Integration Among US Banks

Abhinav Anand
John Cotter*†

Abstract

We study integration among a large sample of 1109 US banks over a quarter-century from 1990–2014. We define a bank’s level of integration (measured in percentages) as the degree of dependence of its stock returns on common national banking factors. We show that the median US bank’s integration has risen from 4.4% in 1990 to 10.1% in 2014. Integration across banks is highly unevenly distributed, appears to obey a power law and for the median “systemically important” bank, corresponding integration levels are 6–10 times higher. The US banking sector is segmented into a small group of “core” banks, strongly integrated with each other; and a large group of weakly integrated banks in the “periphery”. Determinants of US banks’ integration include bank size, its market beta and its idiosyncratic risk, which, all else equal, have a significantly positive impact; while increased reliance on deposit financing and short term financing have a significantly negative impact on integration.

1 Introduction

Among the salient lessons economists, bankers and policymakers learned from the Great Recession was that ignoring mutual interdependence among modern banks can be extremely dangerous. Even sedate banks suffered distress and contagion merely on account of having been integrated with

*Michael Smurfit Graduate Business School, University College Dublin. Carysfort Avenue, Blackrock, Co. Dublin, Ireland
†Acknowledgments
the fortunes of their riskier cousins. Indeed, recent work has uncovered much evidence regarding the negative externalities generated by such high levels of interconnections, especially during systemic crises. From this point of view, the measurement and explication of US banks’ integration demands urgent attention and rigorous scrutiny.

We study integration dynamics for a large sample of 1109 US banks for a quarter-century from 1990–2014. We define a bank’s integration with the banking sector as its degree of dependence on a set of common national banking factors that drive, to varying degrees, returns of all US banks. In order to operationalize this definition, we identify these common factors as the principal components constructed from stock returns of a special set of US banks — the 8 US Global Systemically Important Banks (G-SIBs). Such principal components can be interpreted as a set of anonymous, orthogonal common factors driving each bank’s returns — strongly for those more exposed to such common factors (banks with high integration), and weakly for those more exposed to idiosyncratic factors (banks with low integration). In order to measure the degree of dependence on these common factors, we employ the explanatory power, in terms of adjusted $R^2$, of bank returns regressed on the top few G-SIB principal components (Pukthuanthong and Roll, 2009).

The median American bank shows an increase in its integration level from 4.4% in 1990 to 10.1% in 2014. Such median integration levels, however, hide massive variation in the underlying integration estimates of individual US banks. Indeed, for a special set of 19 banks deemed “systemically important” (“systemic” henceforth) the median integration rises from around 23% in 1990 to 76% in 2014. Systemic banks are the set of 8 Global Systemically Important Banks as well as 11 Domestic Systemically Important Banks (D-SIBs). During financial crises, the corresponding levels are even higher for the median systemic bank.

Integration across US banks is highly unequally distributed, with a small set of strongly integrated banks contributing disproportionately to the aggregate integration. Consequently, the distribution of integration is shown

---

1See Table 1 for the full list of 19 systemic US banks, as defined for our sample.
to conform to a power law$^2$ and the US banking sector displays segmentation into a small set of strongly integrated “core” banks; and a large sample of weakly integrated “periphery” banks. The banks in the core are well explained on the basis of chosen bank characteristics but the peripheral banks resist any explanation. The systemic banks, on account of their extremely high integration, lie in the core but remain unintegrated with banks in the periphery.

We investigate determinants of US banks’ integration and find that banks’ size, market beta and idiosyncratic risk have a significantly positive marginal impact on integration; whereas reliance on deposit financing and short term financing displays a significantly negative marginal impact. Broadly speaking, characteristics positively associated with equity market reliance — bank size, its market beta and its idiosyncratic volatility — display a positive marginal effect on bank integration; while characteristics signifying more debt market based financing — such as the deposit financing ratio and the short term financing ratio — exhibit a negative marginal effect.

Our empirical study contributes to the current literature on interdependence among banks in a variety of ways. Our definition of integration in terms of alignment with G-SIBs’ principal components helps us to estimate integration levels for a very large scaled empirical banking sector comprising a diverse set of 1109 banks from 1990 to 2014. Popular alternative modeling techniques, in which interconnections between two banks are estimated explicitly, are quickly overwhelmed as the number of banks increases. By projecting the very large dimensional space of the entire banking sector onto a maximally informative yet small dimensional linear subspace, we can achieve a high level of computational tractability. One may argue that the cost of such high coverage is reflected in our coarse estimates of “integration.

---

$^2$The phenomenon of power law tails is also termed the “Pareto Principle”, informally known as the “80–20 Rule”: 80% of the observed variation results from 20% of the sample. Such mysterious power laws govern a wide variety of disparate phenomena in economics and finance (among several other disciplines). See Gabaix (2009) for an excellent exposition.
tion” as opposed to finer “interconnectivity” estimates. The main difference between the two concepts is that a bank’s integration is measured only with the sector as a whole while a bank’s interconnectivity can be measured with any other bank directly. Indeed, from this point of view, our implicit, principal component based methodology can be viewed as a mathematically dual approach to explicit, network based interconnectivity modeling.

To the best of our knowledge, this is the first study that establishes US banks’ integration levels to be driven by common bank characteristics like size, beta, short term funding reliance and so on. We show that, all else equal, size, beta and idiosyncratic risk contribute positively; while reliance on deposit financing and short term financing have a negative impact on bank integration. Additionally, we show that the leverage ratio had a significantly negative marginal impact pre-2000 and that bank size has had a negative marginal impact on integration post-2007.

Our explanatory regression methodology is general and controls for certain endogeneities bound to afflict any diverse sample of US banks. In particular, we employ a variety of different unbalanced panel regressions with bank-specific fixed effects; and compute clustered robust standard errors, allowing clustering at the bank level. This is necessary when explaining integration among the massively heterogeneous set of US banks. Our explanatory models provide a good fit to empirical integration estimates. For the whole sample, we explain around 25.3% of the variation in US banks’ integration; and this share increases even further for special subsamples like the systemic banks (44.4%) and the topmost integrated quintile (32.6%).

Finally, our study also establishes a sharp segmentation among US banks into a small, strongly integrated core and a large, weakly integrated periphery, consistent with recent findings. The approach we favor in this paper is agnostic and makes minimal assumptions and our results survive a variety of alternative variable definitions and subsample regressions.

The paper is organized as follows. We describe in full detail, the technique of estimating integration for each of the 1109 US banks over the entire 25 year sample period in Section 2. Section 3 analyzes the trends in US banks’ integration stratified according to special subperiods, as well as
trends in the distribution of integration across US banks. We explain bank integration on the basis of common characteristics in Section 4 and describe the estimation methodology and results in Section 5. Finally, we establish that the US banking sector exhibits the core-periphery phenomenon in section 6 and conclude our discussion in Section 7.

2 Estimating Integration

2.1 Integration, Interconnectivity or Spillovers?

There are several non-equivalent ways to capture the notion of interdependence among economic entities. Hence researchers label such concepts as “interconnectivity”, “integration”, “spillovers”, “contagion”, “systemic risk” etc. Such interdependence measures are based on different observables including returns, realized volatilities, interest rate spreads and so on. In our study, we measure interdependence via “integration” and employ stock returns for its computation. It has become customary in literature to use the term “interconnectivity” or variants thereof when employing an explicit, network-based approach; and to employ the term “integration” when implicit econometric techniques are the focus. Since our study belongs firmly to the latter group, we discuss the phenomenon of banks’ integration with the sector as opposed to its interconnectivity with individual entities in it.

Broadly, two main approaches have emerged — explicit, network based techniques and implicit, econometric measures like principal components.\(^3\) The objects of study in either case are a set of economic entities, such as international markets, banks, insurance or financial sectors etc. Researchers estimate interconnections between these entities either explicitly — by means of a network with said entities as nodes; and edges (directed or otherwise) between nodes that are mutually exposed; or implicitly — by estimating common factors that drive the observables of all entities in that set.

\(^3\)Hüser (2015) is a recent survey of interbank networks; and Eichengreen et al. (2009) and Pukthuanthong and Roll (2009) are early examples of principal component based techniques.
We adapt the key observation made in Pukthuanthong and Roll (2009) — that high integration levels necessarily imply high dependence on external, aggregate factors. They study stock indices of several countries and measure how integrated a country’s equity markets are (with the international equity market) by the adjusted $R^2$ of that country’s index returns regressed on global factors. These global factors influence all countries commonly and are identified with the principal components of a special subset of 17 countries, which the authors deem “largest and most globally integrated economies” (Pukthuanthong and Roll, 2009, p. 223).

Other studies that employ similar econometric measures are Kritzman et al. (2011), which employ principal components as a proxy for systemic risk; and Berger and Pukthuanthong (2012), which aggregate time-varying loadings on a “world market factor” (identified with the first principal component) to create a measure of systemic risk. In particular, Billio et al. (2012), examine the banking, insurance, hedge fund and broker-dealer sectors and employ principal components and Granger causality to conclude that all these sectors have become more interrelated in time.

We exploit the observation that principal components, in the guise of external, common factors that drive all constituent banks’ returns, offer an effective technique of capturing how otherwise disparate banks display co-movements in their stock returns. Indeed, our approach helps in reducing the very high dimensionality of a typical banking sector by using only the first few principal components, thereby making the study of such large scaled systems computationally tractable.

Measuring “spillovers” by generalized vector autoregression (G-VAR) induced networks falls in between these two approaches. For example, building on Diebold and Yilmaz (2009) and Diebold and Yilmaz (2014), Demirer et al. (2016) 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.

---

4 Provided that not all factor exposures ($\beta$s) are identically 0.
5 We note that Elliott et al. (2014) use the word “integration” but define it to measure dependence on counterparties.
We consider such explicit, network based approaches to be ideal when investigating questions whose resolution depends on microscopic, granular data. However, network based methods cannot be scaled up to study very large sectors. Indeed, it is instructive to note that Demirer et al. (2016), even after employing dimensionality reducing LASSO based techniques study a subset of the top 150 global banks for 11 years, while we are able to estimate integration levels of 1109 US banks for 25 years. The price to be paid for such extensive coverage by principal components is that our knowledge of integration in the American banking sector is coarse — we cannot, for example, compute how interconnected individual US banks are. Hence, researchers who investigate microscopic interconnectivity among individual entities will find network based techniques more useful. On the other hand, those who favor aggregate, macroscopic estimates of integration of an individual with the entire large scaled economic sector as a whole should rely on principal components.

2.2 G-SIBs: A Special Subset

Consistent with Pukthuanthong and Roll (2009), we postulate a special subset of banks whose principal components we can interpret to contain “national” factors driving ordinary banks’ returns.

Which US banks belong to this special subset? In order to ascertain this, we note that the Financial Stability Board, based on the methodology pioneered by the Basel Committee for Banking Supervision (BCBS) compiles a list of “Global Systemically Important Banks” (G-SIBs), informally known as the “too-big-to-fail banks” (TBTFs).6

The methodology determines which bank is G-SIB, based on averaging the score of banks on 5 equally weighted factors, which include cross-jurisdictional activity, size, interconnectedness, substitutability and complexity (Basel Committee on Banking Supervision, 2013). This suggests that for the US banking sector the set of US G-SIBs — all of which score

---

6The first such list was released in November 2009 and is updated yearly each November. For the latest list, visit: http://www.fsb.org/2015/11/fsb-publishes-the-2015-update-of-the-g-sib-list/
Table 1: The list of 19 US systemic banks, defined to be the set of 8 Global Systemically Important Banks, as defined in November 2015, as well as 11 Domestic Systemically Important Banks. G-SIBs are designated as such by the Financial Stability Board (FSB) while D-SIBs are those deemed important enough by the Dodd-Frank Act to be included for annual stress testing. Since we exclude funds or financial service providers and include only those banks whose primary listing is in the US, we are left with a set of 11 D-SIBs. The principal components constructed from the eigenvectors of the return covariance matrices of the 8 G-SIBs are interpreted as common national banking factors that drive returns — to varying degrees — of all US banks.

<table>
<thead>
<tr>
<th>G-SIB</th>
<th>D-SIB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bank of America</td>
<td>BB&amp;T</td>
</tr>
<tr>
<td>JP Morgan Chase</td>
<td>Comerica</td>
</tr>
<tr>
<td>Wells Fargo</td>
<td>Huntington Bancshares</td>
</tr>
<tr>
<td>State Street</td>
<td>M&amp;T Bank</td>
</tr>
<tr>
<td>Morgan Stanley</td>
<td>PNC</td>
</tr>
<tr>
<td>Goldman Sachs</td>
<td>Regions</td>
</tr>
<tr>
<td>Bank of New York Mellon</td>
<td>Zions</td>
</tr>
<tr>
<td>Citigroup</td>
<td>Fifth Third</td>
</tr>
<tr>
<td></td>
<td>SunTrust</td>
</tr>
<tr>
<td></td>
<td>US Bancorp</td>
</tr>
<tr>
<td></td>
<td>KeyCorp</td>
</tr>
</tbody>
</table>

the highest on interconnectivity, thereby constituting the largest and most integrated subset — can be used to estimate national factors that are hypothesized to drive returns of all US banks. Indeed, it is quite reasonable to assume that whatever be the true identities of such common factors, they cannot be completely absent from — and thus, must be largely embedded in — the top few principal components of US G-SIBs.

In principle, there is no unique choice for the source of such putative national factors. However, for reasons of computational tractability, picking the smallest such feasible set is preferred. Hence, we choose exactly the 8 US G-SIBs to be the source of principal components for the US banking sector.

Our choice also reflects evidence uncovered in the interbank network literature. Several studies of empirical, interbank networks provide evidence that banking networks display a “core-periphery” structure, where the core of the network includes a small collection of strongly interconnected banks.
and a larger sample of periphery banks that are less interconnected with each other but are connected to the core. Thus it is natural to conclude that the G-SIBs should be contained in the strongly interconnected core.

Hence our choice of US G-SIBs as the set of banks whose principal components drive all US banks’ returns is justified not just from the BCBS methodology but also from the observation of the core-periphery phenomenon for empirical interbank networks.

2.2.1 Common Factors as G-SIB Principal Components

We define a bank’s integration level as the explanatory power of the regression of its returns on US G-SIBs’ principal components. These G-SIB principal components are the eigenvectors of their return covariance matrix and contain all national factors that influence member banks’ integration levels.

It is important to note that such national factors are external factors beyond individual banks’ control. Since the same set of national, external factors affect all banks’ returns, we can interpret the principal components as common factors. Banks that are highly integrated will display high dependence on common factors extracted from G-SIBs and inversely.

We discuss two extreme cases to illustrate this idea more completely:

**Perfectly Isolated Bank:** Suppose a bank is fully decoupled with its banking sector; and ups and downs in other banks’ returns have no effect on its own returns. In particular, this implies that the G-SIBs have no role to play in explaining the bank’s return.

More formally, since the bank is completely isolated, all variation in its return must be completely governed by idiosyncratic factors and hence the adjusted $R^2$ of principal component regressions must be 0.

Clearly, for a bank so completely cutoff from the vagaries of other banks’

---

7 A sequence of recent papers study national, as well as international empirical interbank networks and find support for such a core-periphery hypothesis. Some of these include Minoiu and Reyes (2013), Craig and von Peter (2014), Martínez-Jaramillo et al. (2014), in’t Veld and van Lelyveld (2014) among others.
fortunes that it is independent of all national factors, our definition will correctly estimate integration level as 0%.

**Perfectly Integrated Bank:** Suppose a bank is perfectly integrated. This implies that all its return variation is explained by national factors extracted from the American G-SIBs.

Since all return variation is captured by common factors, there is no idiosyncratic component and hence the adjusted $R^2$ for such principal component regressions will be 1.

In this case, the bank’s returns are perfectly integrated with those of the banking sector. The bank, therefore, is wholly externally driven, with no role for any idiosyncratic factor in explaining return variation. Again, our definition will correctly compute the integration level of this bank as 100%.

Real banks display empirical behavior in between these two theoretical extremes and their integration levels will lie strictly between 0 and 100%. Higher adjusted $R^2$ will indicate higher levels of integration with the banking sector and inversely. 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 zero integration.

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

$$\hat{\text{Int}}_j := \max\{\text{adj } R^2_j, 0\}$$

where $\hat{\text{Int}}_j$ denotes estimated integration, and “adj $R^2_j$” denotes the adjusted $R^2$ of the principal component regression conducted on bank $j$.

### 2.3 Data

Our study analyzes all public banks with primary listings in the US. In order to collect daily closing stock prices for all such banks we use Thomson Reuters Datastream’s database for a period starting from January 1, 1990 to December 31, 2014. The number of such US banks available from Datastream is 1109.

Our attention on public banks with primary listings in the US excludes several multinational banking corporations which might have secondary list-
ings 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.

Since the focus of our paper is to isolate and study integration dynamics of US banks, inclusion of European or Asian banks with secondary listings in the US may bias our estimates. Similarly, choosing mutual funds, shadow banks and financial service providers will influence the estimates of integration among banks; and our measures will then correspond to integration within the general financial sector. Despite this restriction, our sample contains a very large number of US banks with very diverse characteristics.

We note that while our period of study stretches from January 1, 1990 to December 31, 2014, not all banks have stock price data spanning the entire period. This may be due to several reasons — the banks in question could have been private (for example, Morgan Stanley and Goldman Sachs were made public in 1993 and 1999, respectively) — or Datastream did not have access to their market values for the entire duration. Irrespective of the cause, we include such banks’ data from the day their records begin appearing in Datastream’s database. Since we include all such banks in Datastream irrespective of whether they are alive or not, our study is free from survivorship bias.

The choice of our sample period helps us to investigate several important recent episodes including the Great Recession. We discuss our results segregated by subperiods in the subsections 3.1 and 5.5.

2.4 Methodology

2.4.1 Frequency of Estimation

We partition each year into its constituent quarters. Since our duration of study spans 25 years, there are exactly hundred quarters in total — from Q1 1990 to Q4 2014. Under this setup, there are between 62–66 daily observations for each bank’s return each quarter. We compute the covariance
matrix of the US G-SIBs for each quarter and extract 4 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 Datastream. For example, Morgan Stanley has no return data available from Q1 1990 to Q2 1992. Hence, its integration level estimation starts from Q3 1992 and continues until the end of the sample to Q4 2014.

### 2.4.2 Principal Component Extraction

The common factors that form the right hand side (RHS) of the regression equation are the principal components of the G-SIB data matrix. These correspond to the eigenvectors of the 4 largest eigenvalues of the covariance matrices of the G-SIBs. Our choice of restricting attention to 4 top eigenvectors is related to their coverage of 90% of the total variation in returns each quarter, as may be seen in Figure 1.

In case there are G-SIBs with no usable return data, we form principal components from the set of available G-SIBs. For example, Morgan Stanley does not make an appearance until 1993 (quarter 14, counting from Q1 1990); and Goldman Sachs does not do so until 1999 (quarter 39). Hence an ordinary bank is hypothesized to be driven by factors computed from 6 of the 8 US G-SIBs from 1990 to 1993 (or Q1–Q13); 7 of the 8 US G-SIBs from 1993 to 1999 (Q14–Q38); and the full set of 8 US G-SIBs from 1999 to 2014 (Q39–Q100). Hence, the size of the corresponding G-SIB covariance matrix is $6 \times 6$ from Q1 to Q13, $7 \times 7$ from Q14 to Q38; and $8 \times 8$ from Q39 to Q100.

**For Ordinary Banks:** Once eigenvectors are computed in order of largest to smallest eigenvalue, *out-of-sample* principal components are estimated by applying them to observed returns for the *subsequent* quarter. For example, eigenvectors computed from the G-SIB covariance matrix in Q1 1990 are applied to the G-SIB data matrix of observed returns in Q2 1990. This generates out-of-sample principal components to be used as common factors
in the RHS of the regression corresponding to Q2 1990. Such out-of-sample national factors are orthogonal, which lays to rest the possibility that the common factors employed in quarterly regressions suffer from multicollinearity.

**For G-SIBs:** In case the dependent variable is a G-SIB, one cannot rule out the possibility that its returns, when regressed on common factors may suffer from an upward bias for its integration estimate. This is so since the same G-SIB’s return may be disproportionately represented in the principal components of the RHS.

In order to allay such concerns, when one of the G-SIBs is the dependent variable, we exclude it from the list of independent variables in the RHS. This ensures that when out-of-sample principal components are computed as described above, none of the explanatory variables are biased by that same G-SIBs return values.

For example, out of the 1109 US banks in our sample, 8 are G-SIB. When one of these banks, say JP Morgan, is on the LHS (i.e., when we estimate its level of integration with the American banking sector as a whole) the covariance matrix, from which eigenvectors are to be extracted, includes all US G-SIBs except JPM. This step, therefore, precludes the possibility that one of the common factors is unduly influenced by the dependent variable.

### 2.5 Estimating Integration: Results

#### 2.5.1 The Number of Principal Components

In principal component analysis, there is no “correct” method to decide 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 like Pukthuanthong and Roll (2009), employ as many principal components as are required to explain 90% of the total variance. For the US banking sector, four principal components are sufficient, as may be seen in Figure 1.

Principal components 1 and 2, in that order, dominate in terms of
marginal explanatory fraction of the total variance. During tranquil market conditions, contributions by principal components 3 and 4, though relatively modest, account for a sizeable variation; while volatile markets cause their shares to dip substantially, resulting in 75–85% of the total variation being attributable to that due to just the first two PCs. Figure 1 shows marginal contributions of each PC for each quarter from 1990 to 2014.

2.5.2 Summary Statistics

Table 2 reports descriptive statistics for integration estimates across banks in the US. Overall, the average US bank’s integration is 16.10% and the median bank’s integration is 7.57%. Such a large difference between the mean and the median suggests that there is a subsample of banks with extremely large integration values which contribute disproportionately to the aggregate integration.

In order to observe this effect more clearly we study a special subset of “systemic” banks comprising the 8 US G-SIB and 11 US D-SIBs (Domestic
Table 2: Summary statistics for integration estimates for banks in the US, computed over all 1109 banks and all 100 quarters from 1990 to 2014. The minimum, maximum, mean, median and standard deviations are reported for different subsamples of US banks. “All” denotes the full sample of 1109 banks, “Sys” denotes the 19 bank subsample that contains the 8 US G-SIBs and 11 US D-SIBs (Domestic Systemically Important Banks) listed in Table 1. “Qnt 1” and “Qnt 5” denote the topmost integrated quintile (top 20%) and bottommost integrated quintile (bottom 20%) of US banks respectively. Finally, “# obs” denotes the number of observations.

<table>
<thead>
<tr>
<th>Integration</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Med</th>
<th>Std</th>
<th># obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>0.0001</td>
<td>94.4190</td>
<td>16.1053</td>
<td>7.5761</td>
<td>19.0128</td>
<td>1109</td>
</tr>
<tr>
<td>Sys</td>
<td>0.0931</td>
<td>94.4190</td>
<td>49.9359</td>
<td>53.5117</td>
<td>22.5656</td>
<td>19</td>
</tr>
<tr>
<td>Qnt 1</td>
<td>0.0029</td>
<td>94.4190</td>
<td>30.0951</td>
<td>26.9515</td>
<td>21.8622</td>
<td>215</td>
</tr>
<tr>
<td>Qnt 5</td>
<td>0.0001</td>
<td>76.6452</td>
<td>4.7040</td>
<td>2.7024</td>
<td>5.7556</td>
<td>215</td>
</tr>
</tbody>
</table>

Systemically Important Banks). The list of systemic banks in the US, as shown in Table 1, comprises 19 banks, for which descriptive statistics are presented in Table 2. The means and medians of this class of banks are much higher than their full sample counterparts, indeed for even the topmost integrated quintile. All systemic banks fall in the topmost integrated subset and in general, the differences between the topmost and bottommost quintile suggest extreme heterogeneity in the distribution of integration. Indeed, in subsection 3.2, we show that integration among US banks has become progressively more fat-tailed and seems to obey a power law, i.e., a large set of banks are weakly integrated while the others are very strongly integrated.

The standard deviations of banks in the systemic and topmost integrated quintile Qnt 1 are similar (22.56 and 21.86 respectively) but that for the least integrated quintile Qnt 5 is substantially smaller (5.75) suggesting a lack of relative variation in integration levels for the least integrated banks.

---

8The Dodd-Frank Act stipulates that all financial institutions having more than $50 billion in balance sheets undergo annual stress tests and this set of banks is commonly termed as domestic systemically important banks. Since we exclude financial service providers and those without primary listings in the US, we are left with a subset of 11 such D-SIBs — BB&T, Comerica, Fifth Third, Huntington Bancshares, KeyCorp, M&T Bank, PNC, Regions, SunTrust Banks, US Bancorp and Zions.
3 Trends

Figure 2: Median integration levels for the full sample of US banks and the systemic bank subsample, where integration is measured by the adjusted $R^2$ from principal component regressions for individual US banks’ returns. Systemic banks are a special set of 19 US banks listed in Table 1. The dashed lines denote a linear time trend fitted to quarterly integration levels.

Figure 2 shows quarterly variation in median integration levels among US banks. The dashed lines indicate the results of linear trend fitting. As may be seen, integration among US banks shows a positive trend. Overall, the median levels remain low — from 4.42% in Q2 1990 to 10.14% in Q4 2014. In other words, for the full sample in Q2 1990, only 4.42% of return variation is attributable to US G-SIBs’ principal components but this share increases to 10.14% by Q4 2014. The median US bank’s maximum integration is recorded as 14.78% in Q3 2008, coinciding with Lehmann Brothers’ bankruptcy.

However, studying median integration levels for bank subsamples reveals substantial heterogeneity. In particular, the median systemic bank shows integration levels 6–10 times higher. Figure 2 shows the median integration level for the 19 US systemic banks (G-SIB and D-SIB), which starts off in Q2 1990 at a comparatively high level of 22.84% and reaches extremely high median levels of 75.98% by the end in Q4 2014. For the systemic bank subsample, the highest median integration level of 86.81% occurs for Q3 2011 coinciding with the worst of the Eurozone crisis. The trends are
strongly positively significant, as Table 3 shows. By the end of our sample period, more than three-fourths of the total variation in the median systemic bank’s stock returns is driven by the first four G-SIB principal components — a very high fraction indeed.

3.1 Trends: Subperiod Analysis


For the full sample of US banks, trends are highly significant and very steep during P2 (especially post Q2 2002) and GR, which contribute to the overall trend being positively significant but only displaying a mild steepness.

9Note that NBER designated the period between Q4 2007 to Q2 2009 as The Great Recession. Our period from 2007–2009 contains this window.

<table>
<thead>
<tr>
<th>Time Subsample</th>
<th>Bank Subsample</th>
<th>Coeff</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>0.0556</td>
<td>(0.0000)***</td>
</tr>
<tr>
<td></td>
<td>Sys</td>
<td>0.5093</td>
<td>(0.0000)***</td>
</tr>
<tr>
<td></td>
<td>Qnt 1</td>
<td>0.4436</td>
<td>(0.0000)***</td>
</tr>
<tr>
<td></td>
<td>Qnt 5</td>
<td>-0.0098</td>
<td>(0.0679)*</td>
</tr>
<tr>
<td>Full</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P1</td>
<td>Coeff</td>
<td>-0.0164</td>
<td>(0.2051)</td>
</tr>
<tr>
<td></td>
<td>p value</td>
<td>1.1142</td>
<td>(0.0000)***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.0950</td>
<td>(0.0149)**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.0440</td>
<td>(0.0537)*</td>
</tr>
<tr>
<td>P2</td>
<td>Coeff</td>
<td>0.1552</td>
<td>(0.0000)***</td>
</tr>
<tr>
<td></td>
<td>p value</td>
<td>-0.4649</td>
<td>(0.0223)**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.9358</td>
<td>(0.0000)***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.0145</td>
<td>(0.0873)*</td>
</tr>
<tr>
<td>P3</td>
<td>Coeff</td>
<td>-0.0102</td>
<td>(0.3690)</td>
</tr>
<tr>
<td></td>
<td>p value</td>
<td>-0.2970</td>
<td>(0.0316)**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.4877</td>
<td>(0.0029)**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.0190</td>
<td>(0.0510)*</td>
</tr>
<tr>
<td>GR</td>
<td>Coeff</td>
<td>0.5961</td>
<td>(0.0246)**</td>
</tr>
<tr>
<td></td>
<td>p value</td>
<td>-0.9666</td>
<td>(0.4322)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.2460</td>
<td>(0.3810)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.1988</td>
<td>(0.0007)*</td>
</tr>
<tr>
<td># obs</td>
<td></td>
<td>1109</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td></td>
<td>215</td>
<td>215</td>
</tr>
</tbody>
</table>

The median systemic bank shows a rapid rise in integration pre-2000 — rising from 22.8% in Q2 1990 to 63.7% by Q4 1999. This rise is especially rapid post Q3 1995, as may be seen in Figure 3.

The median Qnt 1 bank shows a positive but mild integration rise in P1 but rises strongly during P2 (especially post Q1 2001, see Figure 3) from 7.8% in 2000 to 25.5% in 2006.

For the median Qnt 5 bank subset, except for GR, during which integration exhibits a highly positively significant, steep trend, for all other periods, integration has a very mild, negative trend. The overall trend is mildly negatively significant, with magnitude close to 0.

Table 3 presents linear trends in terms of the Newey-West $T$ statistics (Newey and West, 1987) for the four different subsamples of banks for different subperiods.

For the full duration of the study, presented in the row “Full” in Table 3 the trends are highly significant positively for the full sample, the systemic bank subsample as well as the top quintile subsample. The bottom quintile of banks shows a very mild negative trend over the 25 years from 1990 to 2014. In terms of magnitude, the systemic banks show the maximum
steepness, followed by the Qnt 1 subsample.

The row “P1” exhibits the results of trend fitting during the period 1990–1999. Only the systemic and top quintile banks show highly significant positive trends now, while the bottom quintile continues to show a mildly negative trend. The systemic banks in particular, display very high slopes during P1, as was seen in Figure 3, as well.

During 2000–2006, the full sample, as well as the Qnt 1 subsample post significantly positive trends whereas the bottom quintile again displays a mildly negative trend. As suggested by Figure 3, the magnitude of the trend coefficient is highest for the Qnt 1 subsample of banks. Curiously though, the systemic banks show a weakening in integration during P2 and exhibit a significant, negative trend.

Post-2007, the row “P3” in Table 3 shows that integration has decreased somewhat. Both systemic and Qnt 1 banks post significant negative trends, while the Qnt 5 banks display another period of mildly negative integration trends. Both systemic and Qnt 1 subsample show relatively high negative steepness post-2007.

During the Great Recession 2007–2009, the full sample displays significant positive trends and the Qnt 5 least integrated bank subsample posts positive and significant trends. In both cases, the steepness of the linear trend is relatively high. The systemic banks and Qnt 5 banks, however, show no significance, consistent with Figure 3 as well.

Overall, we observe the following patterns: the median US bank over the full sample period, shows a significant but mildly positive trend which occurs on account of a relatively high trend during P2: 2000–2006 and GR: 2007–2009 and slightly negative but insignificant trends for the other periods. The median systemic bank shows a highly significant, very positive integration trend during the pre-2000 period, followed by falling integration trends during P2 and P3. However, the magnitudes of such negative trends are small and hence aggregated over the whole 25 years, systemic banks show a very significant, high integration trend. Almost the same behavior is observed for Qnt 1 banks which show a significant, though small positive trend in P1 followed by a significantly high positive trend in P2 which even-
ually falls by a small amount during P3. For the Qnt 5 bank subsample, except for the Great Recession, where the median bank shows a positive trend, all other periods exhibit significant, though mildly negative trends leading to a very low negative overall trend.

In Section 5, we investigate bank characteristics based explanatory variables to explain trend dynamics among several bank subsamples as well subperiods.

### 3.2 Distributional Trends

After studying trends of banks’ integration, we investigate how integration varies across US banks over time. For example, if all banks remain equally integrated, the said distribution should be uniform. This, and some other related distributional hypotheses such as the normal distribution seem highly implausible, as Figure 4 illustrates.

![Integration distribution across US banks. Two boxplots, comparing the distribution of integration in the beginning of the sample period (Q2 1990) and the end of the sample period (Q4 2014) reveal that the distribution of integration is highly uneven and has become progressively more skewed to the right. The tops and bottoms of each box are the 25th and 75th percentiles of the samples and the distances between the tops and bottoms are the interquartile ranges. Values beyond 1.5 times the interquartile range are deemed outliers and shown as such. The line in the middle of each box is the sample median.](image)

To analyse the distribution of integration across US banks, we display
boxplots at the beginning (Q2 1990) and end (Q4 2014) of the sample period. Figure 4 presents evidence that integration among US banks is highly unevenly distributed and has become progressively more positively skewed over time. This is consistent with Figure 2, which points out that the small set of systemic banks contribute much more to integration than other, more ordinary banks.

Such a segmentation leads one to suspect that the Pareto Principle may be at play: most variation in aggregate integration is due to a few strongly integrated banks. Under this hypothesis, the distribution of integration across US banks should display fat, Pareto type tails consistent with the power law. Distributions of such a form in which most of the total variation is attributable to a small number of entities are often candidates for an underlying power law, which are distributions whose tails decay polynomially.\textsuperscript{10} The polynomial decay of power law tails implies higher probabilities of extreme observations and hence fatter tails than those for the normal distribution, whose tail decays exponentially.

In order to formally test the hypothesis that integration across banks obeys a power law in the tails, we rely on the Kolmogorov-Smirnov (KS) test, which compares the shapes of empirical distributions to hypothesized distributions. For the implementation of this test, we rely on the statistical framework advocated in Clauset et al. (2009), using \( p \) values computed from goodness of fits based Kolmogorov-Smirnov test statistics.\textsuperscript{11}

We note that in practice, power law tails may be hard to distinguish from exponential or lognormal tails and hence we evaluate both as plausible alternative tail distributions in Table 4.\textsuperscript{12} In order to achieve this, we compute

\begin{equation}
\begin{aligned}
\text{KS} := \sup_x |F_n(x) - F(x)|
\end{aligned}
\end{equation}

where \( F_n \) is the empirical distribution and \( F \) is the hypothesized distribution.

\textsuperscript{10}More formally, \( P(X > x) \propto \frac{1}{x^{\alpha}} \), where \( \alpha > 0 \) is termed as the tail exponent.

\textsuperscript{11}The Kolmogorov-Smirnov test statistic is formally defined as

\textsuperscript{12}Mere visual inspection of Figure 4 rules out distributions like uniform or normal. Other fat-tailed distributions like Student’s \( T \) can also be ruled out on the basis of the KS test. We however, report the comparative performance of only the two closest competitors of the power law in Table 4.
Table 4: Quarterly rejection frequencies of null distributional hypotheses under Exponential, Lognormal and Power Law models. Total number of quarters is 100 for the full sample and 50 for the recent half of the sample. For the entire sample consisting of 100 quarters, except for the 10% significance level, the power law wins by having the fewest number of rejections. Moreover, as the significance level becomes more conservative the margin of outperformance increases in favor of the power law. For the last half of the sample period comprising 50 quarters from Q3 2002 to Q4 2014, the power law uniformly dominates its rivals for all significance levels.

| Sample Duration | Significance Level | Exponential | | Lognormal | | Power Law |
|------------------|--------------------|-------------|-------------|-------------|-------------|
|                   | 10%    | 5%    | 1%    | 10%    | 5%    | 1%    | 10%    | 5%    | 1%    |
| Q2 1990–Q4 2014  | 83     | 74    | 67    | 50     | 43    | 33    | 55     | 41    | 24    |
| Q3 2002–Q4 2014  | 50     | 49    | 44    | 46     | 40    | 33    | 20     | 16    | 12    |

$p$ values based on the KS test each quarter for different null distributional hypotheses. Then we compare the number of quarters for which the null hypotheses of exponential, lognormal and power law distributions are rejected at significance levels of 10%, 5% and 1% respectively. The distribution for which there are fewest rejections is the most plausible candidate.

As Table 4 shows, for the entire sample consisting of 100 quarters, except for the 10% significance level, the power law wins by having the fewest number of rejections. Moreover, as the significance level becomes more conservative (confidence levels are increased), the margin of outperformance increases in favor of the power law. For example, at the 1% significance level, out of 100 total quarters, the power law can be rejected only 24 times, while the corresponding rejection frequency for exponential and lognormals are 67 and 33 out of 100 respectively.

When we look at the most recent half of the sample comprising 50 quarters from Q3 2002 to Q4 2014, the power law uniformly dominates its rivals for all significance levels. For example, for the most recent 50 quarters, at 1% significance level, out of a possible 50, the power law is rejected only 12 times while the corresponding rejection frequencies for exponential and lognormals are 44 and 33 respectively. This shows that the distribution of integration has become progressively more consistent with power law tails.

Analogous to our results Boss et al. (2004) and Cont et al. (2013) find evidence that the degree distribution of interbank networks follow power
laws. This observation may potentially be exploited by future researchers to study the mechanism that governs integration (or interconnectivity for that matter) since often, power laws are manifestations of an underlying random growth model — informally referred to as the “rich get richer” effect (see Gabaix (2009) for a full discussion).

4 Explaining Integration

While the above sections outlined the integration trend in median US banks and how it varies across banks, we now turn to investigating bank characteristics that influence its level of integration with the American banking sector.

The dependent variable in our regression analysis is the integration among US banks for which we have observations from Q2 1990 to Q4 2014.\textsuperscript{13} For each of the 1109 US banks, we have 100 observations on quarterly integration. We investigate bank characteristics that explain its integration levels. In order to conduct this study, we collect quarterly bank characteristics from Q1 1990 to Q4 2014 for each bank in the US banking sector. These characteristics include measures of bank size, leverage, market beta, idiosyncratic risk, and banks’ reliance on deposit, as well as short term financing. We rely on Thomson Reuters Datastream to collect quarterly bank characteristics for each of the 1109 banks in the sample. Each bank’s integration level is then regressed on its characteristics. For a full discussion on summary statistics and trends of the dependent variable (bank integration) we refer the reader to subsection 2.5.2 and section 3. We describe the explanatory variables in the following subsections.

4.1 Data

Since our sample consists of a very large number of banks (1109) over 25 years, we do not report individual banks’ statistics. Instead, we report summary statistics for the entire sample over the whole time period in Table

\textsuperscript{13}We lose the first quarter (Q1 1990) since principal components are out-of-sample.
Table 5: Summary Statistics of explanatory variables, taken over all 1109 banks and the whole sample period from 1990 to 2014. The columns display information about the sample minimum (“Min”), sample maximum (“Max”), sample mean (“Mean”), sample median (“Med”) and the sample standard deviation (“Std”). The explanatory variables are presented in rows. “Size” measures a bank’s size as the log of its market capitalization. “Lev” stands for the bank leverage ratio, computed as the ratio of common equity to total assets. “Mkt $\beta$” denotes market beta, computed as the slope ($\beta$) of excess bank returns regressed on the S&P 500 market index. “Idio Risk” denotes a bank’s idiosyncratic risk, computed as its quarterly idiosyncratic volatility. “DFR” stands for deposit financing ratio and is computed as the ratio of deposit-to-total liabilities. “STFR” denotes short term financing ratio and is defined as the ratio of short term debts (as well as current portion of long term debts) to total liabilities.

<table>
<thead>
<tr>
<th>Explanatory Variable</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Med</th>
<th>Std</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>0.1906</td>
<td>19.4625</td>
<td>8.5937</td>
<td>6.8263</td>
<td>5.1764</td>
</tr>
<tr>
<td>Lev</td>
<td>0.0052</td>
<td>0.4461</td>
<td>0.0931</td>
<td>0.0890</td>
<td>0.0360</td>
</tr>
<tr>
<td>Mkt $\beta$</td>
<td>-24.2616</td>
<td>32.7097</td>
<td>0.4630</td>
<td>0.6681</td>
<td>3.9886</td>
</tr>
<tr>
<td>Idio Risk</td>
<td>0.0049</td>
<td>0.99342</td>
<td>0.1086</td>
<td>0.0318</td>
<td>0.1439</td>
</tr>
<tr>
<td>DFR</td>
<td>0.0013</td>
<td>0.9688</td>
<td>0.2003</td>
<td>0.1717</td>
<td>0.1560</td>
</tr>
<tr>
<td>STFR</td>
<td>$2.69 \times 10^{-6}$</td>
<td>0.8725</td>
<td>0.0907</td>
<td>0.0673</td>
<td>0.0900</td>
</tr>
</tbody>
</table>

5. For each explanatory variable, we report its range, mean, median and standard deviation.

Additionally, we report the correlation coefficients of all variables — both independent and dependent — in Table 6, corresponding to two sets of different variable definitions. In order to motivate whether the explanatory variables are expected to be of the same or different signs as that of bank integration, we refer to Table 6 and follow it up with a rigorous analysis of marginal effects of characteristics on bank integration in section 5.

To the best of our knowledge, there has been no prior study that explains bank integration levels on the basis of bank characteristics. However, several studies in related areas analyse determinants of banks’ “interconnectivity” or their “systemic importance” which are in turn, constructed on the basis of banks’ returns; and are closely aligned with the notion of integration. In the following discussion, we investigate if the aforementioned bank characteristics impact integration the same way as they influence other, related interdependence measures.
4.1.1 Size

In our study, we measure a bank’s size by two different definitions: its market capitalization and its total assets. Several recent studies present evidence that size of a bank contributes positively to its systemic risk or systemic importance. Prominent among such works are Tarashev et al. (2015); Laeven et al. (2015); Hovakimian et al. (2015); Moore and Zhou (2014) and Cont et al. (2013). Based on these studies, we expect that all else equal, the marginal effect of bank size on its integration level should be positive. Indeed, it is plausible to assume that all else equal, as a bank’s size increases, its dependence on US G-SIBs increases — either directly by trading with the G-SIB — or indirectly by means of intermediaries that in turn trade with the G-SIBs. This is also borne out by Table 6 where for both definitions, the correlation between bank size and bank integration is positive with values 0.62 and 0.64 respectively.

We make the scales of the dependent and independent variable compatible, since the range of integration is a percentage between 0 and 100; and bank size is often in billions. We scale down bank size by taking its logarithm. Hence the log of size (log of market capitalization or log of total assets) is studied as a potential explanatory variable in our regression study. Table 5 presents the range, mean, median and standard deviations of the bank size, as measured by the log of its market capitalization. The mean and median of bank size are quite different — 8.5937 and 6.8263 respectively — consistent with the observation that US banks’ sizes vary widely, with a small set of very large banks and a large set of relatively small banks.

4.1.2 Leverage Ratio

For our study, we define two alternative leverage ratios — the ratio of common equity to total assets; and the ratio of total assets to market capitalization — the so called market capitalization leverage (Poirson and Schmittmann, 2013). Among recent works, Beltratti and Stulz (2012) have presented evidence that banks with lower leverage perform better than their overleveraged counterparts during crises; and Hovakimian et al. (2015) sug-
Table 6: Correlation matrices between the dependent variable bank integration (denoted “Int”) and the explanatory variables, where the correlation is taken over the entire sample of 1109 banks and over the entire sample period from 1990 to 2014. Correlations for two different variable definitions are presented one below the other. The explanatory variables include bank size, denoted “Size” and measured as the logarithm of banks’ market capitalization (top) and the log of total assets (bottom); the leverage ratio, denoted as “Lev” and defined as the ratio of common equity to total assets (top) and the ratio of total assets to market capitalization (bottom); the bank’s market beta, denoted “Mkt β” and computed as the slope (market β) of banks’ excess return on the S&P 500 market index (both top and bottom); idiosyncratic risk is measured as the idiosyncratic volatility (top) and 90% bank VaR (bottom), denoted as “Idio Risk”; banks’ reliance on end-consumer financed deposits — the deposit-to-total-liability ratio (top and bottom) is denoted as “DFR”; and finally, the reliance on short term financing is denoted as “STFR” and is computed as the ratio of banks’ short term debt and current portion of long term debt to total liabilities (top) and to total assets (bottom). Integration shows positive correlation with size, market beta, idiosyncratic risk and the short term financing ratio. It displays negative correlation with leverage and deposit financing ratio.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Int</th>
<th>Size</th>
<th>Lev</th>
<th>Mkt β</th>
<th>Idio Risk</th>
<th>DFR</th>
<th>STFR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Int</td>
<td>1</td>
<td>0.6211</td>
<td>-0.0250</td>
<td>0.0874</td>
<td>0.1571</td>
<td>-0.3132</td>
<td>0.1697</td>
</tr>
<tr>
<td>Size</td>
<td>0.6211</td>
<td>1</td>
<td>-0.0926</td>
<td>0.1080</td>
<td>-0.1271</td>
<td>-0.4656</td>
<td>0.3957</td>
</tr>
<tr>
<td>Lev</td>
<td>-0.0250</td>
<td>-0.0926</td>
<td>1</td>
<td>0.0068</td>
<td>0.0922</td>
<td>0.2504</td>
<td>-0.2964</td>
</tr>
<tr>
<td>Mkt β</td>
<td>0.0874</td>
<td>0.1080</td>
<td>0.0068</td>
<td>1</td>
<td>-0.1694</td>
<td>-0.0526</td>
<td>0.0501</td>
</tr>
<tr>
<td>Idio Risk</td>
<td>0.1571</td>
<td>-0.1271</td>
<td>0.0922</td>
<td>-0.1694</td>
<td>1</td>
<td>0.1277</td>
<td>-0.1915</td>
</tr>
<tr>
<td>DFR</td>
<td>-0.3132</td>
<td>-0.4656</td>
<td>0.2504</td>
<td>-0.0526</td>
<td>0.1277</td>
<td>1</td>
<td>-0.7840</td>
</tr>
<tr>
<td>STFR</td>
<td>0.1697</td>
<td>0.3957</td>
<td>-0.2964</td>
<td>0.0501</td>
<td>-0.1915</td>
<td>1</td>
<td>-0.7840</td>
</tr>
</tbody>
</table>

Alternative Definitions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Int</th>
<th>Size</th>
<th>Lev</th>
<th>Mkt β</th>
<th>Idio Risk</th>
<th>DFR</th>
<th>STFR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Int</td>
<td>1</td>
<td>0.6439</td>
<td>-0.1417</td>
<td>0.0862</td>
<td>0.1822</td>
<td>-0.3012</td>
<td>0.1447</td>
</tr>
<tr>
<td>Size</td>
<td>0.6439</td>
<td>1</td>
<td>-0.2112</td>
<td>0.1084</td>
<td>-0.0137</td>
<td>-0.5487</td>
<td>0.3967</td>
</tr>
<tr>
<td>Lev</td>
<td>-0.1417</td>
<td>-0.2112</td>
<td>1</td>
<td>-0.0347</td>
<td>0.1160</td>
<td>0.0971</td>
<td>-0.1142</td>
</tr>
<tr>
<td>Mkt β</td>
<td>0.0862</td>
<td>0.1084</td>
<td>-0.0347</td>
<td>1</td>
<td>0.0396</td>
<td>-0.0514</td>
<td>0.0481</td>
</tr>
<tr>
<td>Idio Risk</td>
<td>0.1822</td>
<td>-0.0137</td>
<td>0.1160</td>
<td>0.0396</td>
<td>1</td>
<td>0.1239</td>
<td>-0.1839</td>
</tr>
<tr>
<td>DFR</td>
<td>-0.3012</td>
<td>-0.5487</td>
<td>0.0971</td>
<td>-0.0514</td>
<td>0.1239</td>
<td>1</td>
<td>-0.7166</td>
</tr>
<tr>
<td>STFR</td>
<td>0.1447</td>
<td>0.3967</td>
<td>-0.1142</td>
<td>0.0481</td>
<td>-0.1839</td>
<td>1</td>
<td>-0.7166</td>
</tr>
</tbody>
</table>
gest that leverage is a key driver of systemic risk. Additionally, Adrian and Shin (2010) and Kalemli-Ozcan et al. (2012) document that leverage is strongly procyclical, especially for large commercial banks.

This should lead us to expect a positive relation between leverage ratio and integration. However, there are other forces at play. Higher leverage via increased deposit financing may decrease bank integration, whereas that due to higher interbank borrowing may increase integration. Hence we are agnostic about the overall marginal effect of leverage ratio on integration. For our sample, Table 6 presents negative correlation coefficients between the leverage ratio and integration at -0.02 and -0.14 respectively. Finally, Table 5 reports leverage ratio summary statistics for our sample of US banks.

4.1.3 Market β

We measure a US bank’s exposure to the market by its market beta with the S&P 500 market index. In order to construct this variable, we regress each bank’s excess quarterly return on the market index for our full sample period 1990–2014. The regression coefficient beta denotes the sensitivity, or exposure of the bank to the national US market as a whole.

In keeping with evidence compiled by Laeven et al. (2015) that more market based activity of banks contributes positively to systemic risk, we expect that all else equal, as a bank exhibits more market beta, it becomes more dependent on the fortunes of the S&P 500’s constituent assets. As finance has risen to a greater share of the GDP, G-SIBs have assumed a larger weight in the US equity markets. Hence an increase in market beta should increase (possibly via both direct and indirect channels) the bank’s exposure to US G-SIBs (holding other variables fixed). Hence we should expect the marginal influence of market beta to be positive on integration. This is also borne out by the correlation of market beta with integration, which is positive at 0.87, as Table 6 reports.

---

14 As usual, the risk free rate is the 3 month T-Bill rate.
15 For example, according to data compiled by Bloomberg, by 2012, the five largest US banks — JPMorgan Chase, Bank of America, Citigroup, Wells Fargo, and Goldman Sachs — had total assets equal to around 56 percent of the US economy.
Table 5 presents summary statistics of quarterly bank betas. As may be observed, the cross-section of US banks displays substantial heterogeneity in their market betas.

### 4.1.4 Idiosyncratic Bank Risk

We measure US banks’ idiosyncratic risk by two common metrics — their quarterly idiosyncratic volatility, as well as by their quarterly idiosyncratic Value at Risk (VaR) at the 90\% confidence level (10\% significance level). The former is simply the standard deviation of banks’ quarterly residuals when quarterly excess returns are regressed on the market index (the S&P 500 for our study); while the latter is simply the negative of the 10^{th} percentile of the empirical residual distribution.

Recent evidence from Moore and Zhou (2014); Hovakimian et al. (2015); Tarashev et al. (2015) and others suggests that bank-specific risk positively impacts banks’ contribution to systemic risk. Further, Bartram et al. (2016) investigate a robust positive relation between market risk and idiosyncratic risk, reinforcing the impact of bank risk on integration indirectly via an increase in market beta. Indeed, this may also be seen in the positive 0.15 correlation between idiosyncratic volatility and integration in the top half of Table 6 and the 0.18 correlation between the 90\% bank VaR and integration in the bottom half of the same table. Finally, Table 5 reports the summary statistics for idiosyncratic bank risk as measured by idiosyncratic volatility.

### 4.1.5 Deposit Financing

Banks rely on two main sources of funding: sources such as demand deposits from end-consumers, termed as deposit funding; and other sources such as debts from their peers, often referred to as wholesale funding.\(^{16}\)

For each bank, we collect quarterly data on total deposit liabilities as well as on total liabilities. The ratio of deposit-to-total-liabilities measures

\(^{16}\)The latter source has become popular and banks often borrow — mostly short term but long term as well — from their peers, as well as from other market participants, including shadow banks and miscellaneous funds. Insofar as sources other than retail, end-consumer are “wholesale”, this funding is referred to as wholesale funding.
how dependent a bank is on traditional, end-consumer financed deposits for its operations. Beltratti and Stulz (2012) argue that deposit funding is positively associated with bank performance during the recent 2007–2008 credit crisis episode; and Cornett et al. (2011) suggest that deposit-reliant banks continued lending during the Great Recession in the period 2007–2009. Analogously, several recent papers argue that more reliance on non-deposit financing increases banks’ fragility, makes them susceptible to crises and was even an important determinant of their vulnerability during the 2007–2010 crisis episode (see in particular, Poirson and Schmittmann (2013); Moore and Zhou (2014) and Huang and Ratnovski (2011) among others). In light of such arguments, we should expect that the deposit-to-total liabilities ratio (“Deposit Financing Ratio” (DFR) henceforth) should marginally impact integration negatively. Indeed, all else equal, increase in DFR entails more dependence on end-consumer financed deposits and hence a corresponding decrease in the reliance on US G-SIBs’ fortunes. Indeed, as Table 6 shows, the overall correlation between a bank’s DFR and its integration with US G-SIBs is -0.31. Finally, Table 5 presents summary statistics for the deposit financing ratio.

4.1.6 Short Term Financing

We measure reliance on short term financing by the proportion of a bank’s current liabilities. We collect quarterly data from Datastream on each bank’s short term debt and current portion of long term debt (often referred to as short term liabilities or current liabilities). Datastream constructs this variable by defining “short term” to include all liabilities payable within 12 months. We form two alternative measures of a bank’s reliance on short term financing: the ratio of current liabilities to total liabilities; as well as the ratio of current liabilities to total assets.

Many recent studies, including Moore and Zhou (2014); Hovakimian et al. (2015); Bruyckere et al. (2012); Beltratti and Stulz (2012); López-Espinosa et al. (2012) among others point out that more reliance on short term funding makes a bank fragile and more prone to contagion and crises. In the same spirit, Dagher and Kazimov (2015) find that banks more reliant
on wholesale funding decreased their credit supply during the US financial crisis; and Demirgüz-Kunt and Huizinga (2010) report that higher reliance on wholesale funding comes at the cost of increasing fragility and risk. Additionally, Karolyi et al. (2012) find that commonality in liquidity increases during volatile periods and Nyborg and Östberg (2014) document that banks resort to liquidity pull-back during times when interbank markets are tight.

Does this imply that one should expect that the marginal impact of increase in the short term financing ratio increases a bank’s integration with US G-SIBs’ principal components? Table 6 provides some evidence for a positive correlation with integration, with correlation coefficients of 0.16 and 0.14 respectively for the two STFR definitions. However, there are other forces at play in the wholesale funding markets on which banks (as well as other market participants) rely for short term financing.

In our study, a bank’s STFR increases in two cases: the first, when the said bank’s current portion of long term debt increases — which should marginally impact integration negatively; and second, when the bank’s short term debt increases — which may increase on account of more activity in the wholesale short term funding markets. Overall, it is not clear which way the latter will affect bank integration, since more dealings in the wholesale market with the G-SIBs themselves will increase integration; but dealings with foreign banks or shadow banks may decrease the same. Hence as far as STFR is concerned, we are agnostic about our prior expectations.

Table 5 reports summary statistics for reliance on short term funding as defined by short term liabilities to total liabilities ratio.

4.1.7 Other Possible Characteristics

Net Interest Margin: Poirson and Schmittmann (2013) use Net Interest Margins (NIM) — the difference between total interest income and total interest expenses — as a proxy for bank profitability, which they show is positively associated with market beta, suggesting that all else equal, more profitable banks may prefer more risky positions. This suggests that NIM should have a positive marginal impact on integration.

However, for our sample of US banks, the variables NIM and bank size
Table 7: Segregating banks by characteristics’ quintiles. The dependent variable (“Int”) is integration. Explanatory variables are bank size (“Size”) measured as the log of market capitalization; the leverage ratio (“Lev”), measured as the ratio of common equity to total assets; market beta (“Mkt β”), computed as the slope of banks’ excess returns on the S&P 500; idiosyncratic risk (“Idio risk”) is the idiosyncratic volatility; banks’ reliance on end-consumer financed deposits — the deposit-to-total-liability ratio (“DFR”); and reliance on short term financing (“STFR”) is the ratio of banks’ short term debt and current portion of long term debt to total liabilities. “Qnt 1 Mean” and “Qnt 5 Mean” denote the means of banks in quintiles top and bottom. The mean is taken over 1990–2014. “Test for equality of means” presents p values for the 2 sample T test where the null hypothesis assumes that both Qnt 1 and Qnt 5 are sampled from populations with the same mean. ***,** and * stand for significance at the 1%, 5% and 10% significance levels respectively.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Qnt 1 Mean</th>
<th>Qnt 5 Mean</th>
<th>Test for equality of means</th>
</tr>
</thead>
<tbody>
<tr>
<td>Int</td>
<td>30.0951</td>
<td>4.7040</td>
<td>(0.000)***</td>
</tr>
<tr>
<td>Size</td>
<td>7.2459</td>
<td>3.7715</td>
<td>(0.000)***</td>
</tr>
<tr>
<td>Lev</td>
<td>0.0889</td>
<td>0.1119</td>
<td>(0.000)***</td>
</tr>
<tr>
<td>Mkt β</td>
<td>0.6178</td>
<td>-0.2593</td>
<td>(0.000)***</td>
</tr>
<tr>
<td>Idio Risk</td>
<td>0.0970</td>
<td>0.1389</td>
<td>(0.000)***</td>
</tr>
<tr>
<td>DFR</td>
<td>0.7957</td>
<td>0.9040</td>
<td>(0.000)***</td>
</tr>
<tr>
<td>STFR</td>
<td>0.1056</td>
<td>0.0484</td>
<td>(0.000)***</td>
</tr>
</tbody>
</table>

are extremely positively correlated at about 91% and hence due to multicollinearity, we do not test the explanatory potential of NIM together with size.

**Tier 1 Capital Ratio:** *Laeven et al. (2015)* demonstrate that systemic risk varies inversely with bank capital, leading to a possibly negative relationship between integration and the Tier 1 capital ratio.

However, for our sample, the data on Tier 1 capital ratio exist for only 183 out of 1109 banks and only for periods after 2007. Hence inclusion of this variable significantly curtails the scope of our study and thus we do not test it for explanatory significance.

## 5 Determinants

### 5.1 Characteristics of the Most and Least Integrated Banks

Since our sample is quite large we only display the means of all variables in our study for two special subsamples: the 215 most integrated subset
of US banks (Qnt 1), as well as the least integrated 215 bank subset (Qnt 5). In Table 7, we present means of both these special subsets Qnt 1 and Qnt 5. We also perform a two sample $T$ test for the equality of means for subsamples Qnt 1 and Qnt 5 for each characteristic and report $p$ values for the same in column 3 of Table 7.

In general, we observe that the topmost integrated quintile of banks is very different from the bottommost integrated quintile. This is so, not merely on the basis of integration, whose mean is about 30% for Qnt 1 and only 4.7% for Qnt 5 but also for all other bank characteristics; and $p$ values for the two sample $T$ test report significant differences even at a highly conservative 1% significance level.

For the explanatory variables leverage ratio, the idiosyncratic bank volatility; and the deposit financing ratio, Qnt 1 banks display lower means than those for its Qnt 5 counterpart. On the other hand, variables like log market capitalization (7.24 versus 3.77), bank beta (0.62 for Qnt 1 but -0.25 for Qnt 5) as well as ratio of current liabilities to total liabilities (0.10 to 0.04) are higher for Qnt 1 banks than for Qnt 5 banks.

Overall, Table 7 suggest that most integrated banks are on average, substantially bigger, have higher bank betas; and have higher utilization of short term financing. On the other hand, the Qnt 1 banks have lower leverage ratios, lower idiosyncratic volatility and lower deposit financing ratios than the least integrated Qnt 5 subpopulation.

However, a problem with these comparisons is that many of these bank characteristics are correlated (see Table 6). Even more worryingly, they might be correlated with relevant, but unobserved bank-specific characteristics. Hence we formally analyse the effect of bank level variables on its integration with G-SIB principal components in the following subsection by conducting unbalanced panel regressions with bank-specific fixed effects.

### 5.2 Regression Methodology

Our large sample of US banks suffers from 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 Datastream.
There is massive heterogeneity in the sample of US banks — not merely in the observed characteristics such as bank integration, size, leverage etc. (see Figure 2 and Table 5 for instance) — but also in potentially several relevant unobserved characteristics, which could introduce an omitted variable bias under naive OLS estimations. We implicitly control for the time-invariant bank-specific fixed effects by employing a fixed effects panel estimator. For the same reason, we suspect heteroskedasticity in bank residuals. Hence we compute robust standard errors for the fixed effects model. This estimator is based on the extension of the White (1980) sandwich estimator for panel data.\(^{17}\) We ascertain the significance of independent variables by clustered robust standard errors using the observation groups (banks in our case) as the different clusters.

5.3 Marginal Effects of Bank Characteristics on Integration

Table 8 displays the results for 8 different unbalanced panel regressions. Five separate regression types focus on different subsamples of US banks in order to ensure that the overall sample effects do not occlude the behavior of special noteworthy subsamples. The following cases are tabulated: “All” denotes the regression for the full sample of 1109 banks; “Sys” denotes the regression for a sample of 19 special banks deemed “systemic” and comprising 8 US G-SIBs and 11 US D-SIBs (see Table 1 for the full list of members); “Qnt 1” denotes the top 215 most integrated bank subset (Quintile 1); “Top” denotes the top third most integrated banks (358 in number) while “Bot” stands for “bottom” and denotes the least integrated two thirds of the sample (751 banks). “Qnt 5” denotes the bottom quintile of least integrated banks (215 in number); and column 8 named “Pool” contains results from a benchmark pooled panel regression disregarding both bank fixed effects and robust standard errors. Column 7 named “All*” contains regression results for an alternative set of explanatory variable definitions whose detailed definitions and correlations can be found in Table 6.

The regression presented in the column “All” of Table 8, reports the re-

Table 8: Results from 8 different unbalanced panel regressions with bank-specific fixed effects; and with clustered standard errors robust to heteroskedasticity. The columns denote the following: “All” denotes the regression for the full sample of 1109 banks; “Sys” denotes the regression for a sample of 19 special banks deemed “systemic” and comprising 8 US G-SIBs and 11 US D-SIBs (see Table 1 for the full list of members); “Qnt 1” denotes the top 215 most integrated bank subset (Quintile 1); “Top” denotes the top one-third most integrated banks (358 in number) while “Bot” stands for “bottom” and denotes the bottom two-thirds of the sample (751 banks). “Qnt 5” denotes the bottom quintile of least integrated banks (215 in number); and column 8 named “Pool” contains results from pooled panel regressions disregarding both bank fixed effects and robust standard errors. Column 7 named “All∗” contains regression results for an alternative set of explanatory variable definitions. For all columns except 7 (“All∗”), the explanatory variables include bank size, denoted “Size” and measured as the logarithm of banks’ market capitalization; the leverage ratio, denoted as “Lev” and defined as the ratio of common equity to total assets; the bank’s market beta, denoted “Mkt β” and computed as the slope (market β) of banks’ excess returns on the S&P 500 market index; idiosyncratic risk is measured as the idiosyncratic volatility, denoted as “Idio Risk”; banks’ reliance on end-consumer financed deposits — the deposit-to-total-liability ratio is denoted as “DFR”; and finally, the reliance on short term financing is denoted as “STFR” and is computed as the ratio of banks’ short term debt and current portion of long term debt to total liabilities. Column 7 uses alternative definitions for the explanatory variables as follows: “Size” is log of total assets; “Lev” is the ratio of total asset to market capitalization (market capitalization leverage); “Mkt β” is bank β for the S&P 500 market index; “Idio Risk” is the 90% bank VaR; “DFR” is the ratio of deposit-to-total-liabilities; and “STFR” is the ratio of current liabilities to total assets. ***, ** and * stand for significance at the 1%, 5% and 10% significance levels respectively. Finally, “# obs” denotes number of observations, “p value, F test” denotes, p values of the test for joint significance, and “adjusted R²”, denotes the explanatory power of the column’s regression.

<table>
<thead>
<tr>
<th>Explanatory Variable</th>
<th>All</th>
<th>Sys</th>
<th>Qnt 1</th>
<th>Top</th>
<th>Bot</th>
<th>Qnt 5</th>
<th>All*</th>
<th>Pool</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Size</strong></td>
<td>5.9450</td>
<td>9.1905</td>
<td>6.6497</td>
<td>6.1148</td>
<td>0.1330</td>
<td>0.5688</td>
<td>9.7032</td>
<td>2.9453</td>
</tr>
<tr>
<td><strong>Lev</strong></td>
<td>3.8492</td>
<td>-14.3709</td>
<td>3.3231</td>
<td>-0.7431</td>
<td>-7.0850</td>
<td>-7.0320</td>
<td>-0.0001</td>
<td>2.7998</td>
</tr>
<tr>
<td><strong>Mkt β</strong></td>
<td>0.1654</td>
<td>0.2534</td>
<td>0.2112</td>
<td>0.1992</td>
<td>0.0117</td>
<td>0.0908</td>
<td>0.07540</td>
<td>0.3561</td>
</tr>
<tr>
<td><strong>Idio Risk</strong></td>
<td>37.9215</td>
<td>51.2562</td>
<td>52.7228</td>
<td>49.1466</td>
<td>1.4769</td>
<td>3.9944</td>
<td>21.7808</td>
<td>39.6754</td>
</tr>
<tr>
<td><strong># obs</strong></td>
<td>1109</td>
<td>19</td>
<td>215</td>
<td>358</td>
<td>751</td>
<td>215</td>
<td>1109</td>
<td>1109</td>
</tr>
<tr>
<td><strong>p value, F test</strong></td>
<td>(0.000)***</td>
<td>(0.000)***</td>
<td>(0.000)***</td>
<td>(0.748)</td>
<td>(0.229)</td>
<td>(0.000)***</td>
<td>(0.000)***</td>
<td>(0.000)***</td>
</tr>
<tr>
<td><strong>adjusted R²</strong></td>
<td>0.2531</td>
<td>0.4446</td>
<td>0.3256</td>
<td>0.3029</td>
<td>-0.0678</td>
<td>-0.0923</td>
<td>0.2612</td>
<td>0.4614</td>
</tr>
</tbody>
</table>
sult for the full sample of 1109 banks. Five out of the six explanatory variables are strongly statistically significant ($p$ values indistinguishable from 0) — three positively (size, market beta and idiosyncratic risk) and two negatively (deposit financing ratio and short term financing ratio). All statistically significant variables are economically significant too. Since size is measured in logs, a 10% marginal increase in the size of a bank leads to a corresponding increase in integration by 0.59%. Similarly, a unit marginal increase in idiosyncratic volatility, DFR and STFR changes the bank’s integration by 0.38%, -0.57% and -0.73%, respectively. Similarly, one unit marginal increase in market beta results in the bank’s integration increasing by 0.17%. Leverage is positive in sign but is statistically insignificant after controlling for other closely related variables. The panel regression displays a healthy explanatory power of 25.31%. All banks display significant fixed effects though we do not report it due to the large sample size.

For the subsample regressions “Sys”, “Qnt 1” and “Top”, the exact same behavior is observed and the same five out of the six explanatory variables are strongly statistically significant. As before, the three characteristics that display positive marginal effects are size, market beta and idiosyncratic risk and the two that display negative association are deposit financing ratio and short term financing ratio. All statistically significant variables are economically significant too, just as the case for the full sample. Leverage remains insignificant after controlling for other relevant characteristics. The panel regression provides strong explanatory power in all cases — 44.46% for the set of 19 systemic banks, 32.56% for the case of the topmost integrated quintile (Qnt 1); and finally, 30.29% for the top one-third most integrated set (358 banks). All banks display significant fixed effects though we do not report it due to the large sample.

However, the panel regressions fail to explain the subsets “Bot” and “Qnt 5”, which denote the least integrated bottom two-third US banks (751 least integrated banks in the US) and the least integrated quintile (Qnt 5) respectively. Our fixed effects panel regression models even fail the $F$ test for joint significance with $p$ values being 0.31 and 0.89 respectively. None of the variables have any significance. This shows that our explanatory model
cannot explain the variation in integration among the weakly integrated subset of US banks.

The regression presented in the column “All*” of Table 8, reports the result for the full sample of 1109 banks for alternative definitions of bank characteristics. The change of definitions has no effect on the overall result, since exactly the same variables show statistical and economic significance with exactly the same sign as in the regression “All”. The explanatory power for this regression is 26.12%, marginally higher than its counterpart regression “All”, for which the corresponding value is 25.31%. Such a close alignment of the two sets of regressions lends credence to the view that the results are relatively robust and are insensitive to minor tweaks in the measurement definitions of bank characteristics. Again, all banks display significant fixed effects.

Finally, the regression “Pool” performs a simple pooled panel regression with no bank fixed effects and no robust standard errors. This set of results forms a naive benchmark to interpret our other results against. Since standard errors are not robust, the \( T \) statistics are overly inflated and the adjusted \( R^2 \) posts a high value of 46.14%; yet the effect of each variable and its statistical and economic significance retains the same orientation as in the regression “All”.

Overall, based on the 8 different types of fixed effects panel estimations with robust standard errors, one is struck by the unity in the nature of marginal effects of bank characteristics. No matter how we define variables, or slice the 1109 bank dataset spread over 25 years, we observe the same behavior: bank size, bank beta and bank idiosyncratic risk affect bank integration positively; while the deposit financing and the short term financing ratios have negative marginal impact for any subsample definition. Leverage is not significant once other related characteristics are controlled for. On the other hand, for the bottom two-thirds of the sample of US banks, and therefore, a fortiori, for the bottom quintile of banks on the basis of integration, all conventional bank characteristics fail in explaining any variation (however mild) in their integration levels.
5.4 Interpretation

In this subsection, we interpret the marginal effect of each explanatory variable over the entire range of regression models as reported in Table 8.

Size: We measure a bank’s size by the log of its market capitalization, as well as by the log of its total assets. For both definitions, and all non-“Bot” subsamples, bank size shows a strong positive marginal effect on bank integration. Its effect is the strongest on the systemic bank subset, followed by Qnt 1 and the topmost integrated one third of the sample. On the other hand, for periphery and Qnt 5 bank subsets, its effect is positive but insignificant. In particular, size impacts bank integration most positively (in terms of coefficient estimate) in the following order: Sys ⪰ Qnt 1 ⪰ Top ⪰ All* ⪰ All ⪰ Bot ⪰ Qnt 5.

As remarked before, several related studies report the same finding: increase in size generates increases in interconnectivity or interdependence. However, some studies like Cont et al. (2013); Moore and Zhou (2014) make the point that while size is an important driver of systemic risk, its effect is the same for all banks beyond a certain threshold size. In light of Table 8, we broadly agree with such related findings. Size is statistically and economically significant for all US bank subsamples, except for those in the bottom two-thirds of the sample. This leads us to interpret the effect of size on US bank’s integration as strongly positive but only beyond a critical level.

Leverage: Leverage is measured by two alternative definitions: the common equity to total assets ratio; and the total assets to market capitalization ratio. However, for all subsamples, and for all definitions, the leverage ratio exhibits insignificance. While some other papers (see references in subsection 4.1.2) do find leverage to be significant in accounting for related phenomena like interconnectivity and systemic risk, we interpret this result to imply that for our sample, once we control for related variables like bank risk, deposit financing and short term financing, leverage has no additional explanatory power. This result is indeed quite plausible since some forms
of increased bank leverage, say, by increasing reliance on deposit financing, may be relatively innocuous.

The insignificance of bank leverage ratio on bank integration in our study displays robustness and holds true for all subsamples of US banks, no matter how strongly or weakly integrated they are; or indeed on the details of definition of the leverage ratio. Note however, our subperiod based explanatory analysis, in subsection 5.5, where we observe leverage to have played a significantly negative role on bank integration pre-2000.

**Market β:** We measure market beta of a bank by the slope of its excess returns on the S&P 500 market index. For the regressions for the full subsample, the systemic subsample, as well as that for the top quintile and top one third most integrated subset, market beta has a statistically and economically significant positive marginal impact on bank integration. This is broadly in keeping with related findings which report that an increase in a bank’s market based activities has a positive marginal association with its contribution to systemic risk. Indeed, among two otherwise identical US banks, an increase in one of the bank’s market beta by means of greater exposure to the market index increases its reliance on the fortunes of US G-SIBs since they contribute disproportionately to the US market index. This is easy to notice especially in light of the observation that the top five US banks (all G-SIB) — JPMorgan Chase, Bank of America, Citigroup, Wells Fargo, and Goldman Sachs — had total assets equal to $15.1 trillion, at around 56 percent of the US economy post-recession in December 2011; which was even higher than the pre-recession values of $13.1 trillion and 43% in 2006 (Source: Bloomberg).

For the bottom two-third banks and the Qnt 5 subsample however, market beta, just as the other explanatory factors fails to be significant. Hence overall, in terms of marginal positive impact (in terms of coefficient estimate) of market beta on US banks’ subsamples, we observe the following order: Sys ≥ Qnt 1 ≥ Top ≥ All ≥ All* ≥ Bot ≥ Qnt 5.
**Idiosyncratic Risk:** As remarked before, both idiosyncratic volatility and 90% bank VaR are used to measure the bank’s idiosyncratic risk. For both these definitions and for the full sample, the systemic, Qnt 1 and top one-third most integrated subsamples, we observe a statistically and economically significant marginal effect of bank risk on bank integration. This is in keeping with some recent work that presents evidence that banks’ asset risk can be a key driver of its contribution towards systemic risk (see references in subsection 4.1.4 for some noteworthy studies). This is also consistent with the documented behavior of co-movement between market risk and idiosyncratic risk as studied in Bartram et al. (2016).

Again, the weakly integrated peripheral banks and the Qnt 5 subsample show resistance to explanations based on any bank characteristics, including idiosyncratic bank risk. The order of marginal impact of bank risk based on coefficient estimates is slightly different than other variables and follows the order: Sys ≈ Qnt 1 ≈ Top ≥ All ≥ All* ≥ Qnt 5 ≥ Bot.

**Deposit Financing Ratio:** The deposit-to-total-liability ratio impacts bank integration negatively, all else held equal. This is so for all subsamples except “Bot” and “Qnt 5”. The marginal effect of DFR on bank integration is negative since a marginal increase in a bank’s deposit financing ratio makes it more dependent on retail, end-consumer funded deposits and moves the bank away from reliance on US G-SIBs. Indeed, in the extreme theoretical case, a bank that is 100% funded from end-consumer financed deposits is insulated from the ups and downs in the fortunes of the G-SIBs.

DFR is insignificant for the Bot and Qnt 5 subsamples, although it displays opposite signs on bank integration for subsets Qnt 5 and Bot. In terms of absolute values, the order of impact is: Sys ≥ Qnt 1 ≥ Top ≥ All ≥ All* ≥ Bot ≥ Qnt 5.

**Short Term Financing Ratio:** Just like the DFR, banks’ reliance on short term financing impacts bank integration negatively, keeping all else fixed. This may seem puzzling, since for both definitions of STFR, the correlations with integration are positive (see Table 6); and to the extent
that such wholesale, short term liabilities are financed through loans from peers, one would expect that increased short term debts might increase a bank’s dependence on G-SIBs marginally, if only via indirect channels.

However, a more detailed analysis based on banks’ sources of financing in the wholesale funding markets reveals the opposite. Volumes of trade in such markets have increased massively post 1980s (Levinson, 2010; Brunnermeier, 2009; Huang and Ratnovski, 2011) and there are three main channels of short term bank funding: the (mostly) overnight Federal Funds market, the eurodollar market\(^\text{18}\) and other miscellaneous sources based on several secured as well as unsecured money market instruments, such as capital notes of varying maturities (overnight or a few months); asset backed securities (ABS) as well as off-balance sheet special investment vehicles (SIVs).\(^\text{19}\) Additionally, to ameliorate maturity mismatch on bank balance sheets, there has been a trend of financing balance sheets with short-term repurchase agreements, or “repos”. In a repo contract, a bank borrows funds by selling a collateral asset and promising to repurchase it at a later date (Brunnermeier, 2009). Parlatore (2016) reports that US money market funds (MMFs) owned 40% of dollar denominated commercial paper and constitute the largest category of repo lenders in Q4 2011. Gorton and Metrick (2012) present evidence that the run on the repo markets was instrumental during the panic of 2007–2008.

The two biggest components of such wholesale funding, however, are Federal Funds and eurodollar loans — both of which are included when constructing the variable “short term debts and current portion of long term debts” in Datastream.

\(^{18}\)The term “euro” in eurodollars refers to the historical accident of dollar denominated loans first issued in Europe. In general, such loans originating in, say Asia, will still be referred to as eurodollars. Such loans are beyond the jurisdiction of the Federal Reserve and are relatively lightly regulated, leading to lower margin requirements.

\(^{19}\)Mortgage backed securities (MBS), several varieties of collateralized debt obligations (CDOs); other forms of asset backed commercial paper (ABCP) etc. are some of the several types of popular ABS in the wholesale money markets. Acharya et al. (2013) suggest that in particular, ABCP conduits were set up by banks to bypass regulatory capital requirements.
Post-crisis, the Federal Funds market has shrunk and of late (Q4 2012) about 75% of lending in the Federal Funds market was due to the 11 US government sponsored Federal Home Loan Banks (FHLB) (Afonso et al., 2013); while lenders in the eurodollar markets are composed of a large number of non-US banks, foreign central banks, money market funds etc. — all of them issuing debt in US dollars (Cipriani and Gouny, 2015).

Among the channels mentioned above, the eurodollar market, in which foreign banks lend US dollars either overnight or for a short duration, remains 3–4 times bigger than the Federal Funds market in terms of volume. For example, the overnight volume of the eurodollar market is currently around $140 billion while the corresponding overnight volume for the market for Federal Funds is around $40 billion. Additionally, the Federal Funds and eurodollars are close substitutes, the main difference between them being that the eurodollar market is relatively lightly regulated and hence banks’ margin requirements are relatively lower. This results in the eurodollar lending rate being slightly higher than the Fed Funds rate which implies larger borrowings from the Fed Funds market by smaller, more risk averse banks; and more reliance on eurodollar borrowings by the bigger banks.

However, this helps us to understand why the marginal effect of STFR on bank integration is negative. If a bank increases its reliance on short term wholesale financing, it does so by increasing its borrowings by one or more of the sources mentioned above: the Fed Funds, the eurodollar market; or via raising funding from other money market funds. More Fed Funds increase a bank’s reliance on the 11 FHLBs, more eurodollar financing increases its exposure to foreign, non-US banks issuing US dollar loans; and more money market instruments’ based funding makes the bank reliant on its counterparties — a large portion of which are institutions based in the shadow banking sector and other money market funds. The marginal

---

20 Source: Data from the New York Federal Reserve and the St. Louis Federal Reserve (FRED).

21 In a related work, Fecht et al. (2011) document that smaller banks pay more for liquidity as captured in borrowing costs in the repo markets.
effect of all of these channels is to make the bank more reliant on non-G-SIB market participants such as FHLBs, foreign banks, shadow banks or miscellaneous funds. All else equal, this will decrease bank integration, insofar as it is defined as dependence on US G-SIBs’ fortunes by alignment with their principal components.

We emphasize that the negative relationship between STFR and bank integration is a consequence of our definition of “bank” as a domestic US commercial bank which excludes several important financial market participants like shadow banks, hedge funds etc. To the extent that integration is alignment with US G-SIBs’ fortunes, increase in STFR has a negative effect on integration owing to increased dependence on non-G-SIB actors in the wholesale funding market. However, if we had defined integration more liberally, say as alignment with the whole of the financial sector, comprising domestic, as well as foreign banks and miscellaneous wholesale money market participants, we would have observed a positive relationship between STFR and financial sector integration.

For both definitions of STFR and for all top one-third bank subsamples, the current liability ratio impacts bank integration negatively and this effect is both statistically and economically significant. In terms of absolute values of coefficient estimates, the order of impact is: Sys ≥ All ≈ Qnt 1 ≈ Top ≥ All* ≥ Bot ≥ Qnt 5.

5.5 Determinants: Subperiod Analysis

In order to study the marginal effect of explanatory variables during notable subperiods occurring in our 25 year sample, we conduct subperiod based panel regressions.

Table 9 reports the results after conducting unbalanced panel regressions with bank fixed effects on various bank subsamples — all banks (“All”), systemic banks (“Sys”), and the topmost and bottommost integrated quintiles (“Qnt 1” and “Qnt 5” respectively) — segregated by four subperiods from subsection 3.1: P1: 1990–1999, P2: 2000–2006, P3: 2007–2014; and the period containing the Great Recession GR: 2007–2009.

In the following discussion, we report results comparing the new set of
Table 9: Unbalanced panel regressions with bank-specific fixed effects and clustered errors robust to heteroskedasticity for four bank subsamples — “All” (the full sample of 1109 banks), “Sys” (a sample of 19 special banks deemed “systemic” and comprising 8 US G-SIBs and 11 US D-SIBs (see Table 1)), “Qnt 1”, (the top 215 most integrated bank subset (Quintile 1)) and “Qnt 5” (the bottom quintile of least integrated 215 banks); and four different subperiods — P1: 1990–1999, P2: 2000–2006, P3: 2007–2014; and the period containing the Great Recession GR: 2007–2009. The definitions of the explanatory variables is the same as that in Table 8.

<table>
<thead>
<tr>
<th>RHS</th>
<th>All</th>
<th>Sys</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>GR</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>GR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>6.99</td>
<td>-0.61</td>
<td>-1.90</td>
<td>1.82</td>
<td>10.02</td>
<td>-8.96</td>
<td>-1.74</td>
<td>7.13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>p value</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.07)*</td>
<td>(0.00)***</td>
<td>(0.04)**</td>
<td>(0.52)</td>
<td>(0.03)**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>p value</td>
<td>(0.01)***</td>
<td>(0.38)</td>
<td>(0.23)</td>
<td>(0.11)</td>
<td>(0.30)</td>
<td>(0.89)</td>
<td>(0.48)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mkt β</td>
<td>5.53</td>
<td>7.38</td>
<td>0.05</td>
<td>0.57</td>
<td>9.03</td>
<td>9.67</td>
<td>0.18</td>
<td>0.12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>p value</td>
<td>(0.00)***</td>
<td>(0.13)</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Idio Risk</td>
<td>1.09</td>
<td>-0.74</td>
<td>0.22</td>
<td>0.25</td>
<td>2.32</td>
<td>0.14</td>
<td>0.27</td>
<td>0.18</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.02)**</td>
<td>(0.04)**</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.02)**</td>
<td>(0.93)</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td></td>
</tr>
<tr>
<td>DFR</td>
<td>-36.83</td>
<td>-20.43</td>
<td>-29.19</td>
<td>-7.56</td>
<td>-41.20</td>
<td>-29.20</td>
<td>-29.73</td>
<td>17.34</td>
<td></td>
<td></td>
</tr>
<tr>
<td>p value</td>
<td>(0.08)*</td>
<td>(0.14)</td>
<td>(0.00)***</td>
<td>(0.55)</td>
<td>(0.56)</td>
<td>(0.16)</td>
<td>(0.44)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>STFR</td>
<td>-41.57</td>
<td>-20.46</td>
<td>3.17</td>
<td>23.81</td>
<td>-25.17</td>
<td>-13.18</td>
<td>24.96</td>
<td>52.96</td>
<td></td>
<td></td>
</tr>
<tr>
<td>p value</td>
<td>(0.04)**</td>
<td>(0.06)</td>
<td>(0.80)</td>
<td>(0.02)**</td>
<td>(0.18)</td>
<td>(0.78)</td>
<td>(0.51)</td>
<td>(0.13)</td>
<td></td>
<td></td>
</tr>
<tr>
<td># obs</td>
<td>1109</td>
<td>1109</td>
<td>1109</td>
<td>1109</td>
<td>19</td>
<td>19</td>
<td>19</td>
<td>19</td>
<td></td>
<td></td>
</tr>
<tr>
<td>p value, F test</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>adjusted R²</td>
<td>0.23</td>
<td>0.05</td>
<td>0.02</td>
<td>0.04</td>
<td>0.40</td>
<td>0.05</td>
<td>0.07</td>
<td>0.04</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>RHS</th>
<th>Qnt 1</th>
<th>Qnt 5</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>GR</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>GR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>7.51</td>
<td>-0.97</td>
<td>-3.31</td>
<td>1.96</td>
<td>2.16</td>
<td>-1.26</td>
<td>0.20</td>
<td>-7.09</td>
<td></td>
<td></td>
</tr>
<tr>
<td>p value</td>
<td>(0.00)***</td>
<td>(0.47)</td>
<td>(0.00)***</td>
<td>(0.21)</td>
<td>(0.22)</td>
<td>(0.54)</td>
<td>(0.69)</td>
<td>(0.17)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lev</td>
<td>-122.39</td>
<td>-222.22</td>
<td>45.08</td>
<td>-9.24</td>
<td>634.72</td>
<td>-76.53</td>
<td>34.22</td>
<td>102.06</td>
<td></td>
<td></td>
</tr>
<tr>
<td>p value</td>
<td>(0.02)**</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.01)**</td>
<td>(0.46)</td>
<td>(0.12)</td>
<td></td>
</tr>
<tr>
<td>Mkt β</td>
<td>7.01</td>
<td>0.40</td>
<td>0.10</td>
<td>1.11</td>
<td>-1.56</td>
<td>1.82</td>
<td>0.09</td>
<td>0.31</td>
<td></td>
<td></td>
</tr>
<tr>
<td>p value</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.03)**</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.06)**</td>
<td>(0.27)</td>
<td>(0.26)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Idio Risk</td>
<td>1.72</td>
<td>-0.77</td>
<td>0.32</td>
<td>0.35</td>
<td>3.08</td>
<td>-0.01</td>
<td>0.05</td>
<td>0.08</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)***</td>
<td>(0.37)</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.96)</td>
<td>(0.28)</td>
<td>(0.11)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DFR</td>
<td>-34.93</td>
<td>-13.89</td>
<td>-45.82</td>
<td>-18.59</td>
<td>-1274.03</td>
<td>8.77</td>
<td>22.07</td>
<td>34.49</td>
<td></td>
<td></td>
</tr>
<tr>
<td>p value</td>
<td>(0.12)</td>
<td>(0.35)</td>
<td>(0.00)***</td>
<td>(0.25)</td>
<td>(0.04)**</td>
<td>(0.50)</td>
<td>(0.02)**</td>
<td>(0.15)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>STFR</td>
<td>-39.75</td>
<td>-14.79</td>
<td>20.17</td>
<td>31.15</td>
<td>55.31</td>
<td>45.11</td>
<td>1.40</td>
<td>-69.43</td>
<td></td>
<td></td>
</tr>
<tr>
<td>p value</td>
<td>(0.07)*</td>
<td>(0.01)</td>
<td>(0.00)***</td>
<td>(0.02)**</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.09)</td>
<td>(0.00)***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>adjusted R²</td>
<td>0.28</td>
<td>0.13</td>
<td>0.08</td>
<td>0.04</td>
<td>0.03</td>
<td>0.09</td>
<td>0.05</td>
<td>0.03</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
results to the baseline, full-duration panel regressions presented in Table 8. Additionally, trend analysis from Figure 3 and Table 3 suggest that the median systemic bank integration rises sharply during pre-2000, then falls mildly during P2 and P3. The median Qnt 1 bank integration rises mildly during P1, sharply during P2 and then falls somewhat during P3; and the median Qnt 5 bank shows very slight negative trends during all periods except the Great Recession.

5.5.1 Period 1: 1990–1999

Pre-2000, for the full sample, the main results from Table 8 continue to hold — size, market beta and idiosyncratic risk continue to be highly positively significant; and DFR and STFR are negatively significant. The explanatory power of the model is a healthy 23%.

In a departure from previous results though, the leverage ratio assumes high negative significance and a one percent marginal increase in the leverage ratio — computed as the ratio of common equity to total assets — induces a 1.32 percent drop in the value of bank integration. The negative relationship between leverage and integration is quite plausible since banks increase their leverage mostly by borrowing from the short term wholesale funding markets. Since such wholesale markets are dominated by non-G-SIB market participants including shadow banks, foreign banks and several money market funds, we expect a bank’s reliance on G-SIBs to decrease with increasing leverage.

For the 19 systemic banks, all variables with positive marginal effects — bank size, market beta and idiosyncratic risk — continue to exercise the same effect. However, DFR is only mildly negatively significant in P1 and in a departure from previous results, STFR ceases to exercise any significance. The leverage ratio is not significant. The explanatory power of the panel regression in P1 for systemic banks is relatively high at 40%.

For Qnt 1 banks, size, market beta and idiosyncratic bank risk display the same positively significant behavior. However, STFR is now mildly negatively significant while DFR ceases to hold any significance. Leverage ratio again posts a significantly negative value. The adjusted $R^2$ of this
Panel regression is 28%.

Panel regressions for Qnt 5 banks in period 1 display poor fits and the explanatory power is a mere 3%. Idiosyncratic risk and DFR display their usual positive and negative significance respectively. However, market beta and leverage ratio assume unusual roles, with market beta being highly negatively significant and leverage ratio being very highly positively significant.

5.5.2 Period 2: 2000–2006

For the full sample of banks in period 2, market beta and STFR reassert their positive and negative significance respectively. Somewhat unusually, size and DFR are no longer significant and idiosyncratic risk assumes a negative marginal effect during P2, with a unit marginal change in its value affecting a -0.74% change in bank integration. The explanatory power during this period is relatively weak at 5%.

For the systemic bank subset, the results deviate as well. During P2, only two variables are significant — market beta has a positive marginal effect, but curiously, size affects systemic banks negatively during P2. All other variables are insignificant and the adjusted $R^2$ for the regression remains low at 5%.

The topmost integrated quintile Qnt 1 displays significance with only two variables — market beta, which retains its positive association with bank integration — and the leverage ratio, which has a highly significant negative marginal impact on Qnt 1 banks’ integration. All other variables are insignificant. The explanatory power of the regression is 13%.

Qnt 5 banks display the same behavior as the Qnt 1 subset for period 2. Market risk has a significant positive marginal impact while the leverage ratio contributes significantly negatively. All other variables are insignificant and the adjusted $R^2$ is reported to be 9%.

5.5.3 Period 3: 2007–2014

Post-2007, for the entire sample of 1109 banks, idiosyncratic risk and DFR retain their significant positive and negative marginal effects respectively.
The size of the bank however, reports significantly negative marginal effects. All other variables show no significance and the panel regression has weak explanatory power at a mere 2%.

For the systemic banks, post 2007, only two variables show significance — market beta and idiosyncratic risk — and their signs are positive. All other variables however, including size, have no significance and the adjusted $R^2$ posts a relatively low value of 7%.

Qnt 1 banks post-2007 display the usual significant marginal dependence on market beta and idiosyncratic risk (positive), as well as on DFR (negative). Size however, influences Qnt 1 banks negatively significantly. STFR and the leverage ratio show no significance in P3 for the top quintile banks. The adjusted $R^2$ is at 8% during this period.

For the bottommost integrated quintile, however, all variables during period 3 are insignificant, except reliance on deposit financing which has a significant negative marginal impact. The panel regression is jointly significant at the 10% level but not at the 5% level and its explanatory power is low at 5%.

5.5.4 The Great Recession: 2007–2009

During the Great Recession, the full sample of banks displays the usual effects for variables with positive marginal impacts. Size, market beta and idiosyncratic risk are significantly positive. Leverage ratio and DFR are insignificant. However STFR, somewhat unusually, assumes a positive marginal impact on bank integration during 2007–2009. The panel regression explains 4% of the aggregate variation during this period.

For the set of 19 systemic banks, size and idiosyncratic risk retain their significant positive marginal impacts, while all other variables exhibit insignificance. The explanatory power of the model remains low at 4%.

For the Qnt 1 banks, market beta and idiosyncratic risk continue to exert a significant positive influence on integration. Leverage ratio, size and DFR are shown to be insignificant. However, in a departure from the baseline full-period model, STFR is significant but positive. The model explains about 4% of the Qnt 1 banks’ integration variation during the Great Recession.
Finally for the least integrated quintile Qnt 5, none of the variables are significant; and the model fails to be jointly significant at the 10% significance level. This suggests that even taken together, the variables have no impact on Qnt 5 banks’ integration during the Great Recession.

Taken together, Tables 8 and 9 contain exhaustive information about the direction in which various explanatory variables affect bank integration — stratified by not only important bank subsamples, but by notable subperiods as well.

Overall, bank size exercises a significantly positive marginal impact on bank integration. The only exceptions are during the period after 2007, in which size seems to have a negative impact on the full sample and the Qnt 1 bank subsample; and during 2000–2006 where it is negatively associated with systemic banks’ integration. For the Qnt 5 bank subset, size seems to play no role at all. Aggregating over the subperiods, size assume high positive significance on bank integration, as results in Table 8 suggest.

The leverage ratio, broadly speaking, exercises limited influence on bank integration except for the pre-2000 period, during which it exercises a significant negative marginal influence on bank integration (except for the systemic banks). For the subsample Qnt 1, it affects bank integration negatively during periods 1 and 2 (1990–2006) as well, while for Qnt 5 its effect in P1 is positive and that during P2 is negative. Overall, however, except for the aforementioned special subperiods and special subsamples, leverage ratio has no significance on bank integration.

The market beta of a bank has a strong positive marginal effect on bank integration. This is true for most subsamples as well as subperiods. The only exception is for the Qnt 5 bank subsample during pre-2000 period, where it contributes negatively to bank integration.

Likewise, the idiosyncratic bank risk has a significant, positive marginal impact on bank integration for most subsamples and subperiods. The only exception to this observation is during period 2 (2000–2006) where the marginal impact is negative.

DFR impacts bank integration negatively significantly in most cases. The only exception to this rule occurs post-2007 for the subsample of the...
least integrated quintile of banks Qnt 5, for which the marginal impact of deposit financing ratio on Qnt 5 bank integration is positive.

Finally, STFR also displays the usual negative marginal impact on bank integration except during the Great Recession during which for both the full sample of 1109 banks and the topmost integrated Qnt 1 subsample it has a positive marginal impact on bank integration.

6 Segmentation in the US Banking Sector

6.1 The Core and the Periphery

The subsample based explanatory analysis undertaken and tabulated in Table 8 reveals a stark segmentation in the US banking sector on the basis of integration. There is a small set of banks in the US which are well integrated and can be well explained on the basis of common bank characteristics. Indeed all 358 banks in the subsample regression “Top”, as well as its strict subsets — the 19 systemic banks in “Sys” and 215 most integrated quintile “Qnt 1” display the exact same behavior, with bank characteristics showing the exact same marginal effects. Moreover, as the average degree of integration increases in a subsample from “Top” to “Qnt 1” to “Sys”, so does the explanatory power of panel regressions — 30.29%, 32.56% and 44.46% respectively. The opposite is true for the 751 bottom two-thirds banks — not only are their integration values relatively low, the fixed effects panel regressions fail to explain the variation in the subsample “Bot” as well as in the least integrated quintile “Qnt 5”.

Consistent with the terminology adopted in the interbank network literature, it seems that the US banking sector is composed of a small, strongly integrated “core” set of banks, and a large, weakly integrated “periphery” set of banks. In particular, since in terms of average integration levels, absolute values of coefficient estimates, as well as on the basis of explanatory power of panel regressions, roughly speaking, we observe the following order among US banks:

\[ \text{Sys} \succeq \text{Qnt 1} \succeq \text{Top} \succeq \text{All} \succeq \text{Bot} \succeq \text{Qnt 5} \]
This suggests that it is not unreasonable to deduce that the 19 systemic banks “Sys”, the 215 most integrated subset “Qnt 1” and the top one-third most integrated set “Top” lie in the core of the US banking sector; and the two thirds least integrated subset “Bot” as well as the least integrated quintile “Qnt 5” lie in the periphery.

In particular, in the next two subsections, we show that consistent with literature from the empirical interbank networks, the systemic banks (members of the core) are strongly integrated — but not with banks in the periphery.

6.2 Systemic Banks Are Strongly Integrated...

![Figure 5: Overall median integration levels for systemic banks. For each systemic bank, the median is computed over the full set of 100 quarters: from Q1 1990 to Q4 2014. The list of 19 systemic banks in the US is presented in Table 1. All systemic banks show very heavy integration with the banking sector.](image)

Figure 5 shows the median integration taken over the full 25 year sample period from 1990–2014 for the 19 systemic banks in the US. All systemic banks show heavy integration and in particular, form the most integrated subset in the entire US banking sector. The lowest median integration value

22We note however, that such a classification is to an extent, heuristic and that there is no clear boundary, at least based on our methodology, that sharply separates core banks from the periphery. We do observe a gradual transition though: systemic banks can be confidently thought to belong to the core; and Qnt 5 banks are almost certainly peripheral.
Table 10: Results for the \( F \) test for joint significance for principal component regressions where the principal components are extracted from the peripheral banks’ covariance matrices. The null hypothesis is that peripheral principal components are jointly insignificant and therefore, the systemic banks are not integrated with the periphery. The column “Mean \( p \) value, \( F \) test” denotes the mean \( p \) value of the \( F \) test over the full set of 100 quarters. There is strong evidence for the null hypothesis, since for 18 out of 19 banks, such regressions are are jointly insignificant.

<table>
<thead>
<tr>
<th>Systemic Bank</th>
<th>Designation</th>
<th>Mean ( p ) value, ( F ) test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bank of America</td>
<td>G-SIB</td>
<td>0.3499</td>
</tr>
<tr>
<td>BB&amp;T</td>
<td>D-SIB</td>
<td>0.3658</td>
</tr>
<tr>
<td>Comerica</td>
<td>D-SIB</td>
<td>0.3952</td>
</tr>
<tr>
<td>Huntington</td>
<td>D-SIB</td>
<td>0.3140</td>
</tr>
<tr>
<td>JP Morgan Chase</td>
<td>G-SIB</td>
<td>0.3051</td>
</tr>
<tr>
<td>KeyCorp</td>
<td>D-SIB</td>
<td>0.4200</td>
</tr>
<tr>
<td>M&amp;T Bank</td>
<td>D-SIB</td>
<td>0.4130</td>
</tr>
<tr>
<td>PNC</td>
<td>D-SIB</td>
<td>0.4367</td>
</tr>
<tr>
<td>Regions</td>
<td>D-SIB</td>
<td>0.4367</td>
</tr>
<tr>
<td>Wells Fargo</td>
<td>G-SIB</td>
<td>0.4185</td>
</tr>
<tr>
<td>Zions</td>
<td>D-SIB</td>
<td>0.4037</td>
</tr>
<tr>
<td>State Street</td>
<td>G-SIB</td>
<td>0.3713</td>
</tr>
<tr>
<td>Morgan Stanley</td>
<td>G-SIB</td>
<td>0.2742</td>
</tr>
<tr>
<td>Goldman Sachs</td>
<td>G-SIB</td>
<td>0.4339</td>
</tr>
<tr>
<td>Bank of New York Mellon</td>
<td>G-SIB</td>
<td>0.4560</td>
</tr>
<tr>
<td>Fifth Third</td>
<td>D-SIB</td>
<td>0.3785</td>
</tr>
<tr>
<td>US Bancorp</td>
<td>D-SIB</td>
<td>0.3385</td>
</tr>
<tr>
<td>SunTrust</td>
<td>D-SIB</td>
<td>0.3736</td>
</tr>
<tr>
<td>Citigroup</td>
<td>G-SIB</td>
<td>0.0458</td>
</tr>
</tbody>
</table>

occurs for Zions Bancorp at 36.83% while the highest occurs for Goldman Sachs, at 67.45%, implying that overall, well over a third of Zions’s stock returns are attributable to the common national factors embedded in G-SIB principal components; while for Goldman Sachs, over two-thirds of its stock return is driven by the other 7 G-SIBs’ principal components. Clearly systemic banks are heavily integrated with the banking sector in general, and with each other, in particular.

6.3 ... But Not With Peripheral Banks

In this subsection, we provide evidence that systemic banks are unintegrated with the peripheral banks. To show this, we construct 4 out of sample principal components from the peripheral banks — the 751 weakly integrated bank subset from Table 8 — and study if such peripheral principal components drive systemic banks’ returns. If systemic banks are integrated with periphery banks, such principal component regressions should explain an
appreciable portion of systemic banks’ returns. At the very least, peripheral principal components should be jointly significant in an explanatory regression for systemic banks’ returns.

We find that such a hypothesis is rejected overwhelmingly, since such principal component regressions are jointly insignificant uniformly for all 19 systemic banks except Citigroup. In Table 10 we report \( p \) values for the \( F \) test for joint significance, averaged over all 100 quarters. Except for Citigroup, whose average \( p \) value is 0.0458, and hence cannot be rejected at the 5% significance level, all other 18 systemic banks show no reliance on the four out-of-sample peripheral principal components since the corresponding regressions are jointly insignificant. This shows that while the periphery banks are (weakly) integrated with the core, the core banks are (strongly) integrated with each other but show no integration with the periphery.

7 Conclusions

We estimate an American bank’s integration by its degree of alignment with US G-SIBs’ principal components — higher alignment, in terms of the adjusted \( R^2 \) of principal component regressions implies higher integration and inversely. The US banking sector exhibits median integration to be rising slowly over the sample period. However, the set of systemic banks show much higher integration levels — often several times that of their ordinary counterparts. We show that US banks exhibit core-periphery segmentation — the core being a small set of well integrated and well explained banks — and the periphery being a large set of weakly integrated banks. Moreover, the systemic banks lie in the core and are unintegrated with the periphery; and as a consequence of this core-periphery segmentation, the integration across US banks follows a power law distribution.

Determinants of integration include bank characteristics like size, market beta and idiosyncratic risk — all of which show statistical and economic significance and impact integration positively. On the other hand, deposit financing and short term financing, while being statistically and economically significant, impact integration negatively. Additionally, we stratify the
results based on several notable subperiods and show that the leverage ratio had a significantly negative marginal impact pre-2000 and that bank size has had a negative marginal impact on integration post-2007.

Our methodology — both for estimating principal component based integration, as well as that for finding determinants — is agnostic and transparent and makes no undue assumptions. Finally, we show that our results continue to hold even as explanatory variables’ definitions are changed or special subsamples from within the core, the periphery; or indeed the full sample of US banks are selected.

References


53


