Size is Not Everything*

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Abstract

Within the largest financial firms, we find that those firms above the size threshold associated with the Systemically Important Financial Institution or SIFI designation, have lower expected returns than firms just below this threshold. This difference in returns is a common risk factor, denoted $SIFI$, that prior to 2007 has significant explanatory power in time series regressions of stock returns for all firms, even after controlling for standard asset pricing factors as well as bank-size, liquidity and leverage factors. The largest firms in the top 10% of market size load negatively on it, implying a "SIFI subsidy," while the remaining firms load positively on it, implying a "SIFI tax." We estimate that the subsidy to be 5.71 million in 2013 dollars per firm per year prior to 2007. After passage of the Dodd-Frank Act, the $SIFI$ loadings decreased in magnitude and significance for all firms. Finally, we show that firms with higher $SIFI$ loadings prior to 2007 had higher systemic risk measures after the fall of Lehman, controlling for size, size risk, leverage and volatility. These results are robust to different TBTF size thresholds and asset pricing models.

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*The views in this paper belong to the authors and do not necessarily reflect those of the Federal Reserve Bank of New York or the Federal Reserve System.

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1 Introduction

Perceived government support for financial firms deemed "too-big-to-fail" (TBTF) does not increase proportionately with size, but rather is viewed as an advantage accruing only to the largest firms (Basset (2014)). Consistent with this notion, the Comptroller of Currency stated in September 1984 that the eleven largest banks were TBTF. More recently, the Dodd Frank Act (DFA) identifies an asset threshold of $50 billion of the book value of assets for 2010, above which a firm is designated as a systemically important financial institution (SIFI).[1] Empirical evidence supports the notion of a size threshold effect on firm values and borrowing costs. Kane (2000) finds that, while acquirer stock values generally decline in large bank mergers, they increase if the merger puts the acquirer's assets above a size threshold. Brewer III and Jagtiani (2013) find at least $15 billion in added premiums for bank mergers that brought the combined firm to over $100 billion in assets. Moreover, the largest financial firms are estimated to have a small funding advantage relative to other large firms (Acharya, Anginer and Warburton (2013), Basset (2014) and Santos (2014)). An implication is that risk-adjusted expected returns of the largest financial firms should be lower relative to large firms below the threshold since the government is anticipated to absorb some of their tail risk.[2] However, the asset pricing implication of this "size threshold" effect is yet to be studied. For example, Gandhi and Lustig (2014) find a size effect (small-minus-big) in bank stocks but do not explore the threshold effect.

In this paper, we construct a SIFI factor (henceforth $SIFI$) for financial firms that is orthogonal to the SMB size factor (Fama and French (1993)) and the bank size factor of Gandhi and Lustig (2014) (henceforth GL), and examine its asset pricing implications. To obtain an asset threshold, we start with the DFA cutoff of $50 billion of the book value of assets for 2010, which equals the 92nd percentile of the distribution of book values. Then, we define our factor as the difference between the returns of financial firms just below the 92nd percentile of the market value of equity and those above this cutoff, while controlling

[1] The DFA was signed into federal law on July 21, 2010 to, among other things, end TBTF and to protect American taxpayers by ending bailouts (https://www.govtrack.us/congress/bills/111/hr4173/text). The DFA set the SIFI threshold at $50 billion for bank holding companies. Subsequently, in 2012, the Financial Stability Oversight Council (FSOC) approved the extension of the $50 billion threshold to non-bank financial firms as well (http://www.treasury.gov/initiatives/fsoc/Documents/Nonbank%20Designations%20-%20Final%20Rule%20and%20Guidance.pdf).

[2] In addition to this ex-ante effect, there may be uncertainty as to shareholder recovery when large financial firms are resolved during a crisis.

for book-to-market ratios.[3] Since both the long and short portfolios are large firms (i.e. in the top 16% of firms by size) and, further, we drop these top 16% of firms when constructing SMB, our TBTF factor is, by construction, orthogonal to SMB. Indeed, the correlation between the two is just -0.04 in our sample (1963 to 2013); moreover, the correlation between $SIFI$ and GL is negative (-0.08 in our sample).

We find that, on average, firm returns just below the SIFI cutoff exceed the returns of firms above the cutoff by 0.62% per annum in our sample, with the difference increasing during recessions and decreasing during expansions. We further find that, for the period before 2007, $SIFI$ is broadly priced into stock returns, even after controlling for the six Fama-French-Carhart factors and GL. In particular, before the bankruptcy of Lehman Brothers, 26 of the 30 portfolios sorted on size and book-to-market load significantly on $SIFI$. The largest firms load negatively on $SIFI$, representing a "SIFI subsidy," amounting to 2 basis points per year or 5.71 million per firm per year in 2013 dollars. Smaller firms generally load positively on the factor, representing a "SIFI tax." These results are robust to additional controls for bank size risk (Gandhi and Lustig (2014)), liquidity risk and leverage risk (Adrian and Muir (2014)), and different choices of the size threshold.

We examine the change in the loadings on $SIFI$ around events that increased or decreased TBTF risk: the bailout of Continental Illinois in May 1984, the bankruptcy of Lehman Brothers in September 2008 and the implementation of the DFA. To the extent that such risk is undiversifiable, the risk-premium associated with $SIFI$ may change. For example, 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. We find that the SIFI subsidy and tax increased following the bailout of Continental; in particular, the $SIFI$ loadings on three of the five largest firm size portfolios were insignificant prior to Continental and became negative and significant aferwards. Conversely, after the failure of Lehman or the passage of the DFA, the SIFI subsidy and tax essentially disappeared; for example, the aggregate SIFI subsidy dropped from 1.48 billion before 2007 to 0.37 billion per year in 2013 dollars after the passage of the DFA. Next, we investigate whether $SIFI$ loadings predict changes in systemic risk. We find that firms with higher $SIFI$ loadings before 2007, and in particular firms with negative $SIFI$ loadings, had higher measures of systemic risk after the failure of Lehman Brothers, even after controlling for their size, size risk, leverage and volatility prior to 2007. These results link $SIFI$ loadings

[3] In 2010, the firm closest to the 92nd percentile by book value had equity market value in the 90th percentile. Our results are robust to a range of alternate cutoff values, as described in Section 6.

to changes in systemic risk.

The rest of the paper is organized as follows. Section 2 describes how this work relates to the literature. Section 3 describes the data and methodology used in the paper. Section 4 presents results for time series regressions of portfolio returns on $SIFI$ for all firms and for different financial sectors. Section 5 explores relate the $SIFI$ loadings to events that increased or decreased TBTF risk and to future changes in systemic risk measures. Section 6 discusses additional investigations and robustness checks, and section 7 concludes.

2 Literature

The literature indicates a size threshold effect in the perceived benefits of government guarantees to TBTF firms. Kane (2000) finds that, while acquirer stock values generally decline in large bank mergers, they increase if the merger puts the acquirer's assets above a size threshold. Brewer III and Jagtiani (2013) find at least $15 billion in added premiums for bank mergers that brought the combined firm to over $100 billion in assets.

A threshold effect is also found to exist in the funding cost advantages for large financial firms, relative to smaller firms, a portion of which might be related to a TBTF subsidy. In particular, very large financial firms are estimated to have a funding cost advantage relative to other large firms, although the magnitude is smaller than when comparing large firms to small firms (or the entire industry). For example, Acharya et al. (2013) estimate a small advantage in bond transactions for the top decile of financial firms compared to firms in the 30th to 60th percentile. 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 nonfinancial corporations. In contrast, Ahmed, Anderson and Zarutskie (2014) find that while CDS spreads are smaller for very large compared to "less large" firms, financial firms do not enjoy a bigger advantage compared to non-financial firms.

The literature generally finds a reduction in large financial firm cost advantage in recent periods and particularly after passage of the DFA or the failure of Lehman Brothers. 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. Barth and Schnabel (2013) find a negative relationship between a bank's systemic risk proxy and its CDS spread, which disappears after the fall of Lehman. Acharya et al. (2013) find that funding costs for the largest financial firms was highest at the peak of the recent financial crisis but declined in 2010 and 2011. GAO (2014) and IMF (2014) also show that funding advantages estimated prior to the recent financial crisis have likely reversed in recent years, although the latter find that recent levels continue to exceed pre-crisis levels.

In contrast to the threshold effect on returns and funding costs, other papers focus on the negative (often taken to be linear) relationship between firm size and returns (see, for example, Banz (1981) and Fama and French (1992)) or borrowing costs, as measured by bond and CDS spreads. Thus, O'Hara and Shaw (1990) find that, within the 11 banks deemed by the Comptroller of Currency to be TBTF, size was positively correlated with abnormal returns on the event day, while for a control group of 53 banks, size was negatively correlated with returns. However, Zhou (2010) and Barth and Schnabel (2013) argue that size is an imperfect measure of systemic risk.

Gandhi and Lustig (2014) investigate a size affect for commercial banks that is orthogonal to SMB. They find that, after controlling for standard risk factors, the largest commercial banks have lower returns than small and medium commercial banks. The factor GL, obtained from the risk adjusted commercial bank returns, is argued to reflect banking sector tail risk. GL is a size factor constructed from the returns of all commercial banks, whereas our SIFI factor is constructed only from the very largest financial firms, and compares the largest firms to the next-to-largest financial firms. Other differences with our analysis include: the method of construction (GL is a statistical factor based on principal components of bank returns), the set of controls (we include the Momentum factor of Carhart (1997)), and the sample (ours includes post crisis which allows us to evaluate the effect of Lehman and DFA).

3 Factor and Portfolio Constructions

This section describes the methodology for constructing our $SIFI$ factor, the GL factor and the test portfolios. We mostly hew closely to the standard Fama-French methodology (Fama and French (1993)), with some exceptions as outlined below.

To determine the asset size threshold for constructing the $SIFI$ factor, it is natural to start with the DFA threshold of \$50 billion of the total consolidated assets above which financial firms are deemed to be SIFIs.[4] For historical analysis, we map the dollar cutoff to a percentile number. We examine the distribution of the book value of financial firm assets in

[4]However, nonbank financial firms above this threshold may or may not have a SIFI designation.

the Compustat North America Database for 2010, and find that the DFA asset size threshold corresponds to the 92nd percentile of the distribution of book value of assets.[5] In keeping with the asset pricing literature, we use market capitalization as our measure of size rather than book assets and, accordingly, consider the largest financial firms to be those in the top 8 % by size each year. Section 6 describes how different choices of cutoffs affects our results.

For constructing the $SIFI$ factor, we consider only the top 16% of financial firms by market size (i.e. the 8% of firms above the SIFI threshold and the 8% of firms just below it). To identify these firms, we filter the universe of firms in Compustat to include only those with monthly returns and stock data in CRSP,[6] and considered to be finance by CRSP.[7] For firms in this sample listed on the NYSE, we calculate in June of every year, the 30th and 70th percentiles of firms by Book to Market (BM), and the 84th and 92nd percentiles of firms by size. We only keep observations with positive size and BM before taking the percentiles. Based on these percentiles, we assign firms in our sample to one of six portfolios for the next year: three BM bins and two size bins. We calculate size-weighted returns for each portfolio in each month, and define $SIFI$ as the average returns of the three BM bins for the next-to-largest firms minus the average returns of the three BM bins for the largest firms.

Since we want to identify SIFI effects separately from the effects of size, we create a version of SMB (Fama and French (1993)) that we denote SMB' that is orthogonal to $SIFI$ by construction.[8] To create SMB', we apply the Fama-French methodology to firms below the 84th percentile. In other words, small firms are those under the 42nd percentile while large firms are those between the 42nd and 84th percentiles. Creating six size-by-BM groups, as above, SMB' is the average returns of the three small size bins minus the average returns of the three large size bins. Over the full sample, SMB' has a correlation of 0.86 with SMB, and a correlation of just -.04 with $SIFI$. Data for the SMB, book-to-market (HML), Market minus risk free rate ($Mktrf$), and momentum (MOM) factors are from Kenneth French's website.[9] Alternate specifications use the excess returns on an index of corporate

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

[6] Our CRSP sample includes only observations with share code of 10 or 11 (common stocks).

[7] We choose the CRSP rather than the Compustat classification because the latter has a large proportion of missing values in the period before 1984, whereas the CRSP classifications identify sufficiently many financial firms to construct our factor starting in 1963. To the best of our knowledge, discrepancies between CRSP and Compustat industry classifications are relatively rare for broad categorizations.

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

[9] 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.

bonds ($CORP$) and the excess returns on an index of 10 year USA Government bonds (GOV) as controls. We obtain these data from Global Financial Data.[10]

To construct GL, we need the portfolio returns and the weights applied to these returns. To replicate the portfolios, we follow Gandhi and Lustig (2014) and start with all firms in CRSP with SIC codes that begin with 60, value weighting returns for firms with more than one common stock issue, dropping non-US firms and suspended, inactive, or delisted stocks.[11] In January of each year, we construct ten size sorted portfolios based on deciles of market capitalization in January. We then calculate value weighted returns for each portfolio, using the size in January for value weighting in each subsequent month of the year. Finally, we apply the weights reported in Gandhi and Lustig (2014) to the value weighted returns of each portfolio to replicate GL.

The liquidity factor is constructed by estimating residuals from an AR(5) model for the Amihud ratio and then taking the spread between the average residuals of the top 8% of stocks relative to the next 8% of stocks. A similar procedure is followed for the turnover liquidity measure.

Finally, we construct 30 portfolios whose size-weighted returns we use as dependent variables in regressions. We follow the same methodology as above using the 20th, 40th, 60th, 80th and 90th percentiles of size to make six size groups; the additional large size group contain the firms expected to benefit from the $SIFI$ perception. We also construct five BM groups, following Fama and French (1993). The 30 portfolios are obtained from taking the intersection of these size and BM partitions. Within each portfolio we calculate a size-weighted return for each month, then calculate an excess return by subtracting the risk free rate.[12]

For sector-level analysis, we create test portfolios using only non-finance firms, only finance firms or firms in particular financial sectors such as banking. As before, we define a firm to be financial if SIC or NAICS consider it to be finance. To obtain disjoint partitions, we define nonfinancial firms to be those that neither SIC nor NAICS consider to be finance. The size and BM percentiles are calculated using these restricted samples. We define banks to be firms with SIC codes starting in 60, 61, or 62, or with NAICS codes beginning with 522 or 523. We define nonbank financial firms as those which SIC or NAICS categorize

[10] In the Global Financial Database, $CORP$ and GOV are called the Dow Jones Corporate Bond Return Index and the USA 10-year Government Bond Total Return Index, respectively.

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

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

as finance, but which neither SIC nor NAICS categorize as banks. We define insurance companies following Antill, Hou and Sarkar (2014), as firms whose SIC codes begin with 63 or 64, or whose NAICS codes begin in 524. For each of these subsamples, we construct 30 BM and size sorted portfolios.

4 Results

This section presents results on the explanatory power of $SIFI$ in the time series of stock returns. Section 4.1 provides descriptive statistics regarding the properties of the $SIFI$ factor. Section 4.2 presents our results from time series regressions of portfolio returns on the $SIFI$ factor, after controlling for bank specific size risk, liquidity risk and leverage risk. Section 4.3 examines which financial sectors have greater exposure to $SIFI$ risk.

4.1 Properties of $SIFI$ Factor

Panel A of Table 1 shows that returns on the $SIFI$ factor is 0.62% per year during the full sample, indicating the additional risk compensation for firms in the 8% to 16% of the size distribution as compared to the largest 8% of firms in the economy. Returns are negatively skewed, and Panel B of the table indicates that this is an outcome of business cycle variations. Although returns vary between different episodes of recessions and expansions, the cumulated return over all recessions is almost 9% while the cumulated returns over all expansions is -16%. Since there are many more months of expansions than recessions, we also calculate the returns per month of recession and expansion. The return per month of recession is 0.10% whereas the return per month of expansion -0.04%. This result suggests that $SIFI$ risk may not be diversifiable.

Table 2 investigates whether return differences in the largest and next-to-largest financial stocks reflect liquidity and funding cost differences. Panel A of the table reports three measures of liquidity: the Amihud ratio (the absolute value of monthly returns divided by the monthly volume, scaled by 10^6 (Amihud and Mendelson (1986)), turnover (the volume of shares traded divided by the number of shares outstanding each month) and the effective spread (the absolute value of the difference between the closing price and the quote midpoint, divided by the quote mid point). We find that the top 8% of stocks are more liquid than stocks in the next 8% size bin, based on the Amihud and turnover measues, and this difference is statistically significant (p-value=0, per the last column of the table). The top 8% of stocks is also more liquid based on effective spreads but the difference is not statistically significant.

To investigate funding costs, we consider the spread on corporate bond issues in Mergent's Fixed Income Securities Database (FISD), as in Santos (2014). The bond issue spread (in basis points) is the bond yield minus the yield on a Treasury bond of the same maturity. We drop bonds that are callable, convertible, or puttable, as well as bonds that have equity warrants or variable coupons. We compare corporate bonds issued by financial firms that are always in the top 8% to those issued by financial firms that are always in the 8-16% size bin. Panel B of Table 2 reports the results. The bond spread is lower for the top 8% of financial firms than for financial firms in the 8-16% bin, and this is statistically significant. Specifically, it is about 29 basis points for the former and about 46 basis points for the latter, a difference of 17 basis points which is larger than the difference in spreads between all bonds and bonds in the 8-16% size bin. Thus, there appears to be a threshold effect in funding costs too.

In summary, we find that that the largest 8% of financial firms have lower expected returns, higher liquidity and lower funding costs compared to the next-to-largest firms in the 8-16% size bin. Thus, even amongst large firms, the largest firms appear to be less risky. The countercyclical variation in the relative returns of the largest firms suggests that some of this risk may not be fully diversifiable.

4.2 Loadings on $SIFI$ Factor

To isolate the effect of SIFI risk, we control for standard risk factors that have been shown to explain variations in stock returns. Specifically, we add our factor to the five-factor model of Fama and French (1993) plus the Carhart momentum factor (Carhart (1997)). We thus estimate the following regression:

$$R_t^i - R_t^f = \alpha + \beta X_t + \gamma SIFI_t + \epsilon_t \tag{1}$$

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

$$X_t = [SMB_t' \;\; HML_t \;\; Mktrf_t \;\; CORP_t \;\; GOV_t \;\; MOM_t]' \tag{2}$$

is the vector of standard risk factors. We estimate these regressions by OLS for each of the 30 size and book-to-market sorted portfolios (hereafter referred to as the test portfolios) separately over the sample 1963 to 2006. Our initial tests exclude the recent financial crisis but we show crisis-period results in later sections. We adjust our standard errors for heteroskedasticity and autocorrelation using Newey-West standard errors (Newey and West (1987)) with a maximum of three lags.[13]

We present the results of estimating (1) in Panel A of Table 3. Each row shows a successively larger size bin reading from top to bottom, while each column shows a higher BM bin reading from left to right. Excepting the largest size portfolio *Largest*, we observe that with few exceptions the loadings are positive and highly statistically significant, indicating that smaller firm returns contained an additional risk-premia due to $SIFI$ prior to 2007. Turning now to the largest portfolio, we find that the coefficients are mostly negative, and statistically significant for three of five portfolios. In other words, the largest firms obtained a $SIFI$ subsidy before 2007 in that their returns were lower when exposed to $SIFI$ risk. Strikingly, the sign of the $SIFI$ loadings abruptly changes from positive to negative when going from size bin five to six; for example, for BM bin three, the estimates change from 0.11 to -0.12 and both are significant. Further, there is no linear relationship between the magnitude of $SIFI$ exposure and size or BM, indicating that $SIFI$ risk is borne similarly by firms below the largest 10 percentile in size. These results clearly bring out the "threshold" nature of $SIFI$ risk.

The $SIFI$ factor may be picking up effects unrelated to the size threshold, for example size effects specific to banks, liquidity and leverage. Accordingly, we add the factor Y to the times series regressions to test whether $SIFI$ retains its explanatory power. Thus, for each of the 30 test portfolios, we estimate:

$$R_t^i - R_t^f = \alpha + \beta X_t + \delta Y_t + \gamma SIFI_t + \epsilon_t \tag{3}$$

where $Y = GL$, or LIQ or LEV, GL is the bank-size factor (Gandhi and Lustig (2014)), LIQ is a liquidity factor based on innovations in the Amihud ratio, and LEV is a financial intermediary leverage factor (Adrian and Muir (2014)).

The coefficients on $SIFI$ after adding GL to the regression are reported in Panel B of Table 3. These regressions start in 1969 since the GL factor cannot be reliably constructed before then. Comparing Panels A and B of Table 3, the addition of GL does not affect the

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

magnitude or significance of $SIFI$ in the time series regressions. Indeed, the coefficients of $SIFI$ are virtually indistinguishable when including or excluding the GL factor. Given the low correlation of $-.08$ between $SIFI$ and GL, this is not surprising. The result shows that the threshold effect on financial firm returns is orthogonal to existing size effects relating to firms in general (i.e. SMB) or banks (i.e. GL).

The $SIFI$ factor may also be incorporating differences in liquidity risk (see Table 2). In Panel C of the table, we add a liquidity factor based on innovations in the Amihud ratio and find that $SIFI$ remains significant with similar magnitude and significance.[14] The liquidity factors themselves are intermittently significant with inconsistent signs on the coefficients.

We next estimate our regressions after adding the leverage factor of Adrian and Muir (2014). This factor represents shocks to the leverage of securities broker-dealers and, intuitively, indicates states of the world associated with deteriorating funding conditions. Since funding costs are shown to be lower for the largest financial firms, the latter may have lower exposure to the leverage factor. Our $SIFI$ factor may be potentially incorporating some of these leverage and funding effects. The results are in Panel D of the table and indicate that the loadings on $SIFI$ are unaffected by the leverage factor.

Table 4 reports $SIFI$ tax and subsidies for 1963 to 2006. In Panel A of Table 4, the implied $SIFI$ discount or premium charged by shareholders is given by the loadings on $SIFI$ times the average return of the $SIFI$ factor. We find that firms in all portfolios except the largest suffer a $SIFI$ premium of up to 0.06% per annum and there is little variation in the $SIFI$ tax within these firms. In contrast, the largest firms in four of five portfolios receive a $SIFI$ discount of between 0.01% per annum and 0.05% per annum. Averaging across BM bins, the $SIFI$ tax is 0.04% per annum for firms in size bin five while the $SIFI$ subsidy is 0.02% per annum for firms in the largest size bin. Panel B of Table 4 shows the per firm dollar value of the $SIFI$ tax or subsidy, obtained by multiplying the numbers in Panel A by the average market capitalization of firms in each portfolio. Averaging across BM bins, the $SIFI$ tax is 2.36 million per year per firm for firms in size bin five while the $SIFI$ subsidy is 5.71 million per year per firm for firms in the largest size bin. Summarizing, the largest firms get a $SIFI$ subsidy whereas the next-to-largest firms pay a $SIFI$ tax, and this discontinuity speaks to the economic significance of the threshold effect.

[14] We have also constructed a liquidity factor based on turnover with the same results.

4.3 SIFI Risk Exposure by Financial Sectors

Having shown that all firms in the economy are exposed to $SIFI$ risk, we turn to estimates for financial firms in general, and for banks, non-bank financial firms and insurance companies in particular. We construct test portfolios of these firms and estimate regression (1) for these portfolios, and report the results in Panels A-D of Table 5. In the early part of the sample period, there are some years where there are insufficient financial firms to construct all 30 of the test portfolios, because the intersection of one of the size bins with one of the BM bins is empty. To estimate Newey West standard errors in the presence of these missing observations, we use the equal spacing estimator of Datta and Du (2012).

Panel A of 5 shows estimates of $SIFI$ loadings for financial firms. For financial firms in size bins four and below, the results are similar to those for all firms, although some portfolio loadings lose significance. However, financial firms in size bins five and six have larger exposures (in absolute value) to $SIFI$ at similar significance levels as the portfolio of all firms. As before, large financial firms in size bin five have positive exposures to $SIFI$ risk while the largest financial firms have negative exposures. Therefore, we find strong evidence that the largest financial firms receive significant $SIFI$ subsidies whereas smaller financial firms pay significant $SIFI$ taxes.

The remaining panels of Table 5 shows the exposure to $SIFI$ risk of banks (Panel B), non-bank financials (Panel C) and insurance companies (Panel D). Examining the results in Panel B, we find weaker evidence that smaller banks pay the $SIFI$ tax as, although the loadings are mostly positive, they are significant in just six of 25 smaller bank portfolios. However, loadings for the largest banks are mostly negative and significant, showing that they are beneficiaries of $SIFI$ subidies. The results in Panel C shows significant $SIFI$ loadings for nonbank financials in all size bins. Notable are the large and positive loadings for non-financial firms in size bin five and the large and negative loadings for the biggest non-financial firms in size bin six. Smaller insurance firms appear to pay significant $SIFI$ tax but, different from other industries, the largest insurance firms do not generally receive $SIFI$ subsidies (Panel D).

In summary, we find that different financial sectors have different exposures to $SIFI$ risk. In particular, while the largest banks and non-bank financial companies enjoy significant $SIFI$ subsidies, this is not the case for the largest insurance firms. In fact, three out of the five largest insurance company portfolios pay SIFI taxes. Billio, Getmansky, Lo and Pelizzon (2012) find that shocks to the financial sector permeate to the insurance industry, though our result is novel in that we find the SIFI effect involves an effective tax for smaller insurance firms without conferring subsidies to the largest insurance firms.

5 $SIFI$ Risk and Systemic Risk

"CIT Group Inc. agreed to buy OneWest Bank NA's parent company for \$3.4 billion in the largest full-bank acquisition announced since 2012. CIT shares rose 11% in afternoon trading as investors cheered the cash-and-stock purchase, which ... will bump CITs assets up to \$67 billion, making the bank large enough to be considered "systemically important" by regulators ... CIT Chief Executive John Thain recently told investors he was looking for a significant deal so that his firm could jump comfortably over the \$50 billion asset level rather than edge over it. That is because the avalanche of regulations that comes with topping \$50 billion isn't worth it without a significantly bigger earnings engine. "If we had grown to just \$52 billion we would be in the worst spot," Mr. Thain said in an interview on Tuesday"

Wall Street Journal, July 22 2014[15]

We have shown the statistical and economic significance of the asset size threshold effect. In this section, we examine the relation of $SIFI$ risk to systemic risk. First, we examine changes in the loadings on our $SIFI$ factor to events that are considered to have increased or decreased TBTF risk in the economy. For example, as the quote regarding CTI indicates, there is an asset threshold above which firms are subject to additional regulatory costs following the DFA of 2010. The quote further suggests that these costs may create an incentive for firms to be large enough to offset these costs; alternatively, other firms may decide to remain below the DFA asset size threshold. Therefore, the expected net benefit of being above the DFA threshold may change following 2010, in turn changing our estimates of the $SIFI$ tax. Second, we investigate whether SIFI loadings predict systemic risk.

5.1 SIFI Loadings Around TBTF Events

We consider three TBTF events: the bailout of Continental Illinois, the failure of Lehman Brothers and the passage of the DFA. The bailout of Continental Illinois is often cited as the

[15] http://online.wsj.com/articles/cit-group-to-buy-onewest-profit-tops-estimates-1406025881

start of TBTF and this event may be expected to have increased the $SIFI$ tax and subsidy. Conversely, as the government allowed Lehman to fail, this event may be expected to have decreased the $SIFI$ tax and subsidy.

To investigate the sensitivity of $SIFI$ to the first two events, we estimate equation (1) for three separate sample periods: before the Continental bailout (1963 to May 1984), after the Continental bailout and before the collapse of Lehman (May 1984 to September 2008), and after the collapse of Lehman (September 2008 through 2013). Panel A of table 6 shows the loadings on $SIFI$ in the period before Continental, Panel B shows results for the post-Continental pre Lehman period, and Panel C shows results for the post-Lehman period. Comparing results in Panel A and Panel B, we find that with few exceptions (mostly in the smallest BM bin), the loadings increase in magnitude and significance in the period after Continental. The majority of the coefficients in panel A are statistically insignificant, and with one exception never exceed 0.1 whereas the vast majority of coefficients in Panel B are significant, and ignoring the lowest BM bin, are generally above 0.1. We confirm the statistical significance of these changes by estimating (1) over the entire pre-Lehman period, and interacting the factors with a dummy variable equal to one in the post-Contiental period.

Comparing results in Panel B and Panel C, we find that there are virtually no statistically significant loadings in the post-Lehman period and, of the few that are statistically significant, there are just as many significant negative coefficients as positive coefficients. Thus we find that the explanatory power of $SIFI$ is almost entirely in the period after Continental, and virtually disappears after the collapse of Lehman. This result strongly suggests that $SIFI$ is related to TBTF risk.

Next, we examine how the sensitivity of firms to SIFI risk changed after the passage of the DFA. The DFA is intended to prevent future government bailouts by imposing additional regulatory and supervisory requirements that could potentially mitigate the systemic risk created by TBTF firms and reduce their funding advantage. We estimate regression (1) for the period after Continental but before DFA (June 1984-June 2010) and the period afterwards (August 2010 - 2013) separately. The results are presented in Table 7, with the pre-DFA results reported in Panel A and the post-DFA results shown in Panel B. The results in Panel A are similar to those we reported earlier: generally positive and significant loadings for firms in size bins five or lower and negative and significant loadings for firms in the largest size bin. By contrast, in Panel B, the loadings on $SIFI$ are mostly insignificant in the period after the passage of the DFA; moreover, there is little evidence of a subsidy to the largest firms as, of the two significant loadings in the largest size bin, one is positive and the other negative.

The reduction in $SIFI$ loadings need not imply a reduction in the $SIFI$ tax. Recall that the latter is a product of the loadings times the return on the $SIFI$ factor. Since the latter has increased in the recent period (4.68% post-DFA compared to 0.32% in the prior period), the overall effect on the $SIFI$ tax may be ambiguous. This is evident from the results reported in Table 8. In particular, Panel B of the table shows that although three of the five BM bins for the largest stocks show zero subsidy in the post-DFA period, and moreover one of the cells report a positive tax, the subsidy for the highest BM cell is large because the $SIFI$ return is large. In addition, the market capitalization of the largest firms increased, so that the average $SIFI$ tax in 2013 dollars actually increased post-DFA.

5.2 Does SIFI Risk Predict Systemic Risk?

The changes in $SIFI$ loadings around TBTF events suggest that these loadings may be informative of future changes in systemic risk. To address this issue, we use $pre-2007$ values of the $SIFI$ loadings to predict firm-level measures of systemic risk in the post-Lehman period (after September 15 2008). Our measure of systemic risk is SRISK, or expected capital shortage of a firm in case of a systemic event (Brownlees and Engle (2012)).[16] We estimate a panel regression of SRISK for the post Lehman period on $SIFI$ and other factors, firm level characteristics for the $pre - 2007$ period and monthly fixed effects. The $SIFI$, SMB and GL loadings are estimated from a firm-level time series regression of excess returns on a 6 factor Fama French model, along with $SIFI$ and GL, using the sample 2000 to 2006. $SIFI + (-)$ and $GL + (-)$ are the positive (non-negative) components of the factors (and equal to 0 otherwise). We also include each firm's average (for 2000-2006) $Srisk$, market capitalization, leverage, volatility, and correlation with the MSCI World Index.

The results are reported in Table 9. We find that firms with higher $SIFI$ loadings in the pre-2007 period had higher SRISK in the post-Lehman period, but the increase is greater for firms with negative $SIFI$ loadings. To the extent that these negative loadings reflect market perceptions of TBTF risk, the result indicates that such firms indeed contributed more towards systemic risk in the post-Lehman period, as measured by SRISK. The other factors and firm characteristics are also informative. For example, leverage, size measures (i.e. market capitalization) and size risk (i.e. GL and SMB) positively predict future systemic risk. Higher correlations with the MSCI World Index is also indicative of greater SRISK,

[16]The data is , downloaded from the NYU Volatility Lab website `http://vlab.stern.nyu.edu/`.

perhaps because these firms have a more global footprint and therefore more interconnected.

6 Additional Investigations and Robustness

Even though $SIFI$ is constructed from financial firms, we find in unreported results that portfolios of non-financial firms also load significantly on it. In particular, smaller non-financial firms load positively on $SIFI$. In part, this suggests that large financial firms create negative externalities for smaller non-financial firms through their business activities.[17] Further, to the extent that nonfinancial firms compete with financial firms for funding (e.g., in the commercial paper market), advantages accruing to large financial firms results in funding risk for nonfinancial firms.[18] Finally, Ahmed et al. (2014) find that financial firms have lower funding costs than non-financial firms, controlling for size, suggesting that non-financial firms bear a "finance risk" that may account for at least a part of the estimated risk-premium of smaller non-finance firms.

To examine the possibility of a "finance risk" that is borne by non-financial firms generally, we calculate a financial risk factor. Specifically, for financial and nonfinancial firms separately, we construct the six size and BM sorted portfolios that are typically used to construct HML and SMB (Fama and French (1993)). We take the average of these six portfolios, for financial and nonfinancial firms separately, and then take the difference between the nonfinance and finance portfolio returns as our $Finance$ factor. We reestimate our regressions after including the $Finance$ factor and find that the loadings on $SIFI$ are virtually unchanged.

There is continuing debate as to the appropriateness of the DFA size threshold. We find that SIFI factors constructed from higher cutoffs remain significant in the time series of returns, up until a cutoff of 300 billion in 2010 assets (corresponding to the top 3 % of financial firms). Conversely, if the cutoff is relaxed, allowing more firms to be deemed $SIFI$, we get qualitatively similar results when using the largest 9 % or 10 % of firms. However, the results get weaker when more than 10% of firms are entered into the largest size bin.

Our results are robust to alternative definitions of SMB and alternative asset size thresh-

[17] For example, William Dudley, President of the Federal Reserve Bank of New York, asserts that "Although the moniker is "too big to fail," the magnitude of these externalities does not depend simply on size. The size of the externalities also depends on the particular mix of business activities and the degree of interconnectedness" (http://www.newyorkfed.org/newsevents/speeches/2012/dud121115.html).

[18] Acharya, Drechsler and Schabl (2014) present a model in which government bailouts of banks can increase sovereign credit risk.

olds. When we use Fama Frenchs SMB (which means that $SIFI$ and SMB are no longer orthogonal) rather than SMB', our results are somewhat weaker, but the loadings are still qualitatively similar and mostly significant.

Finally, there has been a recent trend in the finance literature towards using HSICCD rather than SIC codes to determine industries in CRSP. We have reestimated our regressions classifying finance by HSICCD rather than SIC codes. We again find these results look extremely similar to those we report in the paper.

7 Conclusion

Within the largest financial firms, we find that those firms above the size threshold associated with the Systemically Important Financial Institution or SIFI designation, have lower expected returns than firms just below this threshold. The difference in returns is 0.62% on average and is greater during recessions and lower during expansions. This difference in returns is a common risk factor, denoted $SIFI$, that has significant explanatory power in time series regressions of stock returns for all firms from 1963 to 2006, even after controlling for standard asset pricing and bank-size factors. The largest firms in the top 10% of market size load negatively on it, implying a "SIFI subsidy," while the remaining firms load positively on it, implying a "SIFI tax." We estimate the subsidy to be 5.71 million in 2013 dollars per firm per year. After the bankruptcy of Lehman Brothers or passage of the Dodd-Frank Act, the SIFI loading was sharply reduced but the $SIFI$ tax was similar in basis points as the return to the $SIFI$ factor increased. Prior to the crisis, the SIFI subsidy benefited the largest bank and non-bank financial firms but not insurance companies. These results are robust to different TBTF size thresholds and asset pricing models.

We relate the $SIFI$ loadings to systemic risk. First, we show that the loadings increase (decrease) following events that increase (decrease) TBTF risk. Second, we find that firms with higher $SIFI$ loadings before 2007, and in particular firms with negative $SIFI$ loadings before 2007, had higher measures of systemic risk following the failure of Lehman Brothers.

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Table 1: $SIFI$ Returns in Recessions and Expansions

Panel A shows summary statistics of returns on the $SIFI$ factor in percent. Returns are annualized by multiplying by 12. Panel B shows the cumulative return of the $SIFI$ factor, in percent, over NBER business cycle expansions and recessions. We also report cumulated returns and average returns per month over all expansions and recessions. The sample is from 1963 through 2013.

Panel A: Summary Statistics of $SIFI$ returns, %					
Sample	Mean	Median	Std. Dev	Skewness	
Full	0.62	0.11	42.34	-0.35	
Panel B: Cumulative $SIFI$ returns, by Business Cycle, %					
Expansion			Recession		
start	end	cumulative return	start	end	cumulative return
			1969m12	1970m11	27.81
1970m12	1973m10	-41.41	1973m11	1975m3	11.23
1975m4	1979m12	42.94	1980m1	1980m7	-8.29
1980m8	1981m6	-2.40	1981m7	1982m11	-10.06
1982m12	1990m6	-26.66	1990m7	1991m3	8.67
1991m4	2001m2	5.38	2001m3	2001m11	-5.87
2001m12	2007m11	-13.90	2007m12	2009m6	-9.19
Total Cumulative Return over Recessions=					8.92 %
Total Cumulative Return over Expansions=					-30.94%
Average Return over Recessions=					0.10 %
Average Return over Expansions=					-0.07%

Table 2: Liquidity and Funding Cost Differences: Largest and Next-to-Largest Financial Stocks

This table shows summary statistics for liquidity (Panel A) and funding costs (Panel B) for the largest 8% of financial stocks and the next largest 8% (8-16%) of financial stocks. Largest 8% comprises financial firms that were always in the top 8% by size, the 8-16% bin includes financial firms that were always in that bin while the largest 16% is the union of these firms. The liquidity measures are: the Amihud ratio, turnover and the proportional effective bid ask spread. Funding costs are are given by the yield spread of corporate bonds over treasuries of equivalent maturity at the time of issuance (in basis points). The final column shows P-values of a pooled two sided Welch's t-test between the top 8 % and the next 8 %. The sample is from 1963 through 2013.

	Largest 8 % (1)		Next Largest 8% (2)		Difference	
	Mean	SD	Mean	SD	(2)-(1)	P
Panel A: Liquidity Measures						
Amihud	30.4302	230.202	8.8824	79.693		0
Turnover	0.834	1.2277	0.925	1.3642		0
Effective Spread	0.0002	0.0031	0.0001	0.0031		0.13
Panel B: Bond Spreads						
	Obs	Mean	SD	Min	Max	
All	30115	57.51	93.94	0	955	
Top 16	1289	34.71	55.90	0	707	
Top 8	844	28.93	53.25	0	622	
8-16	445	45.66	59.15	0	707	

Table 3: Loadings on $SIFI$ Factor

This table shows OLS estimates for loadings on the $SIFI$ factor of portfolios sorted by size (reading top to bottom, rows correspond to the 20th, 40th, 60th, 80th, and 90th percentiles of the size distribution) and BM (reading left to right, columns correspond to the 20th, 40th, 60th, and 80th percentiles of the BM distribution). In Panel A, we regress monthly excess returns of each portfolio on the $SIFI$ factor, SMB' (the Fama-French factor SMB made orthogonal to $SIFI$), the Fama-French factors $Mktrf$ and HML , bond market factors GOV and $CORP$, and the Carhart momentum factor MOM. In panel B, we add GL, the bank size risk factor of Gandhi and Lustig (2014). In Panel C, we add a liquidity factor constructed from the Amihud ratio. In Panel D, we add the leverage factor of Adrian and Muir (2014). *, **, *** 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 1963 through 2006.

	Low	2	3	4	High
Panel A: Six Factor Fama-French Model					
Smallest	0	.09***	.08***	.09***	.06**
2	.08**	.12***	.12***	.11***	.09***
3	.07*	.13***	.09***	.14***	.12***
4	.05*	.09***	.11***	.11***	.1***
5	.02	.1***	.1***	.12***	.13***
Largest	-.03	-.05*	-.1**	.02	-.12*
Panel B: Adding Bank Size Factor					
Smallest	-.02	.09***	.08***	.1***	.06**
2	.08*	.14***	.13***	.13***	.11***
3	.07	.13***	.09***	.14***	.14***
4	.05*	.1***	.12***	.12***	.1**
5	.03	.12***	.1***	.12***	.16***
Largest	-.04*	-.04	-.12***	.03	-.13*
Panel C: Adding Amihud Factor					
Smallest	0	.09***	.08***	.09***	.06**
2	.08**	.12***	.12***	.11***	.09***
3	.07*	.13***	.09***	.14***	.12***
4	.05	.09***	.11***	.11***	.1***
5	.02	.1***	.1***	.12***	.13***
Largest	-.03	-.05*	-.1**	.02	-.12*
Panel D: Adding Leverage Factor					
Smallest	-.01	.09***	.08***	.08***	.06**
2	.08**	.12***	.12***	.11***	.09***
3	.07*	.12***	.09***	.14***	.12***
4	.04	.08***	.11***	.11***	.1***
5	.02	.1***	.1***	.11***	.14***
Largest	-.03	-.05*	-.1***	.02	-.11*

Table 4: Estimates of $SIFI$ Tax and Subsidy per Year, 1963-2006

This table shows estimates of the $SIFI$ tax and subsidy per year for portfolios sorted by size (reading top to bottom, rows correspond to the 20th, 40th, 60th, 80th, and 90th percentiles of the size distribution) and BM (reading left to right, columns correspond to the 20th, 40th, 60th, and 80th percentiles of the BM distribution). The column labeled *Average* shows the average across BM bins for each size bin. We regress monthly excess returns of each portfolio on the $SIFI$ factor, SMB' (the Fama-French factor SMB made orthogonal to $SIFI$), the Fama-French factors $Mktrf$ and HML , bond market factors GOV and $CORP$, and the Carhart momentum factor MOM. In panel A, we multiply the loadings on $SIFI$ by the average annualized return of the $SIFI$ factor (equal to 0.45% per year over this period), treating statistically insignificant loadings as 0. In Panel B, we also multiply by the average market capitalization of each portfolio in millions of 2013 dollars, where the average is taken first across firms and then across months. The sample is from 1963 to 2006.

	Low	2	3	4	High	Average
Panel A: Average Annual Tax and Subsidy, in %						
Smallest	0	0.04	0.04	0.04	0.03	0.03
2	0.04	0.05	0.05	0.05	0.04	0.05
3	0.03	0.06	0.04	0.06	0.05	0.05
4	0.02	0.04	0.05	0.05	0.05	0.04
5	0	0.05	0.05	0.05	0.06	0.04
Largest	0	-0.02	-0.05	0	-0.05	-0.02
Largest -5	0	-.07	-.1	-.05	-.11	-0.07
Panel B: Average Annual Tax and Subsidy per Firm, in Millions of 2013 $						
Smallest	0	0.04	0.03	0.03	0.02	0.02
2	0.15	0.22	0.22	0.2	0.16	0.19
3	0.29	0.55	0.38	0.59	0.5	0.46
4	0.53	0.95	1.14	1.16	1.05	0.97
5	0	2.54	2.45	3.03	3.26	2.26
Largest	0	-5.8	-10.61	0	-10.2	-5.32
Largest - 5	0	-8.34	-13.06	-3.03	-13.46	-7.58

Table 5: SIFI Exposures of Financial Sectors

This table shows OLS estimates for loadings on the $SIFI$ factor of portfolios sorted by size (reading top to bottom, rows correspond to the 20th, 40th, 60th, 80th, and 90th percentiles of the size distribution) and BM (reading left to right, columns correspond to the 20th, 40th, 60th, and 80th percentiles of the BM distribution). In each panel, we use a different set of test portfolios constructed from firms in a particular financial sector (Panel A: all financial firms; Panel B: banks; Panel C: non-bank financial firms; Panel D: insurance companies). For each portfolio, we regress monthly excess returns on the $SIFI$ factor, SMB' (the Fama-French factor SMB made orthogonal to $SIFI$), the Fama-French factors $Mktrf$ and HML , bond factors GOV and $CORP$, and the Carhart momentum factor MOM. *, **, *** represent statistical significance at the 10%, 5%, and 1% level, respectively. The sample is from 1963 through 2006. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey West (1987) with a maximum of 3 lags.

	Low	2	3	4	High
Panel A: Financial Firms					
Smallest	-.08	.24***	-.02	.11*	.08
2	-.05	.14*	.15***	.13***	.12
3	.15**	.13	.19***	.15**	.2*
4	.07	.19***	.15**	.11	.05
5	.15*	.38***	.27***	.35***	.47***
Largest	-.29***	-.33***	-.22***	-.31**	-.51***
Panel B: Banks					
Smallest	.1	.26**	.11	.14	.05
2	.06	.4***	-.03	.05	0
3	-.01	.12	.22**	.07	.2
4	-.05	.2*	.08	.18*	.38*
5	.18**	.23**	.04	.25	-.12
Largest	-.23***	-.35***	-.22*	.17	-.38*
Panel C: Non-Bank Financials					
Smallest	-.08	.25***	.14**	.03	.15**
2	0	.15	.13*	.14*	.18**
3	.17**	.14**	.32***	.17**	.22**
4	.21***	.28***	.25***	.23***	.15
5	.18**	.23**	.39***	.24**	.56***
Largest	-.26***	-.23*	-.12	.07	-.75**
Panel D: Insurance					
Smallest	.22**	.27**	.18	.33***	.24***
2	.4**	.39***	.18**	.23*	.37***
3	.18*	.23*	.26**	.35***	.23**
4	.37***	.24*	.47***	.17*	.47***
5	.32**	.22	.34**	.23*	.42***
Largest	.15	-.07	-.28*	.46**	.45*

Table 6: SIFI Loadings Before and After Bailout of Continental Illinois and Bankruptcy of Lehman Brothers

This table shows OLS estimates for loadings on the $SIFI$ factor of portfolios sorted by size (reading top to bottom, rows correspond to the 20th, 40th, 60th, 80th, and 90th percentiles of the size distribution) and BM (reading left to right, columns correspond to the 20th, 40th, 60th, and 80th percentiles of the BM distribution). For each portfolio, we regress monthly excess returns on the $SIFI$ factor, SMB' (the Fama-French factor SMB made orthogonal to $SIFI$), the Fama-French factors $Mktrf$ and HML , bond factors GOV and $CORP$, and the Carhart momentum factor MOM. *, **, *** representing statistical significance at the 10%, 5%, and 1% level, respectively. Continental's bailout occurred in May 1984, and Lehman declared bankruptcy in September 2008. Accordingly, the sample in panel A is from 1963 through April 1984, the sample in panel B is June 1984 through August 2008, and the sample in panel C is October 2008 through 2013. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey West (1987) with a maximum of 3 lags.

Panel A: Pre-Continental					
	Low	2	3	4	High
Smallest	.01	.08**	.04	.04	.06**
2	.08**	.07**	.05*	.05*	.03
3	.05	.09***	.03	.09***	.05
4	.04	.06**	.08***	.04	.07*
5	.04	.06**	.08***	.09***	-.02
Largest	-.01	-.02	-.09*	.01	-.03
Panel B: Post-Continental Pre-Lehman					
	Low	2	3	4	High
Smallest	-.02	.09**	.11***	.14***	.07
2	.07	.16***	.18***	.19***	.18***
3	.09	.15***	.15***	.19***	.18***
4	.05	.1***	.15***	.2***	.13*
5	0	.12***	.1**	.14***	.29***
Largest	-.07**	-.11**	-.08	.04	-.24***
Panel C: Post-Lehman					
	Low	2	3	4	High
Smallest	.02	-.04	.05	-.07*	.02
2	.14**	.02	.06	.09	-.02
3	.11*	-.01	.02	0	.12
4	.04	0	.05	.03	-.01
5	.03	.04	-.06	.08	.2*
Largest	-.06**	.05	0	-.11	-.52***

Table 7: SIFI Loadings Before and After Passage of the Dodd-Frank Act

This table shows OLS estimates for loadings on the $SIFI$ factor of portfolios sorted by size (reading top to bottom, rows correspond to the 20th, 40th, 60th, 80th, and 90th percentiles of the size distribution) and BM (reading left to right, columns correspond to the 20th, 40th, 60th, and 80th percentiles of the BM distribution). For each portfolio, we regress monthly excess returns on the $SIFI$ factor, SMB' (the Fama-French factor SMB made orthogonal to $SIFI$), the Fama-French factors $Mktrf$ and HML , bond factors GOV and $CORP$, and the Carhart momentum factor MOM. We present the coefficient on the $SIFI$ factor, with *, **, *** representing statistical significance at the 10%, 5%, and 1% level, respectively. Continental's bailout occurred in May 1984, and the Dodd-Frank Act was enacted in in July 2010. Accordingly, the sample in panel A is from Jun 1984 (the month after Continental) through June 2010, the sample in panel B is August 2010 through 2013. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey West (1987) with a maximum of 3 lags.

Panel A: Post Continental Pre-Dodd Frank Act					
	Low	2	3	4	High
Smallest	-.03	.04	.08***	.08**	.06
2	.07	.11**	.14***	.16***	.12**
3	.1*	.09**	.11***	.12***	.16***
4	.05	.07**	.11***	.13***	.07
5	.01	.09**	.04	.11***	.25***
Largest	-.06***	-.08*	-.08*	-.01	-.3***
	Panel B: Post-Dodd Frank Act				
	Low	2	3	4	High
Smallest	.02	-.17	.01	-.11	-.15
2	.15	.07	.01	.09	-.09
3	.13	.03	-.04	-.05	.16
4	-.09	-.16	-.04	.17	.08
5	-.18*	-.11	-.05	.1	.27*
Largest	-.06	.19**	.13	.06	-.47***

Table 8: Estimates of $SIFI$ Tax Per Year, Before and After Dodd Frank Act

This table shows estimates of the $SIFI$ tax per year before and after the Dodd-Frank Act (DFA) for portfolios sorted by size (reading top to bottom, rows correspond to the 20th, 40th, 60th, 80th, and 90th percentiles of the size distribution) and BM (reading left to right, columns correspond to the 20th, 40th, 60th, and 80th percentiles of the BM distribution). The tax in basis points is equal to the loading on the $SIFI$ factor times the the average annualized percent return of the $SIFI$ factor (equal to 0.32% per year in the pre-DFA period and 4.68 % per year in the period after DFA). The tax in dollars is the average tax in basis points multiplied by the average market capitalization in millions of 2013 dollars. The $SIFI$ loading is estimated from regressions of monthly excess returns of each portfolio on the $SIFI$ factor, SMB' (the Fama-French factor SMB made orthogonal to $SIFI$), the Fama-French factors $Mktrf$ and HML , bond factors GOV and $CORP$, and the Carhart momentum factor MOM. *Av.Size* is the average market capitalization in each portfolio, in billions of 2013 dollars. The sample period is 1963 to June 2010 in panel A and August 2010 to 2013 in panel B.

	Low (Bp)	2 (Bp)	3 (Bp)	4 (Bp)	High (Bp)	Avg Tax % (Bp) (1)	Av. Size (Billion \$) (2)	Avg. Tax \$ (Million \$) (3=1*2)
Panel A: Pre-Dodd Frank Act								
Smallest	0	0.02	0.02	0.02	0.02		0.09	0.02
2	0.03	0.03	0.03	0.04	0.03		0.44	0.03
3	0.03	0.03	0.03	0.04	0.04		1.02	0.03
4	0.02	0.02	0.04	0.03	0.03		2.51	0.03
5	0	0.03	0.02	0.03	0.05		6.13	0.03
Largest	-0.01	-0.02	-0.03	0	-0.06		26.09	-0.02
Panel B: Post-Dodd Frank Act								
Smallest	0	0	0	0	0		0.18	0
2	0	0	0	0	0		0.87	0
3	0	0	0	0	0		2.02	0
4	0	0	0	0	0		4.75	0
5	-0.84	0	0	0	1.26		12.13	0.08
Largest	0	0.89	0	0	-2.25		58.31	-0.27

Table 9: Predicting Systemic Risk after Lehman

This table shows OLS estimates from panel regressions of SRISK, or expected capital shortage of a firm in case of a systemic event (Brownlees and Engle (2012)) in the post Lehman (September 15 2008) period on $SIFI$ and other factors, firm level characteristics estimated in the $pre-2007$ period and monthly fixed effects. The $SIFI$, GL and SMB loadings are estimated from a firm-level time series regression of excess returns on a 6 factor Fama French model, $SIFI$ and GL using the sample 2000 to 2006. $SIFI+(-)$ and $GL+(-)$ are the positive (non-negative) components of the factors (and equal to 0 otherwise). We also include each firm's average (for 2000-2006) $Srisk$, market capitalization, conditional beta, leverage, volatility, and correlation with the MSCI World Index. We use *, **, *** to represent statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are adjusted for heteroskedasticity.

Pre-2007 variables	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)
Srisk	0.28***	1.29***	1.29***	1.29***
	(0.05)	(0.03)	(0.03)	(0.03)
SIFI+	899.00***	2,065.80***	1,611.25***	2,255.60***
	(272.64)	(213.09)	(243.50)	(226.79)
SIFI-	-15,079.54***	-6,898.89***	-6,312.06***	-6,671.87***
	(1,192.01)	(585.81)	(590.81)	(579.74)
Marketcap		0.52***	0.52***	0.52***
		(0.01)	(0.01)	(0.01)
Leverage		0.09***	0.10***	0.05*
		(0.03)	(0.03)	(0.03)
Volatility		77,335.53	222,961.23	-247,259.94
		(153,993.45)	(179,547.03)	(152,557.84)
Correlation		5,914.43***	6,101.33***	6,931.84***
		(1,018.59)	(1,243.67)	(1,072.64)
GL+			203.22***	
			(33.04)	
GL-			-116.17***	
			(16.72)	
SMB				553.53***
				(78.24)
Period FE	YES	YES	YES	YES
Observations	10,826	10,826	10,826	10,826
Adjusted R-squared	0.08	0.57	0.58	0.57