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US Banks' Exposure to Systematic Risk

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The contents of this paper are fully reproducible and the code repository needed to replicate its figures and tables is maintained at https://github.com/abhinavananddwivedi/US_Banks_SRE_Replication and has been shared under the MIT License. The authors encourage those interested to refer to the detailed replication notes shared under the following link: https://github.com/abhinavananddwivedi/US_Banks_SRE_Replication/blob/master/Replication_Instructions.pdf.

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Abstract

We define and construct the ‘systematic risk exposure’ (SRE), measured between 0–100, for a large sample of 2287 US banks during the period 1993–2019. The measure shows a steady increase in banks’ exposure to systematic risk; and displays significantly high peaks during episodes of market distress such as the LTCM collapse, the Dotcom bust, the Great Recession and the Eurozone crisis. We also show that the imposition of the Dodd-Frank Act has improved US banks’ capitalization levels but has not curtailed their exposure to systematic risk, which has continued to rise unabated. Among characteristics associated with SRE, we find that bank size is the most significant—both economically and statistically.

Keywords: Systematic risk; Bank size; Banking crises; Systemically important banks; Bank risk; Principal component regressions

JEL Classification: G10, G21, G28, C32, C33, C38, C58

1 Introduction

The US banking sector has faced several crises over the past three decades. Due to its critical role in moderating stability (or lack thereof) in the financial sector; and its ability to amplify contagion and disruption in the overall economy, episodes of distress in the banking industry have wreaked havoc several times in the recent past. Policymakers have responded to such crises by the enactment of several regulations whose imposition has not yet managed to put an end to periodic panic in the banking sector. Hence a detailed investigation of US banks' exposure to systematic risk—which affects the fate of the entire US banking and financial industry—and its relation to crises warrants serious attention and rigorous scrutiny.

We define and construct US banks' 'systematic risk exposure' (SRE) for a large sample of 2287 banks over 27 years from 1993 to 2019. Our definition of a bank's exposure to systematic risk measures the degree of dependence of its stock return on a set of common factors that drive stock returns of all US banks.[1] We identify these common banking factors as the principal components constructed from the daily stock return matrix of the full set of 2287 US banks in our sample. Such anonymous, orthogonal principal components can be interpreted to embed within themselves, a set of common factors driving each bank's returns.[2] In order to measure the degree of dependence of bank stock returns on these common factors, we employ the explanatory power, in terms of adjusted R^2, of bank stock returns regressed on the principal components of the US banking sector. Since a bank's exposure to systematic risk is defined as the explanatory power of principal component regressions, each bank in our sample displays an SRE value between 0 and 100.

The median US bank's SRE starts in 1993 from 23.2 and ends in 2019 at 56.7. It attains a minimum of 19.4 in 1995Q3, achieves a peak of 70.4 in 2019Q3; and exhibits a significantly positive trend, which accelerates particularly post-2006.

[1] Thus our notion of systematic risk is related to the classic multi-factor models of the undiversifiable component of risk.

[2] For example, monetary policy changes, in principle, affect stock returns of all banks in a country and hence could be interpreted to be one concrete instantiation of a common factor.

Further, US banks' exposure to systematic risk displays significantly high peaks over and above its trend during episodes of market distress such as the LTCM collapse, the Dotcom bust, the Great Recession and the Eurozone crisis. This phenomenon should be of direct relevance to policymakers and regulators. For example, if the banking sector displays an abnormally high median or aggregate SRE, it can serve as a warning signal for endogenous sectoral overdependence on common factors, which may lead to systematic distress in case of a negative shock to one of the underlying common factors.

Additionally, we show that the imposition of the Dodd-Frank Act in July 2010 has resulted in a better-capitalized US banking sector; but it has failed to curtail the rise in banks' exposure to systematic risk which has continued to rise unabated. Thus US banks remain vulnerable in case of negative shocks to one or more underlying common factors. In other words, we deem the Dodd-Frank Act to be a partial success since it has improved banks' ability to absorb negative shocks to common factors due to increased capital buffers, but the steady rise in US banks' SRE levels continues to pose a threat to the stability of the US banking sector.

Further, we also link US banks' exposure to systematic risk to bank balance sheet characteristics such as size, capital structure, capital buffers, profitability etc. We carry out panel estimations for a set of 1728 US banks and show that bank size, measured in terms of its total assets, is highly positively associated with its level of systematic risk exposure and is the most important bank characteristic in explaining SRE—both economically and statistically. We also find that banks' equity ratios and net interest margins have a noteworthy association with their exposure to systematic risk.

To the best of our knowledge, ours is the first study to define and construct US banks' exposure to systematic risk, its relation to crises, implications for policy; and explanatory associations with a wide variety of bank characteristics. Further, to the best of our knowledge, our paper employs the most comprehensive sample of US banks in terms of coverage—both in cross-section and time series—to establish our results. For example, for computing banks' systematic risk exposure we collect daily stock return data on 2287 unique US banks over 27 years from January 1, 1993 to December 31, 2019; and for estimating bank balance sheet characteristics' association with SRE, we conduct panel regressions for 1728 unique banks for a total of 107 quarters from 1993Q2–2019Q4. Popular alternative modeling techniques, which explicitly construct interconnections between banks cannot be easily scaled up as the number of banks increases. The approach we favor in this paper is characterised by its agnosticism and data-driven nature; and our results are subjected to a variety of alternative subsample regressions and specification tests.

Our study's reliance on computing exposure to systematic risk by means of explanatory power of principal component regressions is inspired from the approach in Pukthuanthong and Roll [2009].[3] An alternative approach is to model banks' interconnectivity and their propensity for generating contagion or systemic risk by means of postulating banking networks in which banks are connected to each other by means of maintaining lending or trading relationships with each other. Prominent recent studies in this tradition are Acemoglu et al. [2015] and Elliott et al. [2014].[4] Measuring spillover effects by generalized vector autoregression (G-VAR) induced networks falls in between these two approaches. For example, building on Diebold and Yilmaz [2009] and Diebold and Yilmaz [2014], Demirer et al. [2018] employ generalized forecast error variance decompositions (G-FEVD) to construct weighted, directed networks of a set of globally largest banks to measure global banking network interconnections.

We offer the following observation regarding these two approaches. In general, network based methods cannot be easily scaled up to study very large sectors for which dimensionality-reducing techniques such as principal components have greater utility. Hence, researchers who investigate microscopic interconnectivity risk among individual banks will find network based techniques more useful. On the other hand, those who favor aggregate, macroscopic estimates of systematic

[3]Several other studies have used principal components to measure the related but fundamentally distinct concept of systemic risk such as Giglio et al. [2016], Berger and Pukthuanthong [2012], Eichengreen et al. [2012], Billio et al. [2012] and Kritzman et al. [2011].

[4]Other recent notable works employing the construction of explicit banking networks include Martínez-Jaramillo et al. [2014], Langfield et al. [2014] and Rogers and Veraart [2013]. Hüser [2015] contains a comprehensive survey of interbank networks.

risk of an individual due to exposure to common factors afflicting the entire sector as a whole should rely on indirect econometric techniques such as principal components.[5]

The paper is organized as follows. Section 2 discusses the sample construction and data filtration process, while section 3 outlines the main methodology used in our study. Section 4 studies trends in US banks' SRE and their relation to various crisis episodes included in our sample. Section 5 investigates policy implications for bank regulators and the impact of the Dodd-Frank Act on US banks' systematic risk exposures. Section 6 discusses the data and methodology used to examine bank characteristics that impact bank SRE. Finally, section 7 presents concluding remarks.

2 Data for estimating US banks' SRE

For estimating US banks' SRE, we access stock returns from the daily security file of the Center for Research in Security Prices (CRSP). Our sample period ranges from January 1, 1993 to December 31, 2019. In order to collect daily stock returns for all admissible US banks, we include in our search all firms that have an SIC classification between 6020 and 6079 (commercial banks, savings institutions, and credit unions) and from 6710 through 6712 (offices of bank holding companies). We eliminate firms incorporated in a non-US country and eliminate all American Depositary Receipts (ADRs). Additionally, we extract common shares by subjecting the sample to filtration based on their share code availability. Only banks with share code either 10 or 11—corresponding to common stock—are selected. Further, we drop all observations with nominal stock price of less than $1 [Fahlenbrach et al., 2018]. For firms whose SIC classifications change from an inadmissible to an admissible class in the sample period, we include data only for the time period during which they are depository institutions or bank holding companies within

[5]For example, our full data matrix representing daily returns of 2287 US banks comprises over 3.57 million rows. By projecting this very large dimensional space of the entire US banking sector onto a maximally informative, yet relatively small dimensional principal component subspace, we are able to achieve a high level of computational tractability. Such a feature cannot be exploited in explicit, network-based approaches.

the admissible codes. For firms whose codes change from one admissible class to another we maintain differences in their classification. For example, the SIC of the bank "AmSouth Bancorporation" has been classified variously as 6711, 6712 and 6022 during the sample period. Correspondingly we maintain three bank-SIC combinations for AmSouth Bancorporation depending on its classification at different points in time. Further, we discard any return which is identical to its immediately preceding value. An identical value would indicate either a holiday or simply a stale value. Our final sample consists of daily stock return observations for 2287 distinct US banks from January 2 1993 to December 31, 2019.

Clearly, not all banks in the sample have full data corresponding to the 27 year sample period. This may be due to several reasons: the banks in question could have been private, or CRSP did not have access to their market values for the entire duration.[6] Irrespective of the cause, we include such banks' data from the day their records begin appearing in the CRSP database. Additionally, since we include all such banks in CRSP database irrespective of whether they are alive or not, our study is free from survivorship bias. Further, our attention on public banks with primary listings in the US excludes several multinational banking corporations which might have secondary listings in the US but primary listings elsewhere. For example, the British bank HSBC has a secondary listing on the New York Stock Exchange but under our definition, we do not include it in the list of US banks. In the same way, financial service providers such as mutual funds, insurance companies etc. are not included in our definition of banks.

After performing all the above filtrations we are left with a sample of 2287 unique US banks which have some return observations during the sample period 1993–2019. According to the FDIC, in 2019Q4 there were a total of 5177 commercial banks and savings institutions insured by it.[7] In terms of banks covered, this represents around 45% coverage of the US banking sector.

[6] For example, the bank "1st Constitution Bancorp" had its IPO on January 14, 2000 but CRSP starts its data coverage only from January 2, 2002.

[7] See press release at https://www.fdic.gov/news/news/press/2020/pr20018.html.

3 Methodology

We define a bank's level of systematic risk exposure as the explanatory power (in terms of adjusted R^2) of the regression of its stock returns on principal components of the stock return matrix of all US banks. These principal components are in turn, the eigenvectors of the stock return covariance matrix for all US banks and are postulated to contain all common banking factors that could potentially influence individual banks' SRE levels.

Banks whose stock returns are highly explainable by US banking sector's principal components can be rightly thought to have a high exposure to systematic risk afflicting the sector. On the other hand, banks with stock returns that cannot be well-attributed to the banking sector's principal components display low dependence on common factors; and hence can be thought to have low levels of systematic risk exposure. To rephrase, if a bank is completely cutoff from the vagaries of other banks' fortunes and thus, is independent of all common banking factors embedded in the sector's principal components, its exposure to systematic risk is 0. Similarly, if a bank's stock returns are completely attributable to common banking factors, the explanatory power of principal component regressions—and hence its SRE—is 100%.

Real banks display empirical behavior in between these two theoretical extremes and their SRE levels will lie between 0 and 100. While empirically it is possible for the adjusted R^2 to display negative values, since in our study such a result will imply zero explanatory power, we interpret such instances as depicting no exposure to systematic risk.

Hence, our formal definition of SRE for a US bank j is:

$$\widehat{\mathrm{SRE}}_j := \max\{\text{adj } R_j^2, 0\}$$

where $\widehat{\mathrm{SRE}}_j$ is bank j's estimated SRE level and "adj R_j^2" is the adjusted R^2 for bank j's corresponding principal component regression.

3.1 Frequency of estimation

We partition each year into its constituent quarters. Since our duration of study spans 27 years, there are 108 quarters in total: from 1993Q1 to 2019Q4. There are between 62–66 daily observations for each bank's stock return each quarter. In order for a bank to qualify for computation of its systematic risk exposure in a given quarter, we demand that it have at least 30 observations in that quarter. We compute the covariance matrix of all admissible US banks' stock return matrix for each quarter and extract as many top eigenvectors as are necessary to explain 90% of return variance that quarter. By applying eigenvectors to observed returns, we compute principal components which are then used as explanatory variables for quarterly regressions for each bank's return. For banks which do not contain data for the entire sample period, we start estimating their SRE levels from the time their data begin appearing in CRSP. For example, the bank '1st Constitution Bancorp' has no return data available from 1993Q1 to 2001Q4. Hence, its SRE level estimation starts from 2002Q1.

3.2 Extracting principal components

The common factors that form the right hand side (RHS) of the regression equation are the principal components of the full set of US banks' stock return matrix. These correspond to the eigenvectors of the largest eigenvalues of the US banks' covariance matrices. Each quarter, we include as many eignevectors as are necessary to cover 90% of the total variation in returns. Hence the actual number of eigenvectors used varies slightly from quarter to quarter. In case there are banks with no usable return data, we form principal components from the set of available banks. For our sample, the minimum number of principal components needed to cover 90% variance is 17, the maximum is 49; with a median of 44 principal components.

Once eigenvectors are computed in order of largest to smallest eigenvalue, out-of-sample principal components are estimated by applying them to observed returns for the subsequent quarter. For example, eigenvectors computed from the full covariance matrix in 1993Q1 are applied to the stock return matrix of observed returns in 1993Q2. This generates out-of-sample principal components to be used as common factors in the RHS of the regression corresponding to 1993Q2. Such out-of-sample common banking factors are orthogonal, which lays to rest the possibility that the common factors employed in quarterly regressions suffer from multicollinearity. By the construction detailed above, we compute out-of-sample principal components for 107 quarters—from 1993Q2 to 2019Q4.

3.3 Results

3.3.1 Number of principal components

In principal component analysis, there is no unique method for deciding how many principal components to use. Most choices therefore, are based on context and special features of the problem at hand. We decide to be agnostic and data-driven and employ as many principal components as are required to explain 90% of the total variance. Hence the number of principal components required varies slightly from quarter to quarter.

Figure 1 presents a plot of the proportion of variance attributable to the top ten eigenvectors each quarter from 1993Q1 to 2019Q4. This figure immediately brings to focus, three important observations:

1. During times of market calm, the marginal contribution of each eigenvector seems somewhat evenly spread out.

2. During times of market distress—the LTCM collapse (1998Q3), the Dotcom bust (2002Q3–Q4), the Great Recession (2007Q4–2009Q2); and the Eurozone crisis (2010Q2–2012Q2)—the contribution of the top eigenvector is the highest and displays local maxima during each of the crises. Further, the marginal contribution of eigenvectors 2, 3 etc. becomes much lower compared to the top eigenvector during crises.

3. After attaining a peak during the Eurozone crisis, the marginal explanatory contribution of the top eigenvector has steadily risen and currently exhibits

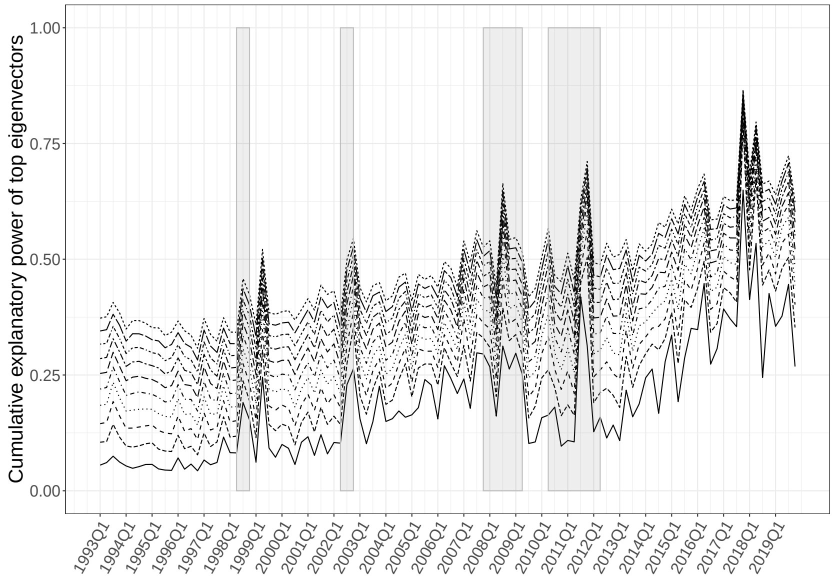

Figure 1: Cumulative proportion of variation explained each quarter by the top 10 eigenvectors. The bottom, solid line is the first eigenvector; the second, dashed line denotes the time series of the explanatory power of top two eigenvectors together; and similarly, the dotted, top line denotes the cumulative proportion of variance explained by the whole set of top 10 eigenvectors. The grey, shaded vertical regions denote crises: LTCM collapse (1998Q3), the Dotcom bust (2002Q3–Q4), the Great Recession (2007Q4–2009Q2); and the Eurozone crisis (2010Q2–2012Q2).

levels even higher than during the Eurozone crisis. Insofar as the top eigenvector's marginal explanatory contribution is positively associated with times of market distress, this is an ominous signal.

3.3.2 Descriptive statistics

Table 1 presents descriptive statistics for the set of US banks' quarterly SRE series for a set of 2287 unique US banks. Since the full set of summary statistics is too voluminous to be included directly in the paper, we resort to displaying summary statistics for the pooled set of observations. Further, we display pooled statistics for the subsample of US banks that are deemed either globally or domestically systemically important.[8] Additionally, two time based subsamples corresponding

[8]The Basel Committee on Banking Supervision (BCBS) maintains a list "global systemically important banks" (GSIBs), 8 of which are US based. In addition, for the United States, the "Domestic Systemically Important Banks" (DSIBs) include those non-G-SIBs, which remain subject to the most stringent annual Stress Test by the Federal Reserve. In this paper, the full set of systemic US banks in our sample can be accessed in Table 3.

Table 1: Descriptive statistics of US banks' quarterly systematic risk exposure (SRE) series.

Sample	Min	Max	Mean	Med	Std Dev	IQR	Skew	Kurt
All	0	99.899	33.942	32.209	26.145	44.390	0.293	1.989
Sys	0	96.758	54.617	58.865	23.349	32.482	-0.679	2.711
H1	0	98.841	27.473	25.768	22.826	39.948	0.419	2.164
H2	0	99.899	43.944	45.837	27.752	47.332	-0.114	1.816

Notes: The minimum, maximum, mean, median, standard deviations, inter-quartile range, skewness and kurtosis are reported for SREs of different subsamples of US banks. "All" denotes the full sample of US banks (2287 banks), "Sys" denotes the set of banks deemed either globally or domestically systemically important (24 banks, listed in Table 3). "H1" denotes the sample period from 1993Q1 to 2006Q2, corresponding to the first half of the sample; while "H2" denotes the second half of the sample from 2006Q3–2019Q4.

to the first and second halves of the sample duration labeled "H1" and "H2" respectively are also included.

For the sample of all US banks and the full sample period, the average SRE level is 33.9, the median is 32.2; a mild positive skewness of 0.3; and the kurtosis level is 2. All these suggest that the cross-sectional distribution of SRE across US banks is not very far from a symmetric normal distribution. Further, the systemically important banks' mean and medians are substantially higher at 54.6 and 58.9 respectively, suggesting that they are on average, more exposed to systematic risk than their ordinary counterparts. The average SRE level of banks rises in the second half of the sample (post-2006Q2) since the second half average is 44 as opposed to the first half's 27.4. For all periods and samples, the closeness of the mean and median; the IQR and the standard deviations; and also the skewness and kurtosis levels suggest a distribution close to the normal.

4 Trends in US banks' SRE

For each US bank in our sample we have estimates of quarterly SRE levels from 1993Q2 to 2019Q4. Not all banks have quarterly SRE estimates for the full set of 107 quarters and in general most banks display several missing values. Since individual banks' full set of quarterly SRE results are too voluminous for display, we focus our attention on the median US bank constructed by computing the median observed SRE values in each quarter, while ignoring banks with missing

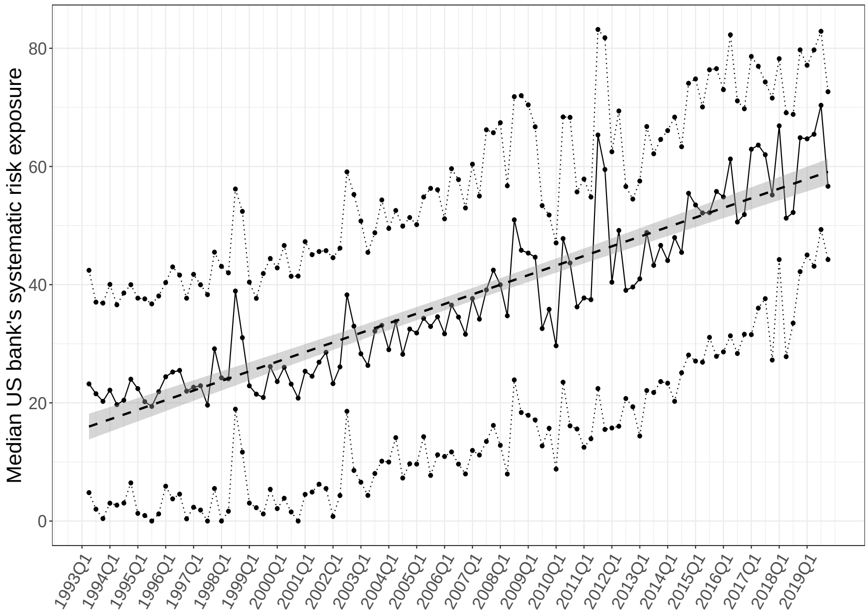

Figure 2: Median (solid line), 25$^{\text{th}}$ and 75$^{\text{th}}$ SRE levels (dotted lines) for the full sample of US banks where SRE is measured by the adjusted R^2 from principal component regressions on individual US banks' stock returns. The dashed line denotes a linear time trend fitted to quarterly SRE levels. The grey region is the 95% confidence interval.

SRE values in that quarter. Similarly, we also construct the median systemic US bank.

Figure 2 shows quarterly variation in SRE levels for the median US bank as well as the 25$^{\text{th}}$ and 75$^{\text{th}}$ quantile values each quarter. The dashed line indicates the result of linear trend fitting and the grey region delineates the 95% confidence interval. For the median US bank, as well as for the ones corresponding to the first and third quartile, systematic risk exposure shows a significant, positive trend. It starts in 1993Q2 from 23.2 and ends 27 years later in 2019Q4 at 56.7. The median bank's SRE reaches a minimum of 19.4 in 1995Q3; and achieves a peak of 70.4 in 2019Q3. Further, the more-or-less even spacing between the 25$^{\text{th}}$ and 75$^{\text{th}}$ quantile and the median US bank suggests that systematic risk exposures are evenly spread out over the banks.[9]

We subject all banks with more than 10 quarterly SRE values (out of a total

[9]This is also borne out by similar plots showing quarterly series for the, say 90$^{\text{th}}$ quantile and the 10$^{\text{th}}$ quantile.

Table 2: US banks' systematic risk exposures' trend behavior

Sample	Significance level	Number	Total	Fraction
Banks with positive trend	10%	579	1579	0.38
	5%	519	1579	0.33
	1%	388	1579	0.25
Banks with negative trend	10%	122	1579	0.08
	5%	86	1579	0.05
	1%	50	1579	0.03

107)—a total of 1579 distinct US banks—to a linear trend fitting with Newey-West standard errors [Newey and West, 1987] and compile results in Table 2. About 38% US banks show significantly positive SRE trends at the 10% significance level; about 33% show significantly positive trends at the 5% significance level; and around 25% show significantly positive trends at the 1% significance level. Hence a large fraction of the admissible bank sample can be said to exhibit significant positive trends.

On the other hand, there are about 8% US banks that show significantly negative trends at the 10% level; around 5% banks that have significant negative trends at the 5% level and about 3% banks with highly significant negative trends at the 1% level. Overall, this suggests that banks with increasing SRE trends heavily outnumber those with negative trends by approximately by 4.75 to 1 at the 10% level; 6 to 1 at the 5% level; and 7.76 to 1 at the 1% level of significance.

Thus the median US bank and a large fraction of the whole sample show a steady increase in their exposure to systematic risk. In case this trend continues, a strong negative shock to any of the common factors could increase banks' distress owing to their large risk exposures. This aggregate increase in systematic risk exposure is even more pronounced for the subsample of systemically important banks, as the next subsection elucidates.

4.1 Trends among systemically important banks

Our sample contains observations on 24 global- and domestic-systemically important banks. All of them qualify for the linear trend tests with Newey-West standard errors and results of their trend-fitting are displayed in Table 3. 20 out of the 24 systemic banks show significantly high positive trends while 2 out of the 24 show significantly negative trends. Most of the systemic banks exhibit slopes between 0.30–0.50 and except American Express and Union Bank San Fransisco all banks have p-values well below the benchmark 1% significance level.

Table 3: Systemic US banks' SRE trends.

Bank	Estimate	Std. Error	t value	p value	Obs
Ally Financial	1.8850	0.3471	5.4301	0.0000	23
American Express	0.1110	0.0727	1.5271	0.1298	107
BNY Mellon	0.2951	0.1000	2.9500	0.0039	107
Bank of America	0.3379	0.0729	4.6370	0.0000	105
Capital One	0.3216	0.0804	4.0016	0.0001	100
Citigroup	0.2420	0.0578	4.1865	0.0001	107
Comerica	0.4915	0.0631	7.7918	0.0000	107
Discover	2.0468	0.6438	3.1794	0.0098	12
Fifth Third	0.4797	0.0660	7.2681	0.0000	107
Goldman Sachs	-4.4606	1.2605	-3.5389	0.0063	11
Huntington Bancshares	0.5319	0.0638	8.3342	0.0000	107
JP Morgan	0.3174	0.0697	4.5536	0.0000	107
Keycorp	0.3861	0.0606	6.3679	0.0000	103
M & T Bank	0.3603	0.1011	3.5648	0.0006	86
Morgan Stanley	0.9766	0.2714	3.5984	0.0042	13
Northern Trust	0.4436	0.0836	5.3027	0.0000	107
PNC	0.4237	0.0782	5.4149	0.0000	107
Regions	0.5401	0.1009	5.3546	0.0000	103
State Street	0.3928	0.0769	5.1053	0.0000	107
Suntrust Banks	0.3857	0.0679	5.6782	0.0000	107
Union Bank San Fransisco	0.3596	1.4105	0.2549	0.8039	12
United States Bancorp	-0.8307	0.2688	-3.0903	0.0075	17
Wells Fargo	0.3443	0.0736	4.6765	0.0000	107
Zions Bancorporation	0.5826	0.0715	8.1529	0.0000	102

We also investigate the behavior of the median systemic bank. For example, figure 3 shows quarterly SRE levels of the median systemic bank juxtaposed with that of the median US bank. The median systemic bank is constructed from taking the quarterly medians of available SRE levels of systemic US banks.

The median systemic bank starts with a systematic risk exposure of 47.4 in 1993Q2 and ends at 76 in 2019Q4. It is quite remarkable that except for a short period very early on in the sample, the median systemic bank displays uniformly higher levels than its full sample counterpart. Moreover, the median systemic bank's quarterly SRE series is much more volatile, with standard deviation 18.6 than that of the median US bank with standard deviation 13.8.

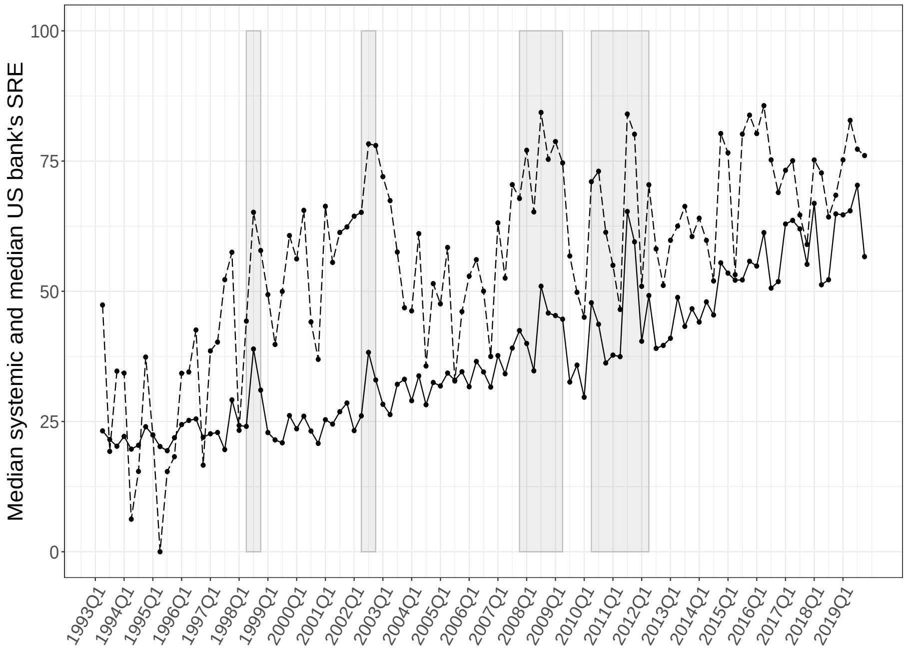

Figure 3: Median US bank's and the median US systemic bank's SRE. The shaded area corresponds to the LTCM collapse: 1998Q3, the dotcom bust: 2002Q3-Q4, the great recession: 2007Q4–2009Q2; and the Eurozone crisis: 2010Q2–2012Q2.

Finally figure 3 shows clearly that during periods of market distress—LTCM collapse: 1998Q3, the dotcom bust: 2002Q3-Q4, the great recession: 2007Q4–2009Q2; and the Eurozone crisis: 2010Q2–2012Q2—the median US as well as the median US systemic banks exhibit significantly high values (local maxima). Another common feature of the two displayed time series is their consistently positive trends which have kept pushing up their SRE values to successively higher levels. Insofar as high systematic risk exposure values denote excessive dependence on the movement of the common factors, such increasing trends suggest a high build-up of risk in the US banking sector.

4.2 First and second halves of the sample duration

To investigate the effect of subsample duration on systematic risk exposures, we subdivide our sample into two equals halves: H1 and H2 corresponding to the periods 1993Q1–2006Q2, dubbed henceforth as “pre-2006” or “H1”; and 2006Q3–2019Q4 dubbed “post-2006” or “H2” in our sample.

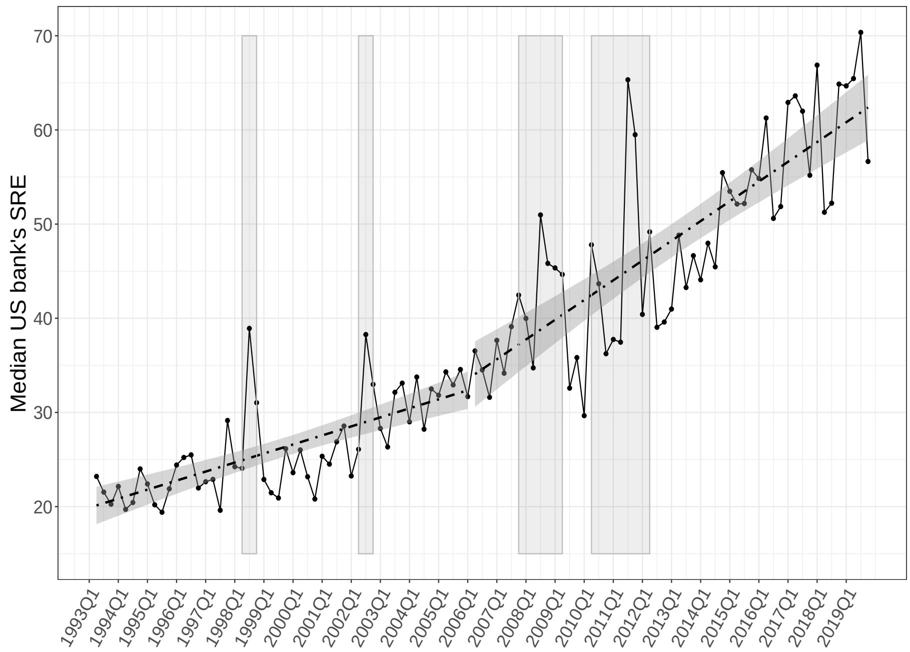

Figure 4: The dot-dashed line denotes a linear time trend fitted to quarterly SRE levels segregated by first (pre-2006) and second (post-2006) halves of the sample duration. The grey region is the 95% confidence interval and the vertical grey bands correspond to the LTCM collapse (1998Q3), the dotcom bust (2002Q3–Q4), the great recession (2007Q4–2009Q2) and the Eurozone crisis (2010Q2–2012Q2).

Figure 4 plots the median US bank's systematic risk exposure with 95% confidence region in grey and vertical grey bands for the four prominent periods of market distress in our sample—the LTCM collapse: 1998Q3, the dotcom bust: 2002Q3-Q4, the great recession: 2007Q4–2009Q2; and the Eurozone crisis: 2010Q2–2012Q2. To highlight the effect of the subsample duration, it fits two separate trend lines to the median US bank's quarterly SRE levels. Visual inspection of the figure strongly suggests that for the median US bank, the positive trend with increasing SRE levels has accelerated in the second half of the sample (post-2006).

Table 4: Median US banks' SRE trends.

Sample	Estimate	Std. Error	t value	p value
Med full	0.4067	0.0245	16.6339	0.0000
Med full H1	0.2398	0.0192	12.4937	0.0000
Med full H2	0.5243	0.0487	10.7723	0.0000
Med sys	0.4197	0.0651	6.4494	0.0000
Med sys H1	0.7284	0.2318	3.1420	0.0028
Med sys H2	0.2717	0.1254	2.1661	0.0348

Notes: "Med full" denotes the median US bank, "Med sys" denotes the median systemic bank, "Med full H1" and "Med full H2" denote the median US bank corresponding to the first and second half respectively of the sample period (pre- and post-2006); and "Med sys H1" and "Med sys H2" denote the median systemic bank pre- and post-2006 respectively. The Newey-West standard errors [Newey and West, 1987] are heteroskedastic and autocorrelation consistent.

To confirm the visual evidence presented in figure 2, we construct Table 4 and compile the results of linear trend fitting on banks' quarterly SRE values. Results are reported for the median US bank, the median US systemic bank over the full duration of the study, as well as on the first and second halves of the sample H1, H2 corresponding to the pre- and post-2006 time period.

For the median US bank for the full sample duration, as well as during the first and second halves respectively, there is a significantly positive slope, especially post-2006. The overall slope is 0.40 (per quarter) which indicates an increase of 16 units (or, percent) of systematic risk exposure in 10 years. The corresponding numbers for the first and second half of the sample are 0.24 and 0.52, indicating 10-unit SRE increase per decade pre-2006; and about 21 units SRE increase per decade post-2006.

Similarly, for the median systemically important bank the full sample slope is significantly positive and suggests about 17 units of SRE increase per decade. The corresponding numbers for the first and second half of the sample are 0.73 and 0.27, indicating about a 28-unit SRE increase per decade pre-2006; and about 11 units SRE increase per decade post-2006. In this respect the median US and the median systemic bank display opposite behavior: their major slope increasing regimes are the opposite. The median US bank increases the steepness of the slope of its linear trend post-2006, while the median systemic bank's high positive trends occur pre-2006.

4.3 Crises

Our sample period from 1993–2019 is able to cover four important market distress episodes that affected US banks—the LTCM collapse: 1998Q3, the dotcom bust: 2002Q3-Q4, the great recession: 2007Q4–2009Q2; and the Eurozone crisis: 2010Q2–2012Q2.

Table 5: Median US banks' SRE trends during crises.

	Estimate	Std. Error	t value	p value
Median Bank:				
Trend	0.4103	0.0263	15.6003	0.0000
LTCM	7.5488	1.7636	4.2803	0.0000
Dotcom	0.4026	1.3907	1.5011	0.1364
GR	3.2204	1.5277	2.1080	0.0375
EZ	1.6524	3.5462	0.4660	0.6423
Median systemic bank:				
Trend	0.4312	0.0530	8.1437	0.0000
LTCM	15.6937	3.5760	4.3886	0.0000
Dotcom	26.8495	3.1402	8.5503	0.0000
GR	17.4276	2.0067	8.6849	0.0000
EZ	3.7769	3.3567	1.1252	0.2632

Notes: "Trend" denotes linear trend, "LTCM" denotes the LTCM collapse (1998Q3), "Dotcom" denotes the dotcom bust (2002Q3–Q4), "GR" denotes the great recession (2007Q4–2009Q2) while "EZ" denotes the Eurozone crisis (2010Q2–2012Q2). The Newey-West standard errors [Newey and West, 1987] are heteroskedastic and autocorrelation consistent. The coefficients, T stats etc. for the regression intercept have been omitted.

For the median US and the median systemic US bank, results from trend regressions with dummy variables for the above four distinct market distress episodes are tabulated and compiled in Table 5. In assessing the significance of estimates, we rely on the Newey-West standard errors [Newey and West, 1987] which are heteroskedastic and autocorrelation consistent.

A brief overview of the results is as follows: the linear trend is positive and significant, postulating an increase in systematic risk exposure of about 16–17 units per decade. For the full median, the LTCM crisis and the Great Recession exhibit the highest increases in SRE respectively, with the LTCM crisis (in 1998Q3) indicating an increase of almost 7.5 units per quarter; and the Great Recession suggesting an increase of 3.2 units per quarter, or equivalently about 22.4 units of increase in SRE over its full course from 2007Q4–2009Q2. The effect of the Dotcom bust (in 2002Q3–Q4) and the Eurozone crisis (2010Q2–2012Q2) is positive but not significantly so.

For the median systemic bank, except the Eurozone crisis, all variables are positive and highly significant, with p values indistinguishable from 0. The LTCM crisis is highly significant, indicating an increase of about 15.7 SRE units per quarter, while the great recession also features significantly high SRE observations over and above the trend, with a 17.4 unit increase in SRE per quarter. However, the most significant variable is the dotcom bust, indicating a 26.9 units SRE increase per quarter.

Thus overall, for the median US bank the strongest economic effect comes from the LTCM collapse, followed by the Great Recession, while for the median systemic bank, the strongest economic effect is exerted by the Dotcom bust, followed closely by the Great Recession and the LTCM collapse.

To test the effect of crises on individual banks' SRE levels over and above their trends, we introduce dummy variables corresponding to the market distress quarters. The results are presented in Table 6 where we count, for each crisis, how many banks show significantly positive SRE observations over and above their trends at the conventional 10%, 5% and 1% significance level benchmarks.

Overall, there are 1579 banks for which such regressions can be run. However, several of these banks have very few usable observations—during tranquil as well as distressed quarters—on the systematic risk exposure and the sample is rife with missing values. To circumvent this issue, we conduct linear trend regressions with crises dummies—LTCM 1998Q3, Dotcom 2002Q3-Q4, the Great Recession 2007Q4–2009Q2; and the Eurozone crisis 2010Q2–2012Q4—for whichever set of

Table 6: US banks' systematic risk exposures during crises

	Crises	10%	5%	1%	Total
Positive effect	LTCM	84	47	18	500
	Dotcom	47	30	3	271
	GR	151	132	86	340
	EZ	74	44	15	255
	Any	190	118	62	710
Negative effect	LTCM	31	10	1	354
	Dotcom	22	8	3	218
	GR	29	18	6	219
	EZ	47	30	11	206
	Any	56	25	4	485

Notes: Columns "10%", "5%" and "1%" denote benchmark significance levels and "Total" denotes the total number of available bank observations. "LTCM" denotes the LTCM collapse (1998Q3), "Dotcom" denotes the dotcom bust (2002Q3–Q4), "GR" denotes the great recession (2007Q4–2009Q2) while "EZ" denotes the Eurozone crisis (2010Q2–2012Q2). "Any" is a dummy variable taking the value 1 for each crisis episode and 0 otherwise.

banks that display SRE observations during these distress events.

4.3.1 LTCM collapse: 1998Q3

For the LTCM collapse in 1998Q3, there are overall 854 banks with usable observations. Out of these, 500 banks display SRE levels more than trends, with 85 banks exhibiting significance at the 10% levels, 47 at the 5% level and 18 at the 1% level. On the other hand, there are overall 354 banks with usable observations with below trend obversations; and among these, 31 banks exhibit significance at the 10% levels, 10 at the 5% level and 1 at the 1% level.

4.3.2 Dotcom bust: 2002Q3–Q4

For the Dotcom bust in 2002Q3–Q4, there are overall 489 banks with usable observations. Out of these, 271 banks display SRE levels more than trends, with 47 banks exhibiting significance at the 10% levels, 30 at the 5% level and 3 at the 1% level. On the other hand, there are overall 218 banks with usable observations with below trend observations; and among these, 22 banks exhibit significance at the 10% levels, 8 at the 5% level and 3 at the 1% level.

4.3.3 The Great Recession: 2007Q4–2009Q2

For the Great Recession during 2007Q4–2009Q2, there are overall 559 banks with usable observations. Out of these, 340 banks display SRE levels more than trends, with 151 banks exhibiting significance at the 10% levels, 132 at the 5% level and 86 at the 1% level. On the other hand, there are overall 219 banks with usable observations with below trend observations; and among these, 29 banks exhibit significance at the 10% levels, 18 at the 5% level and 6 at the 1% level.

4.3.4 Eurozone crisis: 2010Q2–2012Q2

For the LTCM collapse in 1998Q3, there are overall 461 banks with usable observations. Out of these, 255 banks display SRE levels more than trends, with 74 banks exhibiting significance at the 10% levels, 44 at the 5% level and 15 at the 1% level. On the other hand, there are overall 206 banks with usable observations with below trend observations; and among these, 47 banks exhibit significance at the 10% levels, 30 at the 5% level and 11 at the 1% level.

4.3.5 Any crisis

We also test how many banks get affected by any of the four market distress episodes outlined above and check the number of positive versus negative SRE levels in comparison to their trends. Overall there are about 1189 banks for which such tests can be conducted. Out of these, 710 banks show positive effects of crises on SRE, out of which 190 show significance at the 10% level, 118 at the 5% level and 62 at the 1% level. Similarly, 485 banks show negative effects of crises on SRE, out of which 56 show significance at the 10% level, 25 at the 5% level and 4 at the 1% level.

Overall, for each crisis in our sample duration, both the median US bank and the median systemic bank; as well as all admissible individual banks display a marked propensity of significantly increased exposure to systematic risk. Increases in the systematic risk exposure uniformly dominate decreases for all bank subsamples, as well as for all conventional benchmarks for significance.

5 Policy implications

We draw policy implications relevant to bank regulators based on the following inter-related observations outlined in prior sections.

1. *SRE levels during crises are abnormally high*

   In section 4.3, we compile extensive evidence for this assertion, especially in tables 5 and 6. Visual evidence for this claim can be assessed via figures 2, 3 and 4.

   Abnormally high SRE levels over-and-above those warranted by trends, are observed not only for the median US bank, the median US systemic bank, the 25^{th} and 75^{th} percentiles; but also for a large sample of banks individually. This leads credence to the view that during periods of market distress, the exposure of US banks to systematic risk is much higher than that during tranquil periods.

2. *The top eigenvector's explanatory share is highest during crises*

   The explanatory power—in terms of the proportion of variance explained—of the top eigenvector is the highest during times of crises. Equivalently, the marginal contribution in terms of explanatory power of principal components 2, 3 etc. is the lowest during times of crises, as can be seen in figure 1.

This set of results has potentially important consequences for US bank regulators. Excessively high systematic risk exposures denote excessive dependence of banks' stock returns on common banking factors; and a concomitantly low dependence on idiosyncratic factors. Another indication of the same phenomenon may be characterized by the time series of contributions of the top eigenvector to the proportion of explained stock return variance, overly high levels of which denote overdependence of banks' stock returns on the fate of common banking factors. Equivalently, overly low explanatory fraction of the second top eigenvector denotes the same excessive dependence of banks on common factors.

Periods of market distress are characterized by negative shocks to one or more underlying common factors. Thus it is quite natural to observe US banks' SRE levels jump significantly high during crisis episodes. Even more, since our comprehensive sample of US banks exhibits ever-increasing exposures to systematic risk, they remain vulnerable to potential negative shocks to underlying common factors when a future crisis strikes.

Based on our methodology, bank regulators can assess both individual banks' exposure to systematic risk as well as aggregate sector-level exposure. In periods of high market distress, requiring additional stress tests, financial disclosures or mandated increases in capital buffers can mitigate potential heavy losses from such future negative shocks [Hirtle, 2007]. After the Great Recession, the Dodd-Frank Act was one such reform that sought to make the US banking system safer during times of systemic distress. We evaluate its impact on banks' exposure to systematic risk below.

5.1 Effect of the Dodd-Frank Act

The Dodd-Frank Act was enacted on July 21, 2010 in the aftermath of the great recession with a view to overhaul financial regulation in the US. In particular, it gave the Federal Reserve new powers to regulate the too-big-to-fail banks with an aim to contain threats to financial stability emanating from their distress. In fact, the notion of "too-big-to-fail" was formalized under the provision of Title I of the Dodd-Frank Act which classified such entities as systemically important financial institutions (SIFIs). In particular, banks that were identified as posing excessive systemic risk were required to hold increased levels of high quality capital in order to insulate them from sudden market downturns.

We examine the time series of the full median and the median systemic banks' combined tier 1 and 2 capital ratio to verify if the passage of the Dodd-Frank Act has had any effect on banks' behavior. The shaded vertical grey regions correspond to the Great Recession (2007Q4–2009Q2) and the Eurozone crisis (2010Q2–2012Q2); the dashed vertical line corresponds to the passage of the Dodd-Frank Act (2010Q3); and the y axis measures in percentages, the combined tier 1 and 2 ratio.

We observe roughly three regimes in the time series evolution of figure 5. The

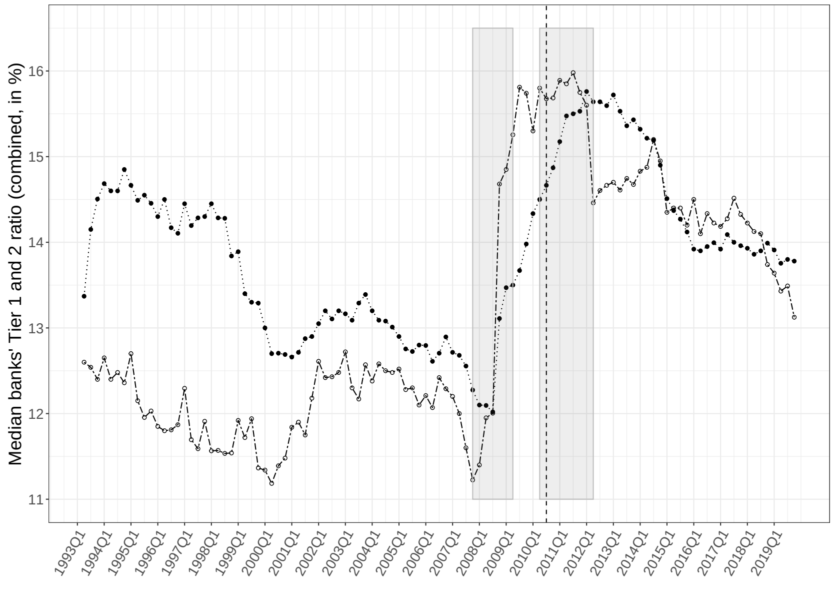

Figure 5: The median US and the median US systemic banks' combined tier 1 and 2 capital ratio, with the dot-dashed line at the bottom (in 1993) denoting the median systemic bank and the dotted line at the top (in 1993) denoting the full median US bank. The shaded vertical grey regions correspond to the Great Recession (2007Q4–2009Q2) and the Eurozone crisis (2010Q2–2012Q2); the dashed vertical line corresponds to the passage of the Dodd-Frank Act (2010Q3); and the y axis measures in percentages, the combined tier 1 and 2 ratio.

first regime starts from the beginning of the sample in 1993 and ends just as the Great Recession begins to set in (2007Q4). During this period, the median US bank's combined tier 1 and 2 ratio is uniformly higher than that of the median systemic bank, suggesting that the former was better capitalized than the latter during this period. The second regime starts from the onset of the Great Recession and lasts till the end of the Eurozone crisis (2012Q2) and features several interesting observations. First, the median systemic bank's T1 T2 ratio is at its minimum in 2007Q4, then builds up rapidly and during just one quarter: 2008Q3–Q4 jumps vertiginously from around 12% to about 14.7%. This jump also helps the median systemic bank's T1 T2 ratio to overcome that of the relatively slow increase of the full median bank. During the Eurozone crisis, the median systemic bank maintains levels around 15.5% while the full median catches up with it during the last legs of the Eurozone crisis in 2012Q1. Finally, in the third regime, starting from 2012Q2, the full median and the systemic median bank's combined tier 1 and 2 ratios seem to be close to each other, especially after 2014Q3.

Quite interestingly we do not observe tier 1 and 2 capital ratios jump after the imposition of the Dodd-Frank Act in 2010Q3. The jumps in capital ratios occur during the Great Recession and hence much before the formal announcement of the Act. This is true for both the full median and the systemic median bank and this observation gives credence to the idea that increases in safe capital levels of US banks were an endogenous reaction to the onset of the Great Recession and not necessarily to the Dodd-Frank Act, which came into effect about two years later. In fact, this development is intricately linked to the enactment of the Emergency Economic Stabilization Act (October 3, 2008) which created the Troubled Asset Relief Program (TARP). Section 128 of the Act allowed the Federal Reserve Board to begin paying interest on excess reserve balances as well as on required reserves.[10] As a result, US banks' deposits with the Fed increased from August 2008's level of about \$10 billion to \$880 billion by the end of the second week of January 2009. By February 11, 2009, total reserve balances had fallen to \$603 billion but by April 1 2009, reserve balances had again increased to \$806 billion. Finally, by August 2011, they had reached \$1.6 trillion [Federal Reserve Bank of St. Louis, 2020]. All of these ups and downs in banks' deposits with the Fed closely mirror the rise and fall in the tier 1 and 2 ratio of the median banks in figure 5. Thus it can be seen that US banks' improvement in the quality of capital post-2008Q3 was prompted by the Fed's policy change of paying interest on reserves and excess reserves in 2008Q3—much before the formal imposition of the Dodd-Frank Act in 2010Q3.

To sum up, insofar as high levels of tier 1 and 2 capital ratio indicate high levels of safe capital assets, US banks can be said to be better capitalized in the wake of the Dodd-Frank reform—having moved from roughly 13% pre-2008, to around 15% during crises (2007–2012), to finally about 14% after 2014.[11] However, it is important to note that the improvement in safe capital levels occurred much prior to the formal imposition of the Dodd-Frank Act.

We also present figure 6 which compares the time series of the median systemic

[10]See the Federal Reserve press release at https://www.federalreserve.gov/newsevents/pressreleases/monetary20081006a.htm.

[11]Similar observations have been made in Goel et al. [September 2019] which present evidence that the global systemically important banks are better capitalized after recent crises and thus have become somewhat less systemically important.

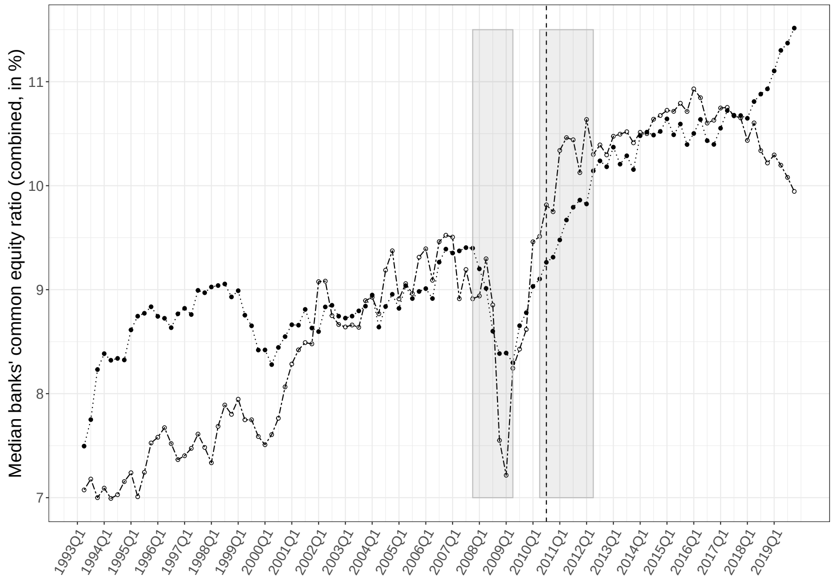

Figure 6: The median US and the median US systemic banks' common equity ratios (in percentages), with the dot-dashed line at the bottom (in 1993) denoting the median systemic bank and the dotted line at the top (in 1993) denoting the full median US bank. The shaded vertical grey regions correspond to the Great Recession (2007Q4–2009Q2) and the Eurozone crisis (2010Q2–2012Q2); and the dashed vertical line corresponds to the passage of the Dodd-Frank Act (2010Q3).

and the full median US banks' common equity ratios (in percentages). The shaded vertical grey regions correspond to the Great Recession (2007Q4–2009Q2) and the Eurozone crisis (2010Q2–2012Q2); and the dashed vertical line corresponds to the passage of the Dodd-Frank Act (2010Q3).

We observe that from 1993 to 2001Q3, the full median bank's common equity ratio dominates that of the median systemic bank; and from then on, the two time series roughly seem to follow each other closely. However, there is one interesting exception to this rule: during a mere two quarters 2008Q3–2009Q1, the median systemic bank's common equity ratio drops precipitously from about 9% to around 7.2%, only to jump sharply again during 2009Q2 to end up at about 8.2%. For both the full median and the systemic median banks, the ratio steadily increases thereafter, especially during the Eurozone crisis. Overall, the common equity ratio rises from about 8.5% pre-2008, to a level of about 10.5% after the Eurozone crisis.[12]

[12] Adrian et al. [2018] also present evidence that leverage has fallen after recent crises and as

We emphasize that just as in the case of the combined tier 1 and 2 ratio, the increase in the full median and the systemic median banks' common equity ratios occur much earlier than the imposition of the Dodd-Frank Act in 2010Q3. Again, this is indicative of the fact that US banks' increase in common equity is prompted by the promulgation of Section 128 of the Emergency Economic Stabilization Act (October 3 2008) which directed the Federal Reserve to begin paying interests to banks on their reserves and excess reserves.

Table 7: Table for comparing the means of systemic banks' (pooled) variable estimates during pre- versus post-Dodd-Frank Act enactment on July 21, 2010.

Variable	Name of test	Alt: $\mathbb{H}_1$	p-value
Tier 1 and 2 capital ratio	Welch test	Smaller	0
	Wilcoxon test	Negative shift	0
	KS test	CDF higher	0
Common equity ratio	Welch test	Smaller	0
	Wilcoxon test	Negative shift	0
	KS test	CDF higher	0
SRE	Welch test	Smaller	0
	Wilcoxon test	Negative shift	0
	KS test	CDF higher	0

Note: 'Welch test' stands for the two-sample Welch's t test, 'Wilcoxon test' stands for the nonparametric Wilcoxon rank-sum test with continuity correction; and 'KS' denotes the Kolmogorov-Smirnoff test. For Welch and Wilcoxon tests, the null hypothesis is of equal means, while the alternative hypothesis suggests that the means before the imposition of the Dodd-Frank Act (2010Q3) are lower. For the Kolmogorov-Smirnov two sample test, the null hypothesis is that the distribution of SRE is the same pre- and post-Dodd-Frank, while the alternative hypothesis is that the empirical distribution of bank SRE before Dodd-Frank lies above (is stochastically dominated) that after Dodd-Frank.

In order to buttress the above mentioned visual evidence more formally, we conduct statistical tests for the sample of all US systemic banks comparing the means of the tier 1 and 2 capital ratio; and the common equity ratio before and after the enactment of the Dodd-Frank Act in 2010Q3. We present the results in Table 7.

The table shows that we can safely reject the null hypothesis that the means of tier 1 and 2 capital ratio and common equity ratio are the same before and after the imposition of the Dodd-Frank Act respectively. The alternative hypothesis

a result, the banking system is safer.

tests the view (compatible with the plots in figures 5 and 6) that the respective ratios are lower before the enactment of the Dodd-Frank Act in 2010Q3. As may be seen, both parametric (Welch's two-sample t test) and non-parametric tests (Wilcoxon's rank-sum test with continuity correction) resolutely reject the null hypothesis of equality in means in favor of the alternative hypothesis, with the p-value indistinguishable from 0. The mean tier 1 and 2 capital ratio before the Dodd-Frank Act is 12.7% while that after the Act is 15%; and the respective means for the common equity ratio are 8.1% and 10.2%. In fact, we find that the tier 1 and 2 capital ratio and the common equity ratio are higher post-Dodd-Frank not just for the median systemic bank bur for *all* individual systemic banks in our sample.

5.1.1 Effect on banks' systematic risk exposure

We test whether the imposition of the Dodd-Frank Act has helped in reducing US banks' exposure to systematic risk. Clearly, if banks' SRE levels are lower post-Dodd-Frank reforms, one could judge it to be a success. However, prior visual evidence as seen in figure 3 indicates that the median US bank and the median systemic bank have continued to exhibit a steady rise in their exposure to systematic risk.[13] Testing this hypothesis more formally in table 7, we find that the null hypothesis of equal SRE before and after the Dodd-Frank Act can be summarily rejected in favor of the alternative hypothesis which states that SRE before the Dodd-Frank Act was smaller. The median systemic bank's mean SRE before the Act is 50 while that after the Act is found to be 68.

In conclusion, the Dodd-Frank Act can be interpreted to be a partial success insofar as one of its mandates required that US banks, in particular, the systemically important banks be better capitalized. However, it has had a very limited effect on systemic banks' SRE which continues to rise.[14] To the extent that overly high SRE

[13] Although the rate of increase (slope) for the median systemic bank has come down from 0.72 to 0.27 post-2006 as may be observed in Table 4.

[14] With the exception of two systemic banks in our sample—Bank of New York Mellon and Northern Trust—all other systemic banks show significantly higher SRE levels after the imposition of the Dodd-Frank Act.

implies overdependence on common banking factors, this suggests that systemic banks continue to be increasingly vulnerable to negative shocks via exposure to common factors.[15]

6 Determinants of US banks' SRE

We now turn to examine bank characteristics that potentially influence the exposure to systematic risk. In order to do so, we conduct panel estimation of banks' systematic risk exposure levels on bank characteristics. The dependent variable in our regression analysis is the quarterly SRE of US banks for which we have observations from 1993Q2 to 2019Q4—a total of 107 quarters. We collect several bank characteristics that could be potentially associated with bank SRE levels. Our main criteria for deciding which characteristics to investigate depend on related literature and access to variables that have high coverage for banks in our sample. These characteristics include measures of bank size, capital structure, banks' reliance on deposit financing, tier 1 and 2 capital ratios, the net interest margins etc. We rely on Standard and Poor's Compustat to collect quarterly bank characteristics for as many banks in the sample as are available. Each bank's SRE level is then regressed on its characteristics. Our final panel consists of 1738 unique US banks with time series observations ranging from 1–104 quarters yielding a total of 55592 bank-quarter observations. We describe the explanatory variables in the following subsections.

6.1 Data

We report summary statistics for the entire pooled sample consisting of 55592 bank-quarter observations over the whole time period in Table 8. For each explanatory variable, we report its minimum, maximum, mean, median, standard deviation and inter-quartile range.

Additionally, we report the correlation coefficients of all pooled variables—both

[15] To combat such sources of fragility, Passmore and von Hafften [2019] advocate even higher levels of capital surcharges for G-SIBs.

independent and dependent—in Table 9.[16] In order to motivate whether the explanatory variables are expected to be of the same or different signs as that of bank SRE, we refer to Table 9. To the best of our knowledge, there have been no prior studies that explain bank SRE levels on the basis of bank characteristics. However, several related studies analyse determinants of banks' beta, idiosyncratic risk, interconnectivity, systemic importance, propensity for contagion etc. Hence, in the following discussion, we investigate if the aforementioned bank characteristics impact SRE the same way as they influence other, related measures of bank risk.

6.1.1 Size

In our study, we measure a bank's size by the log of its total assets. Table 8 presents the summary statistics for the variable bank size. Several related studies present evidence that size of a bank contributes positively to its beta, idiosyncratic risk, systemic risk etc. Prominent among such works are Altunbas et al. [2017], Tarashev et al. [2016], Laeven et al. [2015], Hovakimian et al. [2015], Moore and Zhou [2014], Cont et al. [2013], Haq and Heaney [2012] and Stever [2007]. Based on these studies, we expect that all else equal, the effect of bank size on its SRE level should be positive. Indeed, it is plausible to assume that all else equal, as a bank's size increases, its dependence on common factors of the US banking sector increases. This is also borne out by Table 9 where the correlation between bank size and bank SRE is positive with a value of 0.50.

6.1.2 Deposit ratio

We collect quarterly data on total deposits for banks in our sample and compute the deposit ratio (in percentage) as $100 * \frac{\text{total deposits}}{\text{total assets}}$. Beltratti and Stulz [2012] argue that deposit funding is positively associated with bank performance during the 2007–2008 crisis episode and Cornett et al. [2011] suggest that deposit-reliant banks continued lending during the great recession. Analogously, several other

[16] We note that all correlations reported in table 9 are statistically significant with p-values indistinguishable from 0 up to 4 decimal places.

Table 8: Descriptive statistics for the pooled values of the dependent variable bank SRE and the independent variables.

	SRE	size	deposit	com eq	NIM	npa	t1 t2	non int	cash div	curr debt
Min	0	1.61	13.50	-8.56	-0.44	0	-1.31	-5.53	-1.49	0
Max	99.46	6.44	97.78	60.61	661823	135.25	20330	12.18	50.79	59.46
Mean	37.23	3.27	75.65	9.77	23.35	1.17	16.17	0.28	0.09	4.25
Med	36.32	3.12	77.47	9.26	3.69	0.63	13.8	0.22	0.07	2.14
SD	26.93	0.68	9.81	3.44	3581.45	1.87	141.32	0.32	0.32	5.98
IQR	45.70	0.80	12.73	3.43	0.99	1.00	3.99	0.21	0.09	5.94

Notes: "Min" denotes mimimum, "Max" maximum, "Med" median, "Std" standard deviation and "IQR", the inter-quartile range. All variables are at the quarterly frequency. "SRE" denotes systematic risk exposure, "size" denotes bank size measured as the log of total assets, "deposit" denotes (in percentage) the deposits to total assets ratio; "com eq" is (in percentage) the common equity to total assets ratio; "NIM" stands for the net interest margin; "npa" denotes in percentage the ratio of non-performing to total assets; "t1 t2" signifies the combined Tier 1 and tier 2 capital ratio (in percentage); "non int" denotes in percentage, the total non-interest income to total assets ratio; "cash div" denotes the cash dividend to common stock ratio (in percentage); and "curr debt" stands for the ratio of debt in current liabilities to total assets ratio (in percentage).

papers such as Altunbas et al. [2017], Moore and Zhou [2014] and Huang and Ratnovski [2011] argue that more reliance on non-deposit financing increases banks' fragility, makes them susceptible to crises and constitutes an important determinant of their vulnerability during the 2007–2010 crisis episode.

In light of such arguments, we may expect that the deposit ratio can impact SRE negatively. This is also borne out from the correlation matrix presented in table 9 which states the correlation for our sample as -0.06.

6.1.3 Equity ratio

Many studies suggest a relationship between the capital structure of banks to their risk, fragility or other related ideas. For example, Beltratti and Stulz [2012] and Fahlenbrach et al. [2012] present evidence that banks with lower leverage perform better than their overleveraged counterparts during crises. Hovakimian et al. [2015] suggest that leverage is a key driver of systemic risk. Additionally, Adrian and Shin [2010] and Kalemli-Ozcan et al. [2012] document that leverage is strongly procyclical, especially for large commercial banks.

We define the equity ratio in our study as $100 * \frac{\text{common equity}}{\text{total assets}}$. In light of the literature cited above, one can expect a positive relationship between leverage ratio and SRE, or equivalently a negative relationship between the equity ratio and SRE. However, for our sample, as table 9 suggests, the correlation between the equity ratio and SRE is positive at 0.09; and hence overall we strike an agnostic pose regarding its putative effect on banks' systematic risk exposure.[17]

6.1.4 Net interest margin

According to Poirson and Schmittmann [2013] the net interest margin (NIM)—the difference between total interest income and total interest expenses—is a proxy for bank profitability, which they show is positively associated with bank beta, suggesting that all else equal, more profitable banks may have a positive influence

[17]We also collect other, closely related measures of bank equity such as the shareholder equity ratio, the stockholder equity ratio etc. and note that they yield similar levels of positive correlation with bank SRE as well.

on SRE. On the other hand, insofar as bank profitability is dependent on bank-specific management practices and corporate governance which are idiosyncratic, one should expect a negative relationship between NIM and bank risk as suggested in Xu et al. [2019], Bessler et al. [2015]. Hence, overall, we are agnostic about the presumed effect of NIM on bank SRE. Table 9 suggests that NIM and bank SRE are mildly negatively correlated at -0.007.

6.1.5 Non-performing assets ratio

We collect data on total nonperforming assets for banks in our sample and compute the nonperforming assets ratio by computing $100 * \frac{\text{total non performing assets}}{\text{total assets}}$. A reasonable hypothesis could be that banks with higher levels of nonperforming assets should be associated with a higher exposure to systematic risk. On the other hand, insofar as nonperforming assets indicate idiosyncratic management practices that indicate over-risky bank behavior, one could expect it to be negatively related to exposures to systematic risk and positively with idiosyncratic risk. For our sample of US banks, nonperforming assets are mildly negatively correlated with bank SRE at -0.03.

6.1.6 Tier 1 and 2 capital ratio

In our study we collect data on banks' combined tier 1 and tier 2 capital ratio (measured in percentages between 0 and 100) as a possible determinant of their exposure to systematic risk. Laeven et al. [2015] demonstrate that systemic risk varies inversely with bank capital and quality, leading to a possibly negative relationship between SRE and T1 T2 ratio. Further, Baker and Wurgler [2015] show that equity of better-capitalized banks has lower beta and idiosyncratic risk. However, from table 9 we note that the correlation coefficient between bank SRE and Tier 1 and 2 capital ratio is slightly positive at 0.005. Thus overall we maintain a neutral stance regarding its putative effect on banks' SRE for our sample.

Table 9: Correlation matrix of the pooled values of the dependent and the independent variables. All correlations are statistically significant with p-value indistinguishable from 0 up to 3 decimal places.

	SRE	size	deposit	com eq	NIM	npa	t1 t2	non int	cash div	curr debt
SRE	1.000	0.501	-0.059	0.092	-0.007	-0.026	0.005	0.065	0.021	0.084
size	0.501	1.000	-0.289	-0.027	-0.003	-0.088	-0.012	0.212	0.020	0.275
deposit	-0.059	-0.289	1.000	-0.102	0.005	0.115	-0.015	-0.072	-0.016	-0.475
com eq	0.092	-0.027	-0.102	1.000	-0.004	-0.104	0.029	-0.048	0.064	-0.169
NIM	-0.007	-0.003	0.005	-0.004	1.000	0.001	0.001	-0.003	0.001	0.001
npa	-0.026	-0.088	0.115	-0.104	0.001	1.000	-0.003	-0.031	-0.056	-0.095
t1 t2	0.005	-0.012	-0.015	0.029	0.001	-0.003	1.000	-0.006	0.001	0.005
non int	0.065	0.212	-0.072	-0.048	-0.003	-0.031	-0.006	1.000	0.047	0.120
cash div	0.021	0.020	-0.016	0.064	0.001	-0.056	0.001	0.047	1.000	0.013
curr debt	0.084	0.275	-0.475	-0.169	0.001	-0.095	0.005	0.120	0.013	1.000

Notes: All variables are at the quarterly frequency. "SRE" denotes systematic risk exposure, "size" denotes bank size measured as the log of total assets, "deposit" denotes (in percentage) the deposits to total assets ratio; "com eq" is (in percentage) the common equity to total assets ratio; "NIM" stands for the net interest margin; "npa" denotes in percentage the ratio of non-performing to total assets; "t1 t2" signifies the combined Tier 1 and tier 2 capital ratio (in percentage); "non int" denotes in percentage, the total non-interest income to total assets ratio; "cash div" denotes the cash dividend to common stock ratio (in percentage); and "curr debt" stands for the ratio of debt in current liabilities to total assets ratio (in percentage).

6.1.7 Non-interest income ratio

We define the non-interest income ratio (measures in percentages) for our study as $100 * \frac{\text{total non interest income}}{\text{total assets}}$. Several studies have underlined a positive relationship between banks' non-traditional activities including non-interest income and bank risk, most notable among them being Apergis [2014], Haq and Heaney [2012] and Jonghe [2010]. Other related studies such as Chen et al. [2017] and Bessler et al. [2015] note a significant positive relationship between bank idiosyncratic risk and non-interest income. For our sample we note a positive correlation between bank SRE and non-interest income ratio of 0.07.

6.1.8 Cash dividend ratio

We define the cash dividend ratio in our study as $100 * \frac{\text{cash dividend}}{\text{total assets}}$. Haq and Heaney [2012] report that the dividend payout ratio is negatively related to bank risk. For our sample however, there is a mild positive relationship between the cash dividend ratio and the bank SRE at a level of 0.02.

6.1.9 Current debt ratio

We define the current debt ratio in our study as $100 * \frac{\text{debt in current liabilities}}{\text{total assets}}$. Several studies have pointed out a positive relationship between bank risk and short term debt, prominent among them being Fahlenbrach et al. [2012] and Altunbas et al. [2017]. For our sample of US banks, we find a positive relationship between banks' systematic risk exposure and the current debt ratio at a level of 0.08.

6.2 Regression methodology

Our sample of US banks suffers from several missing values for both the independent variables as well as for the dependent variable. We include all variables as and when they become available in Standard and Poor's Compustat. There is extensive heterogeneity in the sample of US banks—not merely in the observed characteristics such as bank SRE, size, NIM etc.—but also in potentially several relevant unobserved characteristics, which could introduce an omitted variable bias under naive pooled OLS estimations.

Hence we employ the framework of fixed-effects, unbalanced panel estimations with clustered robust standard errors. To counter potential heteroskedasticity in bank residuals; and to ascertain the significance of independent variables, the standard errors are computed allowing clustering at both the bank and quarter levels. We note that this is consistent with studies such as Petersen [2009], Cameron et al. [2011] and Thompson [2011] which advocate double clustering to account for persistent shocks as well as cross-sectional correlation.

6.3 Panel estimation results

Table 10 displays the results for several different unbalanced panel regressions. Each panel estimation focuses on a different aspect—either a different regression (OLS) or a different duration (H1 and H2)—in order to ensure that the overall sample's panel estimates do not occlude the behavior of special noteworthy subsamples. The following cases are tabulated: "OLS" denotes results of naive pooled ordinary least squares; "Full" denotes the results of panel estimations on the full sample of 1738 admissible banks; "H1" denotes the first half of the sample duration 1993Q1–2006Q2; and "H2" denotes the second half of the sample 2006Q3–2019Q4.

All estimations (except the OLS) employ bank and quarter fixed effects and standard errors are required to be robust and are clustered at both the bank and quarter level.

Table 10: Unbalanced, fixed-effects panel estimations with bank and quarter fixed effects. Standard errors are robust and clustered at both the bank and quarter level. "OLS" denotes results of naive pooled ordinary least square; "Full" denotes the results of panel estimations on the full sample of 1738 admissible banks; "H1" denotes the first half of the sample duration 1993Q1–2006Q2; and "H2" denotes the second half of the sample 2006Q3–2019Q4.

Sample	Char	Coeff	Std err	Stats	p-value	N
OLS	Size	21.42	1.12	18.98	0	34150
	Deposit ratio	0.31	0.04	7.01	0	
	Eq ratio	0.94	0.10	9.06	0	
	NIM	-4.5×10^{-5}	1.05×10^{-6}	-42.28	0	

	NPA ratio	0.32	0.16	2.07	0.04	
	T1 T2 ratio	0.002	0.001	1.80	0.07	
	Non-int ratio	-3.08	0.86	-3.59	0	
	Cash div ratio	0.61	0.52	1.17	0.24	
	Curr debt ratio	0.07	0.05	1.25	0.21	
Full	Size	18.92	1.89	10.02	0	34150
	Deposit ratio	0.0003	0.04	0.008	0.99	
	Eq ratio	0.48	0.11	4.55	0	
	NIM	-2.9×10^{-5}	6.88×10^{-7}	-42.39	0	
	NPA ratio	0.01	0.18	0.55	0.58	
	T1 T2 ratio	0.002	0.001	1.51	0.13	
	Non-int ratio	0.21	0.71	0.30	0.76	
	Cash div ratio	0.003	0.24	0.01	0.99	
	Curr debt ratio	-0.02	0.04	-0.59	0.56	
H1	Size	7.40	2.78	2.66	0.0077	16365
	Deposit ratio	0.01	0.05	0.26	0.80	
	Eq ratio	0.41	0.13	3.13	0.0017	
	NIM	-2.9×10^{-5}	6.16×10^{-7}	-46.81	0	
	NPA ratio	0.56	0.35	1.59	0.11	
	T1 T2 ratio	-0.0002	-	-	-	
	Non-int ratio	-0.52	0.88	-0.58	0.56	
	Cash div ratio	-0.40	0.31	-1.27	0.20	
	Curr debt ratio	0.04	0.05	0.88	0.38	
H2	Size	19.80	2.95	6.70	0	17785
	Deposit ratio	0.008	0.06	0.12	0.90	
	Eq ratio	-0.03	0.15	-0.20	0.84	
	NIM	0.03	0.02	1.31	0.19	
	NPA ratio	0.18	0.21	0.84	0.40	
	T1 T2 ratio	0.003	7.6×10^{-6}	406.75	0	
	Non-int ratio	-0.13	0.97	-0.13	0.90	
	Cash div ratio	9.17	3.89	2.36	0.02	

Curr debt ratio	0.04	0.06	0.71	0.47

We also supplement the panel estimation in Table 10 by isolating the set of banks deemed 'large' and subject them to the same analysis. We define a large bank to be one which holds total assets worth at least $1 billion in 2019Q1 [Fahlenbrach et al., 2018]. Overall there are 234 US banks deemed large, with 15046 bank-quarter observations. The results of the panel estimation for large US banks is presented in Table 11. We discuss the panel regression results of both tables in the subsections below.

6.3.1 OLS: All Pooled

The pooled least squares forms a naive benchmark for comparing the results of our panel estimations. Standard errors are not robust and no fixed effects are employed, leading to the statistics being overly inflated.

Table 10 presents least square regression results for the full sample. Overall there are 1738 banks that are represented in the regression and a total of 34150 bank-quarter observations. Out of the nine explanatory variables, seven are deemed to be significant, with the exceptions being the cash dividend ratio and the current debt ratio. The net interest margin and the non-interest income ratio are found to be negatively associated with bank SRE; and size, deposit ratio, equity ratio, NPA ratio and the T1 T2 ratio are found to be positively associated. Bank size has by far the strongest economic effect on bank SRE.

Table 11 presents the least square regression results for the large banks with total assets more than $1 billion. There are 234 such banks with a total of 15046 bank-quarter observations. For the large banks, except the combined T1 T2 ratio, all independent variables are found to be significant. Among those variables deemed significant, except the non-interest income ratio—which is negatively associated—all others are positively associated with bank SRE. Again, for the large bank subsample, the most important bank characteristic is revealed to be its size.

Table 11: Unbalanced, fixed-effects panel estimations of large US banks with bank and quarter fixed effects. Standard errors are robust and clustered at both the bank and quarter level. We define a large bank to be one which holds total assets worth at least $1 billion in 2019Q1. Overall there are 234 US banks deemed large, with 15046 bank-quarter observations. "OLS" denotes results of naive pooled ordinary least square; "Full" denotes the results of panel estimations on the full sample of large banks; "H1" denotes the first half of the sample duration 1993Q1–2006Q2; and "H2" denotes the second half of the sample 2006Q3–2019Q4.

Sample	Char	Coeff	Std err	Stats	p-value	N
OLS	Size	20.54	1.56	13.14	0	15046
	Deposit ratio	0.40	0.09	4.52	0	
	Eq ratio	1.87	0.28	6.73	0	
	NIM	0.002	0.0007	2.03	0	
	NPA ratio	0.07	0.38	0.18	0.04	
	T1 T2 ratio	-0.69	0.18	-3.88	0.85	
	Non-int ratio	-7.97	1.85	-4.30	0.0001	
	Cash div ratio	2.05	5.97	3.44	0.005	
	Curr debt ratio	2.06	0.01	2.10	0.03	
Full	Size	16.11	2.63	6.11	0	15046
	Deposit ratio	-0.06	0.07	-0.94	0.35	
	Eq ratio	0.71	0.20	3.59	0.0003	
	NIM	0.005	0.0001	40.65	0	
	NPA ratio	-0.72	0.40	-1.81	0.070	
	T1 T2 ratio	-0.39	0.14	-2.80	0.005	
	Non-int ratio	1.05	1.29	0.81	0.42	
	Cash div ratio	4.17	3.58	1.16	0.24	
	Curr debt ratio	-0.02	0.08	-0.21	0.84	
H1	Size	4.58	5.52	0.83	0.40	4215
	Deposit ratio	-0.19	0.10	-1.82	0.06	
	Eq ratio	-0.19	0.35	0.55	0.58	
	NIM	0.005	0.0002	26.12	0	
	NPA ratio	-0.26	1.39	-0.19	0.85	
	T1 T2 ratio	-0.059	0.22	-0.27	0.79	
	Non-int ratio	-1.29	2.30	-0.56	0.57	
	Cash div ratio	-5.19	6.26	-0.83	0.40	

	Curr debt ratio	-0.09	0.11	-0.79	0.43	
H2	Size	19.87	3.01	6.60	0	10831
	Deposit ratio	0.03	0.08	0.43	0.67	
	Eq ratio	0.24	0.20	1.23	0.22	
	NIM	-0.11	0.48	-0.24	0.81	
	NPA ratio	-0.52	0.41	-1.29	0.20	
	T1 T2 ratio	-0.11	0.18	-0.60	0.55	
	Non-int ratio	0.13	1.25	0.10	0.91	
	Cash div ratio	6.23	3.94	1.58	0.11	
	Curr debt ratio	0.05	0.07	0.78	0.44	

6.3.2 Full: Whole sample

Table 10 shows the results of the panel estimations for the full set of banks. Bank size, the equity ratio and the net interest margin show high significance in their association with the systematic risk exposure. Of these, bank size and equity ratio have a positive association and the net interest margin has a negative association with SRE. A 1% increase in bank size is associated with an 18.9 unit increase in SRE; a 1% increase in the common equity predicts a 0.5 unit increase in SRE; and a unit increase in the net interest margin predicts a decrease in SRE by 0.00003 units. Once these variables have been accounted for, there is no significant explanatory contribution from the other bank characteristics. Overall, the net interest margin has the highest statistical significance (T stats -42.4) but the lowest economic significance; and bank size has the highest economic significance (coefficient 18.9).

Table 11 contains results of panel regressions for the large banks subsample which are bigger than \$1 billion in total assets in 2019Q1. There are 234 large banks and the total number of bank-quarter observations for this set is 15046. Again the three characteristics—bank size, the equity ratio and the net interest margin—show statistical significance and are all positively associated with bank SRE. However, there are two more characteristics—the NPA ratio and the combined tier 1 and 2 ratio—that are significant for the sample of large banks and are both associated negatively with bank SRE. Bank size again displays the largest economic significance and the net interest margin shows the largest statistical significance (though low economic significance). Among positively associated variables, a 1% increase in bank size predicts 16.1 unit increase in SRE; a 1% increase in equity predicts 0.7 unit increase in SRE; and a unit increase in the net interest margin leads to a 0.005 unit increase in SRE. Among the variables that show negative significance, a 1% increase in the non-performing assets predicts a decline in SRE of 0.7 units; and 1% increase in the combined tier 1 and 2 ratio leads to a decrease in SRE by 0.4 units.

For both the full set of banks and the large bank subsample, bank size and the equity ratio affect banks' exposure to systematic risk positively, with bank size having an outsized economic impact. An increase in the net interest margin predicts a decrease in banks' SRE but for the large bank subsample, its association is changes sign to positive. Finally for the large bank sample (but not for the full sample) the nonperforming assets and the combined tier 1 and 2 assets affect banks' systematic risk exposure negatively, i.e., an increase in their values leads to a lower exposure to systematic risk.

Our findings of positive association of bank size with exposure to systematic risk is in agreement with numerous studies, Altunbas et al. [2017] being a recent, prominent example. Similarly, the results of negative association between the net interest margin (a measure of bank profitability) and SRE is in agreement with the recent study by Xu et al. [2019]; and is in disagreement with Poirson and Schmittmann [2013] which find a positive association of net interest margin to bank betas. Further, our finding that for large banks, the tier 1 and 2 ratio relate negatively with exposure to systematic risk seems to agree with Baker and Wurgler [2015]; and our result that equity ratios are positively associated with bank SRE disagree with many studies that show that higher leverage increases bank risk [Hovakimian et al., 2015].[18]

[18] Closely related measures of common equity such as the stockholder equity and shareholder equity have also been substituted and found to yield very similar results—both in terms of their significance and positive association with SRE.

6.3.3 H1: 1993Q1–2006Q2

For the entire bank sample confined to the first half of the duration of study, we refer to the panel regression results collated in Table 10. Overall, there are 16365 bank-quarter observations for the sample period 1993Q1–2006Q2. The results are essentially the same as that for the full sample duration—bank size, equity ratio and the net interest margin are the set of significant explanatory variables. The signs of the coefficients are also the same as in the full duration counterpart—positive for bank size and equity ratio, and negative for the net interest margin. For the period from 1993 to 2006, a 1% increase in bank size predicts an 7.4 unit increase in SRE; a 1% increase in the common equity predicts a 0.4 unit increase in SRE; and a unit increase in the net interest margin predicts a decrease in SRE by 0.00003 units. Other variables do not have much to contribute in terms of significance once these three bank characteristics are taken into account. Again, the net interest margin has the highest statistical significance (T stats -46.8) but the lowest economic significance; and bank size has the highest economic significance (coefficient 7.4).

For the large bank subsample, we refer to results in table 11. There are 234 large banks and the total number of bank-quarter observations for this set is 4215. For the large banks during the pre-2006 era, the panel regression results are qualitatively different from other sets of results. Firstly, bank size ceases to be statistically significant, although the net interest margin continues to remain significant but with changed sign (positive) on its coefficients. Further, the deposit ratio, which does not feature significantly anywhere before, assumes significance and displays a negative association with bank SRE. For the set of large US banks pre-2006, a 1% increase in deposits predicts a 0.2 unit decrease in bank SRE; and a 1% increase in the net interest margin, predicts an increase of 0.004 units of bank SRE. The net interest margin has the most statistical significance (T stats 26.1) while the deposit ratio has the higher economic significance (coefficient -0.2).

The commonality between the full set of banks (1728) pre-2006 and the set of large banks (234) is generally very high but with opposite effects for the net interest margin—negatively for the full set of banks and positively for the large banks. Although bank size and the equity ratio register significance for the full bank sample, they lose it for the set of large banks in the first half of our sample. The increase in deposits has no significant impact for the full set of banks but pre-2006, for the large banks, it reduces their exposure to systematic risk significantly. Thus, in some important ways, large banks pre-2006 behave quite differently from the benchmark panel regression results which posited a noteworthy role of bank size and the equity ratio in explaining banks' SRE.

6.3.4 H2: 2006Q3–2019Q4

For the whole bank sample post-2006, with 17785 bank-quarter observations, we again observe bank size to be the most important explanatory variable—both statistically and economically. In addition two other bank characteristics register significance—the combined tier 1 and 2 ratio and the cash dividend ratio—both showing positive association with bank SRE. For the period from 2006 onwards, a 1% increase in bank size predicts an 19.8 unit increase in SRE; a 1% increase in the T1 T2 ratio predicts a 0.003 unit increase in SRE; and a 1% increase in the cash dividends predicts an increase in SRE by 9.2 units. The combined tier 1 and 2 ratio exhibits the highest statistical significance (T stats 406.8), while the bank size displays the maximum economic significance (coefficient 19.8).

For the sample of large banks post-2006, with 10831 bank-quarter observations, there is only one bank characteristic that registers any significance—bank size.[19] All other explanatory variables have little to add in terms of significance. For large US banks post-2006 a 1% increase in bank size predicts an increase in exposure to systematic risk by 19.9 units.

Thus overall, there is a broad unity in the nature of bank characteristics' association with bank SRE. In all subsamples (except large banks pre-2006) bank size is found to be highly economically and statistically significant. Hence among all nine potential bank characteristics, we deem size to be the most noteworthy in explaining banks' association with their exposure to systematic risk. This as-

[19] The data coverage for large banks improves quite a lot in our second half. Bank-quarter observations post-2006 for big banks are 10831, while that pre-2006 is 4215.

sociation is strongly positive, implying that all else equal, larger banks are more likely to have higher systematic risk exposure. After bank size, the net interest margin (4 regression specifications) and the equity ratio (3 specifications) are the most important; and to a slightly lesser extent, the T1 T2 ratio (2 specifications) followed by the NPA ratio, deposit ratio and cash dividend ratio (1 specification each).

7 Conclusions

We estimate US banks' exposure to systematic risk by the degree of alignment of their stock returns with the principal components of the banking sector. Higher alignment, in terms of higher explanatory power of principal component regressions implies higher exposure to systematic risk and inversely. Most banks in the sample display significant increases in their SRE levels, especially after 2006. Additionally, banks exhibit significantly increased SRE levels over and above their trend during times of market distress such as the great recession and the Eurozone crisis. We argue that excessive bank SRE can be a warning signal of banking sector distress and our methodology based on principal components can provide regulators with a tool to monitor banking sector stability. We also demonstrate that the enactment of the Dodd-Frank Act has been a partial success in that systemic banks are now better capitalized. However, they continue to pose risks to the US banking sector on account of their increasing dependence on common factors.

We are able to investigate potential determinants of US banks' SRE in terms of bank characteristics including size, capital structure, and profitability and find that bank size and equity ratio influence bank SRE positively, while its net interest margin influences SRE negatively. Finally, we argue that bank size is the most economically and statistically significant of all bank characteristics that are associated with SRE.

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