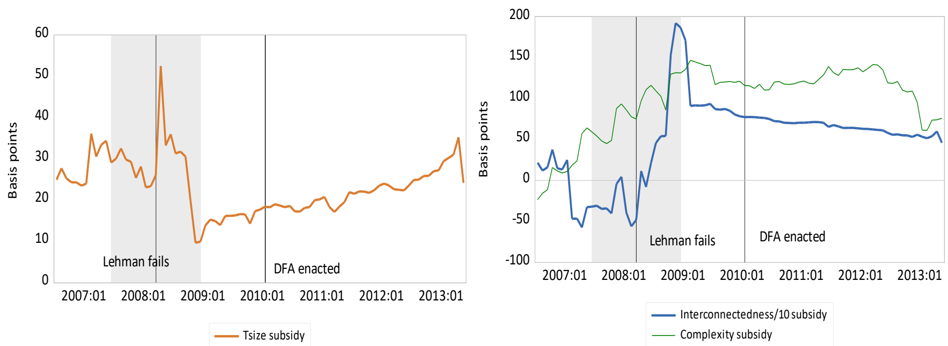


Figure 4: $TSIZE$ Loadings of Banks Around Fitch Support Rating Changes

This figure shows the average $TSIZE$ loading of banks from 6 months before to 6 months after 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 (at t=0). The $TSIZE$ loadings are estimated from 60-month rolling regressions using the SIFI1 specification. 14 banks and 294 bank months are in the sample of rating changes from March 2007 to June 2013.

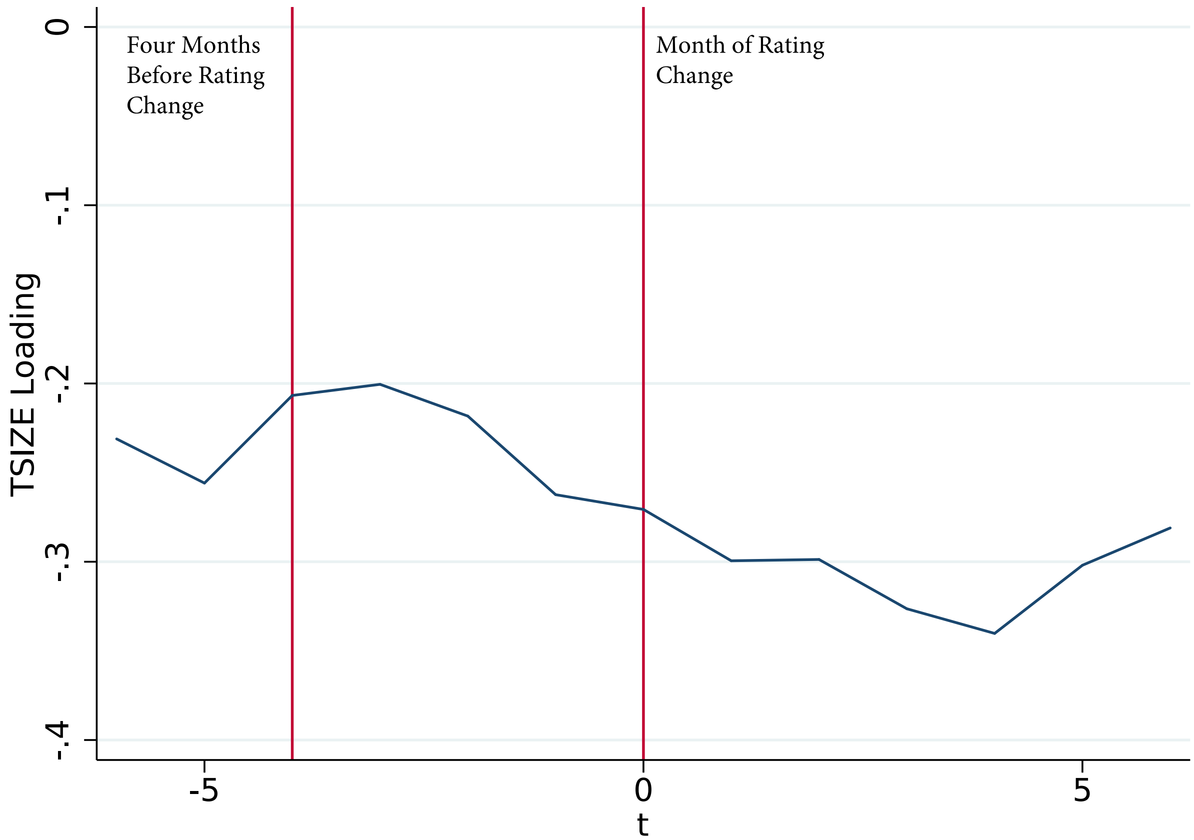
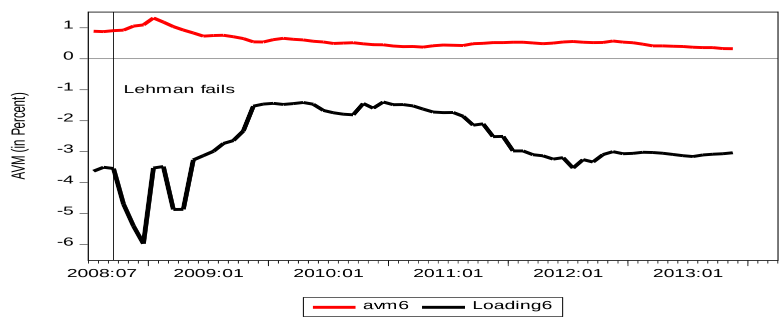


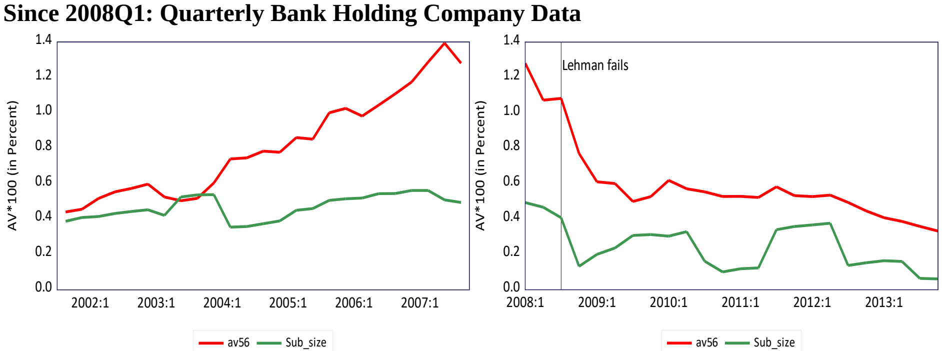
Figure 5: Firesale Risk AV, SRISK and Subsidies Implied by $TSIZE$ Loadings

The figures plot firesale risk AV (i.e. spillover losses as percent of total broker-dealer capital) and $SRISK$ (i.e. the expected capital shortfall in \$ Billion of a firm conditional on a substantial market decline), averaged over firms in the two largest size deciles $S5$ and $S6$. Also shown are implicit subsidies Sub_size implied by $TSIZE$ loadings (equation 4). Panel A shows AVM estimated from monthly Triparty repo data and average $TSIZE$ loadings of firms in $S6$ (denoted $AVM6$ and $Loading6$, respectively). As there are no firms in $S5$, Sub_size is just $Loading6$. The sample is from July 2008 to December 2013. Panel B shows the average AV (multiplied by 100), denoted $AV56$, estimated from quarterly BHC balance sheet data from 2002 to 2013. Panel C shows the average $SRISK$, denoted $SRISK56$, estimated from monthly equity returns from June 2000 to 2013 and Sub_size (multiplied by 30). The Lehman failure occurs in September 2008 (2008 Q3 for quarterly data).

Panel A: AVM and SIFI Loadings of Firms in Largest Size Decile: Monthly Repo Data



Panel B: AV and TSIZE-Implied Subsidies of Firms in Largest Size Quintile Before and Since 2008Q1: Quarterly Bank Holding Company Data



Panel C: SRISK and TSIZE-Implied Subsidies of Firms in Largest Size Quintile Before and Since July 2008: Monthly Equity Returns Data

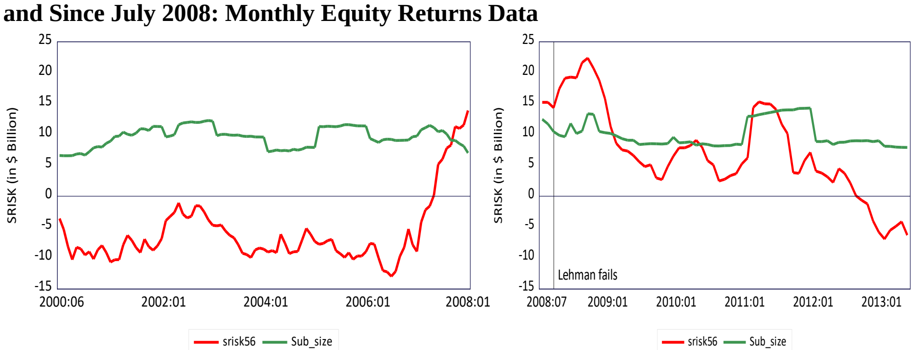
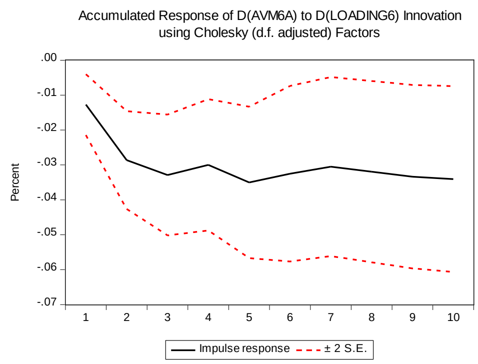
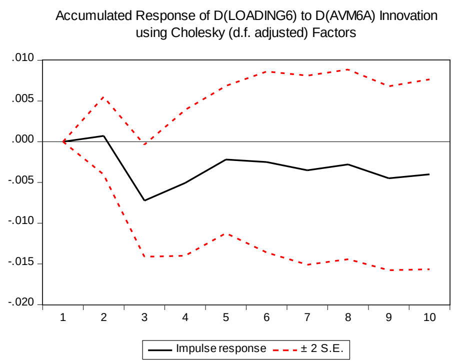


Figure 6: Impulse Responses of Firesale Spillovers AV, SRISK and $TSIZE$ Loadings

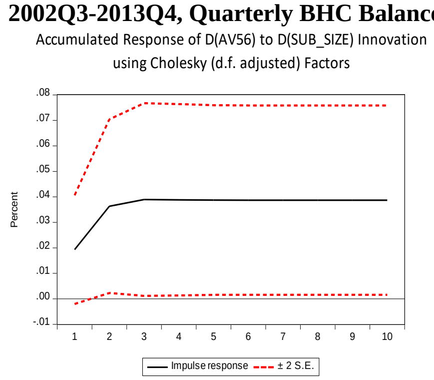
The figures show impulse response functions, along with 2 standard error (S.E.) bands, estimated from a Vector Autoregression (VAR) of the change in the average systemic risk measure $D(Y56)$ and the change in average $TSIZE$-implied subsidies $D(Sub\_size)$ of financial firms in the largest size deciles $S5$ and $S6$. Sub_size is estimated using equation 4. In Panel A, AVM is based on monthly triparty repo data from July 2008 to November 2013. As there are no firms in $S5$, $Y56$ is $AVM6$ or the average AV of firms in $S6$ and Sub_size is $Loading6$, the average $TSIZE$ loadings of firms in $S6$. In Panel B, Y is AV, the firesale spillover based on quarterly BHC balance sheet data from 2002Q1 to 2013. In Panels C, Y is $SRISK$, using data from June 2000 to 2013. Lagged values of the average market capitalization, leverage and correlation of equity returns with the MSCI World stock index of firms in $S5$ and $S6$ are used as exogenous variables in the VAR.

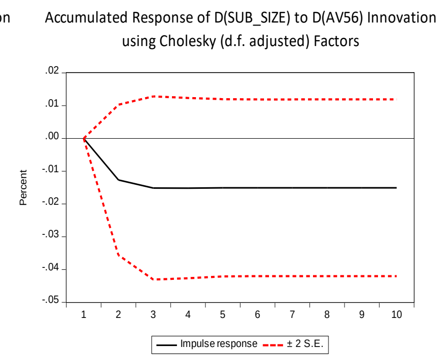
Panel A: TSIZE Loadings and Firesale Risk of Financial Firms in Largest Size Decile: July 2008-November 2013, Monthly Repo Data



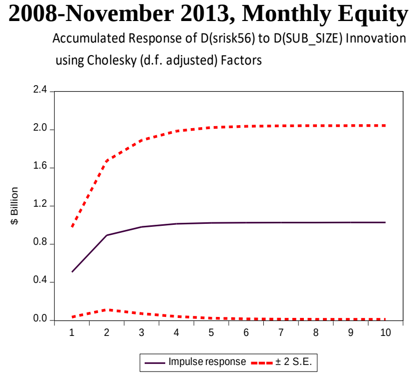


Panel B: TSIZE Subsidies and Firesale Risk of Financial Firms in Largest Size Quintile: 2002Q3-2013Q4, Quarterly BHC Balance Sheet Data





Panel C: TSIZE Subsidies and SRISK of Financial Firms in Largest Size Quintile: July 2008-November 2013, Monthly Equity Returns Data



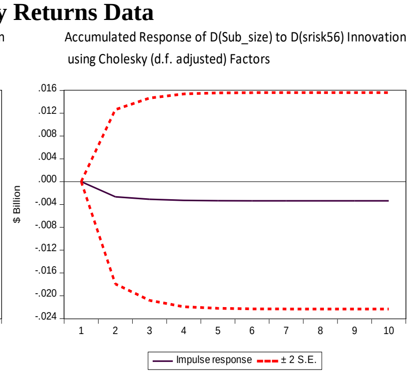
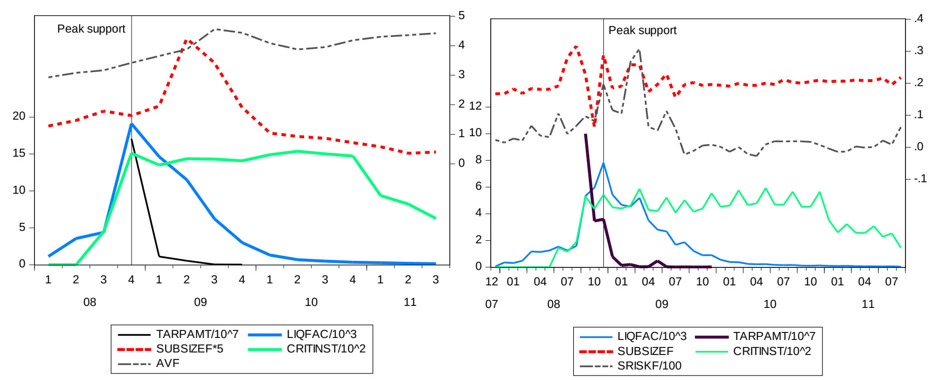


Figure 7: Government Support in Crisis and Implicit Subsidies Predicted with Pre-Crisis $SIFI$ Loadings

The figures show the Fed's crisis-period loans to critical institutions $CritInst$ (in \$100 million) and liquidity facilities $LiqFac$ (in \$ billion), and the Treasury's TARP loans $Tarp$ (in \$10 billion). Panel A shows the out-of-sample forecasts of subsidies $Subsizef$ implied by pre-crisis $TSIZE$ loadings, estimated using equation 8. The forecasts are from a VAR with $TSIZE$ loadings and either AV (LHS chart) or $SRISK$ (RHS chart) estimated on pre-crisis data. Also shown are the forecasts AVF and $SRISKF$ from the same VAR. Panel B shows the out-of-sample forecasts of subsidies from VARs with pre-crisis loadings of $COMP$ or IC and either AV (LHS chart) or $SRISK$ (RHS chart). The pre-crisis period is October 2000 to November 2007 for $SRISK$ and 2002Q3 to 2007Q4 for AV. The prediction period is December 2007 to November 2011 for Fed loans and November 2008 to December 2009 for TARP loans. *Peak support* is December 2008.

Panel A: Subsidies Forecasted by Pre-Crisis TSIZE Loadings, with AV (left) or SRISK (right)



Panel B: Subsidies Forecasted by Pre-Crisis COMP and IC Loadings, with AV (left) or SRISK (right)

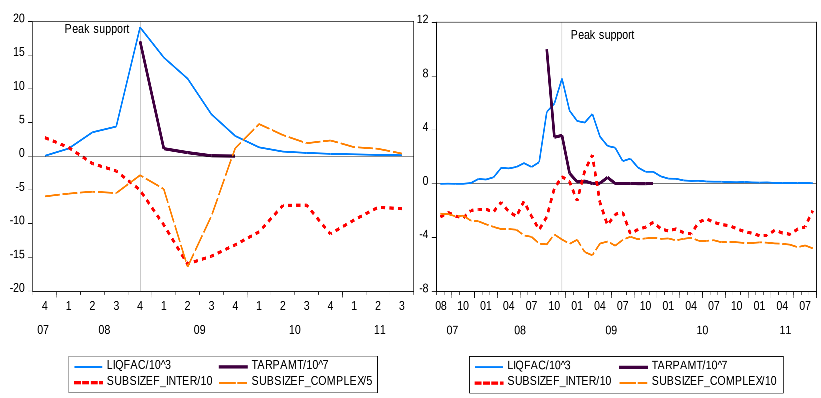
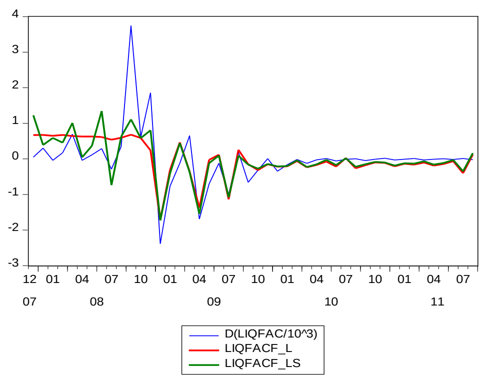
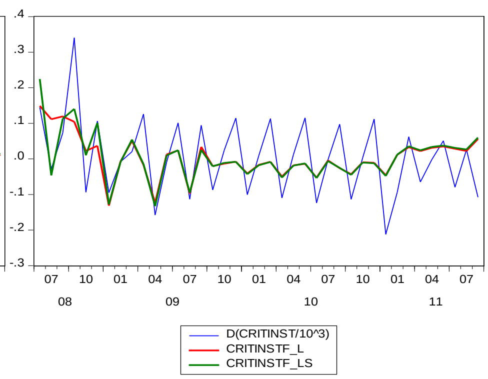


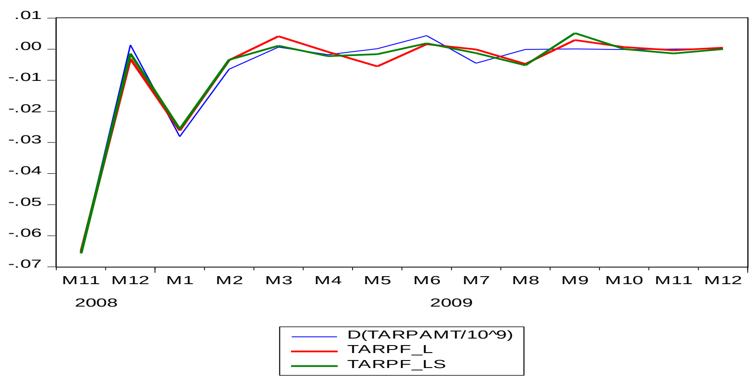
Figure 8: Actual and Predicted Government Support in Crisis: Time-Series Evidence

The figures show actual and fitted changes in the Fed's crisis-period loans to critical institutions $CritInst$ and liquidity facilities $LiqFac$, and in the Treasury's TARP loans $Tarp$. The actual changes (blue lines) are D($CritInst$), D($LiqFac$) and D($Tarp$). The fitted values (red lines) ($Critinf\_l$, $Lfacf\_l$ and $Tarpf\_l$) are from regressions of changes in Fed or Tarp loans on out-of-sample forecasts of subsidies implied by $TSIZE$ loadings. The green lines ($Critinf\_ls$, $Lfacf\_ls$ and $Tarpf\_ls$) are generated by adding the forecast of AV or $SRISK$ to the regression. The forecasts use pre-crisis values of $TSIZE$ loadings and either $SRISK$ (Panel A) or AV (Panel B); see Table 9. The prediction period is December 2007 to November 2011 for $LiqFac$, July 2008 to November 2011 for $CritInst$ and November 2008 to December 2009 for TARP loans.

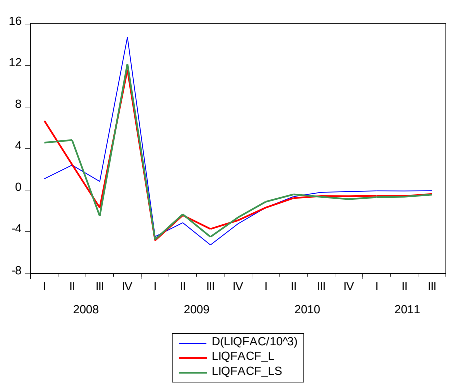
Panel A: Using TSIZE loadings and SRISK







Panel B: Using TSIZE loadings and AV



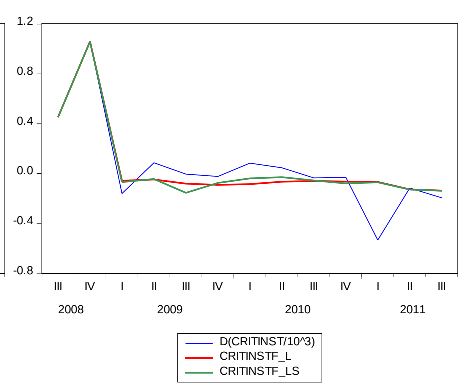
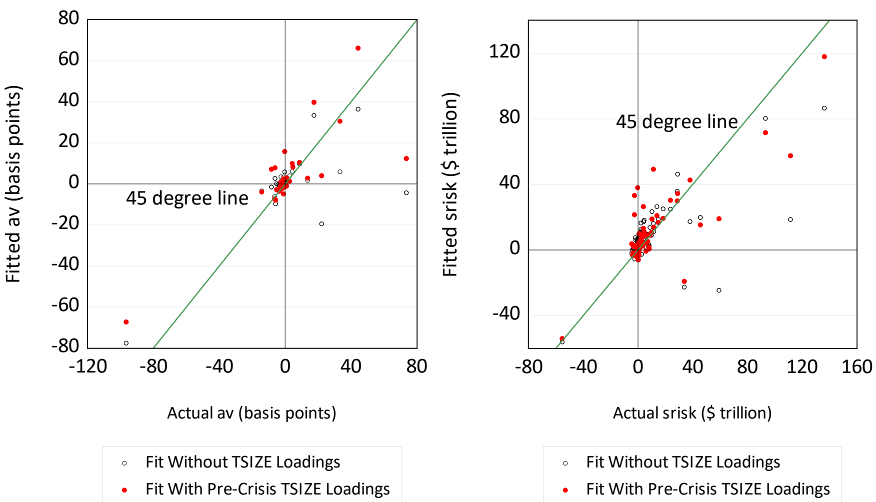


Figure 9: Actual and Predicted Government Support and Systemic Risk in Crisis: Cross-Section Evidence

The figure shows scatter plots of the average actual change in firm's systemic risk measures av and $srisk$ (Panel A) and government support ($lfac$ and $tarp$) during the crisis, against the fitted change obtained from a cross-sectional regression using only crisis-period changes in market cap, leverage and correlation with the World MSCI stock index (black; legend Fit Without $TSIZE$ Loadings) or alternatively, using in addition, pre-crisis average $TSIZE$ loadings (red; legend Fit With Pre-Crisis $TSIZE$ Loadings). av is the firesale risk of bank holding companies and $srisk$ is the expected capital shortage (see Table 10). $lfac$ is the Fed's crisis-period loans via the liquidity facilities and $tarp$ is the Treasury's Tarp loans (see Table 11). The pre-crisis period is 2000 to 2006; the crisis period is August 2007 to November 2013 for systemic risk measures, December 2007 to November 2011 for $lfac$ and November 2008 to December 2009 for $tarp$.

Panel A: Predicting Changes in Firm's Firesale Risk AV and SRISK in Crisis



Panel B: Predicting Firm's Fed Crisis-Period Loans Via Liquidity Facilities and Tarp Loans

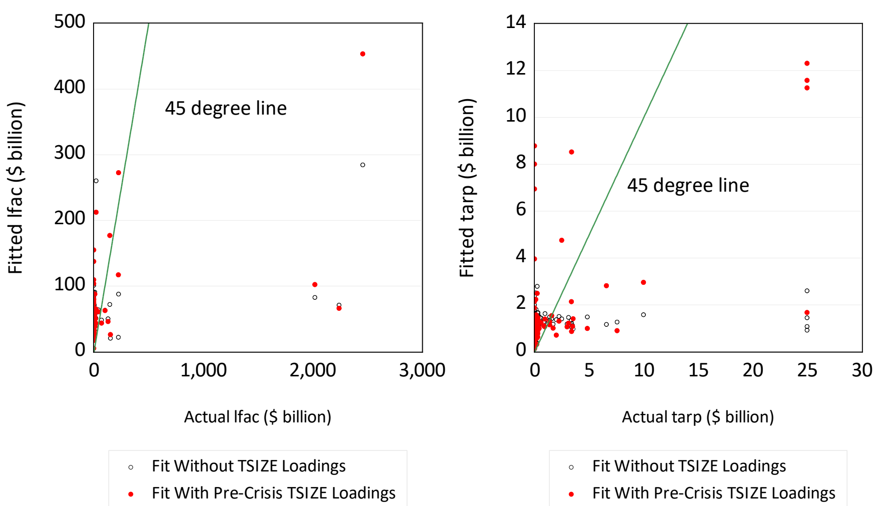


Figure 10: Subsidiaries of GSIB and non-GSIB Bank Holding Companies

This figure shows box-whisker plots of the number of subsidiaries of BHCs, separately for globally systemically important banks (GSIBs) and non-GSIBs in the largest size decile $S6$ and the second highest size decile $S5$ from 1986 to 2014. The box shows the interquartile range (IQR) and the whiskers are adjacent values within 1.5*IQR. The dots are observations exceeding 1.5*IQR.

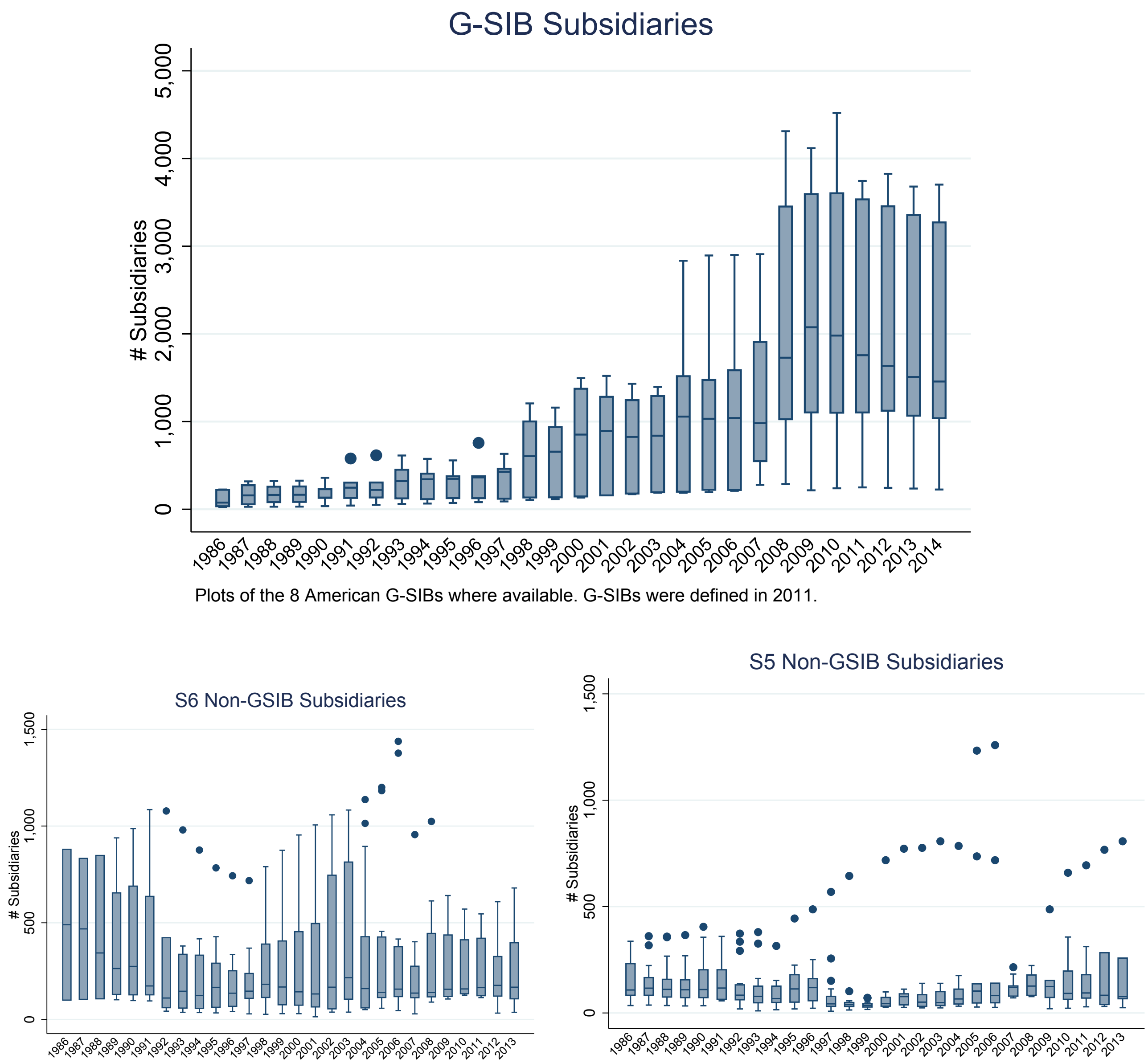
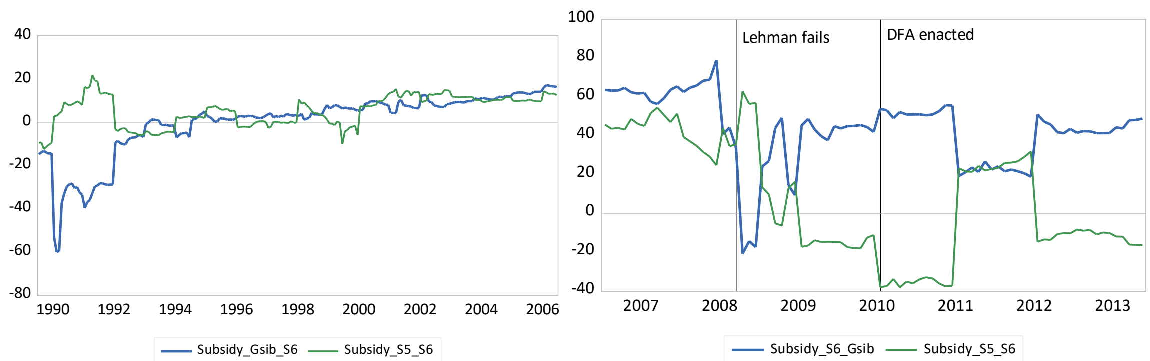


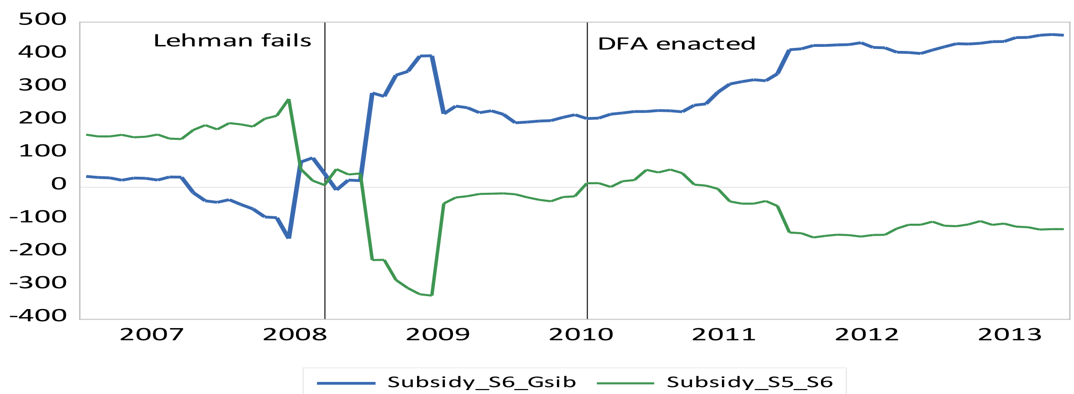
Figure 11: Implicit Subsidies Implied by $TSIZE$, IC and Complexity Factors: Banking Sector

This figure shows implicit subsidies implied by loadings on size $TSIZE$ (Panel A), complexity $COMP$ (Panel B) and interconnectedness IC (Panel C) factors from 60-month rolling window regressions of bank excess returns using the SIFI4+ $COMP$ model. The portfolios are globally systemically important banks (GSIBs) and the two largest size deciles of banks $S5$ and $S6$ excluding GSIBs. The implicit subsidies (in basis points) are *Subsidy-S6-Gsib* (equation 14) and *Subsidy-S5-S6* (equation 4). $COMP$ and IC-implied subsidies are not shown for the pre-crisis period (LHS chart) as both factors had negative average returns in this period. The sample for the RHS chart is 2007-2013.

Panel A: TSIZE Factor: 1990-2006 and 2007-2013



Panel B: COMP Factor: 2007-2013



Panel C: IC Factor: 2007-2013