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The Impact of Regulatory Stress Tests on Bank Lending and Its Macroeconomic Consequences

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Abstract:
We use an expansive regulatory loan-level data set to analyze how the portfolios of the largest US banks have changed in response to the Dodd-Frank Act Stress Test (DFAST) requirements. We find that the portfolios of the largest banks, which are subject to stress-testing, have become more similar to each other since DFAST 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 composition. However, we also find that all the large banks diversified in a similar way, creating a more concentrated systemic portfolio in the aggregate. Finally, we analyze the effects of stress-testing and portfolio sensitivity to macroeconomic scenarios on credit supply. Our findings indicate that banks that experience worse results in the stress tests cut lending relative to their peers and specifically in loans that are most sensitive to the stress-test scenarios. At the borrower level, firms that rely more on credit from banks with poor stress-test results are not able to substitute lost funding and therefore face a larger reduction in credit and cut back investment. These results highlight a macroprudential effect of stress-testing: Credit growth is curtailed during a credit expansion in those banks holding a portfolio that is more sensitive to stressful scenarios. Hence, these banks are expected to be in a more resilient position at the onset of a downturn.

JEL Classifications: G20, G21, G28
Keywords: banking, regulation, stress testing, portfolio similarity, credit supply

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1 Introduction

One of the major US public policy responses to the 2008–2009 financial crisis was the tightening of banking and financial market regulation in order to build a more resilient financial system. In particular, the 2010 Dodd-Frank Act introduced mandatory stress-testing to foster sufficient capitalization of large bank holding companies (BHCs) and thus enhance their loss absorption capacity in an economic downturn (see Tarullo 2019). This regulation effectively requires that BHCs—which, for simplicity, we refer to as "banks" in the remainder of this paper—maintain an equity ratio above the regulatory minimum requirement, not only on a current basis, but also under the hypothetical stress scenarios imposed by the regulator. More specifically, the stress-testing exercise conducted by the Federal Reserve uses macroeconomic scenarios to predict a bank's portfolio return under stress and implied equity values. Thus, the stress-testing exercise reveals how well banks are able to withstand a severe economic downturn and maintain the credit supply to the economy given their current equity position and portfolio allocation.

A key question in this context involves the impact stress-testing has on bank behavior and its broader macroeconomic consequences. In this paper, we shed some light on this question by studying the effects of stress-testing on banks' portfolio allocation, including the effects on financial stability risk, credit supply, and borrowers' investment. We analyze these issues in a stylized model of bank portfolio choice subject to stress-testing and show that stress-testing effectively changes the marginal return structure of banks' assets and thereby affects the optimal asset allocation. In our empirical tests, we use the expansive supervisory loan-level data collected during the Federal Reserve's stress-testing exercise, which allows us to provide a detailed look at the effects of stress-testing on banks' portfolio allocation. Our empirical findings support the model's predictions of portfolio convergence by banks in response to stress-testing driven by credit supply shifts away from loans that have high sensitivity to stress-test scenarios.

As part of the mandated Dodd-Frank Act Stress Test (DFAST), the regulatory agencies collect detailed portfolio information in the supervisory FR Y-14Q data. Specifically, 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 borrower information, on a regular basis to the regulator.[1] In our

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

analysis, we exploit the information in the quarterly reports on banks' wholesale lending, which includes detailed information on nearly all individual commercial and industrial loans held by these banks (Schedule H.1).[2] These unique data allow us to construct similarity measures of banks from individual loans based on portfolio shares along several dimensions: rating, industry, region, and maturity. More precisely, our similarity score for a given pair of banks is based on the mathematical norm of the difference between two banks' vectors of loan portfolio shares along each dimension. We analyze the evolution of similarity over time and across banks and the impact of stress-testing.[3]

We document that—since the inception of stress-testing—the largest US banks have become more similar in terms of their overall asset allocation and also along important dimensions of their corporate loan portfolio allocation. In particular, banks' commercial and industrial (C&I) loan portfolios have become more similar in terms of borrower rating, industry, and geographic region. To investigate whether these increases in similarity are a result of the regulatory changes related to stress-test requirements, we show that the portfolio similarity of banks subject to DFAST has increased more than 5 percent since 2011, on average, while the portfolio similarity of large banks not subject to DFAST (the non-treated reference group) 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 tend to adjust their portfolios so that they more closely resemble those of banks with good DFAST results.

A simple theoretical model predicts this portfolio convergence if banks have common beliefs about the model and asset-return distribution used by the regulator. These results hold without any need for coalition among banks. In our model, banks' behavior is driven by their desire for better regulatory compliance, as there is no learning about the true underlying parameters of the asset-returns distribution. We assume that banks have an optimal target level of equity or Tier 1 capital ratio, which, for example, could be dictated by their risk appetite, in conjunction with a quadratic loss function. Banks do not want to hold too much capital, for profitability reasons, but they also want to avoid the risk of regulatory enforcement action or market scrutiny in case

[2] Banks are not required to report small loans that have less than $1 million in committed exposure.

[3] It is important to highlight that our data source is consolidated at the level of the bank holding company, and therefore the unit of observation is indeed the bank holding company throughout our analysis. However, as mentioned, for the sake of readability, we refer to BHCs simply as banks.

of capital shortfalls, leading to a standard mean-variance portfolio optimization problem. Under the Dodd-Frank Act, the Federal Reserve can prevent banks from distributing dividends if their post-stress capital levels breach the minimum requirements. We therefore incorporate in the banks' asset allocation problem costly deviation from their optimal capital levels under the stress scenario, which changes the marginal return structure of assets and, in turn, affects the optimal portfolio allocation. In particular, we show analytically that banks choose to hold relatively fewer assets that perform poorly under the stress-test scenario and contribute heavily to portfolio losses, while they increase their relative holding of assets that perform well in the stress test. This portfolio rebalancing, that is, the realignment of portfolio shares, leads to an increase in portfolio similarity and an increase in systemic concentration if banks are sufficiently heterogeneous to begin with.

Our empirical analysis also reveals that large banks have converged to similarly diversified portfolios, while the US banking industry as a whole has become more concentrated. These results have important implications for financial stability. From a microprudential point of view, more diversified and well-capitalized banks in general 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 have been holding more diversified portfolios along several risk dimensions.[4] However, from a macroprudential point of view, we present evidence that it is indeed the case that BHC portfolios have reacted to stress-testing in ways that may inadvertently result in a build-up in 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.[5]

Because the increase in bank portfolio similarity could be associated with changes in investment opportunities after the crisis, we rule out potential demand-side variation that could confound the conjectured portfolio rebalancing mechanism. We do so by conducting an in-depth analysis of banks' credit supply shifts in response to stress-testing results at the individual loan level. We first

[4]In fact, academic and nonacademic research, along with speeches by Federal Reserve officials, highlights the improved robustness and resiliency of the financial sector since the post-crisis regulatory reforms were enacted. Federal Reserve Chairman Jerome Powell points this out in a recent speech, which is available at https://www.federalreserve.gov/newsevents/speech/powell20190709a.htm. Some studies, including 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.

[5]De Loecker, Eeckhout, and Unger (2020) document the increase in market power in the US economy as a whole using firm-level data. It is possible that the increase in our systemic concentration measure is given by the economy-wide increase in market power. However, in our analysis, we are able to link the changes in banks' portfolio allocation to the annual stress-testing exercise.

estimate the contribution of different loan characteristics (rating, region, sector) to the bank's total loan losses under the stress scenario, thereby effectively backing out the sensitivity of loan losses to the credit allocation along different risk dimensions of the loan book. Our model predicts that banks would reduce credit along dimensions that are expected to induce a higher loss under the stress test, as these loans carry a higher marginal cost. In a second step, using individual loan-level data, we show that, in line with the model prediction, banks with poor stress-test results reduce loan supply along dimensions that perform poorly under the stress scenario, as characterized by a large and significant contribution to stress-test loan losses. On the other hand, we do not find that those banks increase the supply of loans that perform well under the stress test. This portfolio rebalancing thus leads to an overall reduction of credit supply relative to banks without large stress-test losses. We identify these loan-level supply effects by exploiting (1) variation in stress-test results across banks, (2) variation in credit across different banks for the same borrower, and (3) variation in credit conditions for the same bank across loans. As part of our analysis, we also document that banks' portfolio rebalancing (supply) induces more similar portfolios.

Finally, we also show that the contraction in credit supply and portfolio rebalancing in response to poor stress-test results have real economic effects at the firm level. Borrowers with an ex ante higher reliance on poorly performing banks are not able to substitute a loss in credit by increasing their borrowing from other stress-test banks with good stress-test performance, nor by increasing borrowing from other banks or by tapping market-based funding sources—crucial borrower information that is available in the supervisory stress-test data, including for nonpublic firms. This result is in line with the well-established importance and lack of substitutability of lending relationships in the banking literature (Petersen and Rajan 1995). As a result, borrowers that experience a contraction in credit also significantly decrease investment (capital expenditures). The economic effects are also sizable for a firm that borrows only from banks that perform poorly in the stress test; they face a 14 percentage point greater decline in investment growth compared with a comparable firm that does not borrow from high-loss banks.

Related Literature

This paper is related to several strands of the literature. First, this study relates to the large literature on the role of bank equity in relation to credit supply. In particular, this literature shows that a reduction in bank's equity capital can lead to a contraction in credit. Early work in this area includes Hancock, Laing, and Wilcox (1995) and the seminal work by Peek and Rosengren (2000). More recently, Jiménez et al. (2017) show the credit effects of countercyclical capital regulation in Spain, and Gropp et al. (2018) find that following an increase in capital requirements, banks increase their capital ratio by decreasing their risk-weighted assets. Because of the importance of bank capital for credit, there is a large literature that also addresses its regulation; see the discussion and references in Greenwood et al. (2017).

Second, this paper closely relates to an emerging line of research that studies the impact of post-crisis banking regulation in general and bank stress-testing specifically. For example, Cortés et al. (2020) show that stress-testing affects bank credit supply to small businesses in the United States. Acharya, Berger, and Roman (2018) assess the costs and benefits of stress-testing on bank risk. Bassett and Berrospide (2018) and Berrospide and Edge (2019) explore the relationship between US stress-testing and bank credit supply. Our analysis is closer to the latter studies, as it exploits the multiple bank-borrower relationships for within-borrower estimation—first developed in Khwaja and Mian (2008)—to control for demand effects, but our focus is on the rebalancing mechanism and associated portfolio adjustments leading to portfolio similarity and real effects. Liu, Niepmann, and Schmidt-Eisenlohr (2019) also study the impact of stress-testing on US banks' credit supply, but they focus on the effects on credit supply for emerging markets.

Third, this paper relates to studies of systemic risk in the financial system, especially risk stemming from the portfolio similarity of banks and other investors. The tension between individual portfolio allocation and systemic risk has received considerable attention (e.g., Ibragimov, Jaffee, and Walden 2011; Allen, Babus, and Carletti 2012; Caccioli et al. 2014; Goldstein et al. 2020). Cai et al. (2018) empirically measure interconnectedness using syndicated corporate loan portfolio overlap based on industry and region, arguing that institution-level risk reduction through diversification ignores the negative systemic externalities. Abbassi et al. (2017) study how market measures of risk correlate with bank portfolio similarity. In a similar spirit, we construct bank portfolio similarity measures using detailed loan-level information, and we show convergence of portfolios along several dimensions related to stress-testing.

The rest of this paper is structured as follows. Section 2 provides a theoretical framework to study the stress-test effects on banks' portfolio allocation. Section 3 presents descriptive statistics on banks' C&I portfolios, and describes our measure of similarity across banks and over time along several dimensions. We also show measures of portfolio concentration, both at the individual level and for the banking system as a whole. In Section 4, we relate the similarity measure to the stress-test results. Section 5 discusses the impact on credit supply and portfolio reallocation, and Section 6 concludes.

2 Theoretical Framework

2.1 Capital Regulation and Stress-testing

Capital requirements are a key component of the current approach to bank regulations. In particular, a bank's assets, collected in a $K \times 1$ vector $a \in \mathbb{R}_0^K$, are (potentially) risk-weighted by a $K \times 1$ vector $w \in \mathbb{R}_0^K$, and total equity relative to risk-weighted assets is then required to be larger than a regulatory minimum, $\bar{k} > 0$.[6] Formally, the bank's risk-weighted capital ratio constraint in this setup is given by

$$k = k(a, e, w) = \frac{e}{w'a} \geq \bar{k}, \tag{1}$$

and the associated minimum required capital level (in dollars) is given by $\bar{k}w'a$. If the bank's equity ratio falls below this minimum capital ratio, the regulator imposes penalties in the form of requirements to increase capital, for example, through prohibiting dividend distribution or, ultimately, through the closing of the bank.

In contrast to bank capital regulation, the current stress-testing in the United States works as follows. Each bank submits its asset holdings to the banking supervisor, which then uses an internal model to compute the capital shortfall for different macroeconomic stress scenarios given the bank's asset holdings and initial capital levels. To pass the stress test, for each scenario, s, the bank's capital ratio must be greater than the regulatory minimum,

$$k(s) = \tilde{k}(a, e, w, s, \theta) \geq \bar{k} \quad \forall s, \tag{2}$$

where θ is a parameter vector that characterizes the supervisory model used to evaluate the capital

[6] For simplicity of exposition, we focus only on risk-weighted capital requirements. The framework can be extended to include leverage regulation (unweighted capital ratio).

shortfall. Failing a stress test results in direct restrictions on dividend payments, in addition to various indirect costs associated with stigma that may be even more important.

Typically, the stress-test scenarios consist of hypothetical realizations of M different key macroeconomics variables, such as GDP growth, unemployment rate, or housing market values, collected in the $M \times 1$ vector $s \in \mathbb{R}^M$. For analytical tractability, we assume that the supervisor uses the scenario vector to compute the net returns on the bank's asset portfolio using a linear model

$$\tilde{r} := r(s, \theta) = \Lambda(\theta)s, \tag{3}$$

where the $K \times M$ coefficient matrix Λ maps the supervisory scenario into the implied returns on a bank's submitted portfolio. The matrix Λ itself contains the elements of the vector $\theta \in \mathbb{R}^{MK}$. A bank's capital under scenario s, given its submitted asset allocation and capital, is then computed straightforwardly as

$$e(s, \theta) = e + r(s, \theta)' a, \tag{4}$$

and the respective capital ratio is $k(s, \theta) = e(s, \theta)(w'a)^{-1}$.[7] Importantly, the stressed equity value depends on the scenario and model parameter only through the vector $\tilde{r}$. Notice that under this stress-test design, two banks with identical equity and asset allocation will have the same capital shortfall, because there is no heterogeneity in returns in the supervisor's model.

2.2 Bank's Optimization Problem

We next study how stress-testing and its design affect a bank's portfolio allocation. For this purpose, consider a basic portfolio allocation problem of a risk-neutral bank that considers the allocation of a $K \times 1$ vector of normally distributed net asset returns:

$$r \sim \mathcal{N}(\mu, \Sigma). \tag{5}$$

The mean and covariance matrix could be bank specific to capture differences in bank business models. The actual equity position after realization of the asset returns is given by a linear trans-

[7] Here we assume that the assets used to compute the risk-weighted ratio do not change under the scenarios.

formation of the returns:

$$e = e^0 + r'a, \tag{6}$$

where e^0 is the bank's initial equity, which we consider to be fixed. The resulting capital ratio is given by $k = e(w'a)^{-1}$. Given the normality of the returns, the final equity position is normally distributed as $e \sim \mathcal{N}(\mu_e, \sigma_e)$, where $\mu_e = e^0 + \mu_r' a$, and $\sigma_e^2 = a'\Sigma_r a$; that is, they are both functions of the bank's choice variable a, with partial derivatives $\frac{\partial \mu_e}{\partial a} = \mu_r'$ and $\frac{\partial \sigma_e^2}{\partial a} = 2a'\Sigma_r$.

We model the bank's portfolio optimization as a standard mean-variance portfolio problem. Specifically, without stress-testing, the bank tries to maintain an optimal capital level, e^*, which we take as exogenous, and we think of it as being strongly affected by the regulatory framework, but also by managers' and equity holders' preferences, including risk aversion.[8] Deviation from this optimum are costly, and we capture this cost by a convex (quadratic) function

$$c(a) = c\left(e^* - e(a)\right)^2, \tag{7}$$

where $c > 0$ is a (potentially large) scale parameter, such that any deviation from the optimal target is costly. We can think of this as pecuniary costs—for example, foregone profits in the case of equity that is too high relative to regulatory requirements, or market scrutiny in the case of a shortfall—but we could also think of it as the bank manager maximizing utility.

From this point on, without changing notation, we work with portfolio weights to focus on the relative asset allocations, assuming a fixed balance-sheet size. The bank's optimization problem then involves choosing a vector of portfolio weights a to minimize an expected quadratic cost of deviating from an optimal equity level. Formally, the quadratic problem is given as

$$\begin{aligned} \min_a \quad & c\,\mathbb{E}[(e^* - e)^2] \\ \text{s.t.} \quad & a^\top u = 1 \\ & e^* = e^0 + r^\top a. \end{aligned} \tag{8}$$

As mentioned earlier, the optimal capital level, e^*, is exogenously determined by shareholders or bank managers, and it is potentially affected by regulatory capital requirements. Using the

[8] There is strong support for the idea that factors other than capital regulation affect banks' capitalization (Oztekin and Flannery 2012).

definition of the variance, the Lagrange function to this problem can be written as

$$\mathcal{L} = (e^* - e^0 - \mu_r^\top a)^2 + a^\top \Sigma_r a - \lambda(a^\top u - 1), \tag{9}$$

with Lagrange multiplier λ and unit vector u. The first-order conditions of this quadratic optimization problem are given by

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial a} &= -2(e^* - e^0 - \mu_r^\top a)\mu + 2\Sigma_r a - \lambda u = 0 \\ \frac{\partial \mathcal{L}}{\partial \lambda} &= a^\top u - 1 = 0. \end{aligned} \tag{10}$$

Rearranging terms shows that the optimal asset allocation requires equalization of marginal cost and benefits:

$$-(e^* - e^0)\mu_r + \Omega a - \lambda/2u = 0, \tag{11}$$

where $\Omega = \Sigma_r + \mu\mu^\top$ is the raw second moment of the asset returns. Thus, if the equity is below (above) its target, investing in assets with higher expected returns decreases (increases) the cost, while the marginal cost is (in both cases) higher for assets with larger variance (due to the convex function).

Substituting out the Lagrange multiplier λ and solving for a give the unconstrained optimal asset allocation vector:

$$a^{uc} = \Omega^{-1}\left(\frac{1 - (e^* - e^0)\mu^\top \Omega^{-1} u}{u^\top \Omega^{-1} u} u + (e^* - e^0)\mu\right). \tag{12}$$

The optimal asset allocation depends on the mean and covariance matrix of the returns, as well as the target and initial value of equity.

Next, consider the situation where the bank chooses the asset allocation, but it is subject to stress-testing. That is, the bank needs to submit its portfolio allocation to the supervisor, who determines the stressed equity capital based on returns $\tilde{r}$ computed from stress-test models and scenarios. An important feature of the stress-test design is that the regulator does not disclose $\tilde{r}$.[9] Therefore, we assume banks have a (common) belief distribution over the asset returns in the

[9] The regulator (neither ex ante nor ex post) discloses the model that is used to compute the capital shortfall given the bank's assets and initial equity. The macroeconomic scenarios are released ex post, but they are unknown to banks ex ante.

stress-test scenario:

$$\tilde{r} \sim \mathcal{N}(\tilde{\mu}, \tilde{\Sigma}), \tag{13}$$

where typically asset returns in the stress test would be negative and lead to equity losses, and, potentially, a formal failing of the stress test.

For simplicity, we model the effect of capital shortfall under stress-testing relative to the target capital value as an additive quadratic cost, motivated again by strong evidence that banks try to maintain target equity ratios and that deviations from them are costly. The bank's optimization under stress-testing thus becomes

$$\begin{aligned} \min_{a} \quad & \mathbb{E}[(e^* - e^0 - r^\top a)^2] + c\,\mathbb{E}[(e^* - e^0 - \tilde{r}^\top a)^2] \\ \text{s.t.} \quad & a^\top u = 1, \end{aligned} \tag{14}$$

which shows that the bank's problem now depends on the distribution of the actual returns as well as on the belief distribution the bank has about the asset returns in the stress-testing exercise, $\tilde{r} \sim \mathcal{N}(\tilde{\mu}, \tilde{\Sigma})$. The parameter c determines the relative weight the bank attaches to the cost of capital shortfall in the stress test. Clearly, the problem collapses to the unconstrained problem if r and $\tilde{r}$ have the same mean and covariance matrix.

The solution to this augmented optimization problem is given as

$$a = \hat{\Omega}^{-1}\left(\frac{1 - (e^* - e^0)\hat{\mu}^\top \hat{\Omega}^{-1} u}{u^\top \hat{\Omega}^{-1} u} u + (e^* - e^0)\hat{\mu}\right), \tag{15}$$

where variables with a hat represent weighted sums of the moments of the true and stress-test return distributions, specifically $\hat{\Omega} = \Sigma_r + \mu\mu^\top + c(\tilde{\Sigma}_r + \tilde{\mu}\tilde{\mu}^\top)$ and $\hat{\mu} = \mu + c\tilde{\mu}$.

2.3 Predictions on Portfolio Allocation

We illustrate the basic insight from our model in the two-asset case, for which we can derive tractable analytical solutions. In particular, we derive comparative statics with respect to key model parameters. To sign the derivatives, we further assume that investment is profitable in expectation. Moreover, asset 1 is risky and has a higher return but also a higher variance compared with asset 2, such that $\mu_{r,1} > \mu_{r,2} > 0$, and $\sigma_{r,1} > \sigma_{r,2} > 0$. To simplify notation and isolate the key channel, we assume zero covariance between the two assets. Moreover, the belief for the asset returns under the stress-test scenario is such that the risky asset in expectation performs worse than the other asset, but both have a negative expected return $\tilde{\mu}_{r,1} < \tilde{\mu}_{r,2} < 0$. Finally, the covariance matrix $\tilde{\Sigma_r}$ has zero diagonal elements.

For the two-asset case, in which the asset allocation vector is $(a_1, 1 - a_1)$ with $1 > a_1 > 0$, the closed-form scalar representation of the solution for the portfolio share of the (risky) asset a_1 in the unconstrained allocation—without stress-testing—is given by

$$a_1^{uc} = \frac{(e^* - e^0)(\mu_1 - \mu_2) - \mu_2(\mu_1 - \mu_2) - \sigma_{12} + \sigma_{22}^2}{(\mu_1 - \mu_2)^2 + \sigma_{22}^2 - 2\sigma_{12} + \sigma_{22}^2}, \tag{16}$$

while the allocation for a_2 is $1 - a_1$.

For the constrained problem, that is, if the bank is subject to stress-testing, the solution for the portfolio share of a_1 is given by

$$a_1 = \frac{(e^* - e^0)(\hat{\mu}_1 - \hat{\mu}_2) - \hat{\mu}_2(\hat{\mu}_1 - \hat{\mu}_2) - \hat{\sigma}_{12} + \hat{\sigma}_{22}^2}{(\hat{\mu}_1 - \hat{\mu}_2)^2 + \hat{\sigma}_{22}^2 - 2\hat{\sigma}_{12} + \hat{\sigma}_{22}^2}, \tag{17}$$

where $\hat{x} = x + c\tilde{x}$ for $x \in \{\mu_i, \sigma_{ij}\}$, and $i, j \in \{1, 2\}$.

Using basic algebra, one can show that the investment in the risky asset decreases if the expected return of the asset in the stress test decreases or its variance increases

$$\frac{\partial a_1}{\tilde{\mu_1}} > 0 \quad \text{and} \quad \frac{\partial a_1}{\tilde{\sigma_1}} < 0; \tag{18}$$

that is, the bank reduces exposure to assets that perform poorly under the stress test or whose performance under the stress test is uncertain. As a result, we find that, compared with the optimal portfolio allocation without stress-testing, the bank invests more in assets that it expects will contribute less to equity shortfalls or in assets with low uncertainty.

Further, we can use the model to analyze how the stress-test design affects banks' portfolio similarity. We assume bank heterogeneity in the optimal target level e^*, which introduces heterogeneous optimal asset allocations. For simplicity, consider two banks indexed by i and j and with optimal asset allocations a_i and a_j, respectively. The Euclidean distance between the asset allocations of banks i and j is

$$d_{i,j} = ||a_i - a_j||. \tag{19}$$

Similarly, we define the Euclidean distance between the optimal asset allocations without stress-testing as $\Delta a^{uc}_{i,j} = ||a^{uc}_i - a^{uc}_j||$ and measure the changes in portfolio distance among banks as

$$\Delta d_{i,j} = ||d_{i,j}|| - ||d^{uc}_{i,j}||. \tag{20}$$

Thus, if banks' asset allocations under stress-testing become more similar (smaller Euclidean distance) compared with the unconstrained allocation, the distance measure is negative. Differentiating $\Delta d_{i,j}$ with respect to the mean and variance of the stress-test returns, and signing the derivatives, gives

$$\frac{\partial \Delta d_{i,j}}{\partial \tilde{\mu_1}} = \frac{\partial ||d_{i,j}||}{\partial \tilde{\mu_1}} > 0 \quad \text{and} \quad \frac{\partial \Delta d_{i,j}}{\partial \tilde{\sigma_1}} = \frac{\partial ||d_{i,j}||}{\partial \tilde{\sigma_1}} < 0. \tag{21}$$

Therefore, both a lower stress-test return on the assets and a larger variance of the asset's stress-test return increase portfolio similarity (decrease the Euclidean distance).

3 Portfolio Descriptive Statistics and Similarity

In our empirical analysis, we focus on the portfolios of those large and complex financial institutions operating in the United States that are subject to DFAST. Our main sample period runs from 2011:Q3 through 2016:Q4, ending when the new Basel III capital standards were phased in. These standards include a capital conservation buffer and a surcharge for global systemically important banks (GSIB) and thus could confound our analysis. During our sample period, banks with more than \$50 billion in assets were required to undergo an annual stress-testing exercise performed under adverse and severely adverse scenarios. (As highlighted before, we refer to BHCs simply as banks in this paper, although the unit of observation is really the bank holding company.) DFAST also required these institutions to submit detailed portfolio information in the FR Y-14 reports. In particular, the FR Y-14 contains quarterly reports of all C&I loans on banks' balance sheets, with detailed loan-level information, including several variables about the borrowing firm. For most of our analysis, we fix the sample to the 19 banks that were subject to DFAST from when the first exercise was conducted in 2012 onward; they are henceforth denoted as "DFAST banks." In

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 through 2016:Q4.
Source: Nonconfidential FR Y-9C. This figure uses only publicly available information.

part of our analysis, we complement the confidential Y-14 data with information from the publicly available Y-9C data, which cover a larger cross section of banks as well as a longer time period, but they lack granular loan-level information required for a tight identification.

3.1 Portfolio Shares

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 the 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 DFAST banks. On average, retail loans (20.5 percent), securities (18.6 percent), and C&I loans (12.3 percent) are the most important asset classes for the large US banks in our sample. CRE loans represent only about 6.5 percent of total assets, on average.

For a more granular measure of similarity, we exploit the detailed loan-level data in the regulatory schedule H.1 found in the FR Y-14Q reports. These schedules contain loan-facility-level information on the respective exposures for C&I loans for DFAST banks. We focus on the rating, industry, and geographic region dimensions of C&I loans.

In Table 2, Panel A, we show the descriptive statistics of C&I loans by risk rating. Banks

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

	Portfolio Shares (% of C&I Portfolio)					
	Mean	p10	p25	p50	p75	p90
Panel A: Shares by Rating						
AAA	3.52	0.00	0.00	1.19	2.70	9.78
AA	6.15	0.00	0.67	6.26	9.84	12.85
A	17.47	1.45	11.09	19.23	24.40	28.25
BBB	32.14	19.61	27.57	33.13	37.34	42.73
BB	28.79	12.36	18.80	26.34	39.92	49.05
B	8.74	2.45	4.76	8.39	11.09	15.49
CCC	1.92	0.08	1.14	1.57	2.61	3.91
CC	0.38	0.00	0.00	0.00	0.05	1.25
C	0.03	0.00	0.00	0.00	0.00	0.00
D	0.32	0.00	0.01	0.13	0.44	1.03
NR	0.10	0.00	0.00	0.00	0.00	0.05
Panel B: Shares by Sector						
Financial & Insurance	17.94	6.08	10.98	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	15.72	3.19	12.39	17.09	21.54	24.26
Mining & Oil	4.66	0.64	2.74	4.28	5.81	8.15
Other Services	3.05	0.68	1.17	1.73	2.98	8.45
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	5.06	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	9.08	10.06
Other Sectors	9.83	0.00	0.00	12.41	15.57	16.57
Panel A: Shares by Region						
Foreign	14.36	0.22	2.00	5.95	26.73	32.23
West	17.92	7.63	10.37	14.01	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

Note: The sample includes the 19 banks subject to DFAST from 2011:Q3 through 2016:Q4, a total of 425 observations.
Source: FR Y-14Q.

report their 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. Panels B and C contain the same information by geographic region and industry, respectively. Among the C&I loans that are disclosed in the FR Y-14Q reports, most loan exposures are rated at the lowest investment grade or at the highest non-investment grade, 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 and five years; see Table A.1 in the Appendix. In 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 (for example, the difference between the 90th and 50th percentiles). 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. Figure A.1 shows the evolution of the C&I loan portfolio shares over time.

3.2 Portfolio Similarity Measures

Based on these portfolio shares, we construct pairwise (bank-pair) measures of portfolio similarity. Our key measure of similarity is based on the (normalized) distance between the vectors of each bank's portfolio shares. Specifically, the distance between banks i and j along dimension d is given by the mathematical norm:

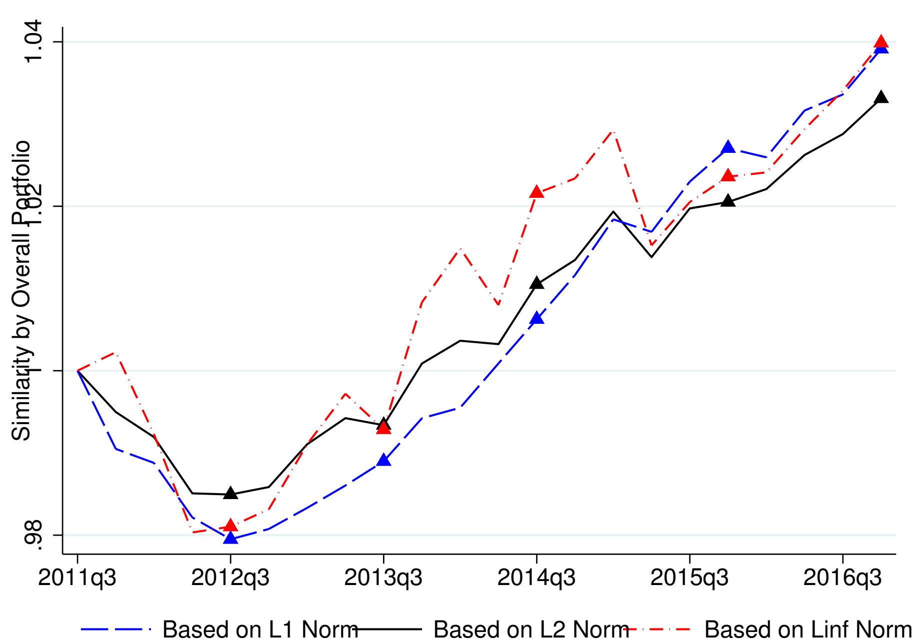
$$d^d_{i,j,t} = ||\alpha^d_{i.t} - \alpha^d_{j.t}||, \tag{22}$$

where we use either the L_1 norm, the L_2 norm, or the L_∞ norm. The baseline results we present for similarity measures are based on the L_1 norm; that is, they are based on $d^d_{i,j,t} = \frac{1}{K}\sum_{k=1}^{K} |\alpha^d_{i.t}(k) - \alpha^d_{j.t}(k)|$, where k indexes the individual elements of the portfolio share vectors, $\alpha^d_{i,t}$, i.e., the different categories within a given dimension d. Our similarity score is then constructed as the rescaled norm:

$$\text{similarity}^d_{i,j,t} = 1 - \frac{d^d_{i,j,t} - \min(d^d_{i,j,t})}{\max(d^d_{i,j,t}) - \min(d^d_{i,j,t})}, \tag{23}$$

such that larger values represent portfolios that are more similar. Obviously, the units of this nonparametric similarity score have no natural interpretation, and most of our discussion will therefore focus on percentage changes in the similarity score, which are not affected by the scaling.

Figure 1: Overall Portfolio Similarity by Different Similarity Measures

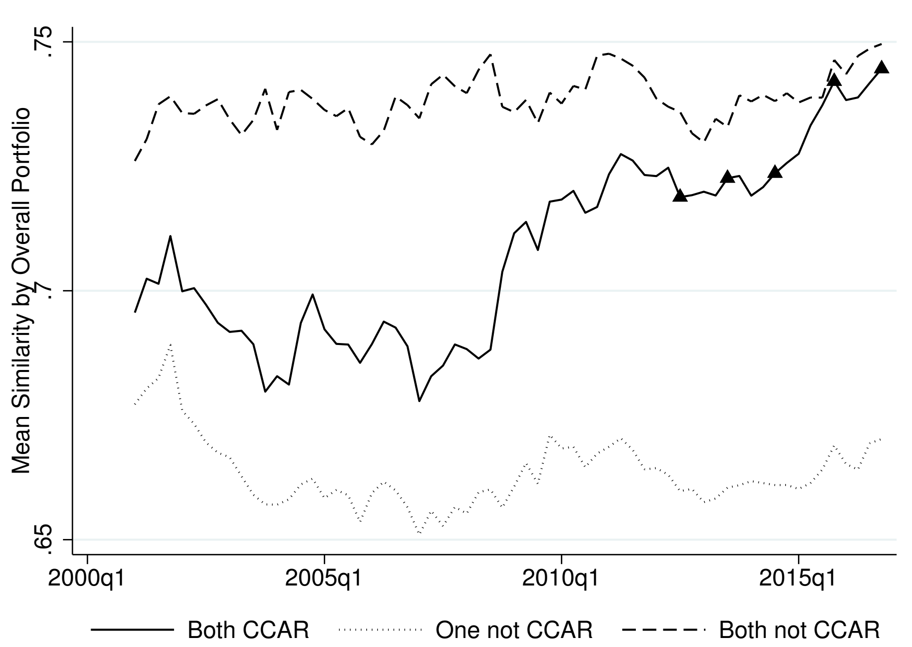


Notes: The figure depicts the mean of the overall portfolio similarity based on the different norms. The sample includes the 19 banks subject to DFAST from 2011:Q3 through 2016:Q4. The solid triangles indicate the quarters when the banks submit portfolios that are used for stress-testing.
Sources: Nonconfidential FR Y-9C and authors' calculations. This figure uses only publicly available information.

Figure 1 shows the evolution of the mean of the pairwise similarities based on the aggregate shares of the broad asset categories using the publicly available FR Y-9C data for the 19 banks that participated in all DFAST exercises during our sample period. The figure shows the different similarity measures for the period 2011:3 through 2016:Q4. The quarters of portfolio submission on which the stress-test results are computed are indicated with triangles, including 2012:Q3, the quarter of portfolio submission for the fist stress-test exercise in 2013. Based on all three measures, the overall portfolio similarity clearly increases over the sample period, with a similar pattern for each of the three measures. For our baseline measure built on the L_1 norm, the increase is about 6 percent. All reported results that follow use the similarity measure based on the L_1 norm, but results using either of the other two measures are qualitatively similar.

Figure 2 expands the cross section of banks and the time dimension of Figure 1. Figure 2 shows that before 2012, the average similarity among the portfolios of pairs of DFAST banks was not significantly different from the average similarity among the portfolios of pairs of large non-DFAST

Figure 2: Overall Similarity Measure for DFAST vs. non-DFAST Bank Pairs



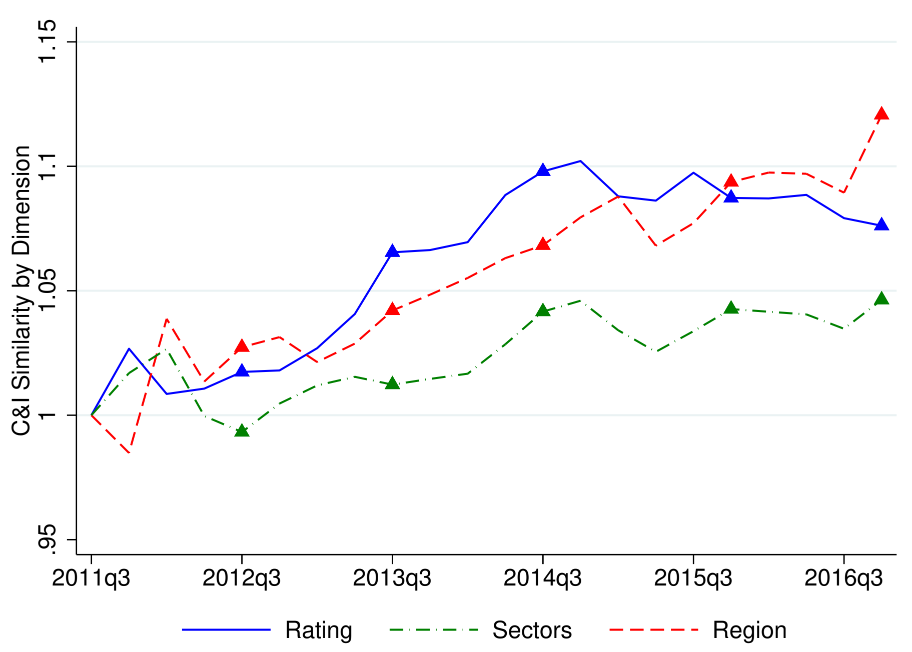
Notes: The figure depicts the within-group mean of the overall portfolio similarity based on the L1 norm. The extended sample covers the period from 2000:Q1 through 2016:Q4. The solid triangles indicate the quarters when the banks submitted portfolios used for stress-testing. The sample is restricted to a constant sample of banks that we observe in the Y-9C data during all quarters of the sample period, hence the difference in CCAR similarity compared with Figure 1.
Sources: Nonconfidential FR Y-9C and authors' calculations. This figure uses only publicly available information.

banks. However, the average similarity among DFAST bank pairs increased substantially after the first proper stress-testing exercise was conducted in 2012.[10] This difference in trends, supported by a simple regression using bank 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 of banks responding to the scenarios considered in the stress-testing exercises.

Next, we explore the more granular information on the corporate loan portfolios contained in the stress-testing data (FR Y-14Q). As described in the preceding section, the different risk dimensions that we consider for the C&I loans are (1) loan-level rating, (2) loan-level industry, and (3) loan-level region. Figure 3 shows the evolution of the mean similarity measure along each dimension.[11] The C&I portfolio similarities, according to ratings and region, increased about 10

[10]Proper in the sense that, for the first time, it was based on the detailed portfolio data collection as of 2011:Q3.
[11]Results are presented for the similarity measure constructed from the L_1 norm. Qualitatively similar results are obtained using either of the other two measures.

Figure 3: Similarity of Commercial and Industrial Loan Portfolios



Notes: The figure shows the mean similarity of banks' C&I portfolios along the rating, sector, and region dimensions based on the L1 norm. The sample includes the 19 banks subject to DFAST from 2011:Q3 through 2016:Q4. The solid triangles indicate the quarters when the banks submitted portfolios used for stress-testing.
Sources: FR Y-14Q and authors' calculations

percent during the sample period. The central tendency of sectoral portfolio similarity increased as well, but only about 5 percent. Interestingly, 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."*[12] Moreover, as Figure A.2 shows, in addition to an increase in measures of central tendency, such as the mean, the distributions of similarity scores 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 became more similar to the rest of the group.

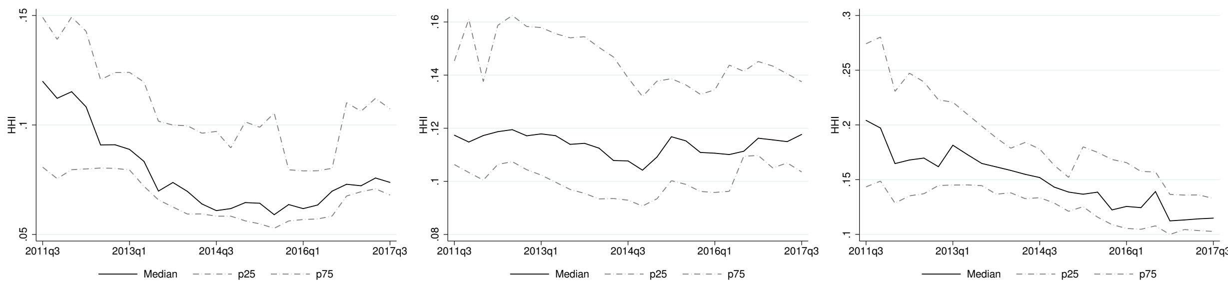
3.3 Implications for Portfolio Concentrations

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 a few similar

[12]In unreported results, we find that neither the average nor the distribution of similarity based on loan maturity exhibited a particular trend over the sample period.

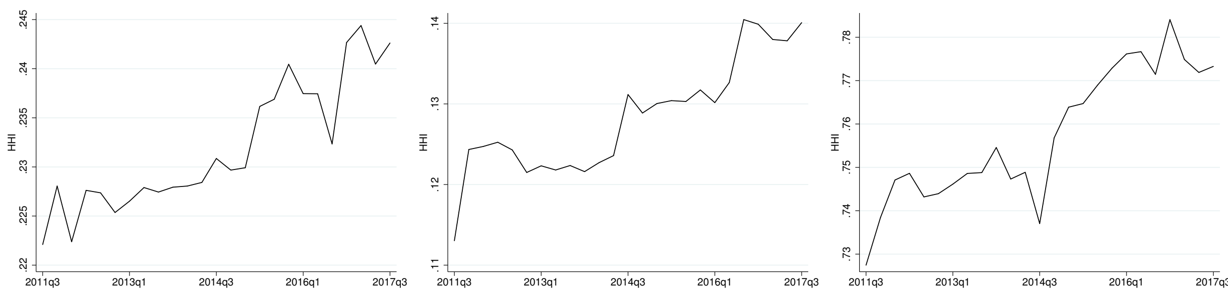
Figure 4: Commercial and Industrial Loan Portfolio Concentration

Panel (A): Distribution of Bank-Level Concentration Measure



Ratings | Sectors | Regions

Panel (B): Concentration Measure at the Banking-System Level



Rating | Sector | Region

Notes: Panel (A) shows the evolution of the distribution of bank-level Herfindhal-Hirschmann indexes of banks' commercial and industrial loan portfolio concentration by rating, region, and sector. Panel (B) shows the evolution of the *aggregate* banking system Herfindhal-Hirschmann index concentration for the same portfolio buckets. The sample includes all banks participating in the five stress tests from 2011:Q3 through 2016:Q4.
Sources: FR Y-14Q and authors' calculations.

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 being equal, a less concentrated bank appears to pose less risk from a microprudential point of view.

Figure 4 shows the Herfindahl-Hirschmann index (HHI) distribution over time for each of the dimensions considered above: ratings, sectors, and regions.[13] Panel (A) reports the time evolution of the cross-sectional distribution of bank-specific HHIs. The overall trend indicates that the portfolios of these large banks became, on average, more diversified, while the HHI trended down over the sample period. DFAST banks tend to have a more diversified portfolio in terms of ratings. Industry diversification shows an overall pattern that is similar but less clear. The same pattern is

[13]For each bank, this index is computed as the sum of squared portfolio shares in each quarter.

observed for exposure diversification by region. Consistent with the HHI result, Figure A.3 shows the distribution of shares in investment-grade C&I loans. There is a tendency toward a better balance between investment-grade and sub-investment-grade shares in banks' portfolios.

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 through 2016:Q4 along the different risk dimensions (ratings, sectors, and regions). Panel B of Figure 4 shows that the HHI for the entire system actually increased along all dimensions of C&I loans, a sharp contrast to the first row, which shows that bank-level concentration decreased over time. Thus, a set of more similarly diversified banks does *not* necessarily result in a more diversified system as a whole. On the contrary, we can conclude that the banking system has become more concentrated, at least when we examine the largest banks in the United States.[14]

4 Capital Shortfall under Stress and Portfolio Similarity

So far our analysis has focused on describing how nonparametric measures of similarity along different portfolio dimensions have evolved over time. In this section, we explore the systematic relationship between capital shortfall under the severely stressed scenario and changes in measures of banks' portfolio similarity. We define a bank's capital shortfall as the difference between its pre-stress testing level of the Tier 1 capital ratio and the hypothetical lowest capital ratio under stress. For the Dodd-Frank Act Stress Test, the Federal Reserve produces a bank-specific forecast of income and losses during a period of two years in which the economic conditions are severely adverse.[15] The initial equity level and the forecast income and losses determine the capital ratio over the forecast period. For example, if a bank has an actual Tier 1 capital ratio of 8 percent, and its lowest Tier 1 capital ratio under the severely adverse scenario reaches 6 percent along the two-year forecast path, the capital shortfall is 2 percentage points (hence, "shortfall" is relative to the bank's actual capital ratio, consistent with our theoretical model).

[14]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.

[15]From 2012 through 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. Since 2015, capital plans have been due at the end of the first quarter, based on portfolios as of the fourth quarter of the previous year.

To identify a possibly causal relationship between regulation and portfolio choices, we exploit the heterogeneity of stress-testing results. In the annual DFAST exercise, the Federal Reserve produces severely adverse macroeconomic scenarios and forecasts each of the minimum capital ratios (Tier 1, common equity, and leverage, among others) that banks would experience under such scenarios. These minimum ratios determine whether the banks' capital plans, including dividend payouts, are approved. The Federal Reserve's exact method is not public information, and the forecasts for each bank are not known in advance; therefore, there is an element of surprise when the results are published. In our analysis, we exploit the variation provided by the heterogeneity in the results and the timing component of the results.[16]

Table 3: Bank Capitalization and Stress-test Losses

Panel A: Summary Statistics.

	Mean	Std. Dev.	P10	P25	Median	P75	P90	Obs.
Tier 1 Capital Ratio (%)	13.8	5.4	10.9	11.5	12.7	14.4	16.7	145
Tier 1 Capital Loss Under SA Scenario (pp)	3.6	2.1	1.5	2.3	3.1	4.5	7.0	145
Δ Tier 1 Capital Loss Under SA Scenario (pp)	-0.17	1.5	-1.7	-1.1	-0.2	0.8	1.7	111
Loss Coming From C&I (%)	10.6	5.8	3.2	6.4	10.4	14.5	18.1	145
Total Assets ($B)	473.6	660.6	72.0	113.1	163.7	366.9	1792.1	145

Panel B: Tier 1 Loss Transition Matrix (Percentages).

	Current Tier 1 Loss			
Last Tier 1 Loss	<p25	>p25 & <p75	>p75	Total
<p25	58.1	38.7	3.2	100
>p25 & <75p	25.0	60.4	14.6	100
>p75	3.5	31.0	65.5	100

Note: The sample includes the 19 banks subject to DFAST from 2011:Q3 through 2016:Q4.
Source: Nonconfidential FR-Y9C and DFAST results available publicly on the Federal Reserve Board's website, https://www.federalreserve.gov/supervisionreg/dfa-stress-tests.htm.

To better illustrate the heterogeneity in stress-test results, Table 3, Panel A, shows summary statistics of Tier 1 capital ratios, both the actual ratio and the decline in the ratio under the severely adverse scenario. The average actual capital ratio is 13.8 percent, and the average loss under the

[16]The DFAST results, which do not take into account banks' proposed capital plans, are released a few days before the Comprehensive Capital Analysis and Review (CCAR) results, which also evaluate other qualitative aspects of capital planning. The CCAR results take into account banks' planned capital distributions, and banks have the option to resubmit their proposed distributions after learning about their DFAST results. The fact that banks have, in some instances, taken advantage of this "second chance" at their capital distribution plans offers evidence supporting the surprise element of DFAST results. For example, in 2019, JP Morgan Chase and Capital One had their capital plans approved once they adjusted their capital distributions to the DFAST results (see BOG 2019).

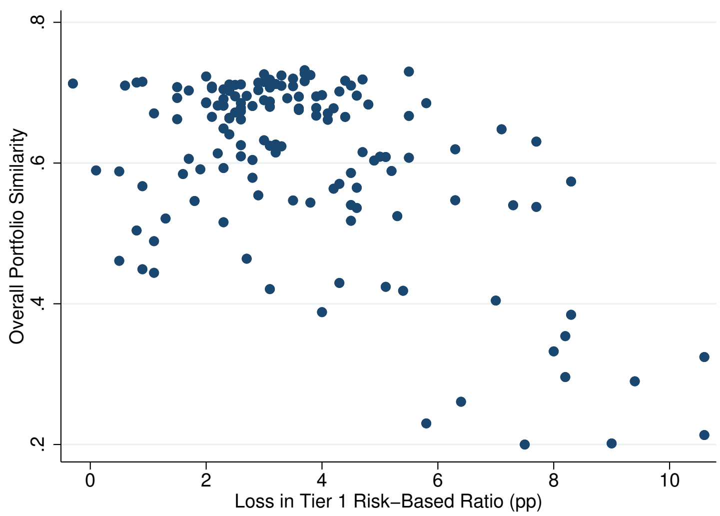
scenario is 3.6 percentage points. The loss distribution is skewed, with the capital ratio declining more than 7 percentage points in 10 percent of the observations. C&I losses account for 10.9 percent of the losses, on average, but they exceed 18 percent for some bank-quarters (90th percentile). The bank-specific change in loss under stress reveals substantial variation in stress-test performance over time for the same bank: While the change in capital loss is close to zero on average, in about 20 percent of the observations, capital loss increases or decreases 1.7 percentage points relative to the preceding stress-test exercise. Panel B further elaborates on the variation of an individual bank's stress-test results over time by reporting probabilities of transitioning from one percentile group of the cross-sectional distribution of capital losses to another over time. The diagonal entries with probabilities of about 60 percent suggest that a bank is likely to roughly maintain its relative performance from one stress test to the next. However, there is also substantial probability mass in the off-diagonals, meaning that banks actually do move in the cross section. For example, a bank with a capital loss between the 25th and 75th percentiles in the preceding stress test has a 25 percent probability of having a relatively lower capital loss below the 25th percentile and a 15 percent probability of having a relatively higher capital loss above the 75th percentile in the current stress test. We exploit exactly this within-bank variation in stress-test performance for empirical identification.

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

$$\text{BHC-similarity}^d_{i,t} = \frac{1}{N-1}\sum_{j\neq i}\text{similarity}^d_{i,j,t}. \tag{24}$$

We then use this bank-level measure in the following bank-level analysis, where we establish a relationship between regulation and bank behavior. Using publicly available data from the FR Y-9C reports that breaks down bank assets into broad categories, Figure 5 shows the unconditional relationship between capital shortfalls and banks' overall similarity to the asset holdings of other banks. The relationship presented in Figure 5 is contemporaneous: Banks with more (less) similar portfolios compared with other banks tend to have lower (higher) capital shortfalls. As Figure A.4 shows, this relationship is not driven by the initial stress tests, but it also holds for the stress tests conducted before and after 2014:Q4. However, the range of both capital shortfall and similarity scores are somewhat smaller after 2014:Q4.

Figure 5: Overall Portfolio Similarity and Tier 1 Capital Ratio Shortfall



Notes: The sample includes all banks participating in the five stress tests from 2011:Q3 through 2016:Q4. The vertical axis shows the mean overall portfolio based on the L1 norm. The horizontal axis shows the capital shortfall (loss in capital) forecast under the severely adverse scenario.
Sources: FR Y-9C data, disclosures of annual DFAST results, and authors' calculations. This figure uses only publicly available information.

We next study whether banks adjust their portfolios in response to a poor stress-test result. In Table 4, we show the relationship between the results of the stress tests (capital losses) and subsequent *changes* in overall similarity with other banks. The dependent variable in all columns is the year-over-year change in a bank's overall similarity score.[17] The independent variables are different measures of Tier 1 capital ratio shortfall under the severely adverse scenario in the current stress test. For the results in column (1), we use the lagged capital shortfall measure, that is, the difference between the pre-stress test Tier 1 capital ratio and the lowest Tier 1 capital ratio forecast under the severely adverse scenario. In columns (2) through (4), instead of looking at the actual capital shortfall variable, we define a dummy variable that equals 1 for capital shortfalls above the 50th, 75th, or 90th percentile of the capital shortfall distribution across banks (computed for each of the annual stress-testing exercises), respectively, and 0 otherwise. That is, we construct dummy

[17]We compute the similarity measure in the quarter that precedes the stress-testing exercise every year and use the difference with respect to the similarity four quarters ahead, right before the next stress-testing exercise is conducted, taking into account that starting in 2015 portfolios were submitted in Q4 instead of Q3.

Table 4: Stress-test Results and Overall Portfolio Similarity

Dep. Var: % Change in Overall Portfolio Similarity to all banks	(1)	(2)	(3)	(4)
Tier 1 Ratio Loss	0.78***			
	(2.91)			
High Tier 1 Loss (p50)		2.73*		
		(1.74)		
High Tier 1 Loss (p75)			2.67**	
			(2.37)	
High Tier 1 Loss (p90)				4.35***
				(2.61)
Observations	108	108	108	108
R-squared	0.117	0.078	0.062	0.084
Controls	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes

Notes: The table reports estimates of percentage changes in overall portfolio similarity as a function of lagged capital shortfall in DFAST. The percentage change in similarity is computed by comparing the current submitted portfolio with the last submitted portfolio. The sample includes all banks participating in the five stress tests from 2011:Q3 through 2016:Q4. Controls include the logarithm of total assets, the percentage of C&I loans in total assets, and the share of stress-test losses from the C&I portfolio as a percentage of total stress-test losses. Robust t-statistics in parentheses are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

variables for banks that fare relatively poorly in the stress tests, seeing particularly high capital shortfalls. We find that banks with higher capital shortfalls subsequently change their portfolios to look more like other banks. Columns (2) through (4) show that the portfolio adjustment is economically and statistically stronger for banks that experience the highest capital shortfalls.[18] Because all specifications in Table 4 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, while time-varying bank characteristics such as size are conditioned out; see the table caption for details. Hence, given the time fixed effects, this result is not driven, for example, by variation in the severity of scenarios across different stress tests or the injection of large amounts of reserves into the banking system by the Fed.

If regulation is a driving influence underlying the increasing portfolio similarity among large US banks, poorly performing banks (those with high capital shortfalls) may adjust their portfolios to look more similar to banks that have good stress-test results (that is, banks with low capital

[18]We have also explored potential nonlinear effects by including an interaction term between the continuous capital shortfall variable and each high-capital-shortfall dummy variable. However, we did not find statistically significantly stronger effects for banks with high capital shortfalls.

Table 5: Stress-test Results and Overall Portfolio Similarity to Different Benchmark Banks

	Dep. Var: % Change in Overall Similarity to		
	Good Banks	Better Banks	Best Banks
Defined as Capital Shortfall	$\leq$ p50	$\leq$ p25	$\leq$ p10
	(1)	(2)	(3)
High Tier 1 Loss (p75)	6.481***	9.902***	15.410***
	(2.275)	(3.373)	(4.175)
Observations	108	108	108
R-squared	0.199	0.249	0.124
Controls	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes

Notes: The table reports estimates of percentage changes in overall portfolio similarity as a function of lagged capital shortfall in DFAST. The percentage change in similarity is computed by comparing the current submitted portfolio with the last submitted portfolio. The sample includes all banks participating in the five stress tests from 2011:Q3 through 2016:Q4. Controls include the logarithm of total assets, the percentage of C&I loans in total assets, and the share of stress-test losses from the C&I portfolio as a percentage of total stress-test losses. Robust t-statistics in parentheses are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

shortfalls). Therefore, instead of showing changes in similarity to all other banks, Table 5 shows the changes in similarity with respect to banks that performed well on the stress tests (in terms of equation (24), we sum only over a subset of banks that perform well). Columns (2) and (3) show the similarity to banks that have low capital shortfalls; that is, those banks with capital shortfalls above the 90th, 75th, and 50th percentiles after each stress test, respectively. The results show that after the stress test, those banks with high capital shortfalls rebalance their overall portfolios so that they look more similar to the better-performing banks (defined as those banks below the lowest 10th, 25th, or 50th percentile of the capital shortfall distribution). 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 6, instead of presenting banks' overall asset allocation, we show the adjustments in banks' C&I loan portfolios along the rating, sector, and region dimensions as a function of banks' stress-testing performance. In particular, our dependent variable is again the change in pairwise similarity to differently defined well-performing banks in the stress-testing. The difference in an individual bank's similarity measure is the difference between its similarity measure in the quarter just prior to the stress-testing exercise and its measure in the quarter just prior to the stress test in the previous year. The results in Panel A show that the more Tier 1 capital losses banks experience under the stressed scenario, the more they rebalance their portfolios to become more similar to the best-performing banks. As we restrict the definition of best-performing banks, the changes in similarity become larger, indicating that poorly performing banks, on average, tend to change the allocation of their C&I portfolio to resemble the very best performers. Panels B and C show the analogous results for the region and sector 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. While the results for sector similarity qualitatively correspond to those for rating similarity, we do not find significant adjustments in the region dimension. Note that for a tight identification, as before, all specifications include quarter fixed effects as well as bank controls.

Table 6: Stress-test Results and Commercial and Industrial Loan Portfolio Similarity

	Dep. Var: % Change in Rating Similarity to		
	Good Banks	Better Banks	Best Banks
Defined as Capital Shortfall	$\leq$ p50	$\leq$ p25	$\leq$ p10
	(1)	(2)	(3)
Panel A: Similarity by Rating			
High Tier 1 Loss (p75)	3.707	5.892*	8.625**
	(2.785)	(3.331)	(3.601)
Observations	108	108	108
R-squared	0.082	0.161	0.222
Panel B: Similarity by Sector			
High Tier 1 Loss (p75)	0.469	2.955	6.681***
	(1.750)	(2.097)	(2.055)
Observations	106	107	107
R-squared	0.152	0.084	0.120
Panel C: Similarity by Region			
High Tier 1 Loss (p75)	1.654	0.803	-0.462
	(1.558)	(1.856)	(2.645)
Observations	108	108	108
R-squared	0.089	0.071	0.104
Controls	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes

Notes: The table reports estimates of percentage changes in C&I loan portfolio similarity as a function of lagged capital shortfall in DFAST. The percentage change in similarity is computed by comparing the current submitted portfolio with the last submitted portfolio. The sample includes all banks participating in the five stress tests from 2011:Q3 through 2016:Q4. Controls include the logarithm of total assets, the percentage of C&I loans in total assets, and the share of stress-test losses from the C&I portfolio as a percentage of total stress-test losses. Robust t-statistics in parentheses are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

5 Effects of Capital Shortfall on Credit Supply and Real Effects

5.1 Loan-level Effects

Previous results show a convergence in banks' C&I portfolios in response to stress-test results, particularly along the ratings and sector dimensions. However, such a convergence in portfolios could, in principle, also be explained by changes in banks' investment opportunities over time; for example, if banks with low capital shortfall lend more to firms with high-net-present-value projects, those firms would, over time, satisfy their demand for funding by increasing borrowing from banks that perform poorly in the stress tests. The results would be a convergence in loan portfolios. In other words, the evidence on increased portfolio similarity presented in the previous section could, in principle, be a result of demand shifts as opposed to changes in credit supply.

We next show that the documented portfolio convergence is (at least partly) driven by supply shifts, in particular, by a decrease in the supply of loans that contribute strongly to losses under the stress-test scenario by banks that fare poorly in the stress tests. To disentangle credit demand and supply, we use loan-level data and estimate changes in credit by multiple banks to the same firm in the same quarter (within-firm estimation) while relating differences in credit growth to banks' stress-test outcomes. This method follows the state-of-the art approach in the empirical banking literature, which uses within-borrower estimation (Khwaja and Mian 2008). Moreover, we isolate the portfolio rebalancing channel by comparing credit supply changes along different dimensions for the same bank-quarter depending on the marginal contributions to stress losses of specific loans.

Our analysis consists of two steps. In the first step, as before, we slice the C&I portfolio into different dimensions (ratings, sector, ...), and, within each dimension, we estimate how an additional dollar in each bucket (for example, for the rating dimension: AAA, AA, A, BBB,...) contributes to the C&I portfolio loss under the severely adverse scenario. Formally, for each dimension d and bucket k, we run the following regression:

$$\text{C\&I Loss}_{i,t} = \beta^{d,k} \cdot \text{Lending}_{i,t}^{d,k} + \alpha_i + \epsilon_{i,t}, \tag{25}$$

where $\text{Lending}_{i,t}^{d,k}$ is the dollar value of loans in bucket k of dimension d associated with the loan book of bank i at quarter t (for example, d could be the rating, and k could be BBB). The dependent variable C&I $\text{Loss}^{i,t}$ measures the C&I loan losses predicted by the Fed stress-test exercise. Our focus is on the parameters $\beta^{d,k}$, which measure the sensitivity of each loan portfolio bucket to the stress-test scenarios. A large positive parameter $\beta^{d,k}$ would thus mean that a dollar invested in bucket k contributes strongly to the C&I losses. We include bank fixed effects to account for compositional shifts in the sample of banks subject to stress-testing.[19] Equation (25) is a reduced

[19]To increase the number of observations, we use all banks in this specific analysis. However, we obtain qualitatively similar result if we focus on a constant sample of banks (those that participate in all stress tests in our sample), as we do in the other parts of this paper.

form approximation of the actual model the Fed uses to map loan portfolios into losses under the severely adverse scenario. Two types of approximations are implicit in equation (25). First, the entire loan book is divided into buckets and dimensions; and second, the relationship is assumed to be linear.

In principle, our view is that banks would learn about the parameters of equation (25) over time from multiple rounds of stress tests based only on information of their own (current and past) submitted portfolios and the related stress-test results and without knowledge of the detailed loan portfolios of their peers.[20] The associated learning problem is challenging and is further complicated by the fact that the Fed's models and scenarios may vary over time, leading to time variation in the reduced-form coefficients. However, even under the assumption of stability of the Fed's models and scenarios, the parameters in equation (25) are not identified for each bank separately. The reason is that, even if we were to use information on all stress tests over time (thereby assuming banks would have a time t information about future portfolios and stress tests), we would have only five observations. Therefore, we assume that banks, at each point in time, would know the current and past portfolios of their peers, too. Effectively, we pool the cross section of banks and estimate equation (25) on an expanding window, using all past and current information on all submitted portfolios.

Table A.2, in the Appendix, shows estimates of C&I loss sensitivity to portfolio buckets along the sector, ratings, and region dimensions. Not surprisingly, loans with a riskier rating, especially with ratings below investment grade, contribute more to loan losses under the severely adverse scenario compared with loans with a higher rating (investment grade). Results for sector buckets indicate that certain industries, including information and manufacturing, make particularly large contributions to stress-test losses; we do not estimate a significant contribution from utilities or public administration.

In the second step of our loan-level analysis, we estimate a bank's credit supply adjustments in response to its stress-test outcome, taking into account the heterogeneous sensitivity of different loans in its portfolio to the stress test. Specifically, our hypothesis is that (1) banks with a high

[20]It is argued that banks hire external consultants and compliance specialists, some of which have worked at the Federal Reserve or other commercial banks, to gain information about the Fed's stress-testing model and the portfolios of other banks. It is plausible that a given bank is thus better equipped to deduce the structure of the Fed's stress-test model and optimizes its response to regulatory stress-testing based not only on information about its own (current and past) submitted portfolios and the related stress-test results.

capital shortfall under stress subsequently reduce their loan portfolio (because capital constraints bind), and (2) the credit supply reduction is stronger in loans that are most sensitive to the stress test. Our regression to test the first part of the hypothesis is given by

$$\Delta \text{Credit}_{i,j,t} = \gamma \cdot \text{Tier-1-Loss}_{i,t-1} + \alpha_{j,t} + \alpha_{i,j} + \epsilon_{i,t}, \tag{26}$$

where $\Delta\text{Credit}_{i,j,t}$ is the change in (log) credit outstanding from bank i to borrower j, where the change is computed based on the submitted portfolio relative to the portfolio submitted for the preceding stress-test round; that is, we compare portfolios that are used in the stress tests to compute the stress-test losses. As before, $\text{Tier-1-Loss}_{i,t-1}$ is the bank's Tier 1 capital loss in the last stress-testing exercise. We use within-borrower estimation, similar in spirit to Khwaja and Mian (2008), by including borrower-time fixed effects ($\alpha_{j,t}$) in all specifications. The inclusion of these fixed effects comprehensively accounts for any time-varying borrower heterogeneity, including, but not limited to, demand shifts. In addition, we exploit in our identification variation within bank-firm pairs by including bank-borrower fixed effects ($\alpha_{i,j}$), which account for potential compositional shifts in the borrower base of a given bank over time and relationship lending effects.

The first two columns of Table 7 show the estimated coefficient γ of equation (27). The first column shows the change in credit outstanding issued to firms borrowing from banks with a Tier 1 loss under the stress test in the top 75th percentile. The second column shows the change in outstanding credit for firms borrowing from banks with a Tier 1 loss under stress in the top 90th percentile. Both estimates are negative. Note particularly that outstanding credit declines by a significant 5.7 percent for those firms borrowing from the banks that performed the worst in the preceding DFAST exercise. As mentioned above, shifts in credit demand are accounted for by including borrower-time fixed effects in the regression.

We evaluate the second hypothesis—that banks rebalance their portfolios away from loans that have a high contribution to stress-test losses—by including an interaction term between a bank's capital shortfall and the loan sensitivity estimated in the first stage. Formally, our regression equation is given by

$$\Delta \text{Credit}_{i,j,t} = \sum_{d} \gamma^{d} \cdot \text{Tier-1-Loss}_{i,t-1} \cdot \text{High Sensitivity}^{d}_{j,t-1} + \alpha_{j,t} + \alpha_{i,t} + \alpha_{i,j} + \epsilon_{i,t}, \tag{27}$$

where High Sensitivity$^d_{j,t-1}$ is a dummy variable that equals 1 if the credit exposure to borrower j is associated with a positive and significant (at the 10 percent level) coefficient estimate in dimension d of the first stage.[21] In this specification, in addition to borrower*time and borrower*bank fixed effects, we include bank*time fixed effects, because we are interested in portfolio rebalancing across different types of credit, while controlling for general time-varying bank characteristics, such as leverage or the Tier 1 losses under the stress-test scenarios, and demand effects with borrower*time fixed effects.[22]

Columns (3) and (4) in Table 7 show the estimates of the coefficients in equation (27). The coefficients of interest are those corresponding to the interaction that captures a firm borrowing from a bank that performed poorly in the preceding DFAST and that borrower belongs to a category to which the bank's losses are particularly sensitive (that is, a particular rating and sector). Our estimation shows that banks that performed poorly in DFAST (Tier 1 capital loss in the top 75th percentile) contract their lending more aggressively from those firms with ratings or belonging to sectors that significantly affect the bank's performance in DFAST. These differential effects are also economically sizable, with high-loss banks contracting credit in highly sensitive loans by 4.6 percentage points (rating dimension) and 5.1 percentage points (sector dimension) more compared with loans with low sensitivity. We also find a significant decline in credit issued by banks in the 90th percentile of Tier 1 capital shortfall to firms in sectors that generate significant losses under stress. It is important to highlight again that we identify these portfolio rebalancing effects after controlling for demand shifts with borrower*quarter fixed effects (within-borrower estimation) and by comparing growth in different loans within the same bank while netting out common bank-time specific heterogeneity, such as a bank's capitalization, size, or capital losses under stress.

In Appendix Table A.3, we also show that, while banks with a high tier 1 capital loss under stress cut back credit to bad loans, they do not increase their lending more to good loans compared with banks without high tier 1 losses. This finding suggests that the credit contraction in bad loans is not offset by an increase in credit in good loans, thereby reducing the overall loan portfolio

[21] Our results are robust to alternative threshold choices of significance level. There are very few cases in which multiple banks report different sector, rating, or region classifications for the same borrower in a given quarter. In such cases, we use the modal classification. This choice has no impact on our results.

[22] In related work, Berrospide and Edge (2019) find that the larger capital shortfalls result in a subsequent lower growth rate of utilized and committed loans. In particular they find that a 1 percentage point increase in capital shortfall due to stress-testing results in a 2 percentage point decrease in the growth of utilized loans and a 1.5 percentage point decrease in growth of committed loans.

Table 7: Loan-level Credit Supply and Portfolio Rebalancing

	Dep. Var.: Credit Growth (%)			
	(1)	(2)	(3)	(4)
	Tier 1 Loss > p75	Tier 1 Loss > p90	Tier 1 Loss > p75	Tier 1 Loss > p90
High Tier 1 Loss Bank	-0.012	-0.057**		
	(-0.94)	(-2.64)		
High Tier 1 Loss Bank			-0.046**	-0.011
× High Sensitivity (Rating)			(-2.47)	(-0.50)
High Tier 1 Loss Bank			-0.051*	-0.063*
× High Sensitivity (Sector)			(-1.98)	(-2.02)
High Tier 1 Loss Bank			-0.007	0.009
× High Sensitivity (Region)			(-0.08)	(0.09)
Observations	48,245	48,245	48,245	48,245
R-squared	0.627	0.627	0.631	0.631
Borrower*Time FE	Yes	Yes	Yes	Yes
Borrower*Bank FE	Yes	Yes	Yes	Yes
Bank*Time FE	No	No	Yes	Yes

Notes: Columns (1) and (2) report the effect of (lagged) stress-test losses on overall credit supply changes estimated from the C&I loan portfolio submitted at the next stress-test round. Columns (3) and (4) show heterogeneous effects of (lagged) stress-test losses on credit supply changes for different loan types (within-bank portfolio rebalancing), also based on the portfolios submitted for stress-testing. All regressions are run at the bank-borrower-quarter level. High Sensitivity is a dummy variable that equals 1 if the estimate for $\beta_{d,k}$ in equation (25) is significant at the 10 percent level. The sample includes all banks participating in the five stress tests from 2011:Q3 through 2016:Q4. Only borrowers with multiple bank-lending relationships at a given quarter are considered (within-borrower estimation), and all facilities of the same borrower with the same lender are aggregated each quarter. Robust t-statistics two-way clustered at the bank and borrower level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Source:* FR-Y14Q, Schedule H.1.

growth (see columns 1 and 2 in Table 7).

Overall, our findings from this analysis show that banks, in response to capital loss under the stress test, reduce their loan supply. Moreover, there is a strong heterogeneous effect, with banks' credit contracting more strongly from firms that contribute to losses under the severely adverse stress scenario, suggesting an active portfolio rebalancing consistent with previously reported increased bank similarity.

5.2 Sensitivity of Loan Portfolio and Changes in Similarity

We next provide more detailed evidence on how the supply-driven credit reduction and portfolio rebalancing away from lending that fares poorly in the stress-test scenarios affect the portfolio similarity of banks. In particular, in the preceding subsection, we established that the sensitivity of individual C&I loans to the stress-test scenarios leads to a portfolio rebalancing, while in this subsection we show that it also induces a greater similarity across banks.

Our previous analysis is based on bank-level measures of similarity built from individual portfolio shares along several risk categories for three key risk dimensions. To understand the contribution of a change in a portfolio share in a given risk category to the change in similarity along a given portfolio dimension, recall that a bank's (average) similarity score in our baseline analysis is given by $d_{i,t}^d = 1 - \alpha \cdot \frac{1}{N-1} \sum_{i \neq j} \frac{1}{K} \sum_{k=1}^{K} |\alpha_{i.t}^d(k) - \alpha_{j.t}^d(k)|$, where α is a scaling factor as implicitly defined in equation (23). We can then define the contribution of category k to the change in similarity along dimension d as[23]

$$\Delta d_{i,t}^d(k) = -\alpha \cdot \frac{1}{N-1} \sum_{i \neq j} |\alpha_{i.t}^d(k) - \alpha_{j.t}^d(k)| + \alpha \cdot \frac{1}{N-1} \sum_{i \neq j} |\alpha_{i.t-1}^d(k) - \alpha_{j.t-1}^d(k)|.$$

Thus, this quantity, $\Delta d_{i,t}^d(k)$, measures the average change in the distance of bank i's share in portfolio category k along dimension d relative to the shares of all other banks in the same category k. In our baseline analysis, we show results from averaging over the subset of the best-performing banks in the stress test, similar to our analysis in Table 6.

Our regression analysis estimates the contribution of bucket k to the similarity change depending on its impact on the hypothetical losses in the stressed scenario. Intuitively, this means we estimate whether poorly performing banks align their portfolio shares in credit types that are most sensitive to stress-test losses to better resemble the respective shares of well-performing banks. The formal regression equation for our analysis is

$$\Delta d_{i,t}^d(k) = \beta \cdot \text{High Sensitivity}_k^d + \alpha_{i,t} + \alpha_{k,t}^d + \alpha_{i,k}^d + e, \tag{28}$$

where $\alpha_{i,t}$ is a bank*quarter fixed effect, $\alpha_{k,t}^d$ is a quarter*risk-category fixed effect, and $\alpha_{i,k}^d$ is a bank*risk-category fixed effect. This rich set of fixed effects controls for, for example, general convergence of a given bank's portfolio toward its peers' portfolios and allows us to isolate the differential treatment effect depending on the contribution of individual portfolio shares to stress-test losses.

[23] As an example, category k could be AAA, A, or C for the rating dimension, but it would be manufacturing, transportation, etc. for the sector dimension.

Table 8: Contribution of Individual Loan Portfolio Shares to Similarity Change

	Dep. Var.: Contribution to Change in Similarity Score			
	(1)	(2)	(3)	(4)
	Tier 1 Loss > p75	Tier 1 Loss > p90	Tier 1 Loss > p75	Tier 1 Loss > p90
High Tier 1 Loss Bank * High Sensitivity (Pooled)	0.903*	0.535**		
	(1.95)	(2.34)		
High Tier 1 Loss Bank * High Sensitivity (Rating)			1.417*	0.529
			(1.90)	(1.56)
High Tier 1 Loss Bank * High Sensitivity (Sector)			0.922	0.625**
			(1.30)	(2.26)
High Tier 1 Loss Bank * High Sensitivity (Region)			-0.530	0.307
			(-0.57)	(0.47)
Observations	6,683	6,683	6,683	6,683
R-squared	0.402	0.402	0.403	0.402
Bank*Quarter FE	Yes	Yes	Yes	Yes
Risk-Dimension*Quarter FE	Yes	Yes	Yes	Yes
Risk-Dimension*Bank FE	Yes	Yes	Yes	Yes

Notes: This table reports how changes in individual portfolio shares along the three risk dimensions (rating, sector, region) contribute to increases in the similarity score depending on the sensitivity to stress-test losses and banks overall capital losses under stress. In columns (1) and (2) the average effect across all three risk dimensions is shown for two different classifications of loss banks. Columns (3) and (4) show heterogeneous effects for the different risk dimensions. All regressions are run at the bank-risk-dimensions-quarter level. High Sensitivity is a dummy variable that equals 1 if the estimate for $\beta_{d,k}$ in equation (25) is significant at the 10 percent level. The sample includes all banks participating in the five stress tests from 2011:Q3 through 2016:Q4. Robust t-statistics clustered at the bank level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Source:* FR-Y14Q, Schedule H.1.

Table 8 reports the regression results. In columns (1) and (2), we show that across all risk dimensions, banks with large capital shortfalls in the stress test, on average, rebalance their portfolios so that they look more similar to those of the best-performing banks in the preceding stress test in terms of the portfolio shares that contribute most to stress-test losses. In columns (3) and (4), we allow for heterogeneous effects depending on the risk dimensions. We show that, as with our bank-borrower-level analysis, results are driven by adjustments along the ratings and sector dimensions. That is, poorly performing banks rebalance their loan portfolios along the rating and sector dimensions away from risk categories that perform poorly in the stress test; thereby, their portfolios closely resemble those of the banks that perform best in the stress test.

5.3 Firm-level Effects

To better understand the impact of banks' loan portfolio adjustments in response to stress-testing performance on borrowers' access to credit and potential real effects, we next move to a borrower-(firm-)level analysis instead of a loan-level analysis. Specifically, we estimate a firm's access to bank debt from Y-14Q banks, access to overall debt (all bank debt and market debt), and investment response as a function of the ex ante reliance on funding from banks with ex post large capital shortfalls under the stress test. Our generic regression equation is given by

$$\Delta\text{Firm Outcome}_{j,t} = \beta \times \text{Reliance on Tier-1-Loss Bank}_{j,t-1} + \alpha_j + \alpha_t + \epsilon_{j,t}, \tag{29}$$

where the dependent variables are *(1)* the firm's credit growth based on all committed bank loans in our data (that is, we aggregate all loans to a given firm and compute the growth in the committed exposure), *(2)* the growth in the firm's debt from all types of bank and nonbank debt (including market debt, such as bonds), or *(3)* the growth of capital expenditures (investment). The key independent variable is Reliance on Loss Banks$_{j,t-1}$, the share of credit obtained from banks that perform poorly in stress tests (defined as banks with capital shortfalls above the 75th or 90th percentile in each stress test) relative to all credit observed in the data, measured after the preceding stress-testing exercise. The purpose of this variable is to capture a given firm's exposure to poorly performing banks, and it is motivated by the large literature on relationship banking and sticky bank-firm relationships in credit markets, typically rooted in asymmetric information problems (e.g. Petersen and Rajan 1994). To account for compositional shifts in the sample of firms over time and related firm heterogeneity, we include borrower fixed effects (α_j) in all regressions. Similarly, we include time fixed effects (α_t).

The first two columns of Table 9 present regression results with credit growth from all Y14Q banks as the dependent variable. We collect information on total debt from the Y14Q data, and importantly, this information is not restricted to firms with publicly traded equity but is also available for firms with a private ownership structure. The coefficient estimates show that firms with a larger ex ante reliance on banks with high capital shortfalls face a larger reduction in credit growth from Y14Q banks. Results are qualitatively robust to changing the definition of high-loss banks based on those banks having capital shorfalls above the 75th or the 90th percentile, although results for the latter definition are intuitively larger in (absolute) magnitude. For example, based on all loans, a one-standard-deviation larger reliance measure decreases credit growth by about 5.7 (–13.3*0.429) percentage points if high-loss banks are defined based on the 75th percentile and by about 9.94 (–30.4*0.327) percentage points if defined based on the 90th percentile.

Overall, these results suggest that firms that rely more on banks with poor stress-test results are

Table 9: Firm-level Borrowing and Real Effects

	(1) Δlog(Y14 Loans)	(2) Δlog(Y14 Loans)	(3) Δlog(Debt)	(4) Δlog(Debt)	(5) Δlog(Capex)	(6) Δlog(Capex)
Reliance on	-0.133***		-0.063*		-0.174*	
Loss Banks (> p75)	(-13.38)		(-1.94)		(-1.82)	
Reliance on		-0.304***		-0.080**		-0.931***
Loss Banks (> p90)		(-22.99)		(-2.03)		(-3.12)
Observations	30,170	30,170	16,557	16,557	6,055	6,055
R-squared	0.360	0.372	0.379	0.380	0.293	0.296
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean RHS	0.301	0.146	0.301	0.176	0.336	0.115
Std RHS	0.429	0.327	0.434	0.359	0.442	0.284

Note: The table reports the impact of stress-testing on firms' debt funding conditions and investment. The dependent variable in columns (1) and (2) is the log difference in credit outstanding from Y-14Q banks (stress-test banks), comparing the submitted portfolios with the portfolios from the last submission. In columns (3) and (4) the dependent variable is the log difference in all credit outstanding (including bank and market debt). In columns (5) and (6), the dependent variable is the log difference in capital expenditures. The dependent variable Reliance on Loss Banks measures the share of credit from loss banks (relative to credit from all Y14Q banks) outstanding computed from the portfolios submitted in the last stress-testing round ($t-1$). The mean and standard deviation of the dependent variable are reported in the table. Controls include Cash/Assets, Debt/Assets, and Total Current Assets. Robust t-statistic clustered at the firm level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Source:* FR-Y14Q and Compustat.

not able to fully substitute the reduction in credit, which we identify at the loan level, by borrowing more from other Y14Q banks. As a result, these firms face a reduction in credit. However, an important question is whether these firms are able to replace the loss of funding by increasing borrowing from other banks that are not in our stress-test database, or even by borrowing from nonbank lenders, including through market-based debt instruments, such as bonds.

To address this important question, in columns (3) and (4) of Table 9, we analyze the overall credit growth of a firm based on all types of debt. Using firms' overall debt growth as the dependent variable, we find evidence consistent with a lack of substitution across a broader set of borrowers and instruments. For example, the point estimates in column (3) suggest that credit growth declines about 2.73 (–6.3*0.434) percentage points (compared with a decline of about 5.7 percentage points in lending growth by Y14Q banks). Interestingly, we do find roughly similar coefficients for the two different high-loss-bank definitions, as debt declines 2.87 percentage points for firms relying on banks in the 90th percentile of loss under stress (compared with the 9.94 percentage point decline in 14Q credit). These two substantially different results indicate that loans obtained from poorly performing banks are not substituted with loans issued by other large (and better-performing) banks. However, firms are able to substitute part of the large-bank credit with either credit from smaller banks (not subject to DFAST) or other types of debt.

Given the relatively strong contraction in large-bank lending and overall credit availability for firms with a higher reliance on high-loss banks, we next investigate the associated real effects by looking at firms' investment behavior. Information on investment is also part of the Y14Q data set, and it is available for both public and private firms, altough this information is available for a smaller set of firms. In columns (5) and (6), we show that firms with a larger reliance on poorly performing banks exhibit a reduction in investment growth relative to unaffected firms. This reduction is substantial: 7.7 to 26.4 percentage points as a result of a one-standard-deviation increase in reliance on poorly performing banks. The contraction in investment expenses by firms that rely on poorly performing DFAST banks is yet another unintended consequence of the portfolio rebalancing that occurs as a result of stress-testing. Banks carefully select investment opportunities that have a positive marginal impact on the capital ratios under stress. We have shown that banks rebalance their portfolios in similar directions; therefore, firms relying on poorly performing banks are not able to find alternative sources of credit among large banks. This loss of credit is partly offset by other types of credit, but not enough to prevent a substantial contraction in investment.

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. From a classic microprudential perspective, a set of individually better-capitalized banks with more diversified portfolios is often viewed as desirable. However, from a macroprudential viewpoint, an entire system of banks with similar portfolios, and one that is more concentrated as a whole, could be a source of concern.

We show that US banks, after stress-testing was implemented, adjusted their portfolios toward more common types of risk exposures. These portfolio adjustments were 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. Our detailed loan-level analysis confirms the credit supply reduction by banks with poor stress-test results in loans that add most to stress-test losses, which is a desirable policy outcome. However, we show that this credit supply reduction comes at a cost, since it has adverse consequences for firms' overall credit and investment behavior, thereby having real economic effects.

The tradeoff between portfolio diversification among individual banks and systemic similarities represents the policy compromise between microprudential and macroprudential regulation. Banks' reaction to stress-testing may result in a build-up of systemic risk along dimensions 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 as careful and as comprehensive as possible. While the current methodology has resulted in an extraordinary increase in loss-absorbing capital buffers, it also has had the unintended consequence of individual banks' portfolios becoming similarly diversified, at the cost of a credit supply contraction with real effects and a US banking system that is systemically concentrated.

References

Abbassi, Puriya, Christian Brownlees, Christina Hans, and Natalia Podlich. 2017. "Credit risk interconnectedness: What does the market really know?" *Journal of Financial Stability* 29:1 – 12.

Acharya, Viral V., Allen N. Berger, and Raluca A. Roman. 2018. "Lending implications of U.S. bank stress tests: Costs or benefits?" *Journal of Financial Intermediation* 34:58 – 90. Assessing Banking Regulation During the Obama Era.

Allen, Franklin, Ana Babus, and Elena Carletti. 2012. "Asset commonality, debt maturity and systemic risk." *Journal of Financial Economics* 104 (3): 519 – 534. Market Institutions, Financial Market Risks and Financial Crisis.

Bassett, William F., and Jose M. Berrospide. 2018. "The Impact of Post-Stress Tests Capital on Bank Lending." Unpublished working paper, Washington, DC: Federal Reserve Board of Governors.

Berrospide, Jose M., and Rochelle M. Edge. 2019. "The Effects of Bank Capital Buffers on Bank Lending and Firm Activity: What Can We Learn from Five Years of Stress-Test Results?" Finance and economics discussion series 2019-050, Board of Governors of the Federal Reserve System (U.S.).

BOG. 2019, June. "Comprehensive Capital Analysis and Review 2019: Assessment Framework and Results." Technical Report, Board of Governors of the Federal Reserve System.

Caccioli, Fabio, Munik Shrestha, Cristopher Moore, and J. Doyne Farmer. 2014. "Stability analysis of financial contagion due to overlapping portfolios." *Journal of Banking and Finance* 46:233 – 245.

Cai, Jian, Frederik Eidam, Anthony Saunders, and Sascha Steffen. 2018. "Syndication, interconnectedness, and systemic risk." *Journal of Financial Stability* 34:105 – 120.

Cortés, Kristle, Yuliya Demyanyk, Lei Li, Elena Loutskina, and Philip E. Strahan. 2020. "Stress Tests and Small Business Lending." *Journal of Financial Economics*, vol. Forthcoming.

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger. 2020. "The rise of market power and the macroeconomic implications." *The Quarterly Journal of Economics* 135 (2): 561–644.

Goldstein, Itay, Alexandr Kopytov, Lin Shen, and Haotian Xiang. 2020, June. "Bank Heterogeneity and Financial Stability." Working paper 27376, National Bureau of Economic Research.

Greenwood, Robin, Samuel G Hanson, Jeremy C Stein, and Adi Sunderam. 2017. "Strengthening and Streamlining Bank Capital Regulation." *Brookings Papers on Economic Activity* 6:1953–2009.

Gropp, Reint, Thomas Mosk, Steven Ongena, and Carlo Wix. 2018. "Banks Response to Higher Capital Requirements: Evidence from a Quasi-Natural Experiment." *The Review of Financial Studies* 32 (1): 266–299 (04).

Hancock, Diana, Andrew J. Laing, and James A. Wilcox. 1995. "Bank capital shocks: Dynamic effects on securities, loans, and capital." *Journal of Banking Finance* 19 (3): 661 – 677. The Role of Capital in Financial Institutions.

Ibragimov, Rustam, Dwight Jaffee, and Johan Walden. 2011. "Diversification disasters." *Journal of Financial Economics* 99 (2): 333 – 348.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina. 2017. "Macroprudential Policy, Countercyclical Bank Capital Buffers, and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments." *Journal of Political Economy* 125 (6): 2126–2177.

Khwaja, Asim Ijaz, and Atif Mian. 2008. "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market." *American Economic Review* 98 (4): 1413–42 (September).

Liu, Emily, Friederike Niepmann, and Tim Schmidt-Eisenlohr. 2019, November. "The Effect of U.S. Stress Tests on Monetary Policy Spillovers to Emerging Markets." International finance discussion papers 1265, Board of Governors of the Federal Reserve System (U.S.).

Oztekin, Ozde, and Mark J. Flannery. 2012. "Institutional Determinants of Capital Structure Adjustment Speeds." *Journal of Financial Economics* 103 (1): 88–112.

Peek, Joe, and Eric S. Rosengren. 2000. "Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States." *American Economic Review* 90 (1): 30–45.

Petersen, Mitchell A., and Raghuram G. Rajan. 1994. "The Benefits of Lending Relationships: Evidence from Small Business Data." *The Journal of Finance* 49 (1): 3–37.

———. 1995. "The Effect of Credit Market Competition on Lending Relationships." *The Quarterly Journal of Economics* 110 (2): 407–443.

Tarullo, Daniel K. 2019. "Financial Regulation: Still Unsettled a Decade after the Crisis." *Journal of Economic Perspectives* 33 (1): 61–80 (February).

Appendix

Table A.1: Summary Statistics of the Commercial and Industrial Loan Portfolio Composition by Maturity

	Portfolio Shares (% of Total Assets)					
	Mean	p10	p25	p50	p75	p90
Maturity 0-1 Years	6.21	0.66	2.83	5.39	7.86	10.92
Maturity 1-2 Years	5.56	1.10	3.31	5.58	7.34	8.81
Maturity 2-5 Years	37.83	27.69	32.35	36.72	44.10	55.46
Maturity 5-6 Years	13.77	7.38	10.71	13.67	16.61	19.25
Maturity 6-11 Years	19.57	7.25	10.65	19.79	27.28	32.55
Maturity 11-31 Years	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 Unknown	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 through 2016:Q4.
Source: FR Y-14Q.

Table A.2: Contribution of Portfolio Dimensions to Capital Losses in Stress Scenario

Sector	β	R^2_w	Rating	β	R^2_w	Region	β	R^2_w
Financial	0.02***	0.22	AAA	-0.03	0.01	Foreign	0.01	0.00
	(0.00)			(0.06)			(0.04)	
Health Care	0.24*	0.14	AA	0.00	0.00	West	0.09***	0.44
	(0.13)			(0.04)			(0.02)	
Information	0.27***	0.58	A	-0.00	0.01	Northeast	0.07***	0.56
	(0.05)			(0.02)			(0.01)	
Manufacturing	0.09***	0.58	BBB	0.03***	0.45	South	0.05***	0.57
	(0.02)			(0.00)			(0.01)	
Mining & Oil	-0.09*	0.03	BB	0.05***	0.58	West	0.09***	0.51
	(0.05)			(0.01)			(0.01)	
Other Services	0.10	0.02	B	0.12***	0.27			
	(0.14)			(0.03)				
Public Admin.	-0.01	0.00	CCC	-0.01	0.00			
	(0.12)			(0.08)				
Real Estate	0.15***	0.49	CC	0.10**	0.16			
	(0.02)			(0.04)				
Retail Trade	0.13**	0.30	C	3.13***	0.24			
	(0.06)			(1.06)				
Transportation	0.50***	0.37	D	0.56*	0.06			
	(0.07)			(0.28)				
Utilities	0.12	0.03	NR	-0.10	0.00			
	(0.16)			(0.10)				
Wholesale Trade	0.25***	0.40						
	(0.05)							
Other Sectors	0.10***	0.33						
	(0.02)							
Observations	134			134			134	
Sample	N			N			N	
Bank FE	Y			Y			Y	
Time FE	N			N			N	

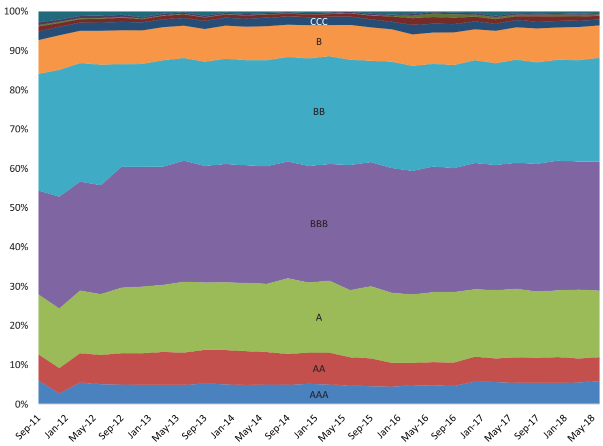
Notes: First-stage estimates, results from univariate regressions for each of the categories within rating, region, and industry. Within-group R^2 reported next to the slope estimates. Robust standard errors clustered at the bank level are reported in parentheses.

Table A.3: Loan-level Credit Supply: Credit Growth by High Tier 1 Loss Banks Declines in Bad Loans, But Does Not Increase in Good Loans

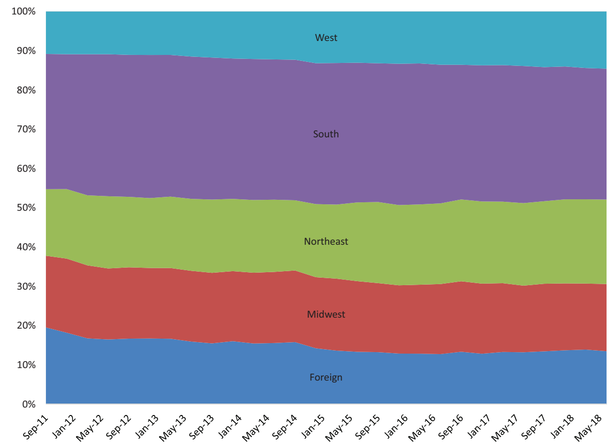
	Dep. Var.: Credit Growth (%)					
	Tier 1 Loss > p75			Tier 1 Loss > p95		
	(1)	(2)	(3)	(4)	(5)	(6)
High Tier 1 Loss Bank	0.007	0.008	0.009	-0.049*	-0.045*	-0.047*
	(0.53)	(0.50)	(0.67)	(-1.98)	(-1.79)	(-1.93)
High Tier 1 Loss Bank	-0.059***			-0.043		
× High Sensitivity (Rating)	(-2.77)			(-1.56)		
High Tier 1 Loss Bank		-0.054**			-0.055**	
× High Sensitivity (Sector)		(-2.31)			(-2.18)	
High Tier 1 Loss Bank			-0.058**			-0.047
× High Sensitivity (Region)			(-2.42)			(-1.53)
Observations	48,245	48,245	48,245	48,245	48,245	48,245
Borrower*Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower*Bank FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table builds on Table 7 and shows the differential credit growth for good versus bad banks (high versus low Tier 1 loss in stress test) depending on the sensitivity of the debtor characteristics to stress testing. In contrast to Table 7, columns (3) and (4), the results shown in this table are based on specifications that do not include bank*time fixed effects, allowing us to infer the differential credit growth between good and band banks for good loans, i.e, without strong stress test sensitivity (see coefficient estimate for High Tier 1 Loss Bank). The results show that while bad banks cut back credit to bad loans, they do *not* increase lending to good loans. Robust t-statistics two-way clustered at the bank and borrower level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Source:* FR-Y14Q, Schedule H.1.

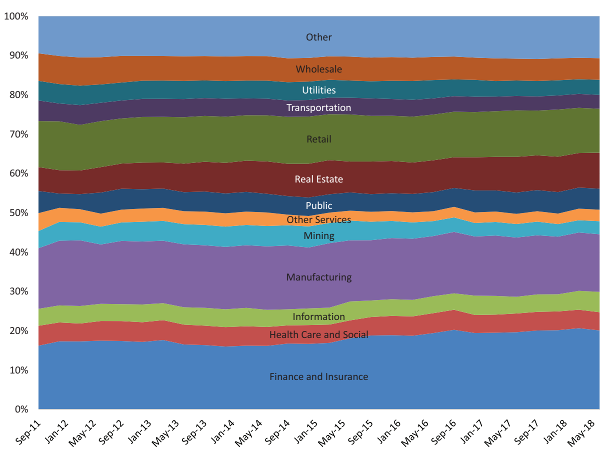
Figure A.1: Evolution of Commercial and Industrial Loan Portfolio Shares over the Sample Period 2011:Q4–2018:Q2



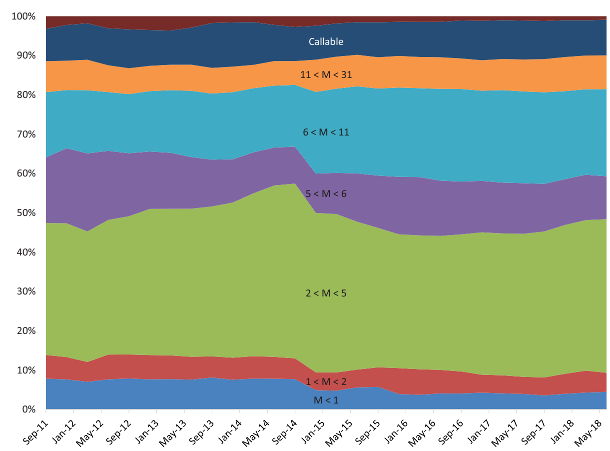
(a) Rating



(c) Region



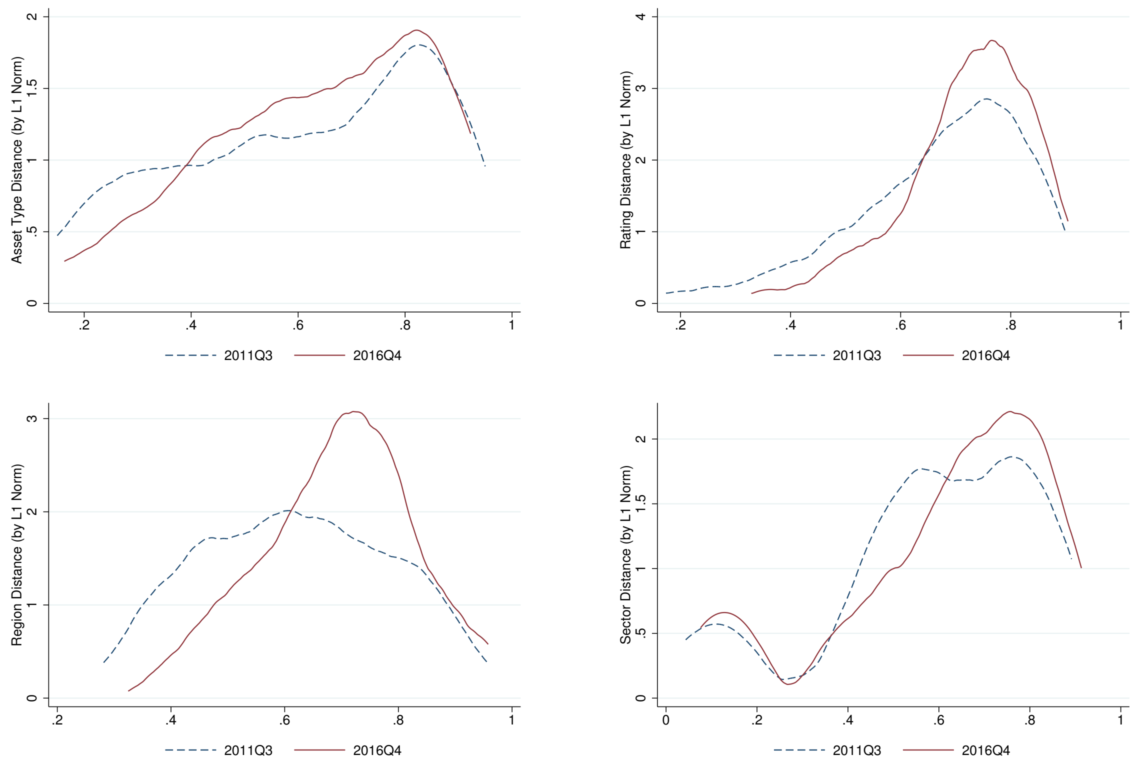
(b) Industry



(d) Maturity

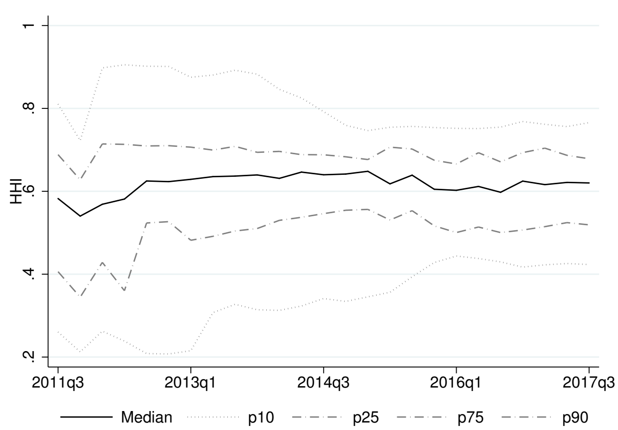
Note: The sample includes the 19 banks subject to DFAST from 2011:Q3 through 2016:Q4.
Source: FR Y-14Q, Schedule H.1.

Figure A.2: Similarity of Commercial and Industrial Loan Portfolios (by L1 Norm)



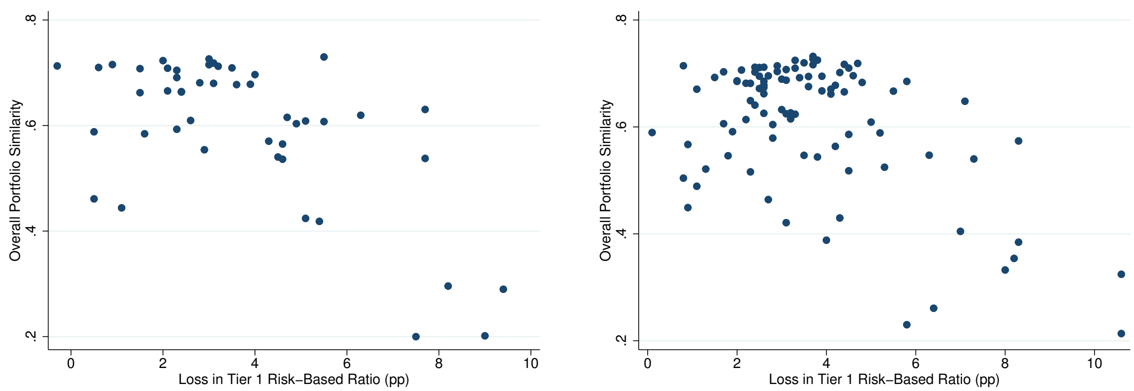
Notes: The sample includes the 19 banks subject to DFAST from 2011:Q3 from 2016:Q4. The upper-left panel shows the evolution of the similarity distribution by rating. The upper-right panel shows the similarity by US Census region. The lower-left and lower-right panels show the similarity distributions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

Figure A.3: 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 through 2016:Q4.
Sources: FR Y-14Q and authors' calculations.

Figure A.4: Average Similarity (by L1 Norm) of the Overall Portfolio and Tier 1 Risk-based Capital Ratio Shortfall (Sample Split)



(a) Before 2014:Q4

(b) After 2014:Q4

Notes: The full sample includes all banks participating in the five stress tests from 2011:Q3 through 2016:Q4. The horizontal axis shows the capital shortfall (loss in capital) forecast under the severely adverse scenario.
Sources: FR Y-9C reports and disclosures of annual DFAST results. This figure uses only publicly available information.