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Stress Testing Effects on Portfolio Similarities Among Large US Banks

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Abstract:

We use an expansive regulatory loan-level dataset to analyze how the portfolios of the largest US banks have evolved since 2011. In particular, we analyze how the commercial and industrial and commercial real estate loan portfolios have changed in response to stress-testing requirements stipulated in the 2010 Dodd-Frank Act. We find that the largest US banks, which are subject to stress testing, have become more similar since the current form of the stress testing was implemented in 2011. We also find that banks with poor stress test results tend to adjust their portfolios in a way that makes them more similar to the portfolios of banks that performed well in the stress testing. In general, stress testing has resulted in more diversified bank portfolios in terms of sectoral and regional distributions. However, we also find that all the large US banks diversified in a similar way, creating a more concentrated systemic portfolio in the aggregate.

Keywords: bank correlations, concentration, portfolio similarity, stress tests, systemic risk

JEL Classifications: G21, G28

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1 Introduction

The post-crisis implementation of the Dodd-Frank Act Stress Testing (DFAST) and the related Comprehensive Capital Analysis and Review (CCAR) has had a substantial effect on the behavior of large US banks.[1] In this paper, we analyze how bank portfolios have changed as a result of stress testing. Our conclusions are twofold. First, bank portfolios have become more similar since stress testing was implemented in 2011.[2] We find that banks with poor stress test results adjust their portfolios to more closely resemble their peer institutions; in particular, those banks with good stress test results. Our second conclusion is that banks' reaction to stress testing has resulted in more diversified portfolios along certain risk dimensions. However, an apparently more diversified portfolio at the individual bank level does not necessarily mean a less risky aggregate portfolio for the banking system. Similarly diversified portfolios across the largest US banks may result in a higher systemic risk level, driven by banks loading on risk factors that are not fully captured by the most severe adverse scenario considered in the CCAR.[3]

Our analysis is also motivated by a 2016 publication of the Board of Governors of the Federal Reserve System (Board of Governors of the Federal Reserve (2016)). Figure 1 shows how the average rolling two-year correlation in the weekly change in credit default swap (CDS) spreads between each of the 78 pairs of systemically important financial institutions (SIFIs) has increased substantially, from an average of about 50 basis points in 2010 to an average of close to 80 basis points in 2015.[4] In general, these systemically important institutions share similar business lines and counterparties, and also rely on a similar set of funding sources. Our portfolio analysis indicates that the increase in market perception of bank comovements could be driven by portfolio changes that cause large banks to more closely resemble each other.

The probabilities of default implied by CDS spreads reflect the market's perception of default risk, which embeds the probability of a government bailout if a default occurs. Figure 2 shows

[1] See Cortés et al. (2018) and Bassett and Berrospide (2018), for example.

[2] Stress testing in its current form, with the corresponding data collection, started in 2011. An earlier version of stress testing was introduced in 2009, with the Supervisory Capital Assessment Program (SCAP).

[3] The relationship between individual portfolio diversification and systemic risk is discussed by, among other studies, Ibragimov, Jaffee, and Walden (2011), Caccioli et al. (2014), and Cai et al. (2018).

[4] The thirteen firms included in the analysis are the global systemically important banks (GSIBs) and systemically important financial institutions (SIFIs) that have been identified by the Financial Stability Oversight Committee (FSOC) over the 2006–2015 period: AIG, Bank of America, Barclays, Citigroup, Deutsche Bank, GE Capital, Goldman Sachs, J.P. Morgan Chase, MetLife, Morgan Stanley, Prudential, UBS, and Wells Fargo. Figure 1 also shows that, while the correlation between SIFIs and nonSIFIs is generally lower, it increased in recent years as well.

the average pairwise correlations among equity returns for the same thirteen SIFIs considered in Board of Governors of the Federal Reserve (2016). Equity return data allow us to explore a longer time series, starting in 1980. The average correlation among SIFIs declined in the late 1980s but has experienced an upward trend since. The introduction of the Riegle-Neal Interstate Banking and Branching Efficiency Act in 1994 marks a turning point in the series, as US banks were permitted to branch across state lines and overlap in other geographic markets. The 2001 economic recession was also followed by a sharp increase in the average correlation, and after 2005, the average correlation among equity returns for large banks experienced an upward trend until the present. The correlations for equity returns experienced a sharp increase at the onset of the crisis, as did the CDS spreads. However, the equity correlations stabilized after the increase in 2008, experienced another sharp increase after 2010, and then remained relatively stable at around 60 percent.

Our nonparametric approach of analyzing how the portfolios of the largest US banks have become more similar is complementary to studies that point out an increased correlation in banks' default probabilities and equity returns since 2010. Instead of exploiting market information, our focus is on the detailed portfolio information contained in the FR Y-14Q data collection. Banks with more than \$50 billion in assets are subject to DFAST and are required to report detailed information on their balance sheets along with obligor information.[5] In particular, we exploit the information in the quarterly reports on banks' wholesale lending, which includes commercial and industrial loans (Schedule H.1), and loans collateralized by commercial real estate (Schedule H.2). These data allow us to define bank similarity based on portfolio shares along several dimensions and to analyze the evolution of similarity over time and across banks. The goal of our paper is to elicit information about how stress testing constraints might have caused banks to adjust their portfolios such that these individual bank portfolios more closely resembled each other, actions that, in turn, resulted in stronger comovements in their default probabilities and equity returns.

We document that the largest US banks have become more similar in terms of their overall asset allocation and also along some dimensions of their corporate loan portfolio allocation. In particular, banks' commercial and industrial (C&I) portfolios have become more similar in terms

[5]The reported data is confidential supervisory information, but the list of reported variables are publicly available at https://www.federalreserve.gov/apps/reportforms/Default.aspx.

of counterparty ratings, industry, and geographic region. In addition, banks' commercial real estate (CRE) portfolios have become more similar in terms of regional distribution, the ratio of net operating income to property value (this ratio is the capitalization rate or *caprate*), and the loan-to-value ratio. To investigate whether these increases in similarity are a result of regulatory changes, we show that the overall portfolio similarity of the banks subject to DFAST has increased by more than 5 percent since 2011, on average, while the portfolio similarity of large banks not subject to DFAST (the nontreated reference group) with each other has largely remained unchanged. Our detailed analysis using loan-level data for banks subject to DFAST shows that banks with poor stress test results, in terms of post-stress capital shortfall, tend to have dissimilar portfolios before the test. However, after receiving the poor stress test results, these banks adjusted their portfolios to more closely resemble those banks with good DFAST results. Moreover, banks with a large share of C&I losses after receiving negative DFAST results adjusted their loan portfolios even more intensely to more closely resemble the portfolios of better-faring banks. Our analysis also reveals that large banks converge to similarly diversified portfolios, while the US banking industry as a whole has become more concentrated. We also use aggregate balance sheet information from FR Y-9C reports, which are available since 1986 for all bank holding companies operating in the United States. The aggregate information over a longer time period and for a larger set of banks allows us to compare the evolution in bank portfolios before and after the stress tests were implemented in 2011, and also to compare the behavior of those banks that are subject to DFAST with the banks that are not required to undergo stress testing.

Our results have implications for financial stability. From a microprudential point of view, more diversified and well-capitalized banks result in lower bank-level risk. Indeed, over the last few years, capital shortfalls under stress have been declining, capital buffers have increased to levels not seen in many years, and banks hold more diversified portfolios along several risk dimensions. The severity of the stress testing scenarios has not declined over time—if anything the severity increased in the recent 2018 exercise, where the unemployment rate peaks at 10 percent, resulting in a sharper rise from the 2017:Q4 starting point of 4.1 percent. These lower capital shortfalls and more highly diversified loan portfolios at the individual bank level could lead to supervisory complacency from a microprudential point of view. In fact, academic and nonacademic research, along with speeches by Federal Reserve officials, have highlighted the improved robustness and resiliency of the financial sector after the post-crisis regulatory reforms were enacted.[6]

However, from a macroprudential point of view, our work shows that part of the decline in the capital shortfall is a result of portfolio reallocations that are similar across banks—evidence that is indicative of a reaction to the stress test's severely adverse scenarios. These reallocations are particularly visible along the rating, industry, and regional dimensions. Notice that the current DFAST methodology disclosure documents describe the Federal Reserve's C&I model as follows: *[...] the probability of default is calculated based on the borrower's industry category and the BHC's internal credit rating for the borrower.* We present evidence that it is indeed the case that bank portfolios have reacted to stress testing in ways that may inadvertently result in a build-up of systematic risk factors for the banking sector as a whole that is not captured by the single severely adverse scenario imposed on all banks undergoing DFAST. Our conclusions imply that the scenario design used in the stress testing exercise should be particularly careful and as comprehensive as possible in order to capture potential unintended risk build-up. While the current methodology has resulted in an increase of loss-absorbing capital buffers, it has had the unintended consequence of bank portfolios becoming more similar; that is, these portfolios are more individually diversified, but more systemically concentrated. Individually diversified portfolios that seem well-insulated from shocks in relatively benign times may result in a more sensitive aggregate banking system in periods of realized stress, particularly if the stress test scenarios do not capture all potential systematic risk factors.

The paper is structured as follows. Section 2 presents descriptive statistics on banks' C&I and CRE portfolios. Section 3 describes our measure of similarity across banks and shows the evolution of this similarity over time along several dimensions. We relate the similarity measure to the stress test results in Section 4. Section 5 shows measures of portfolio concentration, both at the individual bank level and for the financial system as a whole, and Section 6 concludes.

2 Portfolio Descriptive Statistics

The banks that are part of our dataset are those large and complex financial institutions operating in the United States that are subject to DFAST. As mentioned above, during our sample period,

[6] Some studies, like Greenwood et al. (2017), also point to the weakness of recent regulations, but only in the sense of regulatory costs, not necessarily the costs related to regulatory arbitrage opportunities.

banks with more than $50 billion in assets were required to undergo an annual stress testing exercise performed under adverse and severely adverse scenarios. DFAST also required these institutions to submit detailed portfolio information in the FR Y-14 reports.[7] For most of our analysis, we fix the sample to the 19 banks that have been subject to DFAST since the first exercise was conducted in 2012, henceforth denoted as "DFAST banks." We characterize each bank i at quarter t with vectors that capture the relative asset composition, $\alpha_{i,t}$.

In particular, we focus on bank portfolio shares evaluated along different key dimensions, with each dimension d characterized by a separate vector $(\alpha^d_{i.t})$. First, we measure similarity across the overall portfolio composition of banks using FR Y-9C data. In principle, our analysis of the overall portfolio composition does not need to be limited to the 19 DFAST banks. However, to be consistent throughout the description of the data, Table 1 presents the summary statistics of the asset portfolio shares of the 19 banks subject to DFAST. On average, retail loans (20.5 percent), securities (18.6 percent) and C&I loans (12.3) are the most important asset classes for the large US banks in our sample. CRE loans represent only about 6 percent of total assets, on average.

In order for us to use a more granular measure of similarity, we exploit the loan-level data in the regulatory schedules H.1 and H.2 found in the FR Y-14Q reports. These schedules contain loan-facility-level information on the respective exposures for C&I loans and CRE loans for each bank subject to stress testing. We focus on the rating, industry, geographic region, and maturity dimensions for C&I loans, and on the rating, census division, maturity, capitalization rate, loan-to-value ratio, and property type for CRE loans.

In Table 2, we show the descriptive statistics of C&I loans by risk rating. Banks report the internal rating of each credit facility, and they also provide the Federal Reserve with a mapping of their internal risk ratings to a common scale. Table 3 contains the same information by geographic region, Table 4 by industry, and Table 5 by maturity. Among the C&I loans that are disclosed in the FR Y-14Q reports, most loan exposures are rated just at investment grade (lower premium grade) or at the highest non-investment grade rating, while high grade, premium investment grade, and lower non-investment grade exposures on average account for less that 12 percent of C&I loans. In terms of industry exposure, the largest exposures are in manufacturing, finance, and retail trade. As is well-known, the maturity of C&I loan exposures is centered between two to five years. In

[7] Banks are nor required to report small loans that have less than $1 million in committed exposure.

addition to this central tendency (mean), the summary statistics reveal substantial heterogeneity in portfolio shares across banks and time, as indicated by the dispersion of the distribution (e.g., the difference between the 90th and 50th percentile). We focus on measuring this heterogeneity and characterizing its dynamics in recent years, in particular, by linking these dynamics to banks' behavioral responses to enhanced regulation.

Tables 6–12 summarize the descriptive statistics for the CRE portfolios of the same 19 banks along the dimensions that are generally considered to be risk factors in CRE lending, such as internal rating, region (census division), maturity, loan-to-value ratio, capitalization rate, and property type, for both construction and income-producing loans. Generally, most of the CRE exposure is concentrated in loans extended to borrowers with credit ratings just above the investment-grade threshold. The loans are geographically diversified, with an average of 21 percent of the total CRE exposure in the Northeast, 14 percent in the Midwest, 33 percent in the South, and about 25 percent in the West. The average maturity of CRE loans tends to be between two and five years, and loan-to-value ratios are concentrated between 50 and 80 percent. Multifamily properties represent the largest share of the CRE portfolios, both for construction projects and income-producing loans. In the following section, we analyze the evolution of the portfolio shares along each of these dimensions, for both C&I and CRE loans.

Figures 3 and 4 show the banks' overall portfolio shares along some of the dimensions that we have explored in Tables 2–5 for C&I loans and in Tables 6–12 for CRE loans. In Figure 3, there is no obvious trend. Banks, on average, have lowered the portfolio share of the highest-quality borrowers (an investment rating of A and higher). On the CRE side of the balance sheet, this pattern is perhaps more visible, as panel (a) of Figure 4 shows. Banks have substantially increased the amount of construction loans for multifamily properties on their balance sheets, as shown in panel (b) of Figure 4. Panels (c) and (d) show two of the main risk factors for CRE loans: loan-to-value (LTV) ratio and capitalization rates, both measured at origination. According to panel (c), banks have lowered the share of loans with high LTV ratios (more than 80 percent), requiring borrowers to borrow less than in the beginning of the sample for the same property values. Capitalization rates, or caprates, seem to go in the opposite direction (i.e., bank portfolios are becoming riskier, on average, in this dimension). Capitalization rates for new loans have been declining and, according to panel (d), properties with capitalization rates higher than 7 percent represent less than 40 percent of banks' CRE portfolios in 2018:Q2, while those same loans represented more than 50 percent at the beginning of the sample period. Loans with caprates of less than 5 percent have almost doubled their presence, on average, in the portfolios of the banks in our sample.

3 Similarity Measures

The measure of similarity is based on the normalized Euclidean distance between the vectors of each bank's portfolio shares. Specifically, the Euclidean distance between banks i and j along dimension d is given by:

$$ed^d_{i,j,t} = ||\alpha^d_{i.t} - \alpha^d_{j.t}|| = \sqrt{\frac{1}{K}\sum_k^K(\alpha^d_{i.t}(k) - \alpha^d_{j.t}(k))^2}, \tag{1}$$

where k indexes the elements of the portfolio share vectors, $\alpha^d_{i,t}$. The similarity measure is constructed as the normalized Euclidean distance:

$$similarity^d_{i,j,t} = 1 - \frac{ed^d_{i,j,t} - \min(ed^d_{i,j,t})}{\max(ed^d_{i,j,t}) - \min(ed^d_{i,j,t})}. \tag{2}$$

We focus on the evolution of the similarity distribution across all bank pairs over the sample period. A caveat regarding this nonparametric similarity measure is that there is no obvious interpretation of the units or levels. Figure 5 shows the evolution of the distribution of the pairwise similarities (i.e., mean, media, 25th percentile, and 75th percentile) from 2011:Q1 to 2017:Q3 for the aggregate shares of the broad asset categories using FR Y-9C data. The overall portfolio similarity has increased over the sample period by about 5 percent for DFAST banks. Next, we explore the more granular information contained in the stress testing data (FR Y-14Q).

Figure 6 expands the sample of banks and the time dimension of Figure 5. Figure 6 shows that the banks subject to DFAST are not significantly different from the large banks that were not subject to DFAST prior to 2012. However, the similarity among DFAST banks increases substantially after the first proper stress testing exercise was conducted in 2012.[8] This difference in trends, supported by a simple regression using bank fixed effects and a DFAST dummy variable for the post-2011:Q3 period, indicates that the change in portfolio allocation is likely to be a reflection

[8] Proper in the sense that, for the first time, it was based on the detailed portfolio data collection as of 2011:Q3.

of banks responding to the scenarios considered in the stress testing exercises.

3.1 Commercial and Industrial Loans

As described in the previous section, the different risk dimensions that we consider for the C&I loans are (1) loan-level rating, (2) loan-level industry, (3) loan-level region, and (4) loan-level maturity. For each quarter, we compute the measure of similarity for all pairs $\{i, j\}$ of banks. Figures 7 shows the evolution of the distribution (i.e., mean, median, 25th percentile, and 75th percentile) from 2011:Q1 to 2017:Q3. The C&I portfolio similarities, according to ratings and region, have increased during the sample period by almost 10 percent. Moreover, their distributions also narrowed considerably over time, mostly driven by a strong increase in the lower percentiles—meaning that the bank pairs that had been least similar before DFAST then became more similar to the rest of the group. The central tendency of sectoral portfolio similarity increased as well, but less strongly. Coincidentally, the annual DFAST methodology disclosure made publicly available by the Board of Governors of the Federal Reserve states that *"[...] the probability of default is calculated based on the borrower's industry category and the BHC's internal credit rating for the borrower."*[9] Conversely, neither the average nor the distribution of similarity based on maturity exhibit a particular trend over the sample period.

3.2 Commercial Real Estate Loans

Following the same approach used above for C&I portfolios, we show the evolution in the similarity distributions of the CRE portfolios across DFAST banks. Figure 8 displays the results. The dimensions that we use to analyze the evolution of the similarity of portfolio shares are the (1) internal rating, (2) census division, (3) net operating income over loan value (caprate), (4) LTV ratio at origination, (5) construction property type, and (6) income-producing property type. We observe a substantial increase in the similarity of banks' portfolio shares by region, by caprate, and by LTV. Importantly, the capitalization rate and the LTV ratio are two of the most relevant factors of default risk for commercial real estate. Note that while there is an increase in similarity across banks, we cannot conclude that their portfolios have become riskier or more concentrated

[9] See, for example, "Dodd-Frank Act Stress Test 2017: Supervisory Stress Test Methodology and Results, June 2017." This information has been released in the methodology disclosure since the first DFAST.

among borrowers with worse characteristics. Section 5 will explore concentration measures bank by bank. There is no increase in similarity along the other dimensions that we considered. We do not show the maturity results because maturity is more standardized for CRE loans. Construction loans tend to be two-year loans, and income-producing loans tend to be five- or ten-year loans. We do not observe an increase in similarity according to property type or internal rating.

Of course, the measure of similarity is indicative of the behavior of banks but, alone, does not provide positive identification of the causes for such behavior. Bank portfolios could become more similar for demand reasons (e.g., industries or regions that grow strongly over the sample period and experience a growth in demand for credit), or banks could become more similar as they find ratings distributions or asset allocations that are more profitable. To address some of these questions, we focus on the effects of capital shortfalls that result from the implementation of DFAST's severely stressed scenario, and the subsequent changes that result in bank portfolios becoming more similar. In addition, we also investigate the relationship between banks' reported earnings and their portfolio similarities.

4 Capital Shortfall under Stress and Portfolio Similarity

So far our analysis has been limited to exploring how nonparametric measures of similarity have evolved over time. In this section, we explore the relationship between banks' capital shortfall and changes in banks' portfolios.[10] To identify a possible causal relationship between regulation and portfolio choices, we exploit the heterogeneity of banks' stress testing results. In the annual CCAR and DFAST exercises, the Federal Reserve publishes each of the banks' minimum capital ratios (tier 1, common equity and leverage, among others) under the severely adverse scenarios, as forecast by the Federal Reserve. These minimum ratios determine whether the capital plans are approved. The Federal Reserve's forecasts for each of the banks are not known in advance; therefore, there is an element of surprise since the Fed models are not made public. In our analysis, we exploit the variation provided by the heterogeneity in the results and the surprise component of the stress test results.[11]

[10] We define capital shortfall as the difference between the bank's capital ratio and the minimum capital ratio under the severely adverse scenario

[11] The DFAST results, which do not take into account a banks' capital plans, are released a few days before the CCAR results. These CCAR results take into account the banks' planned capital distribution, and banks have the

In order to link banks' reactions to regulation and portfolio similarities, we first aggregate our bank-pair similarity measure at the bank level. In particular, we measure bank i's overall similarity to all other banks as

$$bank\_similarity^d_{i,t} = \sum_{j \neq i} similarity^d_{i,j,t}. \tag{3}$$

We will use this bank-level measure in the following bank-level analysis, where we establish a relationship between regulation and bank behavior.

Figure 9 shows the relationship between banks' capital shortfalls and their overall similarity to the portfolios of other banks using publicly available aggregate data from the FR Y-9C reports. A bank's capital shortfall is defined as the decline in its tier 1 capital ratio resulting from the severely stressed scenario being applied to each individual bank's balance sheet as of the quarter prior to the stress testing exercise.[12] The relationship presented in Figure 9 is contemporaneous: banks with more (less) similar portfolios compared to other banks tend to have lower (higher) capital shortfalls. As Figure 10 shows, this relationship is not driven by the initial stress tests, but holds for the stress tests conducted before and after 2014:Q4, although the range of both capital shortfall and similarity scores are smaller after 2014:Q4.

We next ask if banks adjust their portfolios in response to a poor stress test result. In Table 13, we show the relationship between the results of the stress tests and subsequent *changes* in overall similarity with other banks. We find that banks with a higher capital shortfall, defined as either the 10, 25, or 50 percent of banks with the highest capital shortfall in each stress test, subsequently change their portfolios to look more like other banks. Columns (2) to (4) show that the portfolio adjustment is economically and statistically stronger for banks that experience the highest capital shortfalls. Because all specifications in Table 13 include time fixed effects, the coefficient estimates are not driven by a common time trend in bank similarity. Instead, the coefficient estimates are identified from the cross-sectional variation. Hence, this result is not driven, for example, by variation in the severity of scenarios across different stress tests.

If regulation is a driving influence behind the increasing portfolio similarity among large US

option to resubmit their proposed distributions after learning their DFAST results. The fact that banks have, in some instances, taken advantage of this "second chance" at their capital distribution plans offers evidence of the surprise element of DFAST results.

[12]From 2012 to 2014, banks were required to submit their capital plans by the end of the fourth quarter of the year, based on portfolios as of the third quarter. From 2015 on, capital plans are due at the end of the first quarter, based on portfolios as of the fourth quarter of the previous year

banks, poor-performing banks (those with high capital shortfalls) may adjust their portfolios to look more similar to banks that have good stress test results (those with low capital shortfalls). Therefore, instead of looking at changes in similarity to all other banks, Table 14 shows the changes in similarity with respect to banks that performed well on the stress tests (in terms of equation (3), we sum only over a subset of banks that perform well). Columns (2) through (3) show the similarity to banks that have low capital shortfalls; that is, those banks scoring below the 50th, 25th, or 10th percentile of each stress test, respectively. The results show that after the stress test, those banks with high capital shortfalls (the 10 percent of banks with the largest capital shortfall) rebalance their overall portfolios to look more similar to the better-performing banks (defined as those banks with the lowest 10, 25, or 50 percent of capital shortfall). Indeed, the results are quantitatively larger when benchmarking similarity against the portfolio compositions of the best-performing banks in each stress test (the 10 percent of banks with the lowest capital shortfall).

In Table 15, we look at the adjustments in banks' C&I loan portfolios, particularly along the ratings dimension. Our dependent variable is thus $\Delta bank\_similarity_{i,t}^{rating}$, where the difference in the individual bank's similarity measure is between the quarter prior to the stress testing exercise and the similarity measure prior to the previous stress test. Table 16 shows the analogous results for the region, sector, and maturity dimensions. This information allows us to exploit additional variation in the stress test results to strengthen the identification of the effect of regulation on bank similarity. For a tight identification, all specifications include quarter fixed effects as well as bank fixed effects. Hence, our analysis compares the changes in portfolio similarity in response to a capital shortfall for the same bank, while netting out any common time variation to account for secular trends over the sample period. The regression results indicate that banks that perform poorly overall in the stress testing do not necessarily adjust their similarity to banks with the lowest capital shortfalls following a bad DFAST result. Instead, it is only those banks that both perform poorly on the DFAST *and* have C&I losses under stress that contributes substantially to their capital shortfall, as captured by the positive estimate on the interaction term, that adjust their portfolios. Interestingly enough, banks whose C&I losses are substantial, but perform satisfactorily on the stress tests, do not adjust their portfolios in a way to look more similar to other banks. In column (3), we include growth in net income because poor stress test results may be correlated with a bank's diminishing profitability, in which case a bank's lower profitability could drive its increasing portfolio similarity. Indeed, we find that banks with low income growth adjust their portfolios more. However, our main results are robust to including income growth. The overall results for portfolio, region, and industry are similar.

Similarly, Table 17 shows the results for the adjustments in banks' CRE portfolios along the ratings dimension as well. The results for census division, LTV ratio, caprates, maturity, and property type are presented in Table 18. Contrary to the C&I portfolio, banks do not seem to adjust their CRE portfolios in the direction of the best banks according to their DFAST results. The higher cost of rebalancing CRE portfolios and the smaller materiality of the CRE exposures relative to the rest of the bank's loan portfolio may be driving the lack of statistical significance in terms of banks adjusting their CRE portfolios in order to mimic better-faring banks and improve stressed capital ratios.

5 Concentrations

The evidence presented so far indicates that the portfolios of DFAST banks have become more similar since 2012. Are these portfolios more similar because all banks load on few similar exposures (concentration)? Or is it the case that these banks are more similarly diversified? Loan portfolio concentrations play an important role in microprudential supervision. Everything else equal, a less concentrated bank appears to pose less risk from a microprudential point of view.

The four panels of Figure 11 show the Herfindahl-Hirschmann index (HHI) distribution over time for each of the dimensions considered above: ratings, sectors, regions, and maturity.[13] The overall trend indicates that the portfolios of these large banks are becoming, on average, more diversified, as the HHI is trending down over the sample period. DFAST banks tend to have a more diversified portfolio in terms of ratings, as seen in Figure 11, Panel (a). Industry diversification shows an overall pattern that is similar but less clear, as seen in Figure 11, Panel (b). The same pattern is observed for exposure diversification by region in 11, Panel (c). Consistent with the HHI result, Figure 12 shows the distribution of shares in investment-grade C&I loans. There is a tendency towards a more balanced portfolio between investment grade and sub-investment grade shares.

[13] This index is computed as the sum of squared portfolio shares for each bank in each quarter. The figure reports the time evolution of the cross-sectional distribution of HHI.

We also replicate the concentration analysis for the banking industry's CRE portfolio, based on ratings, census divisions, loan-to-value ratios, caprates, and property types for both construction and income-producing loans. The trends in the HHI are similar to those observed in the C&I portfolio, although we observe a substantial increase in the average concentration along the property-type dimension, for both income-producing and construction loans. For most of the banks in recent years, construction loans have had a tendency to concentrate in multifamily properties.

Finally, we also construct a "systemic" bank by aggregating the loans of all the US banks that participated in the five stress tests from 2011:Q3–2016:Q4. Figures 14 and 15 show that the HHI for the entire system is actually increasing along all dimensions for both C&I and CRE—with the exception of capitalization rates for CRE. The fact that the US banking system as a whole is becoming more concentrated does not necessarily mean that it is becoming riskier. More analysis is needed to determine whether banks are loading on systematic factors not captured by the stress test scenarios or, conversely, if the banking system is concentrating more on lending to safer borrowers.

Thus, a set of more similarly diversified banks does not necessarily result in a safer system as a whole. On the contrary, we can conclude that overall, the banking system has become more concentrated, at least when examining the largest banks in the United States.

6 Conclusion

Combining the evidence on similarity and concentration for the largest banks operating in the United States, we conclude that individual bank portfolios have become more similar and less concentrated, or *similarly diversified*, while the US banking system as a whole has become more concentrated. We also have shown evidence indicating that this behavior could be triggered by a reaction to the severely adverse scenarios considered in stress testing. From a classic microprudential view point, a set of individually better capitalized banks with more diversified portfolios is desirable. However, from a macroprudential point of view, an entire system of banks with similar portfolios, and concentrated as a whole, could be a source of concern.

We show that US banks, after stress testing was implemented in 2011:Q3, adjusted their portfolios toward more common types of risk exposures. These portfolio adjustments are likely a reaction to, and an unintended consequence of, the severely adverse scenarios in the stress testing.

Banks that performed worse in the stress testing converged faster to the C&I portfolios of better-performing banks, which are also more diversified. Banks that do not participate in DFAST and CCAR did not rebalance their portfolios after the introduction of stress testing towards greater similarity with the DFAST banks.

We also motivate this paper with a market-based measure of comovement, the increase in CDS correlations among large banks. Existing evidence on CDS correlations documents an increase in the correlation of default risk among the SIFIs. Our analysis indicates that this increase in comovement is a result of portfolio adjustments, particularly for C&I portfolios rather than for less material CRE portfolios.

The trade-off between portfolio diversification among individual banks and systemic similarities represents the policy compromise between micro and macro prudential regulation. Banks' reaction to stress testing may result in risk build-up along dimensions of systematic risk not captured by the severely adverse scenarios faced by the individual banks. Indeed, individually diversified portfolios that seem well-insulated from shocks in relatively benign times may result in a more sensitive aggregate banking system in periods of realized stress, particularly if the stress test scenarios do not capture all potential systematic risk factors.

Our conclusions imply that the scenario design used for the DFAST should be particularly careful and as comprehensive as possible. While the current methodology has resulted in an extraordinary increase of loss-absorbing capital buffers, it has had the unintended consequence of individual banks' portfolios becoming similarly diversified, while the US banking system as a whole became more systemically concentrated.

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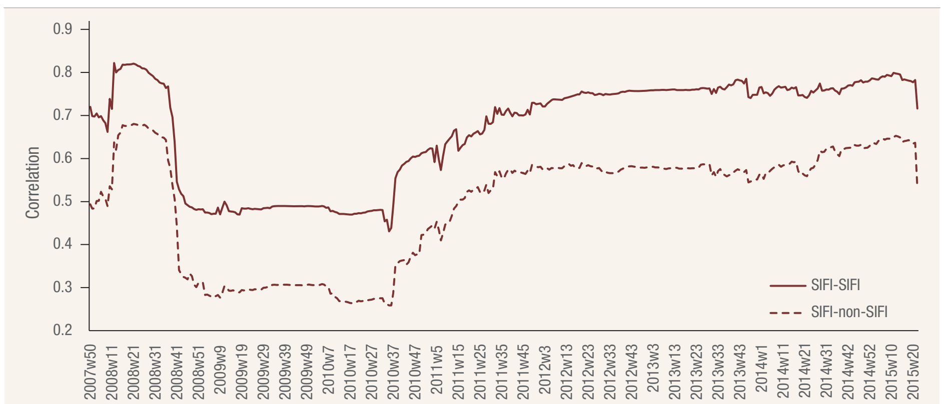
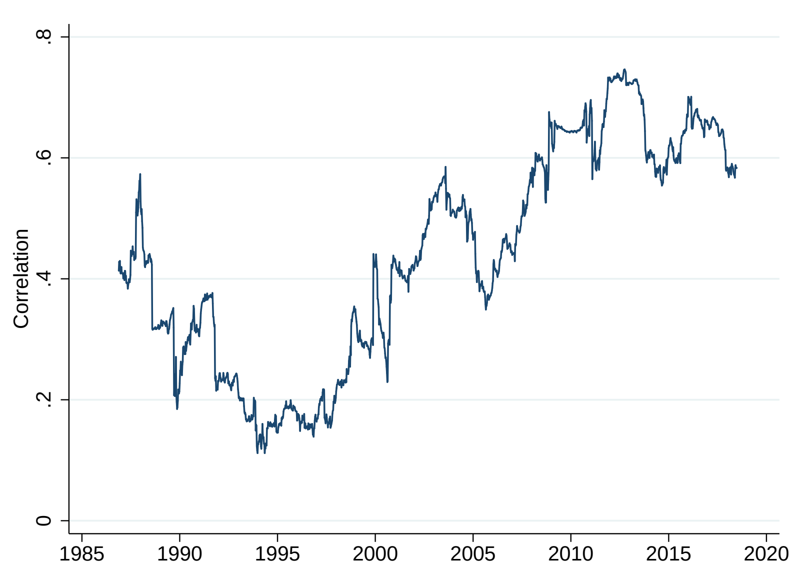
Figures

Figure 1: Average Correlation Between the Changes in CDS Spreads: SIFI-to-SIFI and SIFI-to-NonSIFI



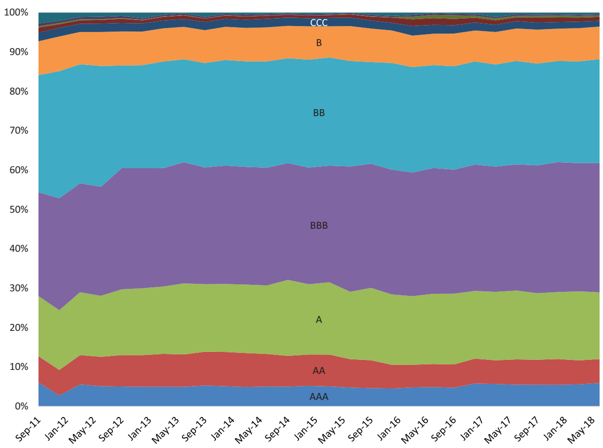
Note: The SIFI firms included in the analysis are 13 global systemically important banks (GSIBs) and systemically important financial institutions (SIFIs) that have been identified by the Financial Stability Oversight Committee (FSOC) over the 2006–2015 period: AIG, Bank of America, Barclays, Citigroup, Deutsche Bank, GE Capital, Goldman Sachs, J.P. Morgan Chase, MetLife, Morgan Stanley, Prudential, UBS, and Wells Fargo. The nonSIFI firms included in this analysis are 256 companies that are cleared by the Intercontinental Exchange (ICE) Clear Credit and for which a continuous record of weekly CDS data over the entire 2006–2015 sample period is available. Source: Calibrating the Single-Counterparty Credit Limit between Systemically Important Financial Institutions, Federal Reserve Board of Governors.

Figure 2: Average Equity Return Correlation Between the Thirteen SIFIs

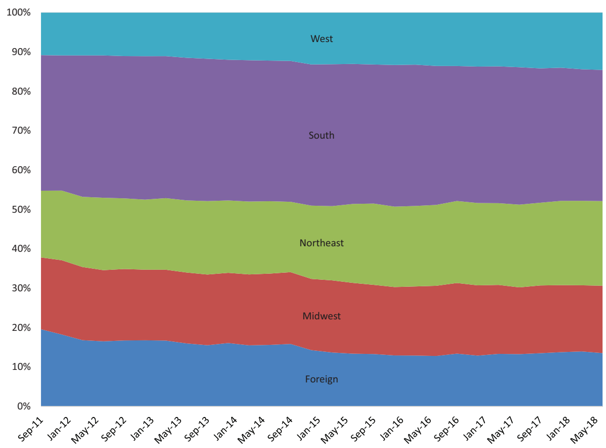


Note: The thirteen firms included in the analysis are: AIG, Bank of America, Barclays, Citigroup, Deutsche Bank, GE Capital, Goldman Sachs, J.P. Morgan Chase, MetLife, Morgan Stanley, Prudential, UBS, and Wells Fargo.
Source: CRSP and authors' calculations.

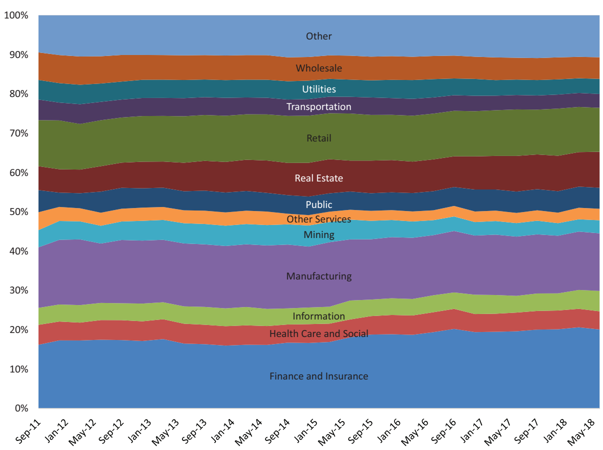
Figure 3: Evolution of Commercial and Industrial Loan Portfolio Shares over the Sample Period 2011:Q4–2018:Q2



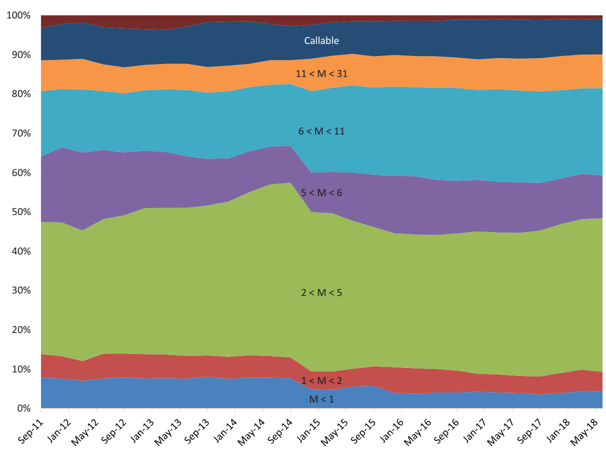
(a) Rating



(c) Region



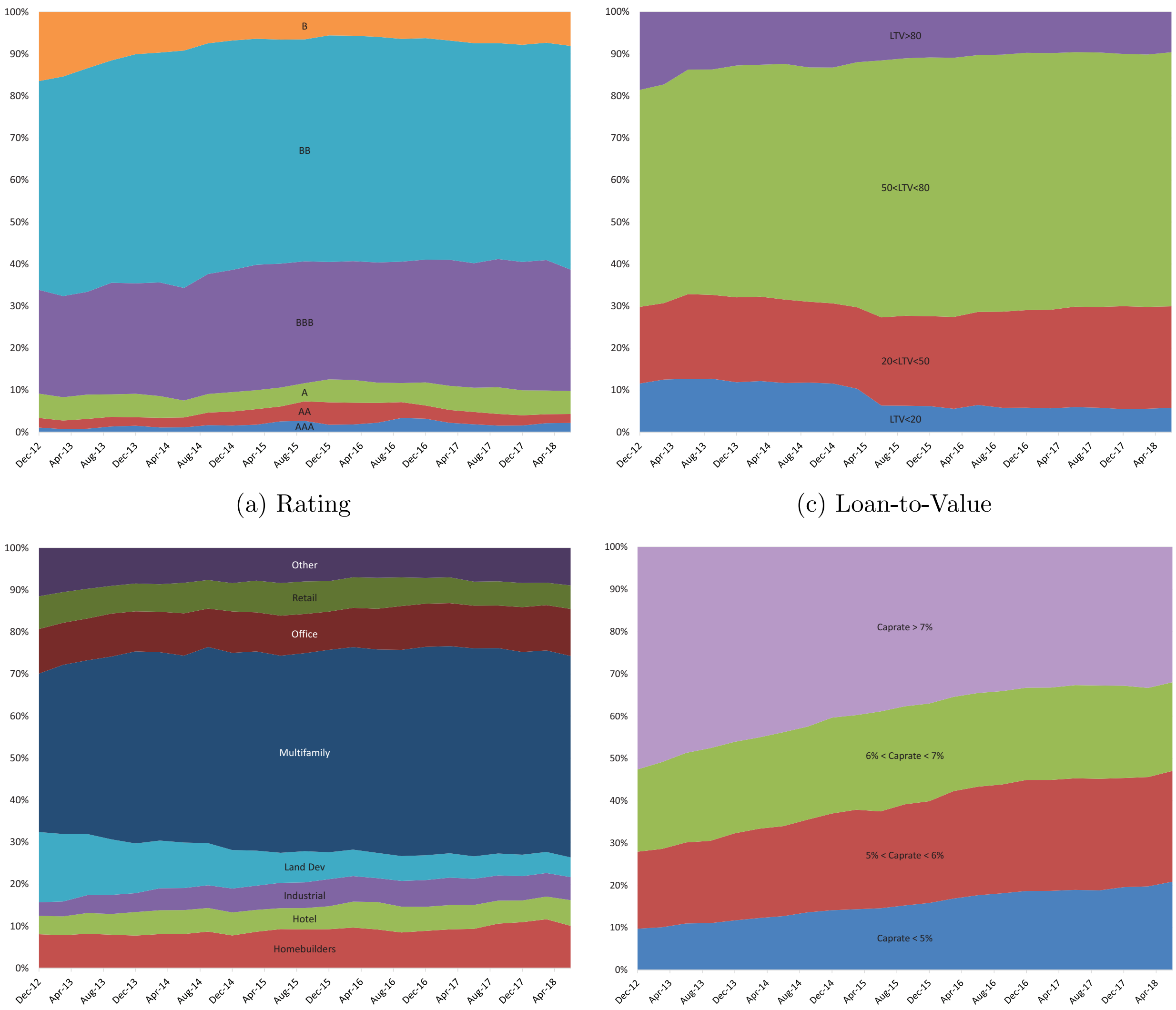
(b) Industry



(d) Maturity

Source: FR Y-14Q, Schedule H.1.

Figure 4: Evolution of Commercial Real Estate Loan Portfolio Shares over the Sample Period 2011:Q4–2018:Q2



(a) Rating

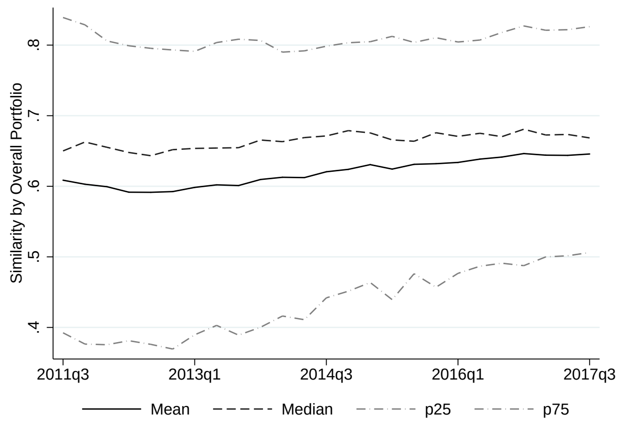
(c) Loan-to-Value

(b) Construction, by type

(d) Caprate

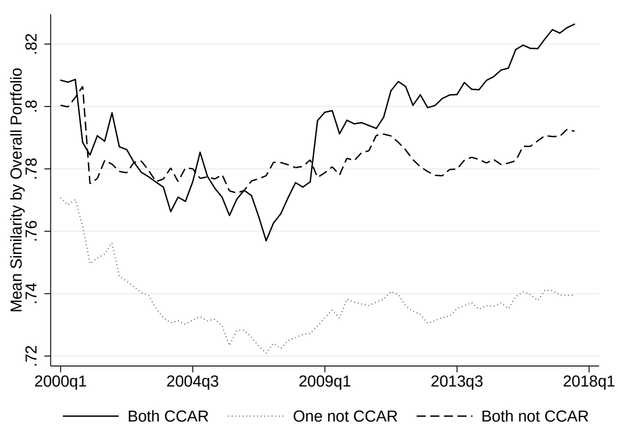
Source: FR Y-14Q, Schedule H.2.

Figure 5: Similarity in Overall Portfolios



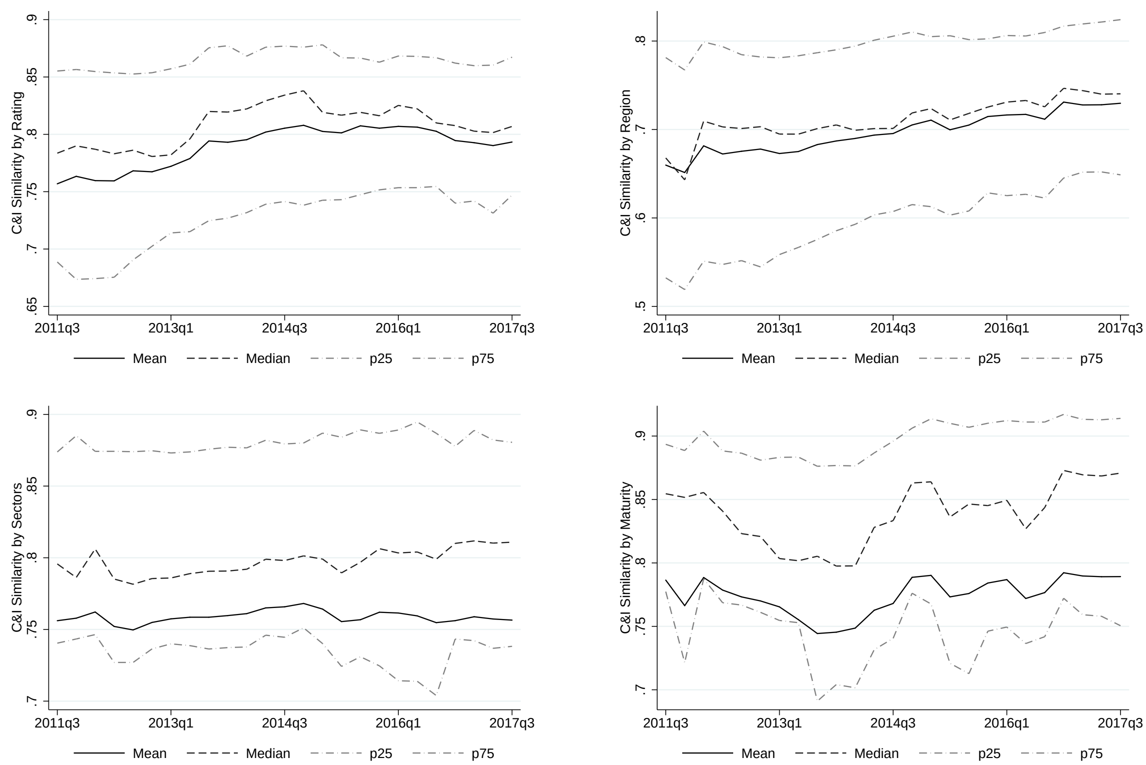
Note: The sample includes the 19 banks subject to DFAST from 2011Q3–2016Q4.
Source: FR Y-9C and authors' calculations

Figure 6: Mean of Overall Similarity Measure for CCAR vs. non-CCAR Bank Pairs



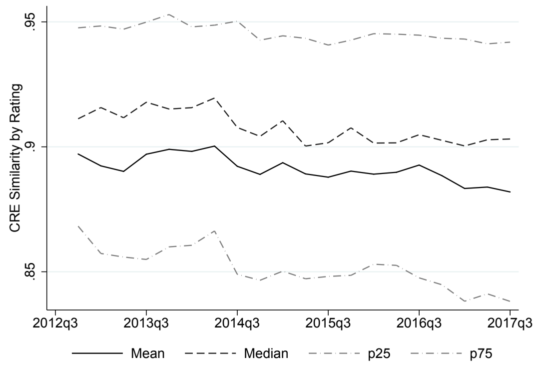
Note: The extended sample covers the period from 2000:Q1–2018:Q1.
Source: FR Y-9C and authors' calculations

Figure 7: Similarity of Commercial and Industrial Loan Portfolios

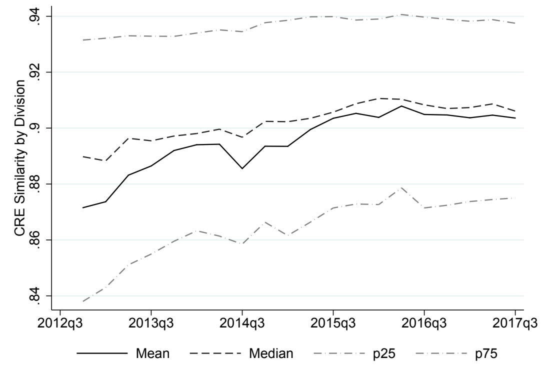


Note: The sample includes the 19 banks subject to DFAST from 2011Q3–2016Q4. The upper left panel shows the evolution of the similarity distribution by rating. The upper right panel shows the similarity by Census region. The lower left and lower right panels show the similarity distributions by sectors and maturity, respectively.
Source: FR Y-14Q and authors' calculations

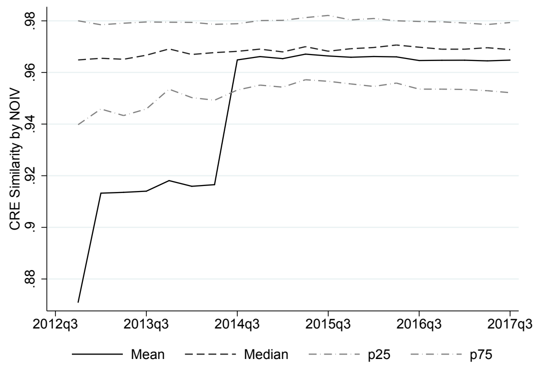
Figure 8: Similarity of Commercial Real Estate Loan Portfolios



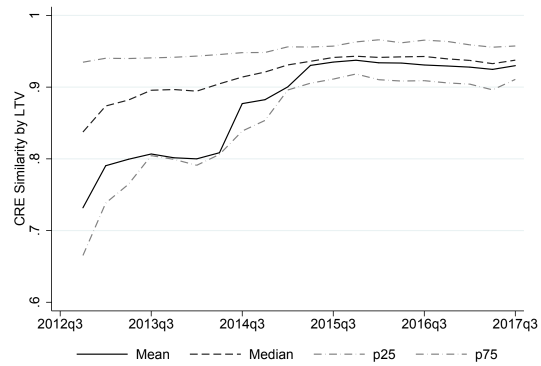
(a) Ratings



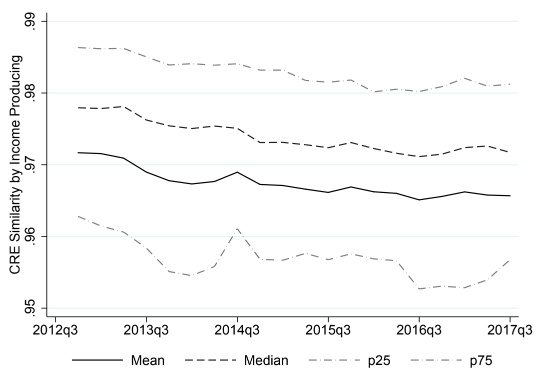
(b) Regions



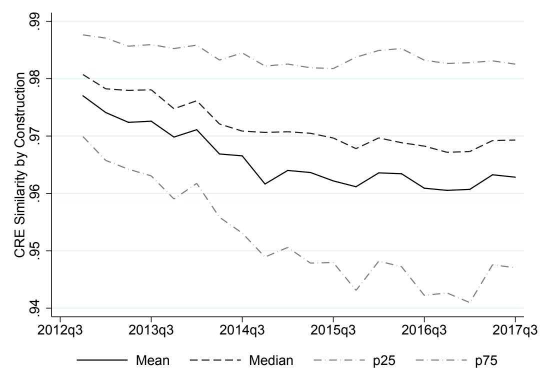
(c) Maturity



(d) LTV



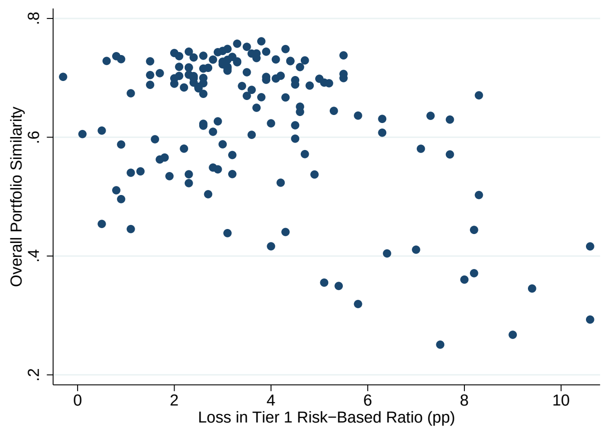
(e) IP - Property Type



(f) CLD - Property Type

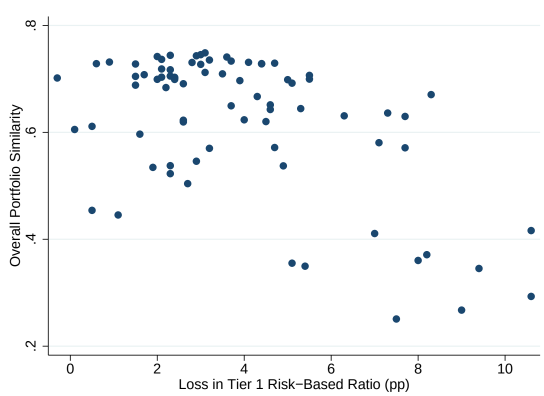
Note: The sample includes the 19 banks subject to DFAST from 2011:Q3–2016:Q4. Panel (a) shows the evolution of the similarity distribution according to rating. Panel (b) shows the similarity according to Census region. Panels (c) and (d) show the similarity evolutions according to maturity and loan-to-value ratios, respectively. Panels (e) and (f) show the similarity evolutions according to property type for both income producing loans (e), and construction and land development loans (f).
Source: FR Y-14Q and authors' calculations

Figure 9: Similarity of the Overall Portfolio and Tier 1 Risk-Based Capital Ratio Shortfall

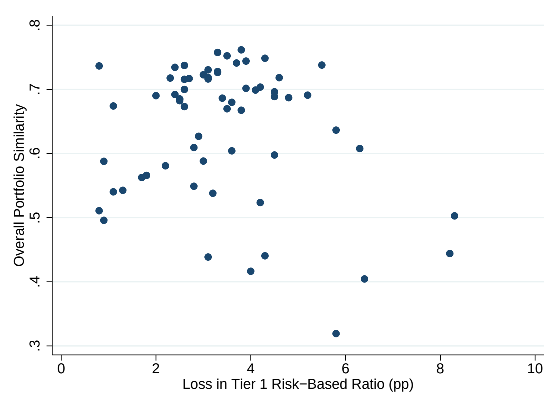


Note: The sample includes all banks participating in the five stress tests from 2011:Q3–2016:Q4. Source: FR Y-9C data, disclosures of annual DFAST results, and authors' calculations.

Figure 10: Similarity of the Overall Portfolio and Tier 1 Risk-Based Capital Ratio Shortfalll (Sample Split)



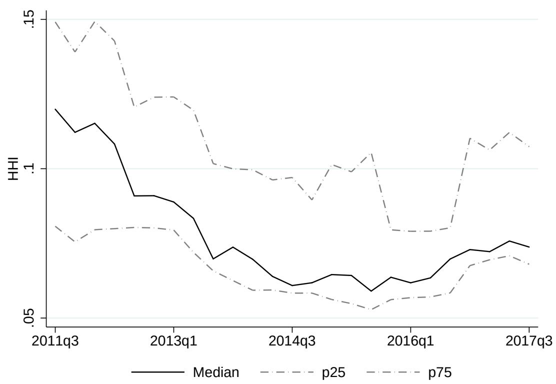
(a) Before 2014:Q4



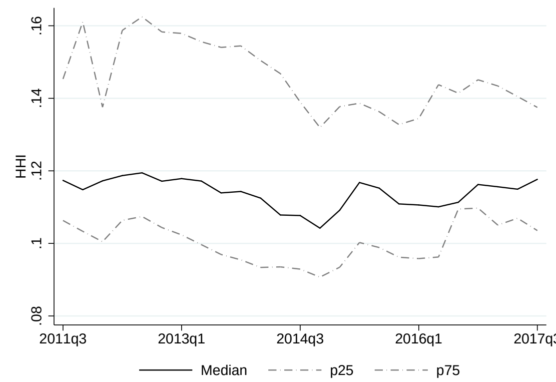
(b) After 2014:Q4

Note: The full sample includes all banks participating in the five stress tests from 2011:Q3–2016:Q4. Source: FR Y-9C reports and disclosures of annual DFAST results.

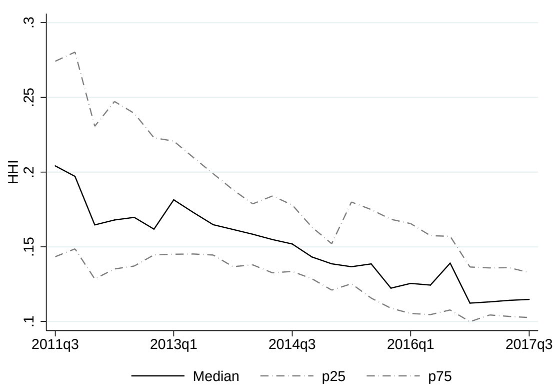
Figure 11: Distribution of Bank-Level Herfindahl Index Measuring Commercial and Industrial Loan Portfolio Concentration by Rating, Maturity, Region, and Sector



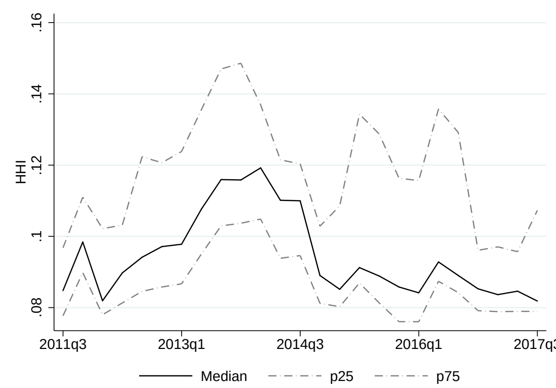
(a) Ratings



(b) Sectors



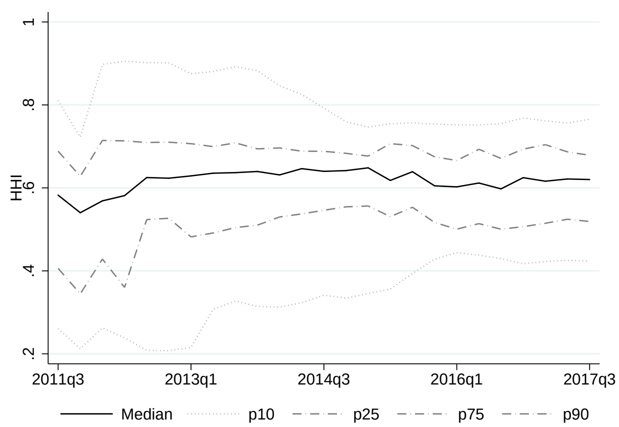
(c) Regions



(d) Maturities

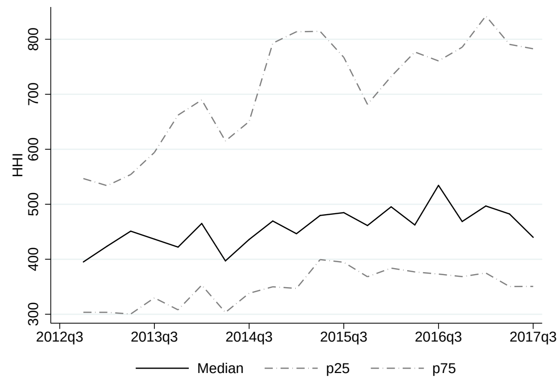
Note: The sample includes all banks participating in the five stress tests from 2011:Q3–2016:Q4. Source: FR Y-14Q and authors' calculations.

Figure 12: Distribution of Bank-Level Shares of Commercial and Industrial Loan Exposures with Investment Grade Rating

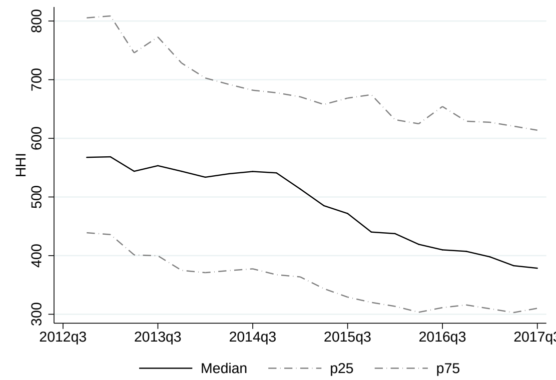


Note: The sample includes all banks participating in the five stress tests from 2011:Q3–2016:Q4.
Source: FR Y-14Q and authors' calculations.

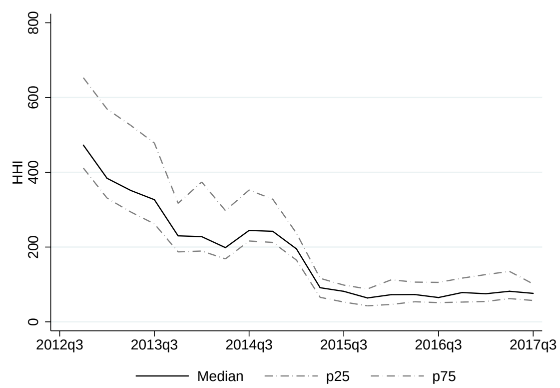
Figure 13: Distribution of Bank-Level Herfindahl Index Measuring Commercial Real Estate Loan Portfolio Concentration by Rating, Census Division, Loan-to-Value Ratio, Caprate, Construction Property Type, and Income-Producing Property Type



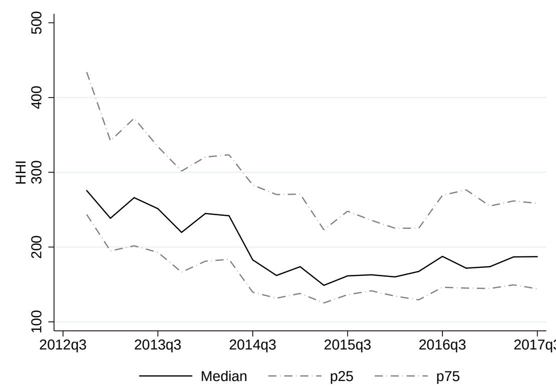
(a) Ratings



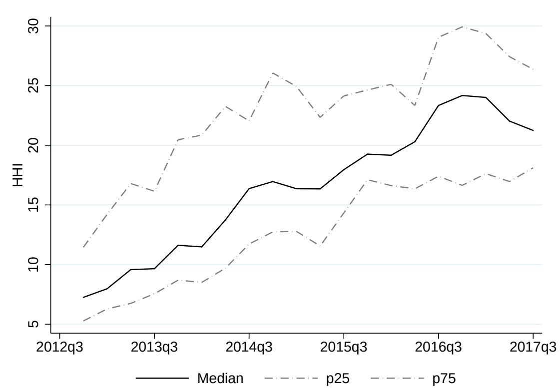
(b) Census Division



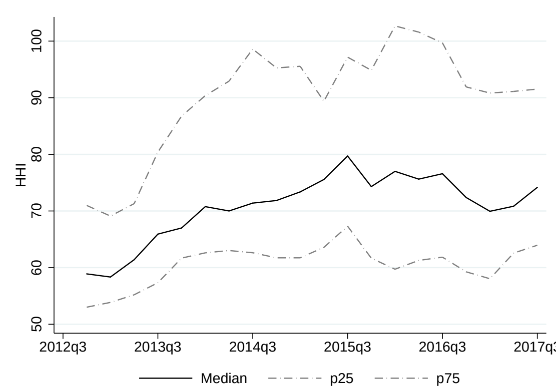
(c) LTV



(d) Caprate



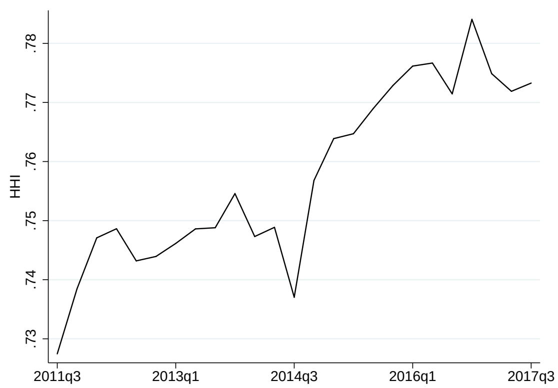
(e) Construction Type



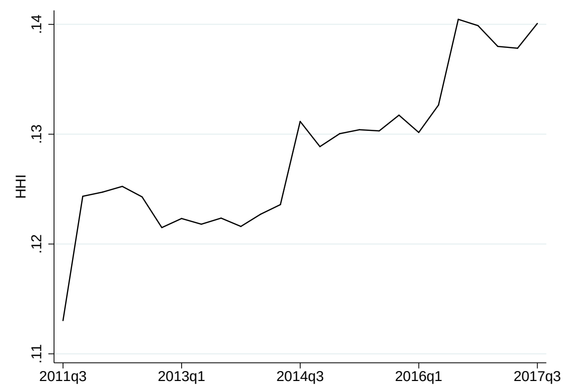
(f) Income Producing Type

Note: The sample includes all banks participating in the five stress tests from 2011:Q3–2016:Q4 who hold material CRE exposures on their balance sheet.
Source: FR Y-14Q and authors' calculations.

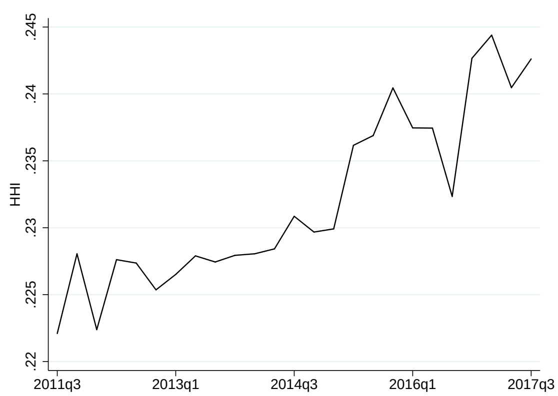
Figure 14: Distribution of Banking System Herfindahl Index Measuring Commercial and Industrial Loan Portfolio Concentration by Rating, Maturity, U.S. Region, and Sector



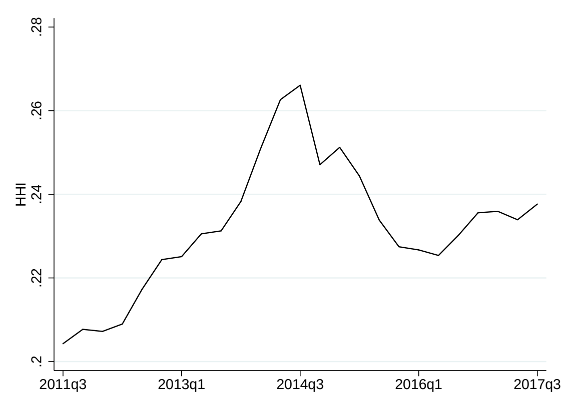
(a) Regions



(b) Sectors



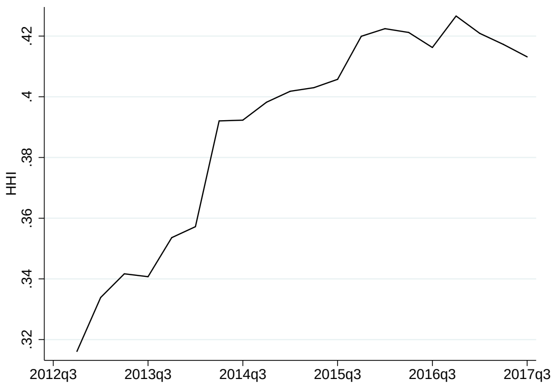
(c) Ratings



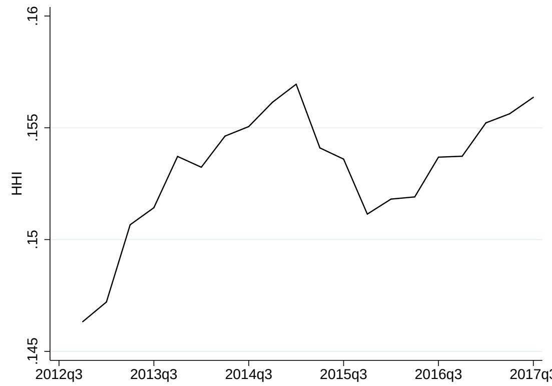
(d) Maturities

Note: The sample includes all banks participating in the five stress tests from 2011:Q3–2016:Q4.
Source: FR Y-14Q and authors' calculations.

Figure 15: Distribution of Banking System Herfindahl Index Measuring Commercial Real Estate Loan Portfolio Concentration by Rating, Census Division, Loan-to-Value Ratio, Caprate, Construction Property Type, and Income-Producing Property Type



(a) Ratings



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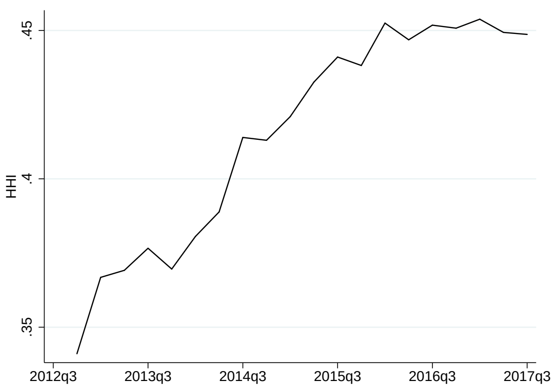
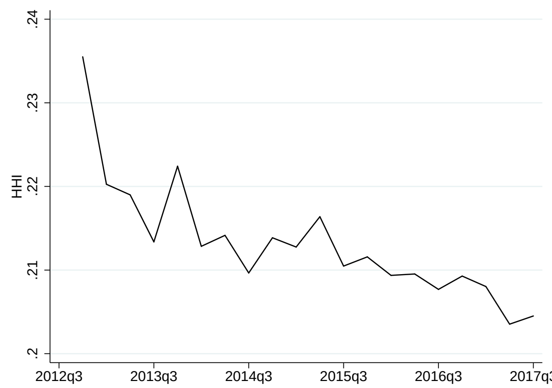
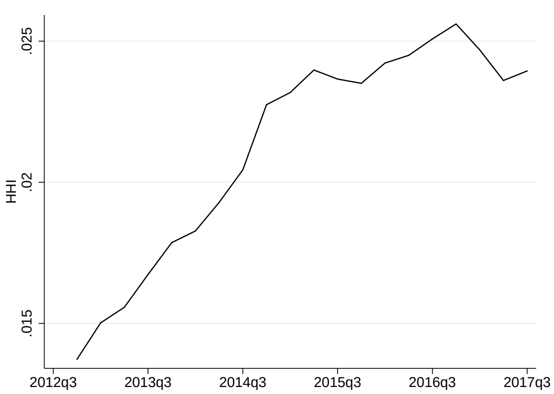


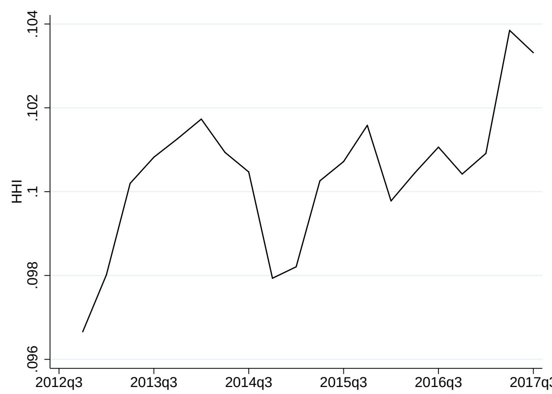
(c) LTV



(d) Caprate



(e) Construction Type



(f) Income Producing Type

Note: The measure is computed on an aggregate bank that includes all banks participating in the five stress tests from 2011:Q3–2016:Q4 who hold material CRE exposures on their balance sheet. Source: FR Y-14Q and authors' calculations.

Tables

Table 1: Summary Statistics of the Overall Portfolio Composition

	Portfolio Shares (% of Total Assets)					
	mean	p10	p25	p50	p75	p90
Cash	8.97	2.09	3.08	6.06	9.91	23.35
Securities	18.57	8.65	13.92	18.72	21.06	28.24
Fed Funds/RRP	6.80	0.00	0.02	0.63	10.75	29.14
Trading Assets	7.67	0.24	0.68	2.01	13.00	29.61
CRE Loans	6.46	0.31	1.78	7.30	9.92	13.22
C&I Loans	12.29	2.05	6.05	10.81	19.02	24.15
Retail Loans	20.51	0.75	13.83	22.27	28.42	41.05
N (Bank-Quarters)	425					

Note: The sample includes the 19 banks subject to DFAST from 2011:Q3–2016:Q4.
Source: FR Y-9C.

Table 2: Summary Statistics of the Commercial and Industrial Loan Portfolio Composition by Rating

	Portfolio Shares (% of Total C&I Loans)					
	mean	p10	p25	p50	p75	p90
Rating A	17.71	1.67	11.76	19.38	24.40	28.25
Rating AA	6.18	0.00	0.67	6.26	9.84	13.18
Rating AAA	3.47	0.00	0.00	1.17	2.61	9.78
Rating B	8.76	2.45	4.71	8.44	11.09	15.49
Rating BB	28.74	12.36	18.71	26.34	39.92	49.05
Rating BBB	31.90	19.61	27.50	32.97	37.06	41.84
Rating C	0.03	0.00	0.00	0.00	0.00	0.00
Rating CC	0.25	0.00	0.00	0.00	0.00	1.08
Rating CCC	2.09	0.24	1.19	1.63	2.83	4.24
Rating D	0.32	0.00	0.01	0.13	0.44	1.03
Rating NR	0.10	0.00	0.00	0.00	0.00	0.05
N (Bank-Quarters)	425					

Note: The sample includes the 19 banks subject to DFAST from 2011:Q3–2016:Q4.
Source: FR Y-14Q.

Table 3: Summary Statistics of the Commercial and Industrial Loan Portfolio Composition by Region

	Portfolio Shares (% of Total C&I Loans)					
	mean	p10	p25	p50	p75	p90
Foreign	14.36	0.22	2.00	5.95	26.73	32.23
Midwest	17.92	7.63	10.37	14.02	26.74	32.57
Northeast	19.15	8.90	14.04	19.60	23.23	29.06
South	35.50	15.95	22.09	28.75	45.80	72.49
West	12.39	5.88	7.36	10.71	15.22	24.77
N (Bank-Quarters)	425					

Note: The sample includes the 19 banks subject to DFAST from 2011:Q3–2016:Q4.
Source: FR Y-14Q.

Table 4: Summary Statistics of the Commercial and Industrial Loan Portfolio Composition by Industry

	Portfolio Shares (% of Total C&I Loans)					
	mean	p10	p25	p50	p75	p90
Financial & Insurance	17.94	6.08	10.95	16.28	24.46	33.80
Health Care & Social	4.18	0.00	1.25	4.18	6.72	7.86
Information	3.64	0.00	0.95	3.43	5.35	8.22
Manufacturing	15.73	3.19	12.49	17.09	21.54	24.26
Mining & Oil	4.68	0.64	2.74	4.36	5.81	8.15
Other Services	3.07	0.68	1.17	1.73	2.98	8.60
Public Administration	4.72	0.09	1.76	3.36	4.91	6.38
Real Estate	7.67	0.28	3.49	7.17	10.95	16.75
Retail Trade	12.00	2.64	4.95	7.04	8.74	14.62
Transportation	4.27	0.37	3.49	4.14	5.04	6.28
Utilities	4.53	0.59	3.00	4.01	5.20	9.49
Wholesale Trade	6.30	0.56	4.11	6.82	9.09	10.06
Other Sectors	9.83	0.00	0.00	12.41	15.57	16.60
N (Bank-Quarters)	425					

Note: The sample includes the 19 banks subject to DFAST from 2011:Q3–2016:Q4. Source: FR Y-14Q.

Table 5: Summary Statistics of the Commercial and Industrial Loan Portfolio Composition by Maturity

	Portfolio Shares (% of Total C&I Loans)					
	mean	p10	p25	p50	p75	p90
Maturity 0–1 Year	6.20	0.66	2.83	5.39	7.84	10.92
Maturity 1–2 Year	5.56	1.10	3.31	5.58	7.34	8.81
Maturity 2–5 Year	37.83	27.69	32.35	36.72	44.10	55.46
Maturity 5–6 Year	13.77	7.38	10.71	13.67	16.61	19.25
Maturity 6–11 Year	19.57	7.25	10.65	19.79	27.28	32.55
Maturity 11–31 Year	7.50	1.77	3.81	8.17	10.60	12.41
Maturity Callable	7.37	0.00	0.08	1.05	5.08	10.64
Maturity Unkown	1.97	0.01	0.14	0.43	1.39	6.68
N (Bank-Quarters)	425					

Note: The sample includes the 19 banks subject to DFAST from 2011:Q3–2016:Q4. Source: FR Y-14Q.

Table 6: Summary Statistics of the Commercial Real Estate Loan Portfolio Composition by Internal Rating

	Portfolio Shares (% of Total CRE Loans)					
	mean	p10	p25	p50	p75	p90
AAA	1.63	0.02	0.05	1.38	3.03	4.15
AA	2.98	0.01	0.06	0.28	3.43	12.08
A	5.14	0.07	0.31	1.87	7.46	15.51
BBB	28.33	8.99	14.44	26.56	38.85	50.42
BB	53.69	28.49	39.90	56.43	67.42	78.28
B	8.55	1.44	3.53	6.74	11.34	17.09
CCC	2.12	0.32	0.66	1.23	2.34	5.00
CC	1.40	0.04	0.43	0.88	1.72	3.37
C	0.52	0.04	0.11	0.20	0.39	1.31
D	1.08	0.02	0.11	0.40	1.53	3.14
N	480					

Note: The sample includes the 19 banks subject to DFAST from 2011:Q3–2016:Q4.
Source: FR Y-14Q.

Table 7: Summary Statistics of the Commercial Real Estate Loan Portfolio Composition by Census Division

	Portfolio Shares (% of Total CRE Loans)					
	mean	p10	p25	p50	p75	p90
New England	3.63	0.27	0.85	1.81	3.88	8.00
Mid Atlantic	18.08	0.66	2.67	10.88	16.26	60.86
East North Central	11.72	1.01	2.54	5.46	11.23	35.21
West North Central	2.35	0.19	0.56	1.34	2.35	3.70
South Atlantic	20.80	4.10	9.18	17.24	25.48	42.42
East South Central	2.67	0.11	0.29	1.36	4.07	6.59
West South Central	9.08	0.87	2.93	6.46	10.38	24.84
Mountain	6.36	0.85	2.04	3.68	8.18	13.36
Pacific	18.76	1.31	3.70	15.09	28.34	43.38
US Territory	0.47	0.01	0.05	0.31	0.53	1.00
US Undefined	4.77	0.12	0.35	2.12	8.00	13.98
Foreign	3.70	0.09	0.27	1.11	3.63	9.02
N	480					

Note: The sample includes the 19 banks subject to DFAST from 2011:Q3–2016:Q4.
Source: FR Y-14Q.

Table 8: Summary Statistics of the Commercial Real Estate Loan Portfolio Composition by Maturity

	Portfolio Shares (% of Total CRE Loans)					
	mean	p10	p25	p50	p75	p90
$M > 2$	10.53	3.07	5.19	8.58	13.67	21.35
$2 \leq M < 5$	48.75	30.42	40.90	49.48	58.86	65.14
$5 \leq M < 10$	24.13	9.22	16.48	21.90	31.15	43.03
$M \geq 10$	15.25	4.47	6.60	11.72	17.97	29.43
Call	1.45	0.01	0.05	0.38	1.32	4.91
Unknown	0.85	0.04	0.09	0.37	0.91	2.21
N	480					

Note: The sample includes the 19 banks subject to DFAST from 2011:Q3–2016:Q4.
Source: FR Y-14Q.

Table 9: Summary Statistics of the Commercial Real Estate Loan Portfolio Composition by Loan-to-Value Ratio

	Portfolio Shares (% of Total CRE Loans)					
	mean	p10	p25	p50	p75	p90
$LVT < 20$	8.50	2.32	3.24	4.79	8.27	12.70
$20 \leq LTV < 50$	20.27	13.40	17.22	20.00	23.36	26.88
$50 \leq LTV < 80$	55.94	45.16	50.40	58.06	64.05	69.01
$LTV \geq 80$	11.61	5.24	7.54	10.37	14.26	19.56
n/a	6.55	0.17	0.61	1.48	4.20	16.40
N	480					

Note: The sample includes the 19 banks subject to DFAST from 2011:Q3–2016:Q4.
Source: FR Y-14Q.

Table 10: Summary Statistics of the Commercial Real Estate Loan Portfolio Composition by Net Operating Income Relative to Loan Value Ratio (i.e., Capitalization Rate or "Caprate")

	Portfolio Shares (% of Total CRE Loans)					
	mean	p10	p25	p50	p75	p90
$Caprate < 4\%$	11.19	4.39	7.67	10.31	13.92	17.24
$4\% \leq Caprate < 5pct$	7.26	2.12	3.70	5.81	9.47	13.29
$5\% \leq Caprate < 6\%$	11.36	4.74	6.69	9.77	14.76	19.98
$6\% \leq Caprate < 7\%$	10.86	5.55	7.25	10.07	14.76	16.97
$Caprate \geq 7\%$	20.20	11.06	14.62	18.94	24.90	31.44
n/a	40.19	20.89	28.76	39.29	48.80	60.38
N	480					

Note: The sample includes the 19 banks subject to DFAST from 2011:Q3–2016:Q4.
Source: FR Y-14Q

Table 11: Summary Statistics of the Construction Commercial Real Estate Loan Portfolio Composition by Property Type

	Portfolio Shares (% of Total CRE Loans)					
	mean	p10	p25	p50	p75	p90
Condo Co-Op	1.49	0.10	0.36	0.86	2.01	3.42
Homebuilders	2.89	0.06	0.20	1.79	4.90	6.88
Hotel	1.82	0.26	0.79	1.47	2.40	4.02
Industrial	1.82	0.21	0.90	1.38	2.29	3.94
Land Dev.	2.90	0.46	0.90	2.20	4.47	6.36
Mixed	1.15	0.16	0.36	0.82	1.40	2.69
Multifamily	15.40	7.02	9.97	13.12	20.59	27.15
Office	3.25	1.16	1.73	2.66	4.07	6.36
Other	2.70	0.39	1.06	2.51	3.97	5.38
Retail	2.28	0.56	1.24	2.24	3.07	3.92
N	480					

Note: The sample includes the 19 banks subject to DFAST from 2011:Q3–2016:Q4.
Source: FR Y-14Q.

Table 12: Summary Statistics of the Income Producing Commercial Real Estate Loan Portfolio Composition by Property Type

	Portfolio Shares (% of Total CRE Loans)					
	mean	p10	p25	p50	p75	p90
Condo Co-Op	0.64	0.01	0.03	0.14	0.40	0.94
Homebuilders	0.29	0.01	0.01	0.09	0.27	0.53
Hotel	5.12	0.81	1.94	4.67	7.79	9.32
Industrial	5.25	2.19	3.19	4.91	6.96	8.48
Land Dev.	0.38	0.02	0.06	0.19	0.43	0.88
Mixed	3.11	0.36	0.63	2.40	4.26	6.50
Multifamily	18.99	8.33	10.27	13.69	22.89	38.44
Office	16.78	8.98	11.90	15.86	21.22	24.83
Other	4.90	0.85	2.05	3.32	6.26	10.49
Retail	11.52	5.93	8.47	11.40	13.46	17.54
N	480					

Note: The sample includes the 19 banks subject to DFAST from 2011:Q3–2016:Q4.
Source: FR Y-14Q.

Table 13: Stress Test Results and Similarity in Overall Portfolio

	Dep. Var: Change in Overall Similarity			
	(1)	(2)	(3)	(4)
Tier 1 Loss	0.003***			
	(3.10)			
High Tier 1 Loss (p50)		0.015**		
		(2.66)		
High Tier 1 Loss (p75)			0.017***	
			(2.83)	
High Tier 1 Loss (p90)				0.025***
				(3.01)
Observations	108	108	108	108
R-squared	0.297	0.301	0.306	0.313
Quarter FE	Yes	Yes	Yes	Yes

Note: The table reports estimates of changes in portfolio similarity as a function of four-quarter lagged capital shortfall in DFAST. The sample includes all banks participating in the five stress tests from 2011:Q3–2016:Q4. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Stress Test Results and Similarity in Overall Portfolio Relative to Different Benchmark Banks

Defined as Capital Shortfall	Dep. Var: Change in Overall Similarity to Good Banks $\leq$ p50 (1)	Better Banks $\leq$ p25 (2)	Best Banks $\leq$ p10 (3)
High Tier 1 Loss (p90)	0.017	0.028**	0.043*
	(1.25)	(2.60)	(1.81)
Observations	108	108	108
R-squared	0.020	0.028	0.217
Quarter FE	Yes	Yes	Yes

Note: The sample includes all banks participating in the five stress tests from 2011:Q3–2016:Q4. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 15: Stress Test Results and Commercial and Industrial Loan Portfolio Similarity (by Ratings Distribution)

	Dep. Var: Change in C&I Portfolio Similarity to Best Banks		
	Rating (1)	Rating (2)	Rating (3)
High C&I Loan Loss	-0.027	-0.129**	-0.078*
	(-0.63)	(-2.17)	(-1.99)
High Tier 1 Loss	-0.013	-0.037	-0.031
	(-0.74)	(-1.42)	(-1.31)
High C&I Loan Loss * High Tier 1 Loss		0.176**	0.120**
		(2.67)	(2.44)
Net Income Growth			-0.013***
			(-3.60)
Observations	107	107	107
R-squared	0.533	0.567	0.669
Quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes

Note: The table reports estimates of changes in portfolio similarity as a function of four-quarter lagged capital shortfall in DFAST and four-quarter lagged stressed C&I losses. Similarity is measured with respect to the best banks in each stress test. The sample includes all banks participating in the five stress tests from 2011:Q3–2016:Q4. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 16: Stress Test Results and Commercial and Industrial Loan Portfolio Similarity (by Regional, Sectoral, and Maturity Distribution)

	Dep. Var: Change in C&I Portfolio Similarity to Best Banks		
	Region	Sector	Maturity
	(1)	(2)	(3)
High C&I Loan Loss	-0.092**	-0.013	-0.005
	(-2.11)	(-0.40)	(-0.07)
High Tier 1 Loss	-0.061	0.013	-0.006
	(-1.08)	(0.50)	(-0.32)
High C&I Loan Loss * High Tier 1 Loss	0.168*	0.069**	0.048
	(1.90)	(2.31)	(0.60)
Net Income Growth	0.010	-0.006	-0.006
	(0.54)	(-0.89)	(-0.97)
Observations	107	107	107
R-squared	0.269	0.326	0.606
Quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes

Note: : The table reports estimates of changes in portfolio similarity as a function of four-quarter lagged capital shortfall in DFAST and four-quarter lagged stressed C&I losses. Similarity is measured with respect to best banks in each stress test. The sample includes all banks participating in the five stress tests from 2011:Q3–2016:Q4. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 17: Stress Test Results and Commercial Real Estate Loan Loan Portfolio Similarity (by Ratings Distribution)

	Dep. Var: Change in CRE Portfolio Similarity to Best Banks		
	Rating	Rating	Rating
	(1)	(2)	(3)
High CRE Losses (p90)	0.003	0.003	-0.019
	(0.45)	(0.35)	(-0.73)
High CRE Losses (p90)*High Tier 1 Loss (p90)		0.000	-0.013
		(0.02)	(-0.45)
High Tier 1 Loss (p90)	0.005	0.005	0.007
	(0.54)	(0.45)	(0.27)
Observations	81	81	78
R-squared	0.031	0.031	0.242
Quarter FE	Yes	Yes	Yes
Bank FE			Yes

Note: The table reports estimates of changes in portfolio similarity as a function of four-quarter lagged capital shortfall in DFAST and four-quarter lagged stressed CRE losses. Similarity is measured with respect to the best banks in each stress test. The sample includes all banks participating in the five stress tests from 2011:Q3–2016:Q4. Robust t-statistics in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust t-statistics in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 18: Stress Test Results and Commercial Real Estate Loan Loan Portfolio Similarity by LTV, Census Division, Caprate, Maturity, and Property Type (for Construction and Income Producing Loans, Respectively)

	Dep. Variable: Change in CRE Portfolio Similarity to Best Banks					
	LTV	Division	Caprate	Maturity	Constr. Type	IP Type
	(1)	(2)	(3)	(4)	(5)	(6)
High C&I Losses (p90)	0.200	-0.004	0.149	0.008	-0.002	-0.002***
	(1.70)	(-0.64)	(1.63)	(1.32)	(-0.58)	(-11.87)
High C&I Losses (p90)×	0.083	0.006	0.005	-0.010	0.008	0.005
High Tier 1 Loss (p90)	(1.58)	(1.07)	(0.23)	(-0.74)	(0.98)	(0.95)
High Tier 1 Loss (p90)	-0.080*	0.001	-0.002	0.000	0.000	-0.001
	(-1.73)	(0.12)	(-0.12)	(0.02)	(0.08)	(-0.24)
Observations	78	78	78	78	78	78
R-squared	0.521	0.607	0.472	0.556	0.479	0.778
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports estimates of changes in portfolio similarity as a function of four-quarter lagged capital shortfall in DFAST and four-quarter lagged stressed CRE losses. Similarity is measured with respect to the best banks in each stress test. The sample includes all banks participating in the five stress tests from 2011:Q3–2016:Q4. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1.