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Bank Regulatory Reforms and Declining Diversity of Bank Credit Allocation

Takeo Hoshi
University of Tokyo

Ke Wang
Federal Reserve Board

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Bank Regulatory Reforms and Declining Diversity of Bank Credit Allocation[1]

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Abstract

This paper addresses the concerns on correlated risks across banks that tightening regulation may have induced. Facing higher required capital ratio after the global financial crisis, a bank can reduce the risk-weighted assets by shifting its portfolios from asset classes with high risk-weights to asset classes with low risk-weights. This may reduce the risk exposures of individual banks, but may end up concentrating various banks' assets to the same set of low risk assets, hence increase the joint default probability and systemic risk of the banking system. Using risk-weighted asset data in Form FFIEC101, reported by the U.S. banks that are allowed to use the advanced approach, we show banks' average risk weights indeed declined since 2010, partly due to portfolio shifts in credit allocation. We measure the convergence in credit allocation by the cosine similarity of portfolio compositions for pairs of banks. We document that the average cosine similarity across the advanced approach banks rose monotonically and significantly since 2010, which coincides with a period of tightened capital regulations. Finally, we observe that the two prevailing systemic risk measures –SRISK and CoVaR –also show signs of convergence among banks during the same time period. We conclude that the capital regulation may have unintended consequences on systemic risk by encouraging herd behavior across regulated banks.

[1] The views expressed herein are those of the authors and do not necessarily reflect the views of the Board of Governors or the staff of the Federal Reserve System.

1. Introduction

In responding to the global financial crisis of 2007-09, financial regulators around the world have moved to strengthen the resilience of financial systems against adversary shocks. They implemented numerous regulatory reforms to improve capital adequacy, better manage liquidity, and limit risk-taking of the regulated financial institutions.

Although many new regulations such as the minimum liquidity ratio, the Volker rule that prohibits insured banks from proprietary trading and sponsoring private equity funds, and the requirement for resolution and recovery plan, capital regulations continues to be the most important regulatory tool for prudential regulation. Post-crisis capital regulations have developed mostly within the framework of Basel III. In addition to increasing risk-based minimum capital adequacy ratios, Basel III introduced non-risk-based minimum ratio requirements such as leverage ratio and supplementary leverage ratio requirement. Supervisory stress tests, which asks the banks to retain sufficient amount of capital even under stress scenarios, have been introduced in many countries including the U.S. Basel III capital regulation also aimed to enhance the quality of capital by imposing a minimum ratio on common equity tier 1 (CET1) capital. Table 1 summarizes post-crisis regulation changes in capital adequacy requirements in the U.S. The complexity of capital regulation framework has increased dramatically following these regulatory changes (Greenwood, et al., 2017).

Facing higher required capital ratio, a bank can do one of the two things (or both) to increase its capital ratio. One is to increase the capital (numerator), and the other is to reduce the (risk-weighted) assets (denominator). If banks increase the capital ratios by increasing the capital without changing their asset holdings (and hence their risk exposures), the resiliency of banking system certainly increases, because the banking system now has a larger amount of buffer for the same amount of risk.

If banks reduce the risk-weighted assets instead without increasing capitals, the implications for the financial system stability can be different. Total risk-weighted asset is essentially the sum of a financial institution's assets in various classes weighted according to the credit risk of each asset class[2]. Thus, a bank can reduce the total risk-weighted assets (RWAs) by shifting their portfolios from asset classes with high risk-weights to asset classes with low risk-weights. This may reduce the risk exposures of individual banks, which contributes to financial stability. Such adjustments, however, may end up concentrating various banks' assets to the same set of low risk assets. In extreme cases, lower default risks at individual banks can be more

[2] For simplicity, we ignore off-balance sheet exposures, operational risk, and eligible credit reserves in this paper while considering the components of risk weighted assets.

than offset by increasing probability of simultaneous defaults coming from the problems of supposedly low risk assets that many banks hold.

Table 1: Capital ratio requirement changes since the financial crisis

Capital ratios & buffers	Ratio definition		Requirement	Scope	Year effective	Change
	Numerator	Denominator				
Common Equity Tier 1 Capital Ratio (CET1)	CET1	RWA	4.5%	All	Internationally Active Banks =2014; else=2015	New
Tier 1 Capital Ratio	Tier 1 Capital	RWA	6%	All	Internationally Active Banks =2014; else=2015	Increased from 4%
Supplementary Leverage Ratio	Tier 1 Capital	Total Leverage Exposure	3%	Internationally Active Banks	Comply by 1/1 2018	New
Enhanced Supplementary Leverage Ratio (eSLR)	Tier 1 Capital	Total Leverage Exposure	2.0% buffer above SLR (Total SLR of 5%)[3]	GSIBs	Comply by 1/1/2018	New
Capital Conservation Buffer (CCB)	CET1	RWA	CET1 capital/RWA at least 2.5% above each of the minimum risk-based ratios	All	Phased in beginning on 1/1/16 and ends 1/1/19	New
Counter-Cyclical Capital Buffer (CCyB)	Weighted average of the countercyclical capital buffer amounts in jurisdictions where bank has private sector credit exposures.		Now zero, set up to 2.5% of RWA	Internationally Active Banks	2016	New
GSIB Surcharge	Two multi-factor methods used		The higher surcharge for risk based ratios under the two calculation methods	GSIBs	Phased in beginning on 1/1/16 and fully effective on 1/1/19	New

Source: Federal Reserve Board staff report.

Concerns on correlated risks across banks that tightening regulation may have induced have been rising in recent years, particularly among finance practitioners and public sector. On February 14, 2017, Senator Pat Toomey from Pennsylvania made a comment during the Semiannual hearing of the Federal Reserve then-Chair Janet Yellen: "*I believe CCAR increases systemic risk by correlating banks' behavior*". His concern finds support from a Federal Reserve publication (Bräuning and Fillat, 2019) that analyzes loan-level data from FR-Y14Q report and shows that stress testing constraints might have caused banks to adjust their portfolios such that

[3] The Federal Reserve recently proposed changing the eSLR buffer to equal half the GSIB surcharge.

these individual bank portfolios more closely resembled each other. A recent article in the quarterly publication of the Clearing House (Carruthers and Faulkner, 2018) also stresses that bank regulation often "*inevitably acts as a standardizing factor*". Kevin Stiroh, the head of Supervision at New York Fed summarizes the central trend reflected in the emerging literature on banking monoculture[4]:

[T]he largest firms in the U.S. appear to be growing increasingly similar in terms of their underlying business models and strategies. This has implications for balance sheet structure, earnings profile, and organizational structure. … [T]his serves to diversify the individual firms, while also making them more similar in terms of the business strategies they pursue, the products they offer, and the customers they serve.

Applying the data on large U.S. banks that are permitted to use internal risk models, or "advanced approaches" for determining risk-based capital ratios , this paper documents such convergence of banks' assets, i.e., credit allocation along classifications of risk-weighted assets. In addition, we find evidences that are consistent with the idea that such convergence in credit allocation may have increases systemic risk. We observe banks' equity betas have moved closer to each other during the same period when we find banks' asset allocation became similar. CoVaR measure of systemic risk has also started to move together for certain financial institutions.

This paper employs the risk-weighted asset data in Form FFIEC101, reported by U.S. advanced approach banks to Federal Reserve and FDIC. The form contains quarterly data on the decomposition of total risk-weighted assets by different asset classes, such as corporate loans and mortgage loans. Following the asset classifications in the form, we are able to decompose the post-crisis changes in overall risk-weighted assets of these financial institutions into the changes due to portfolio shifts across asset classes and the changes due to average risk weights change in each asset class. Our results show that both of these factors contribute to the decline of overall risk weights.

Using the same data and asset classification, we also compare portfolio compositions for pairs of banks by calculating the cosine similarity measure (Kleymenova et al., 2016). We show that the average cosine similarity across these advanced approach banks rose monotonically and significantly since 2010, which coincides with a period of tighter capital regulations. We further decompose such rise in RWA-similarity into changes in similarity across banks on balances of each asset class and changes in similarity on risk-weights of each asset class so as to examine in more details the source of resemblance.

[4] See Stiroh (2018), https://www.bis.org/review/r181109g.pdf

Finally, we explore the link between asset similarity across banks and systemic risk for the banking sector. We focus on two prevailing systemic risk measures – SRISK and CoVaR. Since equity beta is a key driver of SRISK measure, we consider the correlation of dynamic CAPM beta of these bank' equities and find the variation of betas across banks fell as the RWA got similar. Standard deviation in daily CoVaR measures across banks also becomes lower in the same time period.

The rest of the paper is organized as follows. Section 2 starts out by showing that the banks in our sample responded to the higher capital requirements by reducing the risk-weighted assets (RWA) substantially. Then we decomposition of the changes in the average risk weights (RWA divided by total non-risk-weighted assets) into two parts: the part due to the changes in the compositions of assets and the part due to the changes in the risk weights for classes of assets. We find that both parts were important channels of adjustment for the U.S. banks. Section 3 introduces the cosine similarity measure and reports the calculation for pairs of the banks. We find that the banks in our sample have become increasingly similar during the period of regulatory tightening. Section 4 explores the link between our findings on similarity of banks and systemic risk by examining dynamic betas and CoVaRs for our sample banks. Section 5 concludes.

2. Decomposition of Changes in the Average Risk Weight

Capital rules in the U.S. generally follow a framework of rules adopted by the Basel Committee on Banking Supervision (BCBS). In 2013, the FDIC, FRB, and OCC issued regulations for insured depository institutions in the U.S. that align with Basel III capital standards (Basel III). The standards strengthens minimum capital ratio requirements by increasing the minimum Tier 1 capital ratio requirement from 4% to 6% and requiring a capital conservation buffer which starts to phase in from Jan 2014. U.S. regulators also impose additional minimum capital buffer for GSIBs so that the minimum Tier 1 capital ratio required for the largest bank holding company reaches 12% as a percentage of total risk-weighted assets. In simple notations, the minimum capital ratio requirements take the form as the following constraint imposed on banks' equity capital:

$$\text{Capital Ratio} \quad : \mathrm{E} > \gamma\, w\, \mathrm{L} \qquad (1)$$

where E: Equity capital,

γ: Minimum Capital Adequacy Ratio

L: Loan (or "assets")

w: Risk weight on loan

We have found that many banks not only increased capital but also reduced the amount of risk-weighted assets (RWA) to meet the requirement of higher capital ratios. We also find that banks reduced the amount of risk-weighted assets without necessarily reducing the total amount of non-risk-weighted assets. We can see this by looking at the changes in the "average" risk weight, *w*, which is defined to be the ratio of RWA to total (non-risk-weighted) assets.

Data Sample

Our data on risk weighted assets and risk weights come from the bank report form FFIEC101, only requested for advanced approach banks to file quarterly to federal bank regulating agencies.[5] Bank report form FFIEC101 provides the amount of risk-weighted asset and the amount of (non-risk-weighted) asset balances by asset classes for each regulated bank subject to advanced approach on risk-weighted assets. Public version of this data releases the reports after the banks have passed the "parallel run" period during which their internal risk models are under close surveillance by regulators. This paper is based on regulatory version of the data which include reports during the parallel run period. Hence, our analysis can extend time-series data back to 2010 while an analysis based on public version of FFIEC101 data can start only around 2014-2016 period.

FFIEC101 classifies bank assets into five big categories and eleven more granular categories, as listed in Table 2, Panel A. For the analyses in this paper, we ignore assets from securitization and cleared transactions, because there are only a few banks that have non-zero exposures for these categories of assets. [6] We also group the three retail asset classes (mortgage, QRE, and other retail) together in some specifications because there are a few bank holding companies in the sample having positive exposures only in one or two categories of retail asset class. For robustness tests, we carry on our analysis in parallel for three specifications of asset classes, as listed in Table 2, Panel B. They are: 1. three-asset-class – wholesale, retail, and equity; 2. seven-asset-class, which includes five wholesale assets (corporate, banks, sovereign, income-producing real estate (IPRE), high-volatility commercial real estate (HVCRE)), retail, and equity; and 3. nine-asset-class, which includes five wholesale assets, three retail assets, and equity.

To make a meaningful comparison analysis, we require banks in our sample must have at least two years of quarterly FFIEC101 data in all of the three big categories (wholesale, retail, and equity) starting prior to 2013. This requirement limits our sample to ten FFIEC101 filers, as follows: JP Morgan Chase, Citigroup, Bank of America, Goldman Sachs, Wells Fargo, Bank of

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[5] FFIEC stands for the Federal Financial Institutions Examination Council, which consists of major bank regulators in the U.S.: the OCC (Office of the Comptroller of the Currency), the Federal Reserve Board, and the FDIC.
[6] Our total assets and total risk-weighted assets may be smaller than the FFIEC101 reported numbers due to this exclusion.

New York Mellon, Morgan Stanley, Union Bank, PNC, and US Bancorp. They include seven U.S. GSIBs and represent about 60% of U.S. banking sector in terms of total assets.[7]

Table 2. Asset Classification.

Panel A. FFIEC101 Asset Classes

Portfolio	Sub-portfolio
Wholesale	Corporate
	Bank
	Sovereign
	IPRE
	HVCRE
Retail	Mortgage
	QRE
	Other Retail
Equity	Equity
Securitization	Securitization
Cleared Transaction	Cleared Transaction

Panel B. Asset classes in this paper

3 Asset Class	7 Asset Class	9 Asset Class
Wholesale	Corporate	Corporate
	Bank	Bank
	Sovereign	Sovereign
	IPRE	IPRE
	HVCRE	HVCRE
Retail	Retail	Mortgage
		QRE
		Other Retail
Equity	Equity	Equity

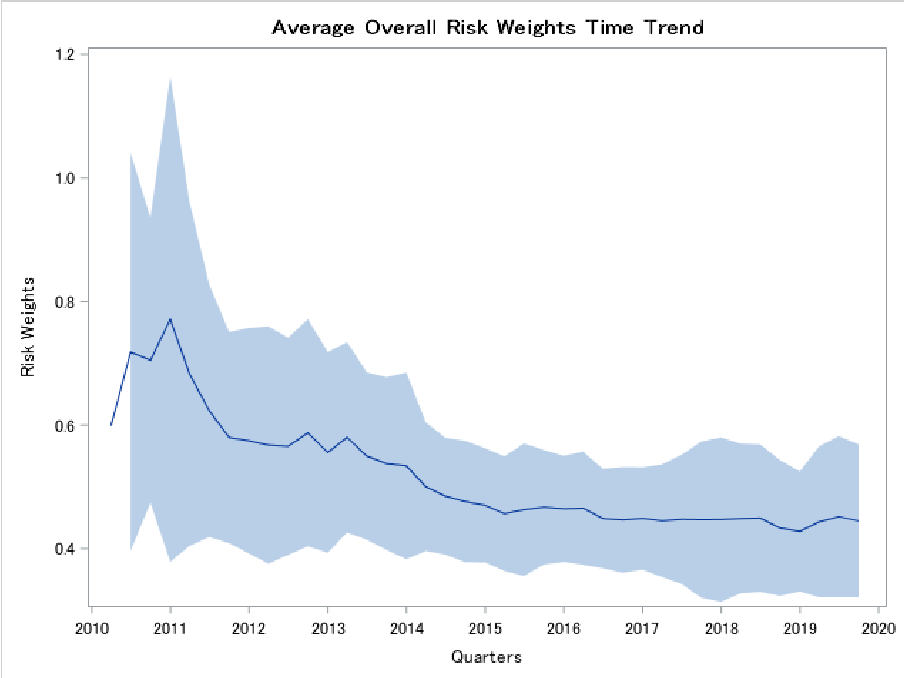
Figure 1 plots the time series of the average overall risk weight for our sample banks, calculated by dividing the total risk-weighted assets by the total non-risk-weighted assets. The shaded area shows the 95% confidence interval. Starting 2010, there is a clear trend of declining in overall risk weights and the average decline is more prominent between 2011 and 2015 when the more stringent bank regulations are imposed on banks.

There are two approaches to risk weight assets: standardized approach and advanced approach. For the sample period covered in this study, the standardized approach is generally designed for small banks, while the advanced approach is for larger and more sophisticated institutions. Basel II (and III) allows large and sophisticated financial institutions to use their internal risk models to assess the risk of their assets.[8]

[7] According to data compiled from FR-Y9C report. The two non-GSIB banks in this sample, PNC and US Bancorp, will not be subject to advanced approaches in the new Federal Reserve tailoring proposal. Since Union Bank was merged into the MUFG holding company in 2014, we use only the bank-level instead of holding company level data to get the longer time series. All other banks use the holding company level data.

[8] An institution that has consolidated total assets equal to $250 billion or more; that has consolidated total on balance sheet foreign exposures equal to $10 billion or more; is a subsidiary of a depository institution or holding company that uses the advanced approaches; or elects to use the advanced approaches is generally subject to the advanced approaches. Standardized approaches are under modification as part of the Basel endgame regulation reform.

Figure 1. Time series of *w* (total risk-weighted assets over total balance ratio).



For standardized approach banks, risk weights of each loan is completely set by the regulation, depending on the asset class, delinquency status, and borrower types. For example, the standardized risk weight for a local revenue bond is 50% while that for a commercial loan that is performing is 100%. The standardized approach requires financial institutions to transition assets that are 90 days or more past due or on nonaccrual from their original risk weight to 150%. So both a revenue bond that is on nonaccrual and a commercial loan that is more than 90 days past due would have the same risk weight of 150%.

Internal risk models used by advanced approach banks are subject to regulators' exams. For the banks in the U.S., total RWA for an advanced approach bank must be the higher of the two: total RWA calculated by the standardized approach or total RWA calculated by the internal risk model. Thus, the U.S. major banks are not entirely free from the standardized approach.

Since the total RWA is sum of the products of risk weights and balances in each asset class, the change in the overall risk weights can be decomposed into a) the change explained by changes in risk-weights, and b) the change explained by the changes in exposures of each category of assets:

$$\Delta\, w = \sum_k \Delta RW_k \cdot BAL\%_k(t_0) + \sum_k RW_k\,(t_1) \cdot \Delta BAL\%_k \qquad (2)$$

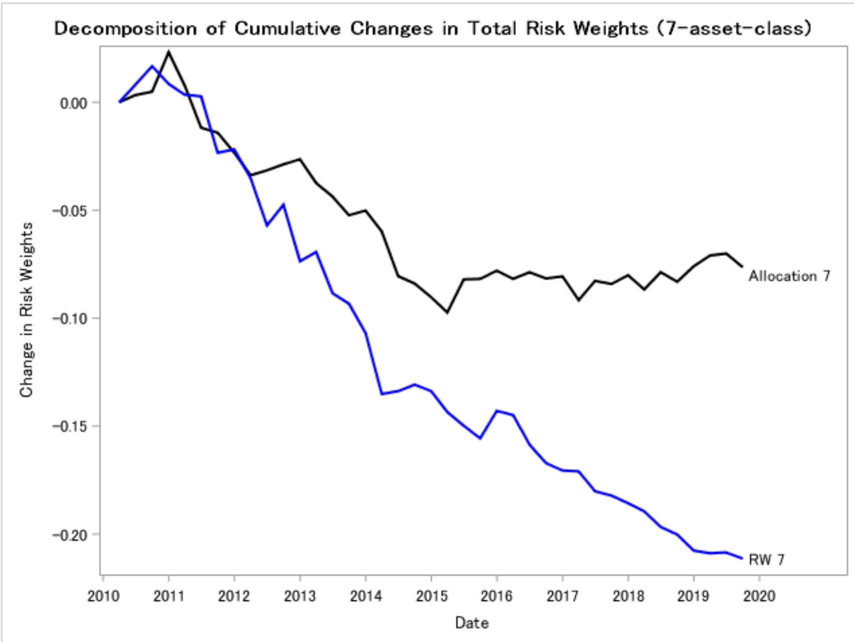
Here RW_k is the risk-weight on asset *k* and $BAL\%_k$ is the (non-risk-weighted) proportion of asset *k*. The first component of equation (2) carries the balance composition of assets as static as in the initial time period t_0 but measures the changes in risk-weights by updating risk weights along the time (RW_k is calculated by using updated risk weighted assets for the *k-th* asset class divided by the updated total balance of that asset class). Thus, the first component represents the contribution of changes in risk-weights within each asset class to the change in overall risk weight. Similarly, the second component of equation (2) keeps the risk weights within each asset class as in the ending period ($RW_k(t_1)$), but varies the balance composition of the asset portfolio. It represents the contribution of changes in asset allocation across our defined asset classes to the change in overall risk weight.

Figure 2 plots such decomposition of the cumulative change in the overall average risk weight with the seven-asset-class specification,[9] averaged across our sample banks, using contemporary total asset balance as the weights. The black curve tracks the contribution of the portfolio shifting component to the overall risk weight decline and the blue line captures the effect from risk-weights change with asset classes. Over the time period of 2010 to 2015, the average of cumulative change in risk weights shows a total decline of about 25% if we add the two curves together. Among them, the portfolio shifts contribute to about 10%, or more than one third of the total decline. After 2015, the contribution of portfolio shifts across these asset classes seems to have stopped contributing to the overall the risk weight changes, while risk weights within each asset classes continues to decline. However, it is important to note that the second component in equation (2) cannot capture the entire effects of portfolio shifts, because a decline of the risk weight for a certain asset class may be partially caused by a portfolio shift within the asset class. For example, banks may start to lend to supposedly low risk firms in an asset class. Since we do not look at portfolio shifts within an asset class, the data in such case would show that the risk weight for that asset class changes. In fact, Bruaning and Fillat (2019) documents exactly the within-asset portfolio convergence using Stress Testing data.

A potential consequence of the portfolio reallocations of banks to reduce the amount of risk weighted assets is reduction of diversity in bank portfolios. Since all the banks respond to essentially the same incentive to reduce high-risk loans, they could start holding the assets of very similar (low) risk characteristics. The tendency would be especially higher for the banks that are subject to the same standardized risk weighting system. In the next section, we provide evidence that banks' asset allocation have been becoming more similar indeed since 2010.

[9] See Appendix for results using other asset classifications.

Figure 2. Decomposition of overall risk weight change.



3. Bank Asset/Credit Allocation Convergence

We use Cosine similarity measure to identify the increasing resemblance of banks' asset allocations. Following Kleymenova et al. (2016), we define the Cosine similarity of portfolio composition for a pair of banks (i, j) as follows

$$\cos BAL\ (i,j) = \frac{\sum_k BAL\%(i,k) * BAL\%(j,k)}{\sqrt{\sum_k \left(BAL\%(i,k)\right)^2}\sqrt{\sum_k \left(BAL\%(j,k)\right)^2}}$$

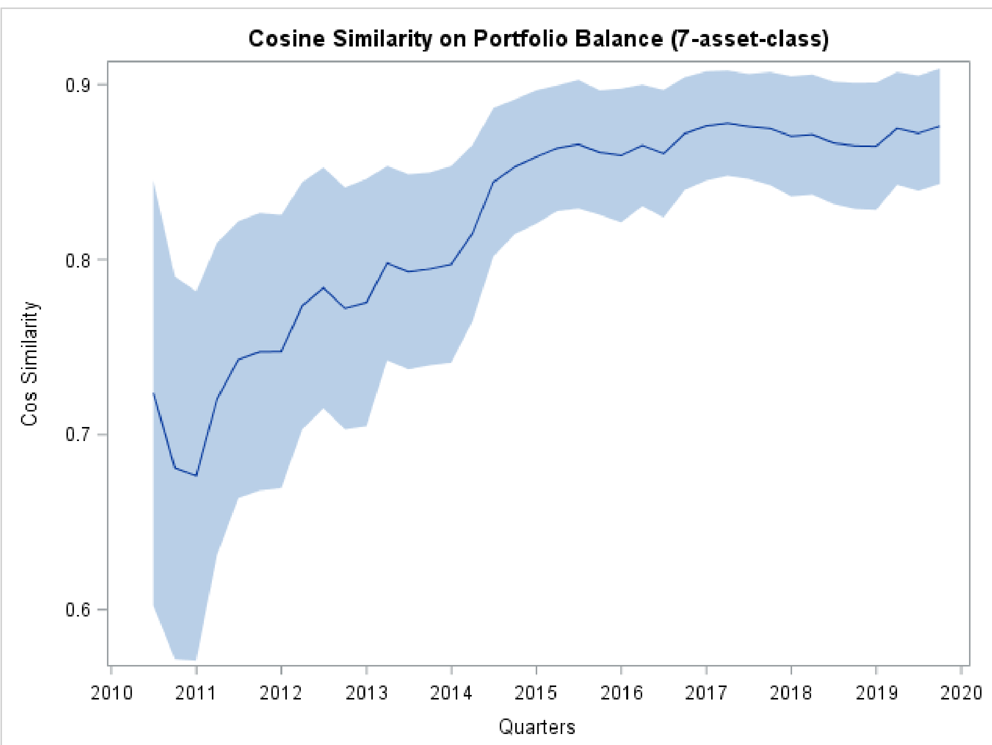
(3),

where for a pair of banks (i,j), Cosine similarity on unweighted balances measures how similar the two asset allocation sets between these two banks are, taking one asset allocation set defined by asset classification as one k-dimensional column vector. This measure takes value between 0 and 1 with higher value indicating two banks are more similar in terms of their asset allocation. In contrast to other similarity measures used in banking literature, this measure is scale independent. It measures only the directional closeness of the two asset allocation sets between two banks regardless of bank size or distribution of the portfolio shares.

We calculate the cosine similarity measures for all asset class specifications but for the sake of brevity, we report only the result on 7-asset-class specification in this manuscript since the trends for the other two types of asset classification are very similar. For the 10 banks in our sample, we calculate cosine similarity on balance for all the 45 possible pairs and take the simple average over each quarter in our sample period. Figure 3 plots the time series of this average cosine similarity with the 95% confidence interval band. Clearly, an upward trend in cosine similarity is identified over our sample period, indicating a fast portfolio convergence, especially during the 2010 to 2015 time period.

The coincidence of a rapid portfolio convergence and a large contribution of portfolio shifting to the decline of risk weights suggests that there might be a link between risk-based capital regulation and portfolio convergence. Further research is need to quantify any causality effects.

Figure 3. Cosine similarity averaged across banks.



4. Asset Convergence and Systemic Risk

A potential problem of increasing similarity of banks' asset allocations is that it can increase systemic risk in the financial system. Although each bank's risk may be reduced through portfolio shifts toward lower risk assets, the risk reduction may be offset by increased correlation across banks through holding of the same type of assets (albeit low risk). This can be regarded as a straight-forward implication of the Modern Portfolio Theory. A simple example can illustrate our conceptual framework:

Suppose, there are two identical banks - A and B - with the same levels of liability and the same level of capital. There are three assets 0, 1, and 2 with uncorrelated returns that banks can invest. Asset 0 is a safer asset than the other two such that: if a bank holds only Asset 0, probability of failure, Pr{Value of Asset < Liability} , equals to 0.5%. On the other hand, if a bank holds only Asset 1 or Asset 2, Pr{Value of Asset < Liability} = 5%.

Let us compare two situations:

First, Bank A holds Asset 1 and Bank B holds Asset 2. In this case, Pr{Bank A becomes insolvent} = Pr{Bank B is insolvent} = 5%. If we define systemic risk to be the probability that both banks become insolvent, then the probability of systemic risk is 0.25%.

Second, Bank A holds Asset 0 and Bank B also holds Asset 0. Then, Pr{Bank A becomes insolvent} = Pr{Bank B is insolvent} = 0.5%. Each bank is safer than in the first situation. However, the probability of both bank default is also 0.5%, which is higher than before.

Recent development in network studies also find that common asset holdings is one important source of interconnectedness among financial institutions and interconnectedness can post potential risk to financial stability.[10] However, we have not found strong positive correlation between the cosine similarity measure and the prevailing systemic risk measures, such as SRISK and CoVaR. Instead, we find that portfolio convergence has stronger link to the *correlation* of these individual bank's systemic risk measures instead of their *levels*. This suggests that portfolio similarity measure could complement the systemic risk measures that regulators are closely monitoring for financial stability.

In the following analysis, we consider two measures of systemic risk: SRISK and CoVaR. Both SRISK and CoVaR measure the contribution of individual financial institution to the risk of the entire financial system. Strictly speaking, the impact of increasing similarity of bank asset allocations to the systemic risk is in theory best linked to the joint probability of default of multiple financial institutions. Since SRISK and CoVaR have become the standard

[10] See Brunetti, et al. (2018), and Hale and Lopez (2018), among others.

measures of systemic risk in recent years, however we consider the relation between these systemic risk measures and similarity of bank asset allocations.

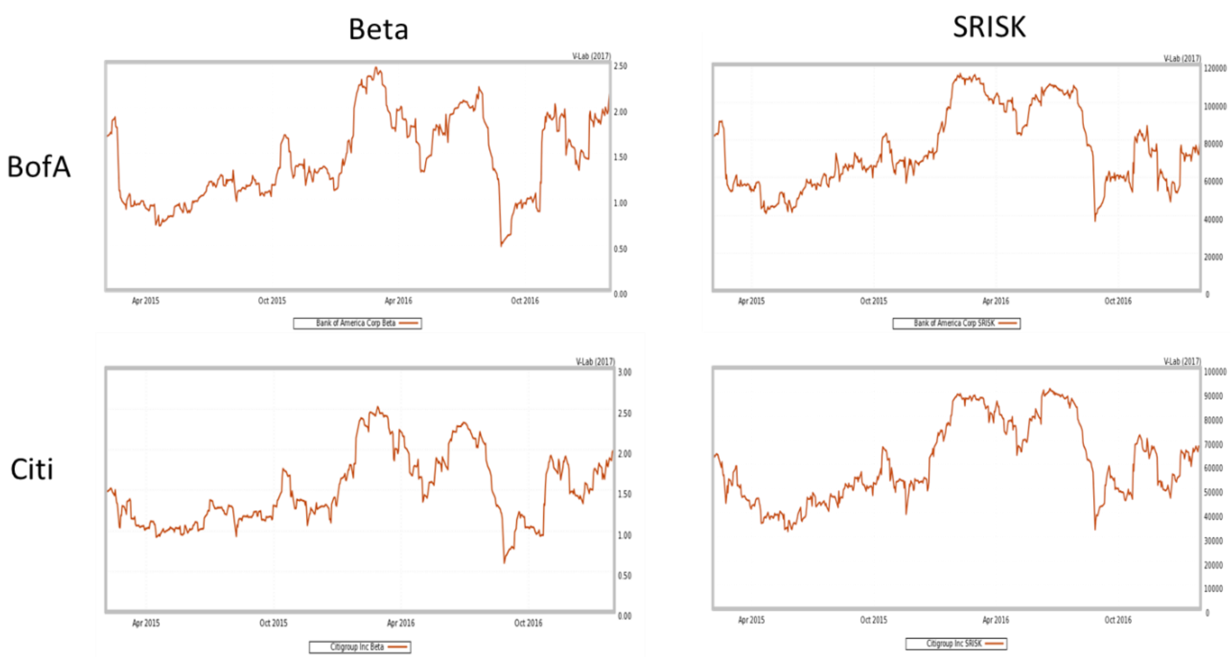
According to Brownlees and Engle (2017), SRISK measures individual bank's systemic risk by the long-run marginal expected shortfall (LRMES), which is in turn determined by equity beta.

$$\mathrm{SRISK} = k \cdot \mathrm{DEBT} - (1\text{-}k) \cdot \mathrm{EQUITY} \cdot (1\text{-}\mathrm{LRMES})$$

$$\mathrm{LRMES} = 1\text{-} \exp(\log(1\text{-}d) \cdot \mathbf{beta}) \qquad (6)$$

In the New York University V-Lab published SRISK reports, we observe SRISK and banks' equity CAPM-beta are highly correlated. (See Figure 4 for a snapshot of SRISK and beta for Bank of America and Citi Group as an example.) Since beta is a key driver of SRISK, we focus on the equity beta of our sample banks and examine how betas changed over time during our sample period.

Figure 4. Examples of SRISK and CAPM-beta.



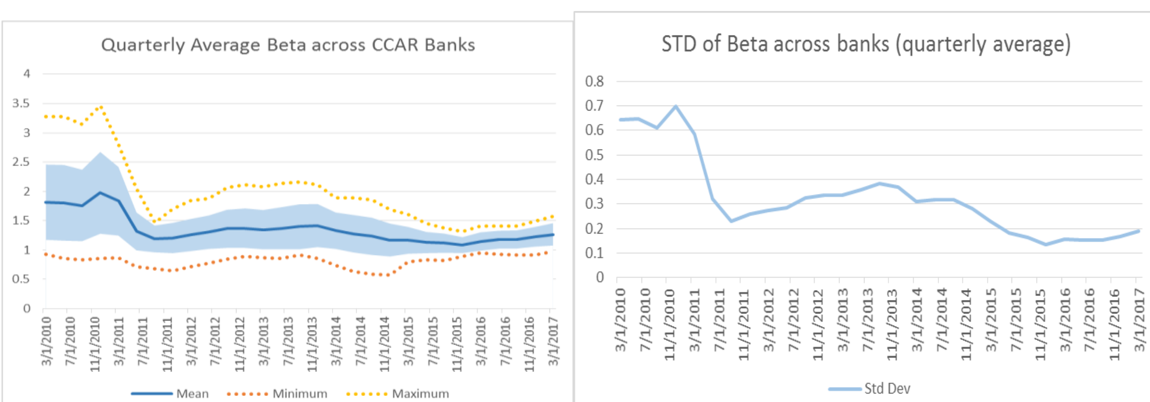
Source: Bloomberg Finance, LP and New York University V-Lab

We downloaded daily equity beta from Bloomberg for each CCAR banks and calculate their quarterly average[11]. Panel A of Figure 5 shows the mean, 95% confidence interval, and min-max points of these betas across banks. Panel B shows the standard deviation of betas over time. Together they provide evidence that the dispersion of betas across these large banks fell significantly in 2010, from 2014 to 2016 and remains low during the post-2011 period.

The increase in the correlation of beta may reflect the increase in correlation of individual banks' default probabilities (given a large negative shock to the stock market), and hence increase the joint probability of default of these large banks, given the same individual bank's default probability. But of course, during the same period that we observe the convergence in asset allocation, individual bank's default probability has also come down, partly due to the same tighter capital regulation, partly due to other policies in response to the financial crisis and business cycle effect. As a result, we observe the overall systemic risk has decreased since the financial crisis, shown by the time series trend of the aggregate level of SRISK. However, we argue, even each banks' portfolio may become safer, but we cannot ignore the detrimental effect of the asset co-movement on the correlation of default, or joint default probability while measuring the systemic risk. In other words, part of the benefits of lower risk in bank assets from risk-based capital regulation could have been offset by the loss of diversification induced by the same regulation.

Figure 5. Dispersion of equity beta.

Panel A Panel B



Source: Authors' calculations using Bloomberg Finance, LP.

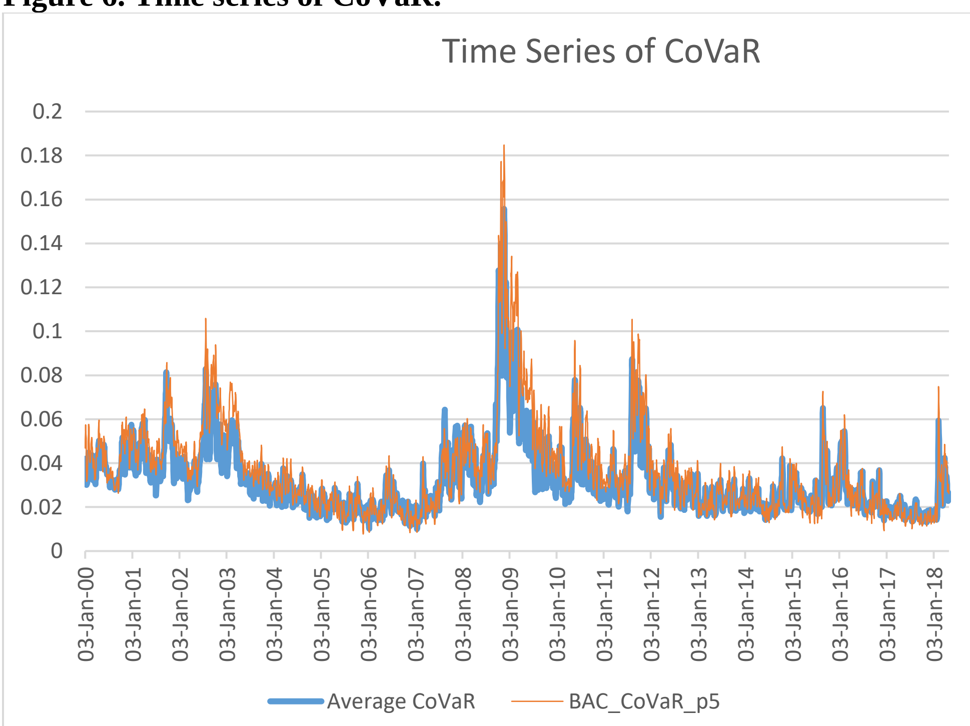
[11] Beta downloaded from Bloomberg is historical beta estimated from daily closing price of individual stocks and S&P index, using past two years of data. (Bloomberg ID RK167 "EQY_RAW_BETA")

CoVaR

Adrian and Brunnermeier (2016) use quantile regressions to compute CoVaR, the value at risk (VaR) for the financial sector conditional on a bank having had a VaR loss. We look at the daily CoVaR estimated by the New York Fed based on market equity returns for publicly traded financial intermediaries. In principle, CoVaR measure is close to the joint probability of default we have been trying to link to since the VaR for the financial sector is embedded in the CoVaR formula. But in practice, the financial system return is calculated by taking the value-weighted average of individual financial intermediaries' returns without considering default correlation, so we still cannot read the impact of asset allocation convergence on systemic risk directly from the level of CoVaR[12].

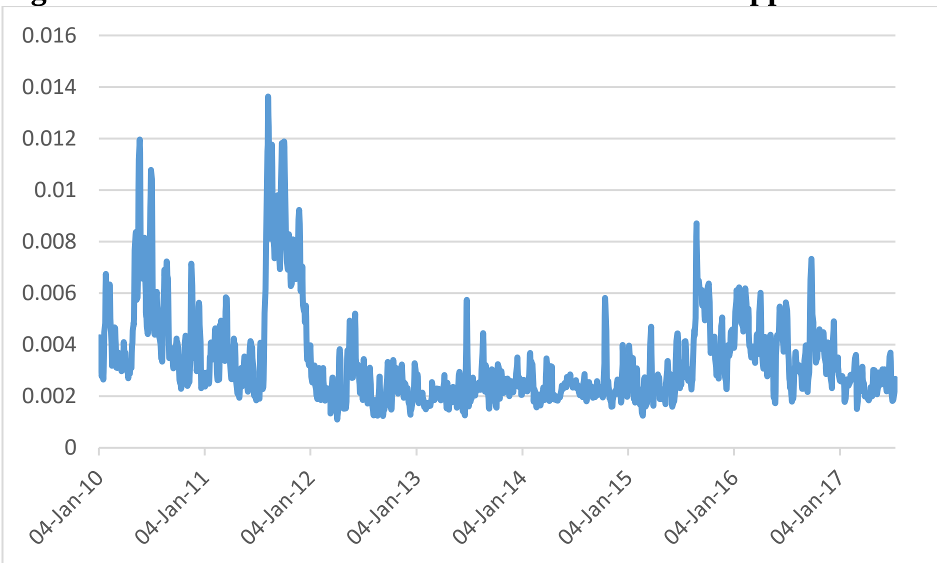
Figure 6 shows the time series of daily CoVaR since 2000, for the average across all our sample banks and for a typical bank in our sample. Maybe due to the definition of CoVaR, we can see from this chart that banks' CoVaR are always highly correlated.
Similarly as equity beta, we also plot the standard deviation of CoVaR across banks since 2010 in Figure 7, which shows the variation of CoVaR among the advanced approach banks is smaller after 2012, although the variation has always been small.

Figure 6. Time series of CoVaR.



[12] Similar to SRISK, if individual bank's risk is lower, CoVaR measure tends to be lower in absent of asset correlation effect.

Figure 7. Standard deviation of CoVaR for advanced approach banks.



5. Conclusion

Using U.S. regulatory data on large advanced-approach banks, we find evidence that banks' credit allocation converge and such portfolio shifting contributes to lower the effective constraint of risk-based capital requirements. Portfolio convergence could be an unintended consequence of post-crisis capital regulation because higher minimum risk-based capital requirement reinforces banks' incentive to lower asset risk weights by shifting their portfolio in a similar way, given the similar regulatory environment. The potential negative impact of portfolio convergence is that it could increases systemic risk even though the risk of each individual bank's failure become smaller. Idiosyncratic shocks in a less-diversified financial system, such as a regional public health catalyst, are harder to absorb and may get amplified through common holdings of financial institutions.

Our novel analysis may have important policy implications. Although business model convergence might be inevitable given regulation enhancement and technology advances, such structural changes should be considered in the agenda of impact studies during the process of policy development. If structural consequences can be anticipated in advance, some of their adverse effects might be avoid if we twist part of the design of financial regulation to make it more incentive compatible. On the other hand, understanding such structural consequences ex post could also provide policy makers useful information for policy implementation and risk mitigation. For example, knowing banks portfolio convergence could increase systemic risk, policy makers may pay more attention to the disclosure of risk exposures from regulated banks and employ such information to the resolution planning process.

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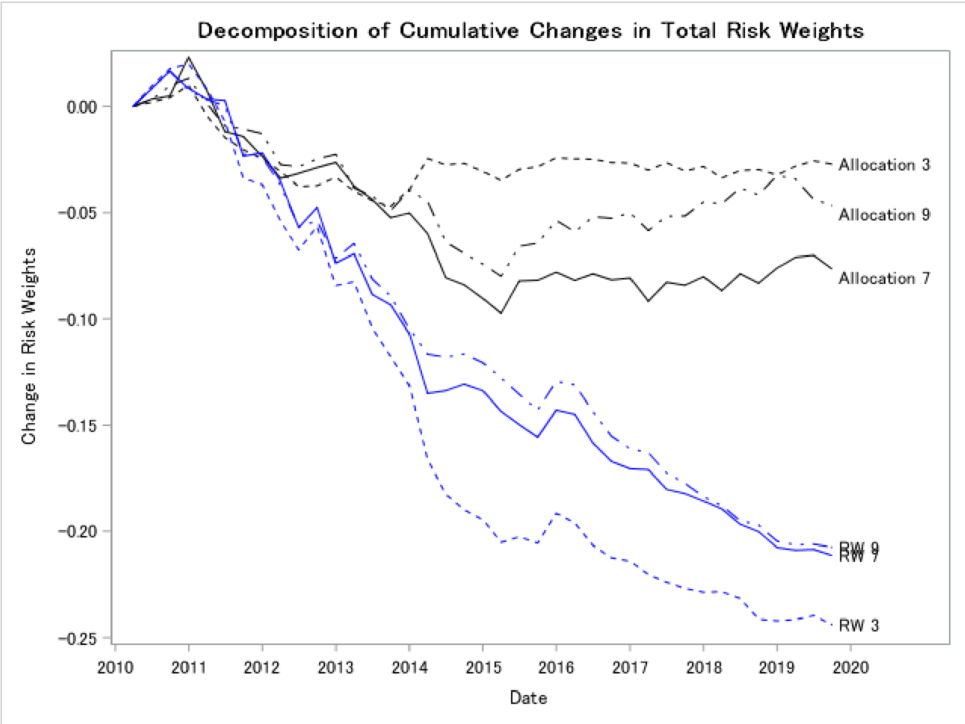
Appendix

A. Decomposition of Change in Risk Weights with all Asset Class Specifications

Figure A.1



Note: This chart plots the decomposition of overall risk weight decline by the three asset class specifications: 3-asset-class, 7-asset-class, and 9-asset-class. Black lines indicate contributions from portfolio shifting across specific asset classes and blue lines indicate contributions from within-asset changes in risk weights.