IIMB-WP N0. 597/2022

WORKING PAPER NO: 597

Integration Among US Banks

Abhinav Anand
Assistant Professor
Finance and Accounting
Indian Institute of Management Bangalore
Bannerghatta Road, Bangalore – 5600 76
abhinav.anand@iimb.ac.in

John Cotter
Professor
Banking & Finance
University College Dublin
Dublin
john.cotter@ucd.ie

Year of Publication – June 2022

Integration Among US Banks*

Abhinav Anand† John Cotter‡

June 9, 2022

*Abhinav Anand acknowledges financial support from the IIM Bangalore Visiting Research Scholar Program (VRSP). John Cotter acknowledges the support of Science Foundation Ireland under grant numbers 16/SPP/3347 and 17/SP/5447. The authors thank Utpal Bhattacharya, Michael Brennan, Hans Degryse, Franco Fiordelisi, Stuart Gabriel, Balagopal Gopalakrishnan, Maureen O'Hara, Mark Hallam, Niall McGeever, Philip Molyneux, Steve Ongena, Jalaj Pathak, Srinivasan Rangan, Richard Roll, Tanseli Savaser, Matthew Spiegel, René Stulz, Anita Suurlaht, Anand Venkateswaran and Josef Zechner. The authors also thank conference participants at the Irish Academy of Finance's 2018 annual meeting and the FMA 2017 annual meeting; and seminar participants at the Central Bank of Ireland, Dublin, Indian Statistical Institute Delhi (ISID); Indian Institute of Technology Kanpur (IITK); Indira Gandhi Institute of Development Research, Mumbai (IGIDR) and the Indian Institutes of Management Ahmedabad (IIMA) and Bangalore (IIMB).

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_Bank_Int_Replication and has been shared under the MIT License. The authors encourage those interested to refer to the notes for replication shared under the following link: https://github.com/abhinavananddwivedi/US_Bank_Int_Replication/blob/master/US_Bank_Int_Replication.pdf.

†Indian Institute of Management Bangalore, Finance & Accounting

‡University College Dublin, Michael Smurfit Graduate Business School, Banking and Finance

Abstract

We define 'integration' for 2287 US banks from 1993–2019 as the explanatory power of common banking factors in explaining stock returns. Integration has risen steadily, and shows significantly high peaks during financial crises. This is worrisome, since a negative shock to common factors depresses sector-wide returns more intensely when the sector is tightly integrated. The Dodd-Frank Act has improved capital adequacy but has not arrested rising levels of integration. Further, banks' current integration predicts their instability up to 4 quarters in advance; and during crises, past integration levels explain a healthy (6–7%) variation in US banks' volatilities.

Keywords: Bank integration; 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 few decades. Due to its critical role in moderating stability 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 tame periodic panic in the sector. Even sedate banks have suffered distress and contagion merely on account of having been integrated with the fortunes of their riskier cousins. Hence a detailed investigation of US banks' integration and mutual interdependence, and their relation to crises, warrants serious attention and rigorous scrutiny.

We define and construct US banks' integration for a large sample of 2287 banks over 27 years from 1993 to 2019. We define a bank's integration as the explanatory power of common banking factors in explaining its stock returns. 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 all US banks' stock returns.[1] In order to measure the level of dependence of bank stock returns on these common factors, we employ the goodness-of-fit, in terms of adjusted R^2, of bank stock returns regressed on the principal components of the US banking sector. Since a bank's integration is defined as the explanatory power of principal component regressions, each bank in our sample displays an integration value between 0 and 100.

We offer a clear and straightforward interpretation of our measure of bank integration. Without loss of generality, a bank's stock returns can be explained by common factors and idiosyncratic factors. Common factors drive the returns of all banks, while idiosyncratic factors are specific to each bank. Higher (lower) integration levels equate to higher (lower) exposure to common factors and lower

[1]For example, tax policy changes, monetary policy changes etc. in principle, affect stock returns of all banks in a country and hence would represent two plausible common factors.

(higher) dependency on idiosyncratic factors. Thus our notion of integration is in effect, a parametrization of common factor exposure in the range 0–100. A bank having an integration level of, say, 60 means that collectively, common factors explain 60% of its returns and idiosyncratic factors, the residual 40%.

In general, if banks show a spike in their integration time series, it means that their exposure to common banking factors has shot up at the expense of idiosyncratic factors. This in turn implies that their fortunes are at the mercy of movements in common factors and a negative shock to one or more common factors will lead to a plunge in all well-integrated banks' stock returns. High exposure to idiosyncratic factors does not imply distress for the sector as a whole: in the case of downward movement in an idiosyncratic factor, while the particular bank's stock returns will suffer, other banks will remain insulated from distress. On the other hand, negative shocks to common factors lead to stock returns of all tightly integrated banks to plummet together, which could lead to a sector-wide crisis. We emphasize that high integration by itself does not lead to crises but simply highlights the fact that during such times banks are especially vulnerable on account of being overdependent on the movement in common factors; and if for some reason, one or more common factors suffer a negative shock it could well lead to a genuine crisis. From this perspective, the steadily rising levels of US banks' integration should be a matter of concern.

If the number of common factors is one, our setup is comparable to the CAPM framework [Sharpe, 1964, Lintner, 1965]. If the number of such factors is more than one, it is equivalent to other well-known multi-factor frameworks for explaining stock returns [Ross, 1976, Fama and French, 1992, Carhart, 1997, Fama and French, 2015, Hou et al., 2015]. The main difference however, between our respective frameworks is that we measure exposure to common factors by calculating the explanatory power of common factor regressions; while the other frameworks compute regression coefficients (factor loadings) to evaluate how sensitive returns are to such factors.[2] Both approaches are, of course, complementary: when we wish to know how much do common factors—taken collectively as a whole—influence stock

[2] As a result, our measure is bounded in 0–100, while there is no such restriction for betas.

returns, our approach is more suitable; if instead we wish to measure the sensitivity of stock returns to individual risk factors, the classic multi-factor framework has more value.

Our main findings are as follows. The median US bank's integration starts in 1993 from 23.2 and more than doubles by reaching 56.7 in 2019. 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. Further, US banks' integration 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 integration, it can serve as a warning signal for endogenous sectoral overdependence on common factors, which may lead to widespread distress in case of a negative shock to one of the underlying common factors.

Additionally, consistent with recent studies such as Gao et al. [2018], Balasubramnian and Cyree [2014], Acharya and Richardson [2012] we show that regulatory intervention (such as the Dodd-Frank Act 2010) has led to a better capitalized US banking sector; but it has failed to curtail the rise in banks' exposure to common factors which continues to rise unabated. Thus US banks remain vulnerable in case of negative shocks to one or more underlying common factors. In other words, crisis-era regulations succeeded in improving US banks' ability to absorb negative shocks due to increased capital buffers; but the steady rise in US banks' dependency on common factors has eroded this advantage, and continues to pose a threat to the stability of the US banking sector. While there have been several papers which have posited a role between banks' stability (or lack thereof) on competition [Goetz, 2018, Kick and Prieto, 2015, Thakor, 2014] capital adequacy [Schliephake, 2016], transparency [Nier, 2005], business model [Köhler, 2015] etc., to the best of our knowledge, ours is the first paper to relate banks' instability to their exposure to common factors.

Consistent with the negative relationship between bank stability and integration, we further show that US banks' current integration is significantly positively associated with future values of bank volatility and beta up to 4 quarters in advance. Thus, an increase in bank integration in the current quarter leads to rising bank volatilities and betas up to one year later. Moreover, panel estimations show high explanatory power (up to 13%) during crises, and lags of integration explain 6-7% of the variation in bank volatilities during crises.

Our study's reliance on computing integration by means of goodness-of-fit of principal component regressions adapts 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 postulating banking networks in which banks are connected to each other by maintaining lending or trading relationships. Prominent studies in this tradition are Acemoglu et al. [2015] and Elliott et al. [2014].[4] Measuring spillover effects by generalized vector autoregression 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 alternative 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.[5] Hence, researchers who investigate microscopic interconnectivity among individual banks will find network-based techniques more useful. On

[3] Several other studies have used principal components to measure the related but 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 Castiglionesi and Navarro [2020], Duffy et al. [2019], Martínez-Jaramillo et al. [2014], Langfield et al. [2014] and Rogers and Veraart [2013].

[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. One may argue that the cost of such high coverage is reflected in our coarse estimates of 'integration' as opposed to finer 'interconnectivity' estimates.

the other hand, those who favor aggregate, macroscopic estimates of integration with respect to the entire sector as a whole should rely on indirect econometric techniques such as principal components. The main difference between the two concepts is that interconnectivity between two banks can be measured directly but it is not meaningful to compute integration among two banks. It only makes sense to measure a bank's integration with the rest of the sector and in this sense it is an indirect measure.

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' integration 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' integration levels. Section 6 presents evidence that integration can predict banks' instability—in terms of their volatility and beta—up to one year in advance. Finally, section 7 presents concluding remarks.

2 Data for estimating US banks' integration

For estimating US banks' integration, 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 the admissible codes. For firms whose codes change from one admissible class to another we maintain differences in their classification.[6] 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.[7] 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.[8] In terms of banks covered, this represents around 45% coverage of the US banking sector.

[6]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.

[7]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.

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

3 Methodology

We define a bank's level of integration 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' integration 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 common factors driving 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 integration. 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 integration 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 integration—is 100%.

Real banks display empirical behavior in between these two theoretical extremes and their integration 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 integration.

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

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

where $\widehat{\mathrm{Int}}_j$ is bank j's estimated integration 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 integration 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 integration 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 integration level estimation starts from 2002Q1.

3.2 Extracting out-of-sample 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 in the spirit of Pukthuanthong and Roll [2009].

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 retain their orthogonality, which lays to rest the concern 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

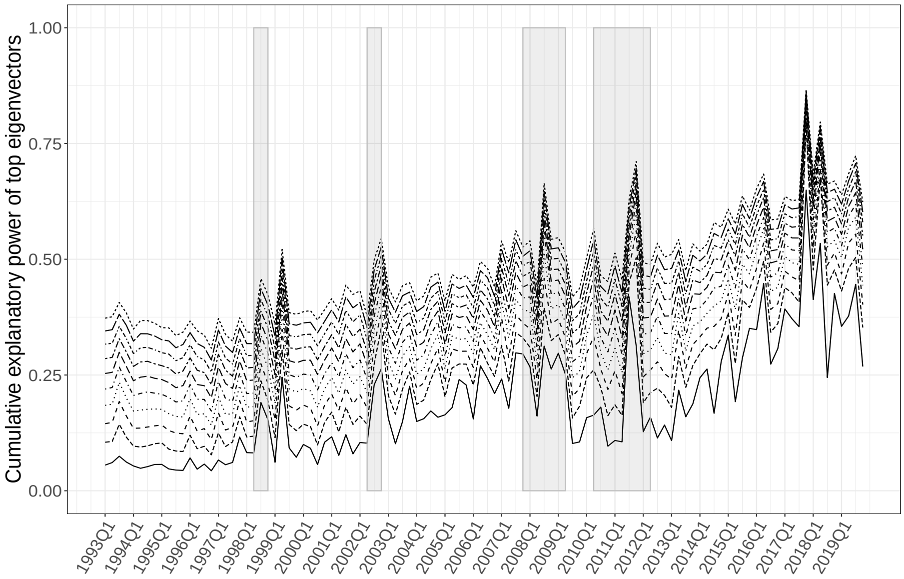

Figure 1: Cumulative proportion of variation explained each quarter by the top 10 eigenvectors. The bottom, solid line is the first eigenvector; the second, dashed line denotes the time series of the explanatory power of top two eigenvectors together; and similarly, the dotted, top line denotes the cumulative 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).

contribution of the top eigenvector has steadily risen and currently exhibits levels even higher than those 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 integration 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.[9] Additionally, two time based subsamples

[9]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

Table 1: Descriptive statistics of US banks' quarterly integration 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 integration levels 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.

corresponding 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 integration level is 33.9, the median is 32.2; a mild positive skewness of 0.3; and the kurtosis level is 2. 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 common factors than their ordinary counterparts. The average integration 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.

4 Trends in US banks' integration

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

Figure 2 shows quarterly variation in integration levels for the median US

set of systemic US banks in our sample can be accessed in Table 3.

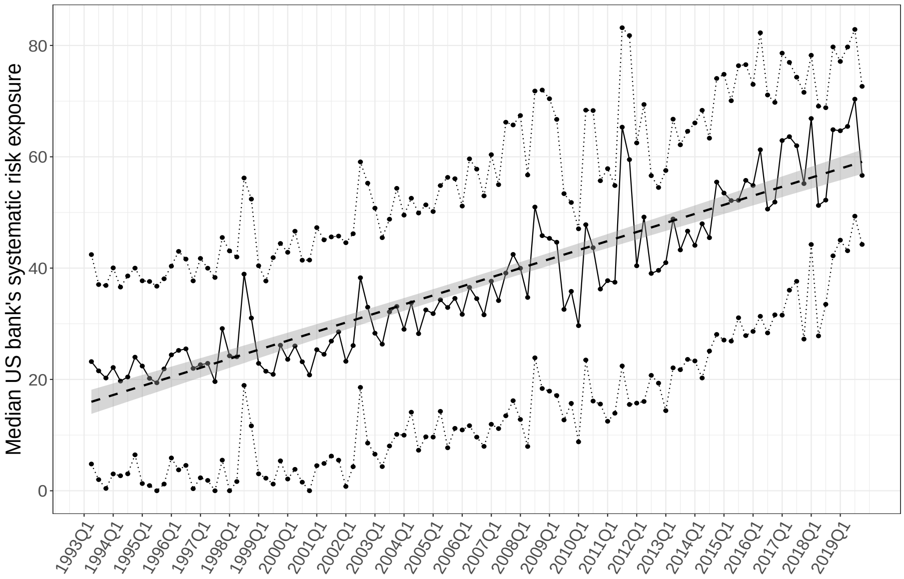

Figure 2: Median (solid line), 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile integration levels (dotted lines) for the full sample of US banks where integration is measured by the adjusted R^2 from principal component regressions on individual US banks' stock returns. The dashed line denotes a linear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

bank as well as the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile 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 bottom and top quartile, integration 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 integration reaches a minimum of 19.4 in 1995Q3; and achieves a peak of 70.4 in 2019Q3.

We subject all banks with more than 10 quarterly integration values (out of a total 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 integration 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 nega-

Table 2: US banks' integration levels' 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

tive 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 integration 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 integration. In case this trend continues, a strong negative shock to any of the common factors could increase banks' distress owing to their large exposure to common factors. This aggregate increase in integration 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 or 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.

We also investigate the behavior of the median systemic bank. For example, figure 3 shows quarterly integration levels of the median systemic bank juxtaposed

Table 3: Systemic US banks' integration trends.

Bank	Estimate	Std. Error	T-stats	p-value	N
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

Notes: The Newey-West standard errors [Newey and West, 1987] are heteroskedastic and autocorrelation consistent.

with that of the median US bank.[10] The median systemic bank starts with a integration 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 integration time series is much more volatile, with standard deviation 18.6 compared to that of the median US bank whose standard deviation is 13.8.

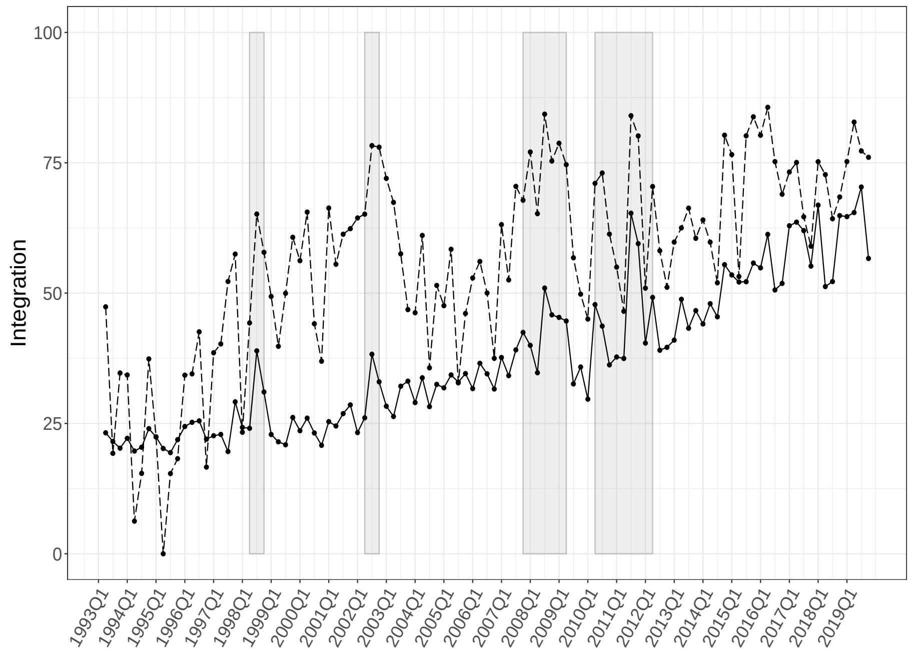

Figure 3: Median US bank's and the median US systemic bank's integration. The shaded area corresponds to the LTCM collapse: 1998Q3, the dotcom bust: 2002Q3-Q4, the great recession: 2007Q4–2009Q2; and the Eurozone crisis: 2010Q2–2012Q2.

Further, 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 integration values to successively

[10]The median systemic bank is constructed from taking the quarterly medians of available integration levels of systemic US banks.

higher levels. Insofar as high integration values denote excessive dependence on the movement of the common factors, such increasing trends suggest a high build-up of aggregate risk in the US banking sector.

4.2 First and second halves of the sample duration

To investigate the effect of subsample duration on integration levels, 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.

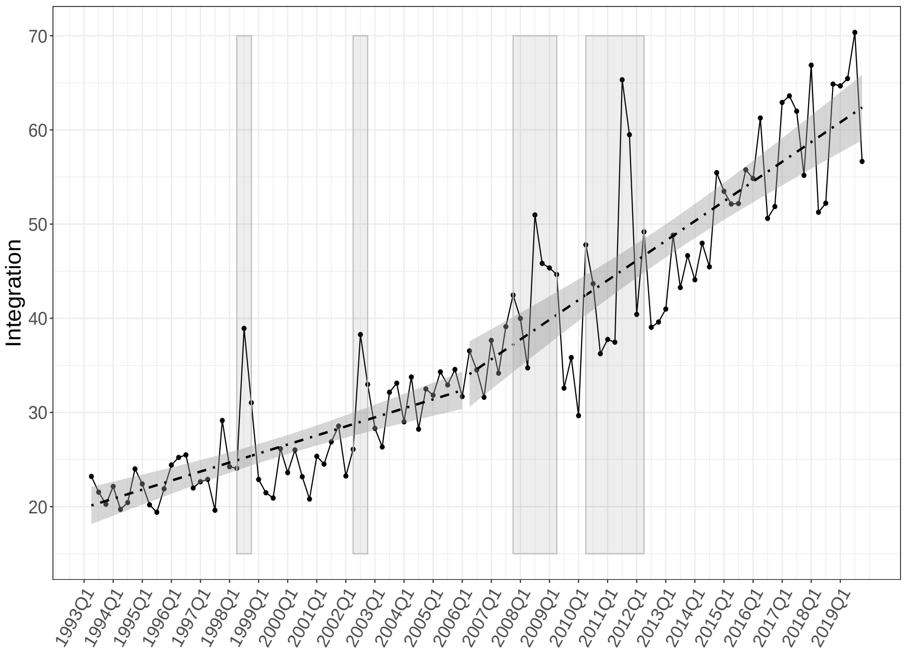

Figure 4: The dot-dashed line denotes a linear time trend fitted to quarterly integration levels segregated by first (pre-2006) and second (post-2006) halves of the sample duration. The grey region is the 95% confidence interval and the vertical grey bands correspond to the LTCM collapse (1998Q3), the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

Figure 4 plots the median US bank's integration with 95% confidence region in grey and vertical grey bands for the four prominent periods of market distress in our sample—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 integration levels. Visual inspection of the figure strongly suggests that for the median US bank, the positive trend with increasing integration levels has accelerated in the second half of the sample (post-2006).

Table 4: Median US banks' integration trends.

Sample	Estimate	Std. Error	T-stats	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 integration values. Results are reported for the median US bank and the median US systemic bank over the full duration of the study, as well as on the first and second halves of the sample 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 that common factor exposure increased by 16 percentage points in a decade. The corresponding numbers for the first and second half of the sample are 0.24 and 0.52, indicating 10 percentage points increase in common factor dependency per decade pre-2006; and about 21 percentage points increase per decade post-2006.

Similarly, for the median systemically important bank, the full sample slope is significantly positive and suggests about 17 percentage points of integration 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-percentage points integration increase per decade pre-2006; and about 11 percentage points integration 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 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—LTCM collapse (1998Q3), the dotcom bust (2002Q3-Q4), the Great Recession (2007Q4–2009Q2); and the Eurozone crisis (2010Q2–2012Q2).

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

		Estimate	Std. Error	T-stats	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 integration of about 16–17 percentage points per decade. For the median bank, the LTCM crisis and the Great Recession exhibit the highest increases in integration respectively, with the LTCM crisis (in 1998Q3) indicating an increase of almost 7.5 percentage points per quarter; and the Great Recession suggesting an increase of 3.2 percentage points per quarter, or equivalently about 22.4 percentage points of increase in integration 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 integration percentage points per quarter, while the Great Recession also features significantly high integration observations over and above the trend, with a 17.4 percentage points increase in integration per quarter. However, the most significant variable is the dotcom bust, indicating a 26.9 percentage points integration 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' integration 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 integration 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—and the sample is rife with missing values. To circumvent this issue, we conduct linear trend regressions with crises dummies—LTCM (1998Q3), Dotcom bust (2002Q3-Q4), the Great Recession (2007Q4–2009Q2); and the Eurozone crisis (2010Q2–2012Q4)—for whichever set of banks that display integration

Table 6: US banks' integration levels during crises

	Crises	10%	5%	1%	N
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 "N" denotes the total number of available banks. "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.

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 integration levels significantly 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 integration levels significantly 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 integration levels significantly 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 Eurozone crisis in 2010Q2–2012Q2, there are overall 461 banks with usable observations. Out of these, 255 banks display integration levels significantly 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.

Finally, we also test how many banks get affected by any of the four market distress episodes outlined above. Overall there are about 1189 banks for which such tests can be conducted. Out of these, 710 banks show positive effects of crises on integration, 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 integration, 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 integration. Increases in bank integration uniformly dominate decreases for all bank subsamples, as well as for all conventional benchmarks for significance.

5 Policy analysis

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

1. *Integration levels during crises are abnormally high*

   In section 4.3, we compile extensive evidence that integration is abnormally high during crises, especially in tables 5 and 6. Visual evidence for this claim can be assessed via figures 2, 3 and 4.

   Abnormally high integration 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 common factors 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 integration levels 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' integration levels jump significantly high during crisis episodes. Even more, since our comprehensive sample of US banks exhibits ever-increasing dependency on common factors, they remain vulnerable to potential negative shocks to them when a future crisis strikes.

Based on our methodology, bank regulators can assess both individual banks' integration 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 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 market-wide distress. We evaluate its impact on banks' exposure to common factors 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.

In figure 5 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

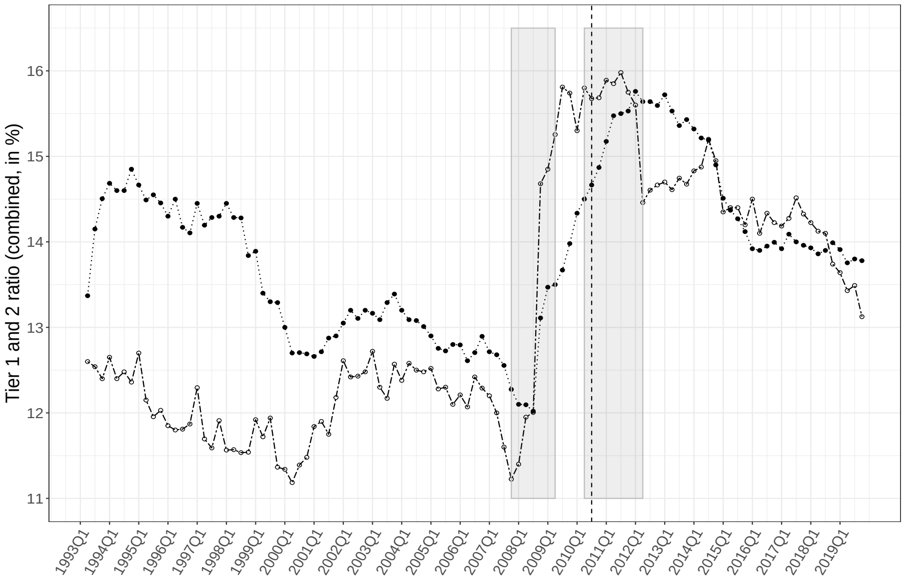

Figure 5: The median US and the median US systemic banks' combined tier 1 and 2 capital ratio, with the dot-dashed line at the bottom (in 1993) denoting the median systemic bank and the dotted line at the top (in 1993) denoting the full median US bank. The shaded vertical grey regions correspond to the 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.

tier 1 and 2 ratio.

We observe roughly three regimes in the time series evolution of figure 5. The 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.[11] 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 fell to $603 billion but by April 1 2009, they increased to $806 billion. Finally, by August 2011, reserves reached $1.6 trillion.[12] 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.[13] However, it is

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

[12]Source: Federal Reserve Bank of St. Louis. See the reserve balance time series here: https://fred.stlouisfed.org/series/WRESBAL

[13]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

important to note that the improvement in safe capital levels occurred much prior to the formal imposition of the Dodd-Frank Act and in fact, was due to the policy change of paying interest on reserves and excess reserves.

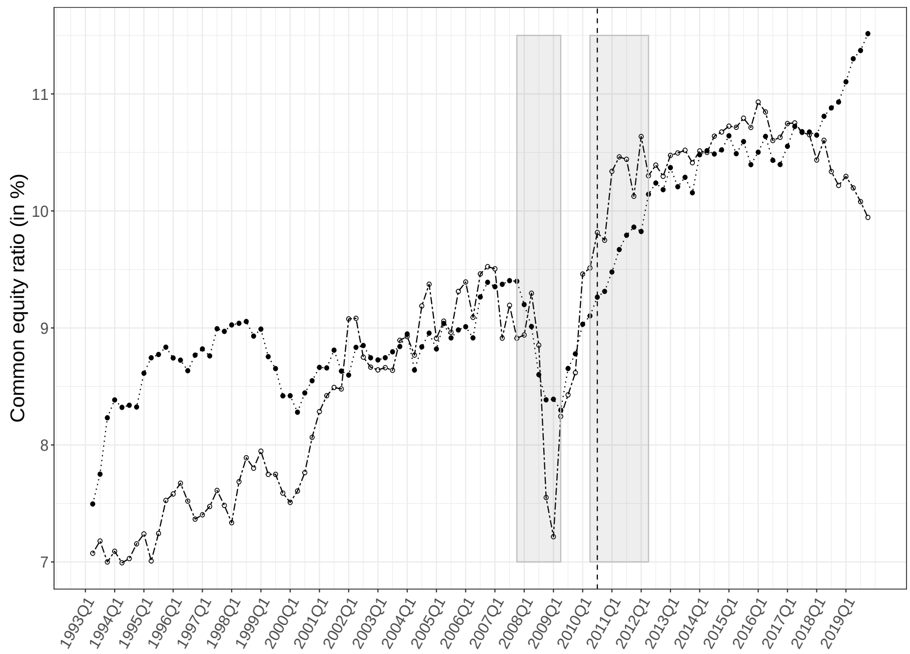

Figure 6: The median US and the median US systemic banks' common equity ratios (in percentages), with the dot-dashed line at the bottom (in 1993) denoting the median systemic bank and the dotted line at the top (in 1993) denoting the full median US bank. The shaded vertical grey regions correspond to 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).

Since common equity is an important component of tier 1 capital, we also present figure 6 which compares the time series of the median systemic 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

have become somewhat less systemically important.

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.[14]

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
Integration	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 integration is the same pre- and post-Dodd-Frank, while the alternative hypothesis is that the empirical distribution of bank integration before Dodd-Frank lies above (is stochastically dominated) that after Dodd-Frank.

In order to buttress the above mentioned visual evidence more formally, we

[14] Adrian et al. [2018] also present evidence that leverage has fallen after recent crises and as a result, the banking system is safer.

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 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.

5.2 Effect of Dodd-Frank on banks' integration

We test whether the imposition of the Dodd-Frank Act has helped in reducing US banks' exposure to common factors. Clearly, if banks' common factor exposure 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 dependency on common factors.[15] Testing this hypothesis more formally in table 7, we find that the null hypothesis of equal integration before and after the Dodd-Frank Act can be summarily rejected in favor of the alternative hypothesis which states that integration before the Dodd-Frank Act was smaller. The median

[15] 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.

systemic bank's mean integration 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' common factor exposure, which continues to rise.[16] To the extent that overly high integration implies overdependence on common banking factors, this suggests that US banks continue to be increasingly vulnerable to negative shocks via high dependency on common factor movements.[17]

6 Can integration predict banks' instability?

In this section, we present evidence that US banks' instability—in terms of their volatility and beta—can be predicted by past values of their integration.

6.1 Background

Our methodology assumes that the common factors which influence returns of all US banks are well-represented in the linear space spanned by the top principal components. While their precise identities remain unknown, our model falls squarely within the classic multi-factor framework of modern asset pricing theory. On the other hand, the one-factor framework of the CAPM is also closely aligned with our setup. If there is only one common factor which drives all US banks' returns, our goodness-of-fit based measure of integration is equivalent to the explanatory power (R^2) of the CAPM. From this line of reasoning, it follows that bank integration—the multi-factor model's goodness-of-fit—will be at least as large as the CAPM R^2. Moreover, it is worth investigating if US banks' CAPM R^2 is systematically related to their integration, and if they show comovement across

[16] 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 integration levels after the imposition of the Dodd-Frank Act.

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

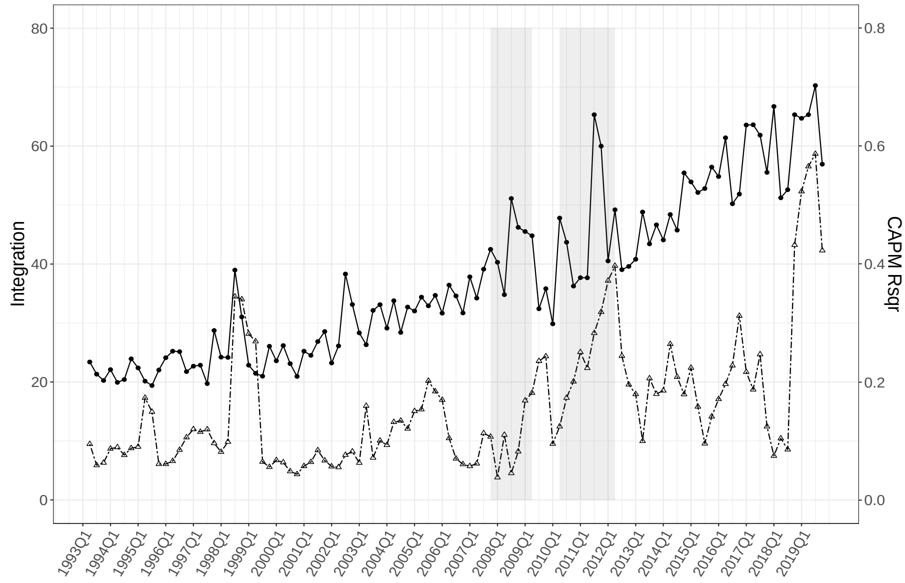

Figure 7: The median US bank's integration is represented as the solid line on the primary $y-$axis and its CAPM R^2, by a dashed line on the secondary $y-$axis. The grey region denotes the Great Recession and the Eurozone debt crises.

our sample period. In order to investigate such issues, we present the median US bank's integration and its CAPM R^2 in figure 7.

The primary axis displays the median US bank's integration, and the secondary axis shows its CAPM R^2. Some important observations stand out immediately: there is appreciable comovement between bank integration and the CAPM R^2 (correlation $\sim$0.26) with the former dominating, and the latter displaying local maxima at the LTCM crisis, and 2-3 quarters after the end of the Dotcom bust, Great Recession and the Eurozone debt crisis. Global maxima of the two series also coincide in the same quarter: 2019Q3. For the median CAPM R^2, there is a positive, though mild trend—especially after the Great Recession—which is relatively low compared to that of the median bank's integration. On the other hand, there are some dissimilarities also: the CAPM R^2 shows small peaks at 1995Q2, and 2005Q3 for which there are no counterparts in the bank integration time series. In particular, the median bank's CAPM R^2 shows a very steep rise during 2018Q3–2018Q4 which is absent in the median bank's integration time series. The comovements captured in figure 7 lead us to believe that bank integration and its

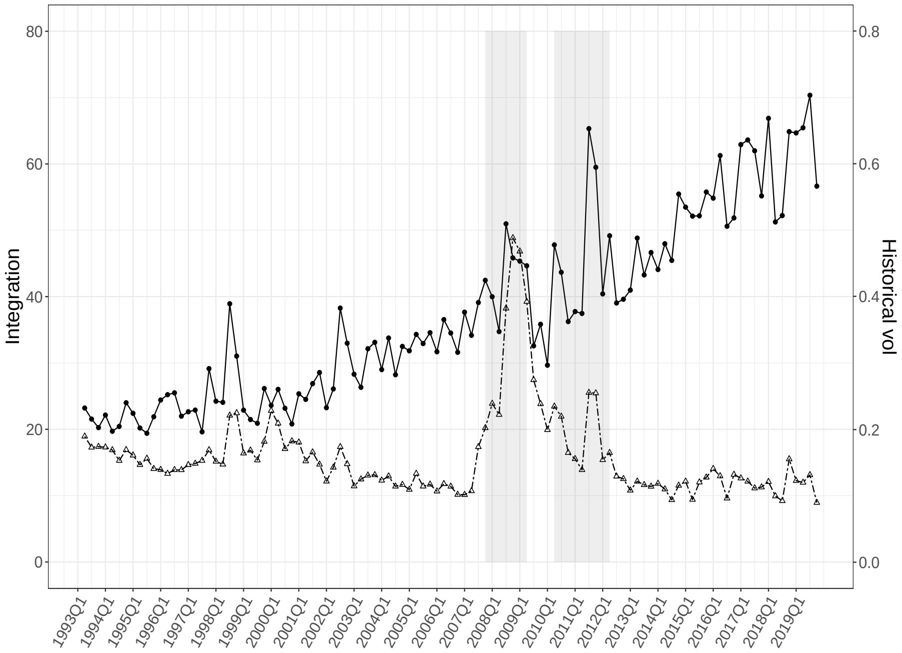

Figure 8: The median US bank's integration is represented as the solid line on the primary $y-$axis and its historical return volatility, by a dashed line on the secondary $y-$axis. The historical return volatility is calculated at the quarterly frequency from daily returns by scaling daily returns' standard deviation by the number of trading days in that quarter. The grey region denotes the Great Recession and the Eurozone debt crises.

lags can contain information with predictive power for US banks' beta and their volatility. Since the multi-factor framework of asset returns is more plausible than the one-factor CAPM, we can use current bank integration levels to predict future bank (CAPM) betas and their volatilities.

6.2 Predicting bank volatility with bank integration

We present the plots of the median bank's integration with median historical return volatility, and with the median CAPM idiosyncratic and total volatility to visualize systematic comovement between these time series.

Figure 8 displays the median bank integration on the primary $y-$axis, and its historical return volatility on the secondary $y-$axis. The historical return volatility is calculated at the quarterly frequency from daily returns by scaling daily returns' standard deviation by the square root of the number of trading days in that quarter. While admittedly simple, the chief advantages of this method are

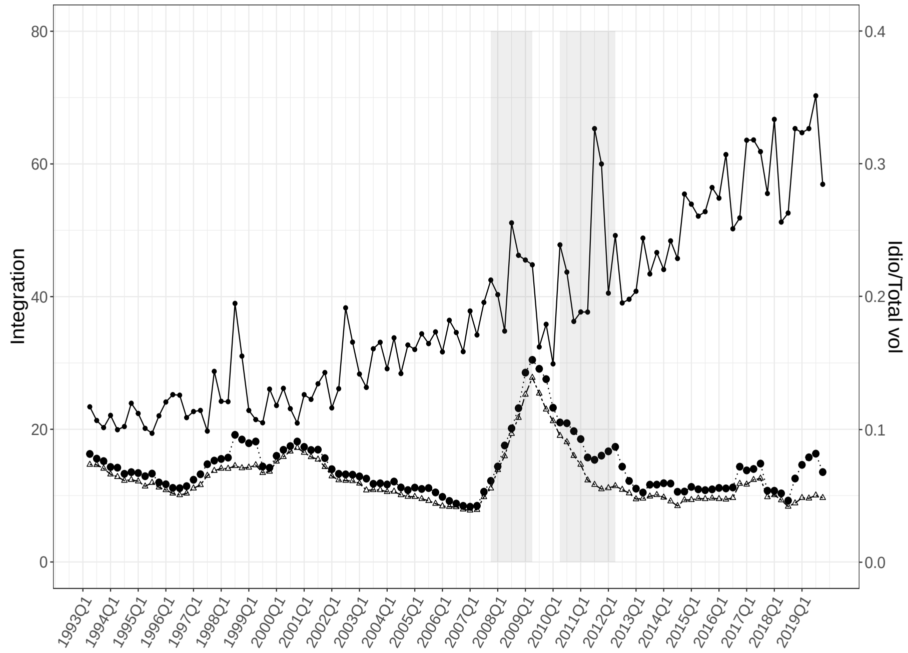

Figure 9: The median US bank's integration is represented as the solid line on the primary $y-$axis and its CAPM idiosyncratic and total volatility, by dotted and dashed lines on the secondary $y-$axis respectively. The grey region denotes the Great Recession and the Eurozone debt crises.

that it is model-free, nonparametric and is consistent with the empirical regularity that the underlying return time series evolves as a Wiener process.

Visual inspection suggests that the median bank's historical return volatility peaks during the Great Recession (2008Q4), and displays local maxima one quarter after the LTCM crisis (1998Q4), and the Eurozone debt crisis (2011Q3). However, historical volatility shows no positive trend and in fact, after the Eurozone debt crisis, tends to display low values trending mildly downwards.

Similarly, figure 9 displays the median bank integration on the primary $y-$axis, and on the secondary $y-$axis, plots the median US bank's idiosyncratic and total volatility as calculated according to the CAPM. The time series of idiosyncratic volatility shows smooth increases and falls, with the highest value attained at the end of the Great Recession (2009Q2). Total volatility also displays its maximum at the same point, though it does exhibit more variation and displays local peaks around the LTCM crisis (1998Q3), at the end of the Eurozone debt crisis (2012Q2), and towards the end of the sample (2019Q3). However, again in contrast to the median bank's integration, which steadily rises, neither the idiosyncratic nor the total volatility show any positive trend either prior to or post the Great Recession.

Overall, the comparison of bank integration with its volatility displays one important similarity: both time series peak during periods of market distress, though integration shows more sensitivity to crisis episodes owing to its underlying multi-factor model. The most important dissimilarity between the integration and volatility is that integration is clearly trending upwards, in particular, after 2006, but volatility levels do not show any appreciable trend.

To formally test the hypothesis that integration can impact future bank volatility, we resort to panel estimations with bank volatility as the dependent variable and lags of integration (and controls) as the independent variables.

6.2.1 Regression Methodology

We test the following regression specification for ascertaining whether there is evidence for predictive association of bank integration with bank volatility:

$$Vol_{t,k} = \sum_{i=1}^{5} \beta_i * Int_{t-i,k} + \sum_{j=1}^{J} \gamma_j * Control^j_{t,k} + u_{t,k} \tag{1}$$

Here bank k's volatility (expressed in percentages) in quarter t is regressed on its lagged integration values up to five quarters back, as well as on contemporaneous controls which have been shown to be influence bank volatility in previous studies. Our choice of controls rests on concerns regarding comprehensive coverage inasmuch as consistency with recent literature. We include the following bank characteristics as controls: bank size (log total assets), tier 1 and 2 ratio (combined), the non-performing assets to total assets ratio (expressed in percentages), and the loss provisions to total assets ratio (expressed in percentages). We note that our choice of controls is consistent with the choice of determinants of bank risk in several related papers [Avino et al., 2019, Bessler et al., 2015, Leung et al., 2015, Delis and Staikouras, 2011, Stiroh, 2006].

Our sample of US banks features 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 integration, size, common equity etc.—but also in potentially several relevant unobserved characteristics, which could introduce an omitted variable bias under naive pooled OLS estimations.

We adopt the methodology of unbalanced, two-way (bank and quarter) fixed effects panel estimation. 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. Further, to forestall concerns that the explanatory variables on the right hand side suffer from multicollinearity, we present the correlation matrix of all variables—dependent and independent—in table 8. The highest magnitude of correlation occurs among the lags of integration which range in 0.45–0.51, which is quite moderate and raises no concerns regarding multi-collinearity.

6.2.2 Predicting banks' historical return volatility

Table 9 presents the results of our panel estimations. We summarize the content of our findings thus: the benchmark panel estimation with only controls features ∼40,000 observations, explains ∼4% of the variation, and suggests strong statistical significance for bank size, tier 1 and 2 capital ratios, as well as loss provision (as percentages of total assets). The signs of the coefficients also have intuitive interpretations: all else equal, increased bank size and higher T1 T2 ratios lead to lower bank volatility; and higher loss provisioning leads to increased bank volatility.

For the whole sample with the inclusion of five quarterly lags of integration, we have ∼33,000 observations and our specification explains ∼11% of the total variation, implying that the five quarterly integration lags add around 7% of explanatory power. The findings show that all four controls—bank size, T1 T2 ratio, NPA and loss provisions—have coefficients which are statistically significantly

Table 8: Correlation among the dependent and independent variables according to the regression specification in equation (1). 'vol_qtr' denotes the quarterly bank volatility, 'int_lag1' denotes the previous quarter's bank integration, bank size is calculated as the log total assets, 't1_t2_ratio' is the tier 1 and 2 ratio (combined), 'npa_ratio' is the non-performing assets to total assets ratio (expressed in percentages), and 'loss_prov_ratio' is the loss provisions to total assets ratio (expressed in percentages)

	vol_qtr	int_lag1	int_lag2	int_lag3	int_lag4	int_lag5	bank_size	t1_t2_ratio	npa_ratio	loss_prov_ratio
vol_qtr	1.000	0.004	-0.020	-0.020	-0.015	-0.016	-0.130	-0.004	0.424	0.396
int_lag1	0.004	1.000	0.511	0.482	0.469	0.463	0.470	0.003	-0.026	0.016
int_lag2	-0.020	0.511	1.000	0.507	0.480	0.467	0.465	-0.004	-0.023	0.011
int_lag3	-0.020	0.482	0.507	1.000	0.500	0.476	0.458	0.004	-0.017	0.024
int_lag4	-0.015	0.469	0.480	0.500	1.000	0.497	0.451	-0.001	-0.014	0.027
int_lag5	-0.016	0.463	0.467	0.476	0.497	1.000	0.447	-0.004	-0.009	0.027
bank_size	-0.130	0.470	0.465	0.458	0.451	0.447	1.000	-0.012	-0.110	0.012
t1_t2_ratio	-0.004	0.003	-0.004	0.004	-0.001	-0.004	-0.012	1.000	-0.004	-0.008
npa_ratio	0.424	-0.026	-0.023	-0.017	-0.014	-0.009	-0.110	-0.004	1.000	0.477
loss_prov_ratio	0.396	0.016	0.011	0.024	0.027	0.027	0.012	-0.008	0.477	1.000

Table 9: This table presents the results of unbalanced, two-way (bank and quarter) fixed effects panel estimation with clustered robust standard errors allowing clustering at both the bank and quarter levels. The row for coefficients is followed by the row featuring coefficients' p-values. The coefficients highlighted in bold are statistically significant, with corresponding p-values ≤ 0.10.

$Vol_{t,k} = \sum_{i=1}^{5} \beta_i * Int_{t-i,k} + \sum_{j=1}^{J} \gamma_j * Control_{t,k}^{j} + u_{t,k}$					
	Bench	Full	Large	Pre-DF	Post-DF
int_lag1		**0.0229**	**0.0191**	**0.02312**	**0.0199**
p value		0	0	0	0.014
int_lag2		**0.0078**	**0.0100**	**0.00924**	0.0009
		0.007	0.007	0.009	0.862
int_lag3		**0.0061**	0.0016	0.00484	0.0046
		0.059	0.684	0.217	0.382
int_lag4		**0.0056**	0.0042	**0.00694**	-0.0026
		0.071	0.185	0.061	0.665
int_lag5		0.0013	0.0009	-0.00006	0.0007
		0.643	0.803	0.985	0.890
Controls					
size	**-1.8996**	**-1.6454**	-0.0257	-1.82008	2.0083
p value	0.01	0.023	0.976	0.112	0.161
t1_t2	**-0.0006**	**-0.0006**	**-0.1415**	**-0.00045**	**-0.1989**
	0	0	0.003	0	0
npa	0.1466	**1.6519**	**1.4103**	**1.66459**	**1.52705**
	0.30	0	0	0	0
loss_prov	**7.6634**	**4.5679**	**6.4365**	**4.53947**	**2.4783**
	0	0	0	0	0
N	40029	32869	15108	21884	10985
R^2	0.043	0.112	0.094	0.104	0.102

Notes: The dependent variable is US banks' quarterly historical return volatility (expressed in percentages) which is calculated as the daily volatility scaled by the square root of the number of trading days in the quarter. 'bench' refers to benchmark regression results for the full sample for the whole duration with only controls; 'Full' refers to results with all US banks over the entire sample duration; 'Large' refers to the subsample of large banks, defined to have more than \$1 billion in total assets in 2019; 'Pre-DF' and 'Post-DF' denote the subsamples before the formal imposition of the Dodd-Frank Act in July 2010. 'int_lag1', ... 'int_lag5' (quarterly lags 1–5 of bank integration), 'size' (bank size), 't1_t2' (tier 1 and 2 combined), 'npa' (nonperforming asset percentage), and 'loss_prov' (loss provision as percentage of total assets) are explanatory variables.

away from 0. Bank size and T1 T2 ratio have the expected negative association with bank volatility, while loss provisions and the NPA percentage have a significant positive association with banks' historical return volatility. In addition, we find that bank integration values from up to four quarters back (one year) have (uniformly) significantly positive association with bank volatilities, suggesting that (all else equal) an increase in bank integration in the current quarter leads to rising bank volatility up to 4 quarters in the future. For the subsample of large banks, bank size loses its negative significance but all other controls retain their significance in influencing volatility, and bank integration retains its predictive power up to two quarters in the future. Finally, for the pre- vs. post-Dodd-Frank Act (July 2010) subsample, we find that except bank size, all other controls retain their significance, while bank integration also retains its predictive power both pre- and post-Dodd-Frank, though its impact reduces somewhat, after the Act's imposition.

Similarly table 10 presents panel estimation results for four relevant time-subsamples: crises (LTCM or Dotcom or Great Recession or Eurozone Debt), periods of high/low VIX as well as high/low TED spreads. During crises, we find that all controls, and bank integration up to three quarters past, retain predictive significance, and our regression specification explains a healthy 12.7% of the variation in bank volatility during crises. As expected, bank size and tier 1 and 2 ratio have negative effects on volatility, while all others—NPA, loss provisions, past quarters' bank integration—have a significantly positive influence on US banks' historical return volatility. During periods of high VIX, only NPA, loss provisions and previous quarter's bank integration have statistically significant, positive effects, whereas during low VIX periods, bank size and NPAs retain their significance, while bank integration lags up to four quarters have significant, positive association with bank volatility. Finally, during periods of high credit risk, as proxied by the TED spread, NPAs and loss provisions retain their significance, tier 1 and 2 ratio impacts bank volatility positively, while past four quarters' bank integration values positively impact bank volatility. On the other hand, during periods of low credit risk, bank integration lags up to 5 quarters display significant association with bank volatility but with a negative sign, suggesting that

Table 10: This table presents the results of unbalanced, two-way (bank and quarter) fixed effects panel estimation with clustered robust standard errors allowing clustering at both the bank and quarter levels. The row for coefficients is followed by the row featuring coefficients' p-values. The coefficients highlighted in bold are statistically significant, with corresponding p-values ≤ 0.10.

$Vol_{t,k} = \sum_{i=1}^{5} \beta_i * Int_{t-i,k} + \sum_{j=1}^{J} \gamma_j * Control_{t,k}^{j} + u_{t,k}$					
	Crises	VIX H	VIX L	TED H	TED L
int_lag1	**0.026**	**0.021**	**0.011**	0.011	0.006
p value	0.024	0.009	0.005	0.209	0.126
int_lag2	**0.021**	0.014	**0.007**	0.007	**-0.014**
	0.019	0.195	0.086	0.349	0.006
int_lag3	**0.014**	-0.002	**0.012**	0.010	**-0.014**
	0.091	0.756	0.014	0.242	0.018
int_lag4	0.012	0.007	**0.013**	**0.014**	**-0.017**
	0.229	0.272	0.005	0.042	0.001
int_lag5	0.003	-0.005	0.002	0.002	**-0.013**
	0.692	0.432	0.481	0.741	0
Controls					
size	**-5.010**	0.617	**-1.880**	1.543	-1.286
p value	0.016	0.714	0.008	0.499	0.502
t1_t2	**-0.3280**	-0.121	-0.055	**0.192**	**-0.344**
	0.003	0.267	0.339	0.079	0
npa	**2.032**	**1.809**	**.840**	**1.516**	**1.437**
	0	0	0.009	0.025	0
loss_prov	**2.640**	**4.272**	0.710	**5.967**	**1.982**
	0.003	0	0.532	0.002	0.086
N	7343	6467	4417	6268	6510
R^2	0.127	0.103	0.029	0.081	0.127

Notes: 'Crises' refer to the subsample of crisis episodes in the sample: LTCM (1998Q3), Dotcom bust (2002Q3–Q4), the Great Recession (2007Q4–2009Q2), and the Eurozone debt crisis (2010Q2–2012Q2); 'VIX_H' and 'VIX_L' refer to subsamples for quarters during which the VIX (the 'fear index') was more than 0.75 quantiles/less than 0.25 quantiles in its distribution respectively; and finally the same definition is applied for 'TED_H' and 'TED_L' where TED denotes the difference between the three-month Treasury bill and the three-month LIBOR based in US dollars, which is used as a proxy for the credit risk in the economy. 'int_lag1', ... 'int_lag5' (quarterly lags 1–5 of bank integration), 'size' (bank size), 't1_t2' (tier 1 and 2 combined), 'npa' (nonperforming asset percentage), and 'loss_prov' (loss provision as percentage of total assets) are explanatory variables.

Table 11: This table, based on the p-values of the Clarke-West test [Clark and West, 2007] for predictive accuracy presents the number of banks that show significant predictive accuracy for lags of bank integration. The dependent variable is US banks' historical return volatility and the explanatory variables are integration lags and controls according to the panel regression specification in equation (1).

Bank sample	Significance Level			N
	10%	5%	1%	
Full	897	739	288	1003
Large	214	190	85	232
Systemic	20	17	7	21
Pre-Dodd-Frank	828	668	255	919
Post-Dodd-Frank	365	282	96	400

during low credit risk environments, integration negatively impacts volatility. The controls (except size) retain their usual explanatory significance.

To formally evaluate forecast performance we use the commonly employed Clark and West [2007] test for equal predictive accuracy, which tests the null hypothesis that the forecasts obtained from two nested forecasting models perform equally well. Rejection of the null implies that the nested benchmark model is outperformed by the extended model that incorporates lags of banks' integration in line with the regression specification in equation (1).

Table 11 presents our results for various US banks' subsamples. For the full sample of admissible banks, 897 (out of 1003) report rejection of the null at the 10% significance level, 739 at the 5%, and 288 at the 1% significance level. Similarly, out of 232 large banks, for 214 we can reject the null at 10%, 190 at 5%, and 85 at 1% significance level. Among 21 systemic banks, 20 report significance at the 10% level, 17 at the 5% level, and 7 at the 1% level. Finally, among 919 admissible banks in the pre-Dodd-Frank period, for 828 we can reject the null at the 10% level, for 668 at the 5% level, and for 255 at the 1% level. After the imposition of the Dodd-Frank Act (2010 July), out of 400 admissible banks, 365 post significant results at 10%, 282 at 5%, and 96 at the 1% level. Overall, this presents strong evidence that the predictive accuracy of the model with lags of bank integration (in line with regression specification in equation (1)) is high, compared to the specification without lags.

Insofar as large values of banks' historical return volatility proxy instability,

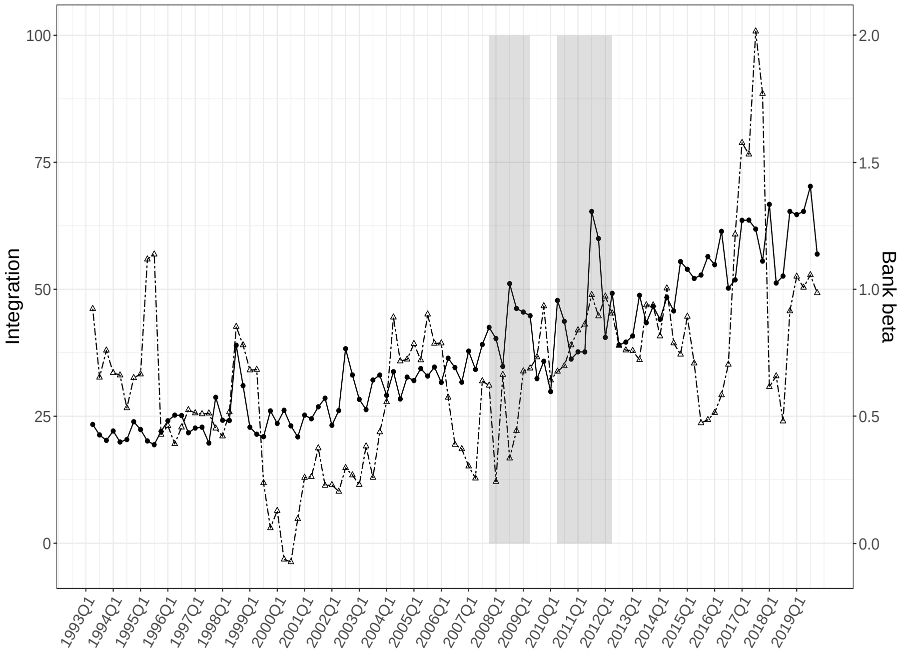

Figure 10: The median US bank's integration is represented as the solid line on the primary $y-$axis and its CAPM beta, by a dot-dashed line on the secondary $y-$axis respectively. The grey region denotes the Great Recession and the Eurozone debt crises.

the three tables described above suggest that bank integration is a good predictor of their instability—especially during periods of market distress.

6.3 Predicting bank beta with bank integration

A bank's CAPM beta is simply its sensitivity to the market factor, while bank integration is the goodness-of-fit of a multi-factor model where factors are assumed to be well-embedded in the principal component subspace. Insofar as banks' CAPM beta can be a proxy of their instability (higher the beta, more the instability) a positive, predictive association between banks' integration and their future betas lead to the conclusion that current levels of bank integration can contain important information about their future instability.

In figure 10 we present the median bank integration on the primary $y-$axis, and the median bank beta on the secondary axis. At first glance, it seems that the median bank's beta rises with time but on closer inspection, beta shows falling levels in the period 1993–2007, and then increasing values for 2007–2019. The positive trend is strongly amplified by the global maximum of the median bank's beta being attained in 2017Q3. Further, the median bank's beta does not exhibit maxima during crisis episodes encountered in our sample (except for LTCM). While somewhat dissimilar in details, the two plots do suggest an overall healthy comovement, which leads us to test a regression specification similar to equation (1). We follow the same methodology for panel estimations viz. unbalanced, two-way (bank and quarter) fixed effects regression. Again, to counter potential heteroskedasticity in bank residuals, and to ascertain the significance of independent variables, we cluster the standard errors at both the bank and quarter levels.

$$beta_{t,k} = \sum_{i=1}^{5} \beta_i * Int_{t-i,k} + \sum_{j=1}^{J} \gamma_j * Control^{j}_{t,k} + u_{t,k} \tag{2}$$

Table 12 displays the results of panel estimations using the regression specification in equation (2). The benchmark regressions display the effect of the bank characteristics used as controls. Bank size is the only characteristic which is significantly away from 0 and it impacts the contemporaneous bank beta positively, i.e., all else equal, a rise in bank size leads to higher bank beta. For the full sample of banks, for the entire sample duration, we observe that all bank integration lags 1–5 influence bank beta significantly positively. In other words (all else equal) a rise in current bank integration level leads to higher future bank beta uniformly up to five quarters in advance. Among controls, bank size and the tier 1 and 2 ratio impacts bank beta positively. For large banks, again, all five quarterly integration lags impact bank beta positively, and size and the nonperforming asset percentage significantly impact bank beta among bank characteristics. Bank integration displays significantly positive, predictive association with bank beta uniformly up to three quarters in the future—both before, and after the imposition of the Dodd-Frank Act in July 2010. Among controls, the tier 1 and 2 ratio and loss provisioning exert a positive influence on bank beta before the Act imposition, while bank size and the loss provision impact bank beta after the Act is implemented.

Table 12: This table presents the results of unbalanced, two-way (bank and quarter) fixed effects panel estimation with clustered robust standard errors allowing clustering at both the bank and quarter levels. The row for coefficients is followed by the row featuring coefficients' p-values. The coefficients highlighted in bold are statistically significant, with corresponding p-values ≤ 0.10.

$beta_{t,k} = \sum_{i=1}^{5} \beta_i * Int_{t-i,k} + \sum_{j=1}^{J} \gamma_j * Control_{t,k}^{j} + u_{t,k}$					
	Bench	Full	Large	Pre-DF	Post-DF
int_lag1		**0.001771**	**0.0017**	**0.001250**	**0.00230**
p value		0	0	0	0
int_lag2		**0.001294**	**0.0015**	**0.000883**	**0.00146**
		0	0	0.006	0.045
int_lag3		**0.001375**	**0.0018**	**0.000647**	**0.00231**
		0	0	0.020	0
int_lag4		**0.000426**	**0.0006**	0.000202	0.00023
		0.095	0.091	0.484	0.672
int_lag5		**0.000574**	**0.0007**	0.000432	-0.00001
		0.011	0.009	0.119	0.985
Controls					
size	**0.3771**	**0.229647**	**0.2973**	0.135322	**0.52818**
p value	0	0.002	0	0.169	0
t1_t2	0.0001	**0.000273**	-0.0026	**0.000277**	0.00017
	0.453	0	0.523	0	0.962
npa	0.0007	0.013710	**0.0429**	0.007122	0.03357
	0.687	0.233	0.043	0.638	0.100
loss_prov	0.0549	0.034091	-0.0150	**0.122352**	**-0.14636**
	0.202	0.408	0.888	0.002	0.077
N	39442	32854	15107	21875	10979
R^2	0.005	0.015	0.025	0.008	0.022

Notes: The dependent variable is US banks' quarterly CAPM beta. 'bench' refers to benchmark regression results for the full sample for the whole duration with only controls; 'Full' refers to results with all US banks over the entire sample duration; 'Large' refers to the subsample of large banks, defined to have more than $1 billion in total assets in 2019; 'Pre-DF' and 'Post-DF' denote the subsamples before the formal imposition of the Dodd-Frank Act in July 2010. 'int_lag1', ... 'int_lag5' (quarterly lags 1–5 of bank integration), 'size' (bank size), 't1_t2' (tier 1 and 2 combined), 'npa' (nonperforming asset percentage), and 'loss_prov' (loss provision as percentage of total assets) are explanatory variables.

Table 13: This table presents the results of unbalanced, two-way (bank and quarter) fixed effects panel estimation with clustered robust standard errors allowing clustering at both the bank and quarter levels. The row for coefficients is followed by the row featuring coefficients' p-values. The coefficients highlighted in bold are statistically significant, with corresponding p-values ≤ 0.10.

$beta_{t,k} = \sum_{i=1}^{5} \beta_i * Int_{t-i,k} + \sum_{j=1}^{J} \gamma_j * Control_{t,k}^{j} + u_{t,k}$					
	Crises	VIX H	VIX L	TED H	TED L
int_lag1	**0.0022**	**0.00100**	**0.0031**	**0.0011**	0.0007
p value	0	0.043	0	0.012	0.238
int_lag2	0.0004	0.00018	**0.0024**	**0.0012**	0.0005
	0.488	0.708	0.008	0.008	0.441
int_lag3	0.0005	0.00003	**0.0018**	**0.0008**	**0.0017**
	0.313	0.936	0.020	0.095	0.006
int_lag4	-0.0006	0.00044	**0.0012**	-0.0004	**0.0013**
	0.180	0.368	0.068	0.491	0.048
int_lag5	0.0002	0.00028	**0.0010**	-0.0002	**0.0014**
	0.611	0.408	0.056	0.493	0.006
Controls					
size	**0.1971**	**0.23729**	**0.3538**	**0.3631**	-0.0420
p value	0.067	0.063	0.043	0.004	0.841
t1_t2	**0.0120**	0.00362	-0.0049	0.0004	0.0002
	0.005	0.488	0.550	0.931	0.976
npa	0.0059	**0.03728**	-0.0438	-0.0111	**0.0293**
	0.731	0.021	0.464	0.609	0.059
loss_prov	0.0235	0.03715	-0.1934	0.0481	0.1390
	0.531	0.374	0.376	0.459	0.115
N	7340	6463	4417	6265	6506
R^2	0.009	0.015	0.033	0.011	0.017

Notes: 'Crises' refer to the subsample of crisis episodes in the sample: LTCM (1998Q3), Dotcom bust (2002Q3–Q4), the Great Recession (2007Q4–2009Q2), and the Eurozone debt crisis (2010Q2–2012Q2); 'VIX_H' and 'VIX_L' refer to subsamples for quarters during which the VIX (the 'fear index') was more than 0.75 quantiles/less than 0.25 quantiles in its distribution respectively; and finally the same definition is applied for 'TED_H' and 'TED_L' where TED denotes the difference between the three-month Treasury bill and the three-month LIBOR based in US dollars, which is used as a proxy for the credit risk in the economy. 'int_lag1', ... 'int_lag5' (quarterly lags 1–5 of bank integration), 'size' (bank size), 't1_t2' (tier 1 and 2 combined), 'npa' (nonperforming asset percentage), and 'loss_prov' (loss provision as percentage of total assets) are explanatory variables.

Similarly, table 13 exhibits the results of panel estimations during crises, and periods of high/low VIX and TED spread. During crisis episodes, bank size and the tier 1 and 2 capital ratio influence bank beta contemporaneously. In addition, bank integration level from one quarter past shows statistically significant, positive association with bank beta during crises. During times of high VIX, bank integration from one quarter past, is seen to significantly impact current bank beta. Among controls, size and NPA percentage display their usual positive influence. During low VIX episodes, the predictive associations of bank integration with bank beta intensifies, and current integration values impact bank beta up to all five quarters into the future. Bank size is the only characteristic in this regime to display any significant effect. Finally, during periods of high credit risk (TED spread) integration levels today impact positively, bank beta levels up to three quarters in the future, while bank size remains the only influential control. During low credit risk periods, integration lags from the past 3, 4 and 5 quarters are seen to positive influence current bank betas.

6.4 Interpreting integration's impact on bank instability

US banks' quarterly integration levels display quite significant predictive associations uniformly up to 3-4 quarters in the future, with their volatilities, as well as with their CAPM betas. This is true not just for the full sample, but also for special cross-sectional, as well as, time-based subsamples, and especially, during episodes of market distress. In particular, bank integration lags show a significant marginal explanatory power ($\sim$ 6-7%) during the four crises encountered in our sample—the LTCM collapse, the Dotcom bust, the Great Recession, and the Eurozone debt crisis. The sign of the association is positive which suggests, quite reasonably, that (all else equal) as integration (exposure to common factors) rises, so does the bank volatility, as well as its beta (sensitivity to one common factor—the market index).

Among bank characteristics, size is somewhat significant in explaining US banks' volatilities, but quite significant in being associated with their betas. It impacts bank volatility negatively suggesting that as bank size rises, (all else equal) its volatility falls. T1 T2 ratio is quite significant in its association with bank volatility, but not so much with its beta. Its sign of association is negative, suggesting that all else equal, increases in the T1 T2 ratio leads to a fall in banks' volatility, which seems quite reasonable. The non-performing assets of banks are the strongest in terms of association with banks' volatility, but not much association with their betas. Finally, the loss provisions are also quite significant in explaining banks' volatility, but its association is much reduced for their betas. Overall, bank size shows strong positive association with bank betas, and T1 T2 ratios, NPAs and loss provisions display strong association with bank volatilities.

7 Concluding remarks

We introduce a new metric: 'integration', which captures banks' stock returns' dependence on common banking factors. We show that for a large fraction of US banks, integration levels are rising, especially after 2006, and argue that large exposures to common factors can pose a threat to the stability of the banking sector in case of a negative shock to one or more common factors. We also find that current bank integration levels can predict bank volatilities and beta up to one year in advance, and in particular, during crises, integration lags have significant explanatory power.

Relatedly, we also demonstrate that the Dodd-Frank Act has improved US banks' capital adequacy which can offset the ill-effects of a negative shock to the US banking sector, but the ever-increasing aggregate exposure of banks to common factors has eroded this advantage. Further, during times of high integration, downward movement in one or more common factors can lead to sector-wide falls in bank returns, which could precipitate a crisis if the negative shock is large enough. From this perspective, the steady rise in US banks' integration levels highlights their continued vulnerability despite improved capital buffers as mandated by the Dodd-Frank Act.

From a methodological standpoint, our technique of using the explanatory power of common factor regressions is complementary to the standard multi-factor asset pricing framework which relies on factor loadings (betas) to assess the sensitivity of stock returns to individual factors. Consequently, our metric of bank integration is in-effect, a parametrization of common factor exposures in the range 0–100, while there is no such restriction on betas.

Further, our approach of capturing common factor exposures by means of principal component regressions offers an alternative way to model interconnections among entities. Researchers who wish to investigate the macroscopic aspects of 'integration' of an entity with the sector as a whole will find our technique more useful. However, those who study microscopic, granular interconnections between entities and their inter-related reactions to shocks will find network-based methods more useful.

Appendices

Appendix A Predicting idiosyncratic volatility

In this section we use banks' idiosyncratic volatility (as calculated according to CAPM) as a proxy of their instability and test if integration can impact their future values. We test if banks' CAPM residuals are significantly predicted by their past integration values, over and above the impact of explanatory bank characteristics in table A1.

For the benchmark regression with no integration lags, there are ∼40,000 observations and the goodness-of-fit is 3.5%. Among bank characteristics, we observe that tier 1 and 2 combined capital ratio, and loss provisions as percentages of total assets have estimates significantly different from 0. Their direction of impact is the usual: all else equal, an increase in tier 1 and 2 ratio lowers US banks' CAPM idiosyncratic volatility, while higher loss provisions lead to amplified idiosyncratic volatility.

Including additional five integration lags leads to ∼33,000 observations and 10% goodness-of-fit, suggesting that integration lags collectively add ∼6.5% ex-

Table A1: This table presents the results of unbalanced, two-way (bank and quarter) fixed effects panel estimation with clustered robust standard errors allowing clustering at both the bank and quarter levels. The row for coefficients is followed by the row featuring coefficients' p-values. The coefficients highlighted in bold are statistically significant, with corresponding p-values ≤ 0.10.

$$IVol_{t,k} = \sum_{i=1}^{5} \beta_i * Int_{t-i,k} + \sum_{j=1}^{J} \gamma_j * Control_{t,k}^{j} + u_{t,k}$$

	Bench	Full	Large	Pre-DF	Post-DF
int_lag1		**0.00590**	0.0019	**0.00578**	**0.0060**
p value		0	0.346	0	0.079
int_lag2		**0.00320**	0.0012	**0.00319**	0.0033
		0.025	0.526	0.020	0.241
int_lag3		0.00130	-0.0005	0.00143	0.0011
		0.353	0.770	0.290	0.643
int_lag4		0.00121	0.0003	0.00182	-0.0007
		0.389	0.850	0.207	0.813
int_lag5		-0.00068	-0.0017	0.00042	-0.0028
		0.624	0.369	0.774	0.175
Controls					
size	-0.49954	-0.56227	0.3742	-0.19122	**1.8675**
p value	0.196	0.185	0.381	0.746	0.0308
t1_t2	**-0.00014**	-0.00007	**-0.0725**	-0.00002	**-0.1032**
	0	0.223	0.003	0.419	0
npa	0.06890	**0.73171**	**0.9171**	**0.61775**	**0.973**
	0.291	0	0	0	0
loss_prov	**2.89840**	**1.47458**	**1.7220**	**1.82398**	-0.2327
	0	0.002	0.031	0	0.610
N	39442	32854	15107	21875	10979
R^2	0.035	0.101	0.112	0.088	0.131

Notes: The dependent variable is US banks' quarterly CAPM idiosyncratic volatility. 'bench' refers to benchmark regression results for the full sample for the whole duration with only controls; 'Full' refers to results with all US banks over the entire sample duration; 'Large' refers to the subsample of large banks, defined to have more than $1 billion in total assets in 2019; 'Pre-DF' and 'Post-DF' denote the subsamples before the formal imposition of the Dodd-Frank Act in July 2010. 'int_lag1', ... 'int_lag5' (quarterly lags 1–5 of bank integration), 'size' (bank size), 't1_t2' (tier 1 and 2 combined), 'npa' (nonperforming asset percentage), and 'loss_prov' (loss provision as percentage of total assets) are explanatory variables.

planatory power. Among controls, the NPA and loss provisioning percentages exhibit significantly positive association with the CAPM idiosyncratic volatility. Current bank integration values positively impact CAPM idiosyncratic volatilities uniformly up to two quarters ahead. For the panel estimation for large US banks, none of the integration lags seems to have significant impact, but banks' NPA, loss provisions and tier 1 and 2 ratios impact idiosyncratic volatility with their usual signs. Finally, for pre- and post-Dodd-Frank Act imposition, we observe integration positively impacting bank-specific volatility up to two quarters and one quarter ahead respectively. Among bank characteristics, NPA shows explanatory significance both before and after the Act's imposition in 2010 July.

In table A2, we present results of panel estimations during crises, as well as during periods of high/low VIX and TED spreads. During crises, we find that bank size, the tier 1 and 2 ratio, and the NPA percentage impact CAPM idiosyncratic volatility significantly. Among bank integration lags, we observe a statistically significant, positive impact of integration from 3 and 4 quarters past. During periods of high and low VIX respectively, integration shows predictive, positive association with idiosyncratic volatility up to two quarters, and one quarter ahead respectively. NPA percentage positively impacts idiosyncratic volatility both pre- and post-Dodd-Frank Act, while loss provisions show positive association during high VIX episodes. Similarly, for periods of high/low TED spread, the NPA percentage retains its usual positive association, while loss provisions exert impact during high credit risk regimes (high TED spread) while tier 1 and 2 capital ratios negatively impact CAPM idiosyncratic volatility during low TED spread regimes. Bank integration values from the past 2 and 4 quarters display significant positive predictive association during high credit risk periods, but none of the lags have any significant impact during low credit risk periods.

Appendix B Predicting total volatility

In table B1, the benchmark regression without any integration lags has ∼40,000 observations and its goodness-of-fit is ∼3.5%. Only the loss-provision (as percentage

Table A2: This table presents the results of unbalanced, two-way (bank and quarter) fixed effects panel estimation with clustered robust standard errors allowing clustering at both the bank and quarter levels. The row for coefficients is followed by the row featuring coefficients' p-values. The coefficients highlighted in bold are statistically significant, with corresponding p-values ≤ 0.10.

$IVol_{t,k} = \sum_{i=1}^{5} \beta_i * Int_{t-i,k} + \sum_{j=1}^{J} \gamma_j * Control_{t,k}^{j} + u_{t,k}$					
	Crises	VIX H	VIX L	TED H	TED L
int_lag1	0.005	**0.0090**	**0.0031**	0.003	-0.0008
p value	0.201	0.010	0.044	0.356	0.791
int_lag2	0.004	**0.0059**	0.0006	**0.005**	-0.0010
	0.298	0.052	0.755	0.013	0.689
int_lag3	**0.006**	0.0005	0.0027	0.004	0.0011
	0.058	0.857	0.123	0.159	0.681
int_lag4	**0.007**	0.0020	0.0021	**0.006**	-0.0005
	0.032	0.567	0.229	0.009	0.802
int_lag5	0.002	-0.0008	0.00038	0.002	-0.0026
	0.545	0.807	0.790	0.384	0.199
Controls					
size	**-3.719**	-0.7755	-0.4255	0.837	-0.9380
p value	0	0.368	0.341	0.346	0.353
t1_t2	**-0.108**	-0.0573	-0.0341	0.041	**-0.1253**
	0.003	0.300	0.157	0.365	0.008
npa	**0.783**	**0.7527**	**0.6447**	**0.364**	**0.8060**
	0	0	0	0.068	0
loss_prov	0.557	**1.6476**	-0.6410	**2.074**	0.7473
	0.145	0.001	0.385	0.005	0.177
N	7340	6463	4417	6265	6506
R^2	0.125	0.117	0.037	0.063	0.115

Notes: 'Crises' refer to the subsample of crisis episodes in the sample: LTCM (1998Q3), Dotcom bust (2002Q3–Q4), the Great Recession (2007Q4–2009Q2), and the Eurozone debt crisis (2010Q2–2012Q2); 'VIX_H' and 'VIX_L' refer to subsamples for quarters during which the VIX (the 'fear index') was more than 0.75 quantiles/less than 0.25 quantiles in its distribution respectively; and finally the same definition is applied for 'TED_H' and 'TED_L' where TED denotes the difference between the three-month Treasury bill and the three-month LIBOR based in US dollars, which is used as a proxy for the credit risk in the economy. 'int_lag1', ... 'int_lag5' (quarterly lags 1–5 of bank integration), 'size' (bank size), 't1_t2' (tier 1 and 2 combined), 'npa' (nonperforming asset percentage), and 'loss_prov' (loss provision as percentage of total assets) are explanatory variables.

Table B1: This table presents the results of unbalanced, two-way (bank and quarter) fixed effects panel estimation with clustered robust standard errors allowing clustering at both the bank and quarter levels. The row for coefficients is followed by the row featuring coefficients' p-values. The coefficients highlighted in bold are statistically significant, with corresponding p-values ≤ 0.10.

$$TVol_{t,k} = \sum_{i=1}^{5} \beta_i * Int_{t-i,k} + \sum_{j=1}^{J} \gamma_j * Control_{t,k}^{j} + u_{t,k}$$

	Bench	Full	Large	Pre-DF	Post-DF
int_lag1		**0.00866**	**0.0048**	**0.00746**	**0.0010**
p value		0	0.025	0	0.001
int_lag2		**0.00605**	**0.0038**	**0.00544**	**0.006**
		0	0.020	0	0.013
int_lag3		**0.00373**	**0.0024**	**0.00340**	0.003
		0.008	0.094	0.031	0.156
int_lag4		0.00187	0.0010	**0.00277**	-0.002
		0.208	0.584	0.074	0.544
int_lag5		-0.00023	-0.0011	0.00075	-0.004
		0.870	0.583	0.616	0.119
Controls					
size	0.02586	-0.17685	**0.8583**	-0.01955	**2.768**
p value	0.952	0.701	0.073	0.977	0.002
t1_t2	-0.00003	**0.00026**	**-0.0640**	**0.00030**	**-0.094**
	0.823	0	0.022	0	0.001
npa	0.07202	**0.76619**	**0.9659**	**0.68219**	**0.959**
	0.291	0	0	0	0
loss_prov	**3.04850**	**1.55139**	**1.7654**	**1.96701**	-0.289
	0	0.001	0.043	0	0.546
N	39442	32854	15107	21875	10979
R^2	0.034	0.101	0.107	0.093	0.124

Notes: The dependent variable is US banks' quarterly CAPM total volatility. 'bench' refers to benchmark regression results for the full sample for the whole duration with only controls; 'Full' refers to results with all US banks over the entire sample duration; 'Large' refers to the subsample of large banks, defined to have more than \$1 billion in total assets in 2019; 'Pre-DF' and 'Post-DF' denote the subsamples before the formal imposition of the Dodd-Frank Act in July 2010. 'int_lag1', ... 'int_lag5' (quarterly lags 1–5 of bank integration), 'size' (bank size), 't1_t2' (tier 1 and 2 combined), 'npa' (nonperforming asset percentage), and 'loss_prov' (loss provision as percentage of total assets) are explanatory variables.

of total assets) shows any impact significantly different from 0. Including additional five bank integration lags decreases the number of observations to ∼33,000 but the goodness-of-fit rises to ∼10%, which implies that bank integration lags collectively explain about 6.5% of the total variance in CAPM total volatility. Bank integration levels positively impact future total volatility uniformly up to three quarters ahead. Among bank characteristics, NPA and loss provisions have their usual positive explanatory significance, while the tier 1 and 2 ratio impacts the total volatility positively, in contrast with its usual direction of influence. For large banks also, integration levels predict up to three quarters ahead, and all explanatory bank characteristics exert their usual influence, except for bank size which impact total volatility positively. Before the Dodd-Frank Act's imposition, integration up to four quarters past displays positive, predictive association with CAPM total volatility, while this impact weakens post-Dodd-Frank as integration lags from only two quarters past are able to predict total volatility. Among controls, NPAs show uniformly positive contemporaneous association both pre- and post-Act.

We present panel estimations during crises, as well as during periods of high/low fear and credit risk in table B2. Integration levels from past 1, 3 and 4 quarters show significant positive impact on CAPM total volatility, while among the controls variables, bank size (negative), tier 1 and 2 ratio (negative) and the NPA percentage (positive) assert their usual significant impact with their usual signs. As before, the explanatory power of our regression specification is high, and is able to account for a healthy 11.7% of the total volatility's variance. During high VIX periods, integration predicts total volatility up to two quarters ahead, and among controls, NPA and loss provision exert their usual influence. During quarters with low VIX as well, bank integration predicts up to four quarters ahead, and among controls, only NPA percentage has significant associative impact. During high TED spread periods, bank integration displays its usual positive associative significance for lags 1, 2 and 4, but loses all significance during periods of low credit risk. Among controls, NPA retains its usual uniformly positive significance, while loss provisions exhibit their usual impact during high credit risk periods but not

Table B2: This table presents the results of unbalanced, two-way (bank and quarter) fixed effects panel estimation with clustered robust standard errors allowing clustering at both the bank and quarter levels. The row for coefficients is followed by the row featuring coefficients' p-values. The coefficients highlighted in bold are statistically significant, with corresponding p-values ≤ 0.10.

$TVol_{t,k} = \sum_{i=1}^{5} \beta_i * Int_{t-i,k} + \sum_{j=1}^{J} \gamma_j * Control_{t,k}^{j} + u_{t,k}$					
	Crises	VIX H	VIX L	TED H	TED L
int_lag1	**0.0098**	**0.012**	**0.006**	**0.006**	0.0006
p value	0.008	0.002	0	0.0717	0.861
int_lag2	0.0043	**0.006**	0.003	**0.008**	0.0020
	0.145	0.040	0.209	0	0.438
int_lag3	**0.0061**	0.002	**0.005**	0.006	0.0048
	0.030	0.666	0.027	0.114	0.125
int_lag4	**0.0055**	0.002	**0.004**	**0.006**	0.0024
	0.069	0.591	0.074	0.008	0.465
int_lag5	0.0009	-0.002	0.001	0.002	-0.0010
	0.674	0.630	0.383	0.295	0.712
Controls					
size	**-3.1497**	-0.215	-0.059	1.148	-1.2319
p value	0.003	0.825	0.904	0.226	0.264
t1_t2	**-0.0804**	-0.047	-0.037	0.031	**-0.1193**
	0.030	0.417	0.150	0.519	0.031
npa	**0.8122**	**0.865**	**0.595**	**0.417**	**0.8853**
	0	0	0.001	0.076	0
loss_prov	0.4341	**1.589**	-0.823	**1.859**	1.0600
	0.213	0.003	0.305	0.020	0.104
N	7340	6463	4417	6265	6506
R^2	0.117	0.119	0.036	0.061	0.117

Notes: 'Crises' refer to the subsample of crisis episodes in the sample: LTCM (1998Q3), Dotcom bust (2002Q3–Q4), the Great Recession (2007Q4–2009Q2), and the Eurozone debt crisis (2010Q2–2012Q2); 'VIX_H' and 'VIX_L' refer to subsamples for quarters during which the VIX (the 'fear index') was more than 0.75 quantiles/less than 0.25 quantiles in its distribution respectively; and finally the same definition is applied for 'TED_H' and 'TED_L' where TED denotes the difference between the three-month Treasury bill and the three-month LIBOR based in US dollars, which is used as a proxy for the credit risk in the economy. 'int_lag1', ... 'int_lag5' (quarterly lags 1–5 of bank integration), 'size' (bank size), 't1_t2' (tier 1 and 2 combined), 'npa' (nonperforming asset percentage), and 'loss_prov' (loss provision as percentage of total assets) are explanatory variables.

during times of low TED spreads.

References

Daron Acemoglu, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. Systemic risk and stability in financial networks. *American Economic Review*, 105(2):564–608, February 2015.

Viral V. Acharya and Matthew Richardson. Implications of the Dodd-Frank act. *Annual Review of Financial Economics*, 4(1):1–38, 2012.

Tobias Adrian, John Kiff, and Hyun Song Shin. Liquidity, leverage, and regulation 10 years after the global financial crisis. *Annual Review of Financial Economics*, pages 1–24, 2018.

Davide Avino, John Cotter, and Tom Conlon. Credit default swaps as indicators of bank financial distress. *Journal of International Money and Finance*, 94: 132–139, 2019.

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

Dave Berger and Kuntara Pukthuanthong. Market fragility and international market crashes. *Journal of Financial Economics*, 105:565–580, 2012.

Wolfgang Bessler, Philipp Kurmann, and Tom Nohel. Time-varying systematic and idiosyncratic risk exposures of US bank holding companies. *Journal of International Financial Markets, Institutions & Money*, 35:45–68, 2015.

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

A. Colin Cameron, Jonah B. Gelbach, and Douglas L. Miller. Robust inference with multiway clustering. *Journal of Business & Economic Statistics*, 29(2): 238–249, 2011.

Mark M. Carhart. On persistence in mutual fund performance. *Journal of Finance*, 52(1):57–82, 1997.

Fabio Castiglionesi and Noemi Navarro. (In)efficient interbank networks. *Journal of Money, Credit and Banking*, 52(2-3):365–407, 2020.

Todd Clark and Kenneth West. Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, 138(1):291–311, 2007.

Manthos Delis and Panagiotis Staikouras. Supervisory effectiveness and bank risk. *Review of Finance*, 15(3):511–543, 2011.

Mert Demirer, Francis X Diebold, Laura Liu, and Kamil Yilmaz. Estimating global bank network connectedness. *Journal of Applied Econometrics*, 33:1–15, 2018.

Francis X Diebold and Kamil Yilmaz. Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal*, 119: 158–171, 2009.

Francis X Diebold and Kamil Yilmaz. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1):119–134, 2014.

John Duffy, Aikaterini Karadimitropoulou, and Melanie Parravano. Financial contagion in the laboratory: Does network structure matter? *Journal of Money, Credit and Banking*, 51(5):1097–1136, 2019.

Barry Eichengreen, Ashoka Mody, Milan Nedeljkovic, and Lucio Sarno. How the subprime crisis went global: Evidence from bank credit default swap spreads. *Journal of International Money and Finance*, 31(5):1299–1318, 2012.

Matthew Elliott, Benjamin Golub, and Matthew O Jackson. Financial networks and contagion. *American Economic Review*, 104(10):3115–3153, 2014.

Rüdiger Fahlenbrach, Robert Prilmeier, and Renè M Stulz. Why does fast loan growth predict poor performance for banks? *Review of Financial Studies*, 31 (3):1014–1063, 2018.

Eugene F. Fama and Kenneth R. French. The cross-section of expected stock returns. *Journal of Finance*, 47(2):427–465, 1992.

Eugene F. Fama and Kenneth R. French. A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22, 2015.

Yu Gao, Scott Liao, and Xue Wang. Capital markets' assessment of the economic impact of the Dodd-Frank act on systemically important financial firms. *Journal of Banking & Finance*, 86:204 – 223, 2018.

Stefano Giglio, Bryan Kelly, and Seth Pruitt. Systemic risk and the macroeconomy: An empirical evaluation. *Journal of Financial Economics*, 119:457–471, 2016.

Tirupam Goel, Ulf Lewrick, and Aakriti Mathur. Playing it safe: global systemically important banks after the crisis. *BIS Quarterly Review*, pages 35–48, September 2019.

Martin R. Goetz. Competition and bank stability. *Journal of Financial Intermediation*, 35:57–69, 2018.

Beverly Hirtle. Public disclosure and risk-adjusted performance at bank holding companies. Staff Reports 293, Federal Reserve Bank of New York, 2007.

Kewei Hou, Chen Xue, and Lu Zhang. Digesting Anomalies: An Investment Approach. *The Review of Financial Studies*, 28(3):650–705, 09 2015.

Thomas Kick and Estaban Prieto. Bank risk and competition: Evidence from regional banking markets. *Review of Finance*, 19(3):1185–1222, 2015.

Matthias Köhler. Which banks are more risky? the impact of business models on bank stability. *Journal of Financial Stability*, 16:195–212, 2015.

Mark Kritzman, Yuanzhen Li, Sebastien Page, and Roberto Rigobon. Principal components as a measure of systemic risk. *Journal of Portfolio Management*, 37(4):112–126, 2011.

Sam Langfield, Zijun Liu, and Tomohiro Ota. Mapping the UK interbank system. *Journal of Banking & Finance*, 45:288–303, 2014.

W S Leung, N Taylor, and K.P. Evans. The determinants of bank risks: Evidence from the recent financial crisis. *Journal of International Financial Markets, Institutions & Money*, 34:277–293, 2015.

John Lintner. Security prices, risk, and maximal gains from diversification. *Journal of Finance*, 20(4):587–615, 1965.

Serafín Martínez-Jaramillo, Biliana Alexandrova-Kabadjova, Bernardo Bravo-Benítez, and Juan Pablo Solórzano-Margain. An empirical study of the Mexican banking system's network and its implications for systemic risk. *Journal of Economic Dynamics and Control*, 40:242–265, 2014.

Whitney K Newey and Kenneth D West. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3):703–708, 1987.

Erlend W. Nier. Bank stability and transparency. *Journal of Financial Stability*, 1:342–354, 2005.

Wayne Passmore and Alexander H. von Hafften. Are Basel's capital surcharges for global systemically important banks too small? *International Journal of Central Banking*, pages 107–156, 2019.

Mitchell A. Petersen. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, 22(1):435–480, 2009.

Kuntara Pukthuanthong and Richard Roll. Global market integration: An alternative measure and its application. *Journal of Financial Economics*, 94:214–232, 2009.

L. C. G. Rogers and L. A. M. Veraart. Failure and rescue in an interbank network. *Management Science*, 59(4):882–898, 2013.

Stephen A Ross. The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, 13(3):341–360, 1976.

Eva Schliephake. Capital regulation and competition as a moderator for banking stability. *Journal of Money, Credit and Banking*, 48(8):1787–1814, 2016.

William F. Sharpe. Capital asset prices: A theory of market equilibrium under certain conditions of risk. *Journal of Finance*, 19(3):425–442, 1964.

Kevin J. Stiroh. New evidence on the determinants of bank risk. *Journal of Financial Services Research*, 30:1787–1814, 2006.

Anjan V. Thakor. Bank capital and financial stability: An economic trade-off or a Faustian bargain? *Annual Review of Financial Economics*, 6(1):185–223, 2014.

Samuel B. Thompson. Simple formulas for standard errors that cluster by both firm and time. *Journal of Financial Economics*, 99(1):1–10, 2011.