United They Fall: Bank Risk After the Financial Crisis*

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Abstract

Explicit model-based regulation is a standard tool to control risk-taking in the banking sector. Using the enactment of annual stress-test under the Dodd-Frank Act as an empirical setting, we show that such regulations can lead to a significant increase in commonality in risk exposure across banks. Specifically, stress-tested banks have become increasingly similar in their risk exposure after the formalization of stress tests, a pattern that is absent in non-tested banks, non-financial firms, or non-bank financial firms. Consistent with a causal interpretation, after a bank fails the stress test its risk exposure becomes similar to other stress-tested banks. The results of the stress test itself have also become similar across banks over time. Our findings raise concerns about the buildup of correlated risk in the system in response to model-based regulation.

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Introduction

In the aftermath of a financial crisis, policymakers often impose new regulations to control the risk of financial institutions under their jurisdiction. The global financial crisis of 2008-09 was no different. The benefits of such regulation, however, come with a potential cost: if the regulated banks change their business model to comply with the new regulation in a similar fashion, they become more likely to fail in the same states of the world. Such correlated risk exposure can impose substantial cost on the economy in bad states of the world, even if the unconditional probability of a bank's default comes down as a result of the regulation. For example, homogeneity in asset holdings across banks can increase fire-sale externality (Goldstein, Kopytov, Shen, and Xiang, 2020) and lead to excessive volatility in financial markets (Morris and Shin, 1999) if banks fail. Correlated failure of banks can be especially costly if intermediaries' capital position affects asset prices (He and Krishnamurthy, 2018).

While several regulatory changes have been implemented since the financial crisis, stress test is arguably the most important post-crisis regulation for the measurement and monitoring of risk in the financial system. These tests evaluate whether the bank holding companies have sufficient capital to absorb losses in adverse macroeconomic scenarios that are determined by a well specified model (see Schuermann (2014)). If all banks do well on the stress test models, regulators can be reasonably confident that the banking sector has enough capital to withstand these adverse shocks. The enactment of these tests provides an attractive empirical setting to address the broader question of the impact of explicit ex-ante model-based regulation (see Behn, Haselmann, and Vig (2022)) on homogeneity across banks for three key reasons: (a) stress tests are model-based, (b) the key features of the tests are well-known, and (c) the test only affected a set of banks, which provides a rich set of control firms both from financial and non-financial industries.

The possibility that stress test can result in correlated risk exposure across banks has been raised as a concern by the regulators as well since such behavior has immediate implications for the design and implementation of these tests.[1] Should the regulator disclose the key features of the model to the regulated entities (Leitner and Williams (2022))? More broadly, what should be the most effective way to design and implement a macroprudential regulation (Diamond, Kashyap, and Rajan (2017))? How should a regulator assess the choice between an explicit ex-ante regulation that are susceptible to gaming versus ex-post discretion in dealing with failures (Greenwood, Stein, Hanson, and Sunderam (2017))? It is critical to understand the effect of a model-based regulation, such as stress test, on risk exposure to address each one of these questions.

We first develop a stylized model to formalize the intuition behind increased commonality across banks in response to a model-based regulation like the stress test.[2] There are two risky assets in the model, each exposed to a macroeconomic risk factor and an additional uncorrelated shock. The macroeconomic risk factor enters the regulator's risk model, whereas the additional shock is a hidden risk privately known to the bank. Banks vary in terms of their screening and monitoring technologies across the two assets, which generates heterogeneity in their risk exposures even in a frictionless world. We compare homogeneity in their risk exposure across two economies: (i) one in which they manage risk on their own in the face of frictions such as bankruptcy cost, collateral constraints, or costly external financing (Smith and Stulz (1985), Froot, Scharfstein, and Stein (1993), Purnanandam (2008), Rampini and Viswanathan (2010)), and (ii) the other under the stress test regulation.

In the self-imposed risk model, the bank considers the contribution of each asset to the entire variance-covariance matrix of risk exposure. It optimally tilts its portfolio towards

[1]While discussing the impact of higher disclosure of stress test scenario, the regulators have expressed concerns about correlations in asset holdings that may be counterproductive from a risk-management perspective. For example, see the discussion in Federal Register,Vol. 82, No 42, 2017, page 59548: "One implication of releasing all details of the models is that firms could conceivably use them to make modifications to their businesses......Further, such behavior could increase correlations in asset holdings among the largest banks, making the financial system more vulnerable to adverse financial shocks".

[2]We use the terms commonality and homogeneity interchangeably in the paper.

the lower skill asset if it lowers the overall risk. With stress test, however, exposure to the hidden risk becomes relatively less costly. The optimal portfolio now depends on a tradeoff between the bank's skill in an asset and mainly its contribution to risk exposure to the tested factor. The level of homogeneity in the economy, in turn, depends on the distribution of technological skills across banks, the proportion of risk-exposure of an asset that comes from its sensitivity to the macroeconomic factor, and the cost of failing the stress test. Stress test increases homogeneity when the volatility of the macroeconomic factor is sufficiently high compared to the overall volatility of risky assets, and when the stress test capital requirement is more binding. In the end, whether stress tests increase homogeneity or not remains an empirical question that we tackle in the rest of the paper.

We begin our empirical analysis by documenting the evolution of pairwise correlation in bank stock returns over time. We compute the CAPM-adjusted returns for every bank in the sample on an annual basis to focus on the evolution of risk exposure specific to the banking sector net of market movements. The average pair-wise correlation in the CAPM-adjusted returns of bank stocks was between 0.01-0.10 from 1987 to 2008. Between 2009-2013, i.e., during the period that includes the financial crisis, the correlation increased to 0.10-0.15. Increased correlation during the crisis period is not surprising. However, after the first formal stress test under the DFA in 2013, the average pairwise correlation increased steadily and substantially, eventually reaching a level of about 0.40 by the end of 2019. Thus we document a four-fold increase in pairwise correlation in the decade following the financial crisis, and the increase happened predominantly after the first test under the DFA. Notably, the post-DFA correlation is even higher than the correlation during the financial crisis period when banks experienced a common negative shock due to the subprime mortgage crisis.

While the discussions about stress tests began soon after the financial crisis, it was formalized under the Dodd-Frank Act only in 2013. In the interim period of 2009-12, the Fed conducted three stress tests for some of the largest banks in the country, but the first test under the formal guidelines of the DFA occurred in 2013. By 2013 banks had more clarity on the stress test model, and they also had enough time to adjust to the post-crisis regulations. We consider 2013 as the year of stress test enactment for our formal tests. It allows us to separate the effect of stress tests from the effect of financial crisis itself; however, we ensure that our results are not driven by any changes in the interim period of 2009-12.

We compare pairwise correlation in the banking industry with other financial firms, i.e., non-bank financials such as insurance and trading companies, over this time period. Both groups follow a parallel trend till 2013, after which the banking group shows a significant upward departure from the trend. Firms in non-financial industries do not show such a pattern either. The pattern is unique to banks. Consistent with the correlation result, we show that the first principal component explains almost four-fold higher variance in daily bank stock returns in the post-2013 period compared to the earlier periods, a pattern that is absent in non-financial firms or non-bank financial firms.

Is the increase in return correlation driven by banks' desire to take similar risks to perform well on stress tests? We answer this question in several steps. We first show that the increase in correlation is most pronounced for banks that are subjected to stress tests as per the DFA, i.e., banks with more than $10 billion in assets.[3] In a difference-in-difference setting, we show that the stress tested banks have become significantly more correlated with each other after the enactment of the DFA, compared to the non-stress tested banks over the same time period. The estimated coefficient on the difference-in-difference estimate is around 0.08-0.10 increase in pairwise correlation for the stress tested banks. Results are stronger when we compare stress-tested banks to non-financial firms or financial firms that are not banks. We control for the bank's size and leverage in these regressions to rule out the alternative

[3] All banks above the $10 billion size threshold were subject to stress tests as per the DFA. In addition, test results for banks above the $50 billion threshold were disclosed to the public as well. See the OCC's final ruling on stress testing published on October 9, 2012 here: https://www.occ.treas.gov/news-issuances/federal-register/2012/12fr46.pdf

that the increase in correlation is simply an artifact of bank size or bank leverage. Similar results hold when we compare the first principal component of bank equity return before and after the DFA: a 20% increase in variance explained by the first principal component for stress-tested banks compared to the non-tested ones.

The increase in correlation is not driven by the largest banks alone. We divide stress tested banks into two groups: large and non-large banks. Large banks are defined as banks whose stress tests are conducted by the Federal Reserve Bank. These banks are considered systemically important by the Fed and they face stricter disclosure requirements. Non-large stress tested banks are the ones whose tests are conducted by themselves in coordination with their primary regulators. We show that the increase in correlation is present for both groups. Hence our primary result is unlikely to be explained away by bank size or higher disclosure requirements; it is more likely an outcome in response to the stress tests.

In our second set of tests, we measure bank stock returns' sensitivity to factors that the regulators use as hypothetical scenarios for stress tests. We focus on two sets of factors: market-based factors and macroeconomic factors. Motivated by the stress test scenario under the DFA and the availability of long time-series of data, we consider three market factors: (a) total returns on an index of BBB-rated corporate bonds, (b) the CBOE volatility index (VIX), and (c) the average interest rate on fixed-rate 30 year mortgage. Similarly, we consider three macroeconomic factors: (a) personal consumption expenditure, (b) the consumer price index (CPI), and (c) the Case-Shiller national home price index. We find that stress-tested banks' sensitivity to these shocks has become very similar in the post-2013 period compared to the non-tested banks. Specifically, the increase in similarity is significantly higher for the stress tested banks compared to the non-stress tested banks for 5 out of 6 factors. In line with our theoretical model, the homogeneity increase was highest for risk exposure to the VIX factor, the factor with highest volatility of all the factors we consider.

A concern with our interpretation that stress test caused increased correlation is that there have been a number of other changes in markets and banking sector during the post-2013 period. Three changes deserve special consideration: (a) changes in the conduct of monetary policy during the post-crisis period, (b) increased importance of ETFs over time, and (c) changes in other regulation for the banking sector such as governance changes and disclosure policies. For our interpretation to be invalid, it must be the case that these changes only affected stress-tested banks and only affected them after 2013. Quantitative easing started much earlier than 2013, as early as November 2008, and it affected all banks and some non-bank financial firms as well. Similarly, it is unlikely that increase in correlated trading by the ETFs affected stress-tested banks disproportionately since ETFs cover practically every sector of the U.S. equity markets.

To provide further evidence in support of our interpretation, in our third test we exploit an interesting feature of DFA stress tests. Some banks fail the tests. Failure has immediate implications for dividend payouts and capital requirements, and it comes with increased regulatory scrutiny. Hence, failed banks have strong incentives to pass the test in the subsequent rounds by altering their business models. As we show in our theoretical model, when banks face higher cost of stress-test noncompliance, they have stronger incentives to take correlated exposure. Failed banks provide such a sample. We analyze the changes in equity return correlation for failed banks after the failure compared to the corresponding changes for the non-failed banks. The identifying assumption is that the failure event is uncorrelated with any simultaneous changes in other confounding factors that only affect the failed banks. It is unlikely that the importance of monetary policy interventions or ETF trading or other banking regulation changed only for the failed banks precisely after the failure of the stress tests. We show that the failed banks' stock returns become increasingly similar to the other stress-tested banks after the failure event, lending support to our interpretation that a strong desire to pass the stress tests generate increased correlation across banks.

In addition to the market returns information, we also have information on the actual result of the stress test itself for a subset of banks. These results effectively provide information on the loss distribution of banks' portfolios; for example, how much equity capital a bank would have in the severely adverse economic scenario modeled by the stress test. If banks' risk exposure become similar over time, then we expect their results to become similar as well. We show that the standard deviation of the output of the stress test across banks, such as their minimum capital ratio in the severely stressed scenario, has decreased considerably. Using the output of stress tests and guided by our theoretical model, we uncover the underlying parameters of the distribution of the bank's losses over time using the method of moments. Our estimation results show that the banks' loss distribution has become similar during the later periods of stress tests (2016-18) compared to the earlier period (2013-15). As they learn more about the test scenario and adjust their portfolios to look attractive on these scenario, their loss distribution has become similar as well. Since these results are directly related to stress tests, they lend further support to our causal interpretation that the mechanism behind increased correlation is stress tests.

What actual decisions are banks taking to increase their correlations with each other? In the next part of the paper, we investigate whether banks' business activities, as measured by their asset holdings and sources of income, have become more similar after the DFA for the entire sample of banks. We construct several measures of distance across banks based on the granularity of asset holding data available to us. The distance across stress-tested banks has shrunk in the post-DFA period compared to the non-tested banks. Finally, we show that their sources of income derived from categories such as loans & leases, securitization, trading income and brokerage fees, have also become similar. Collectively, these findings show that banks changed their business model after the enactment of DFA in a manner that has led to increased correlation in their equity returns.

If banks are becoming similar, what sources of risk are they increasingly exposed to? In our final test, we construct a traded factor that is orthogonal to the shocks to the factors that enter the stress tests. Using a difference-in-difference empirical design, we show that the stress tested banks increased exposure to this orthogonal factor after the enactment of the DFA compared to the non-tested banks.

Our findings have important implications for policy decisions aimed at limiting systemic bank failures. Bank stress tests provide valuable information to policymakers on a forward-looking measure of risk (Goldstein and Sapra (2013)). However, our results document a cost: the cost of correlated risk-taking. This finding is similar to a large literature in economics that studies the effect of "teaching to test" on student performance and the literature on gaming incentives to achieve desired results from a model (Griffin and Tang (2012)). Specific to the banking sector, our work relates more closely to the efficacy of different types of regulation on bank's risk-taking behavior (Behn, Haselmann, and Vig (2022); Glaeser and Shleifer (2001); Leitner and Williams (2022); Greenwood, Stein, Hanson, and Sunderam (2017)).

1 Background and literature review

The Dodd-Frank Wall Street Reform and Consumer Protection Act (henceforth, DFA) establishes the framework for stress testing bank holding companies and financial firms. DFA requires the Federal Reserve, in coordination with appropriate regulatory agencies such as the Office of the Comptroller of Currency (OCC) or the Federal Deposit Insurance Corporation (FDIC) to directly conduct stress tests for large, systemically important bank holding companies and financial firms. Systemically important firms are designated as such by the Financial Stability Oversight Council. Bank holding companies and financial firms with total book value of assets exceeding $10 billion, but not deemed systemically important, conduct and report results for annual stress tests by themselves in coordination with their primary regulatory agency. In May 2018, Congress via the Economic Growth, Regulatory Relief, and Consumer Protection Act raised the size threshold for firms to be stress tested from $10 to

$250 billion in total assets. Since our sample covers data till 2020, and we focus on annual measures of risk taking, we consider all banks above $10 billion as stress-tested banks in the sample. Our results do not change if we restrict our attention strictly till 2018, i.e., before the change in the limit.

The stress tests evaluate whether bank holding companies and financial firms have sufficient capital to absorb losses resulting from adverse economic conditions. The specific nature and design of the stress tests were left by Congress to the regulatory agencies, raising a number of unresolved issues on both the design and disclosure of these tests (see Goldstein and Sapra (2013)). In practice, each year, the Federal Reserve develops test parameters and consequences, including adverse economic scenarios under which capital held by large and systemically important bank holding companies and financial firms is evaluated. These parameters and models remain largely stable over time capturing risk exposures to factors such as inflation, unemployment rate, house prices, security prices and interest rates. Other regulatory agencies, such as, the OCC and the FDIC, then apply the same test parameters and conditions while stress testing non-systemically important, large bank holding companies and financial firms exceeding the required size threshold (i.e., total assets of $10 billion).

Our paper uses stress test as an empirical setting to address the broader issue of how model-based regulation affect bank behavior. The literature has documented the effect of such regulation on the regulated entities' incentive to underreport their risk (see, Behn, Haselmann, and Vig (2022); Begley, Purnanandam, and Zheng (2017); Plosser and Santos (2018)). Our study focuses on a different aspect of bank behavior: changes in their risk exposure that can result in higher commonality across them.

There is a large literature covering different aspects of stress tests such as the effectiveness of the test in detecting risk, informativeness of these tests and their impact on real economic activities. A number of papers have analyzed issues surrounding the design of tests and how effective they are in detecting losses ex-post (e.g., see Philippon, Pessarossi, and Camara

(2017), Pritsker (2017), Frame, Gerardi, and Willen (2015), Orlov, Zryumov, and Skrzypacz (2020)). Related, a number of papers focus on the issue of disclosure, namely, whether the test results should be made public or not (e.g., Goldstein and Sapra (2013), Goldstein and Leitner (2018)). Flannery, Hirtle, and Kovner (2017) and Heitz and Wheeler (2022) study the effect of stress test disclosures on the production of private information.

Our study is related to the effect of stress tests on credit decisions. Acharya, Berger, and Roman (2018) document that stress-tested banks reduced credit supply to relatively risky borrowers. Cortés, Demyanyk, Li, Loutskina, and Strahan (2020) show that banks change their lending behavior due to stress-test induced increase in their capital requirements. Pierret and Steri (2020) who show that stress-tests lowered the risk-taking of banks in the syndicated lending market. Kok, Müller, Ongena, and Pancaro (2021) show that the reduction in credit risk occurs because of regulatory scrutiny. The findings of these papers support the underlying idea of our work that stress tests incentivized banks to make changes in their portfolio decisions.

Our paper differs from the literature in its focus on correlated risk-taking across banks, which is an important aspect of risk-taking from the systemic financial stability perspective. One part of our paper, namely the increased homogeneity in asset holdings, is similar to Bräuning and Fillat (2020) who study the portfolio allocation and credit supply decisions of the 19 largest banks after the stress test. Our focus on stock return based measures of similarity across the entire banking sector allow us to capture the market's forward looking assessment of similarity, which is especially valuable to assess financial stability from the perspective of investor beliefs. These measures avoid the limitation of asset based tests that are susceptible to reporting biases such as window dressing and off-balance sheet hiding, and the fact that assets in the same class may vary greatly in terms of their risk exposure. Further, our measures allow us to evaluate the evolution of a much longer time series of equity correlations across different sectors of the economy and changes in the banking sector's exposure to the stress tested factors.

Our paper is also related to the literature on too-big-to-fail (O'hara and Shaw (1990), Minton, Stulz, and Taboada (2017)), too-many-to-fail (Acharya and Yorulmazer (2007)), and bank contagion. Finally, our paper is also related to the vast literature on herding. Devenow and Welch (1996) provide a comprehensive survey of the literature. Herding can arise from sequential decisions, with the decision of one agent conveying information about some underlying economic variable to the next set of decision-makers. Alternatively (as in our setting), herding can arise from a coordination game i.e., from a simultaneous ex-ante decision of banks to coordinate correlated investments. Bank herding or correlated investment decision can also have welfare costs relative to the first-best as superior projects are bypassed.

2 Theoretical Model

We develop a stylized model to derive conditions under which stress test regulations can increase homogeneity in the system. A bank i makes a portfolio decision at time $t = 0$ and payoffs are realized at $t = 1$. There are two risky assets in the economy indexed by $a \in \{1, 2\}$. The bank has w_0 of initial wealth, comprising of $e\%$ of equity capital and the remainder of debt. It picks a portfolio $\theta = [\theta_1, \theta_2]$, representing the fraction of investment in assets 1 and 2, respectively.

The assets deliver the following returns to a market investor for every unit of investment: $\tilde{r_a} = \beta_a \tilde{f} + \epsilon_a$. β_a captures the sensitivity of the asset a's returns to a macroeconomic risk factor $\tilde{f} \sim N(\mu_f, \sigma_f^2)$. Regulations are written to control a bank's exposure to this source of risk. ϵ_a are shocks uncorrelated to the macroeconomic factor, either hidden to the regulator or simply not a part of the stress testing scenario. We assume that and $\epsilon_a \sim N(0, \sigma_a^2)$ for asset a, and $corr(\epsilon_1, \epsilon_2) = \rho$.

The bank has some specific technology in screening and monitoring the two assets, allowing it to earn some return in excess of the return available to the market investors. The technology or the skill varies with $\{bank, asset\}$ pair, consistent with the idea that banks specialize in different markets and products. Differences in relative skills leads to heterogeneity of asset holdings across banks even in the absence of any regulation or market frictions. We assume that bank $i's$ skill in asset a, for a level of investment I, is given by $s_a^i(I)$ such that $s_a^{'i}(I) \geq 0$ and $s_a^{''i}(I) \leq 0$, i.e., the skill function is an increasing and concave function of the amount of investment a bank makes in an asset.

Therefore, for I units of investment in assets $a \in \{1, 2\}$ at $t = 0$, bank $i's$ gross payoffs at $t = 1$ is given by the following:

$$\tilde{X_a^i}(I) = s_a^i(I) + (1 + \beta_a \tilde{f} + \epsilon_a)I \tag{1}$$

Frictionless benchmark: As shown in Appendix A, in a frictionless world, the bank picks a portfolio that equates the marginal return across the two assets as per the following condition:

$$s_1'(\theta_1 w_0) + \beta_1 \mu_f = s_2'((1 - \theta_1)w_0) + \beta_2 \mu_f \tag{2}$$

As expected, the bank tilts its investment in favor of the asset in which it has more skill.

Asset holdings with frictions but no stress tests: The frictionless benchmark provides an interesting starting point; however, it is not a realistic benchmark. Even in the absence of regulatory constraints, a bank is likely to care about the risk of its portfolio. We therefore solve for the portfolio choice problem when banks care about risk-management even in the absence of any stress tests. Frictions such as bankruptcy costs (Smith and Stulz (1985)), financial distress costs (Purnanandam (2008)), or costly external financing (Froot, Scharfstein, and Stein (1993)) provide motivations for managing the downside risk of a bank.

In practice, banks often maintain their own internal risk controls and make use of tools such as Value-at-Risk or impose limits on positions. Motivated by these theoretical models and real world practice, we now solve for a bank's portfolio choice problem when it cares about its Value-at-Risk (VaR). Denoting the expected payoff at $t = 1$ for a portfolio choice θ by μ_θ, the bank now picks a portfolio based on the following optimization problem:

$$\begin{aligned} \max_{\theta} \quad & \mu_\theta - w_0 \\ \text{s.t.} \quad & VaR(\theta) \leq ke \end{aligned} \tag{3}$$

The VaR constraint puts a limit on the extent of risk a bank can take in relation to equity capital e it has. We assume that the bank's VaR must be below a factor k of its equity capital due to its desire to manage risk due to frictions. As shown in Appendix A, the optimal portfolio is given by the following first order condition, where λ is the shadow cost of VaR constraint:

$$s_1'(\theta_1 w_0) - s_2'((1-\theta_1)w_0) + (\beta_1 - \beta_2)\mu_f = \frac{\lambda}{1+\lambda}\Phi^{-1}(1-\alpha)\frac{\partial\sqrt{\theta'\Omega_\theta\theta}}{\partial\theta_1} \tag{4}$$

The left hand side of the above equation is the marginal benefit of investing an extra unit in a_1 compared to the same investment in a_2. In the unconstrained optimization, this marginal benefit was set to zero. With the risk-management concerns in place, the bank also takes into account the additional risk the marginal investment in asset one presents to the overall portfolio. The right hand side of the equation captures that effect. The key feature of this solution is the fact that the bank considers the effect of an additional unit of investment in any risky asset on the entire variance-covariance matrix of its risk, including the factor risk and the hidden (to the regulator) risk.

Asset holdings with stress test: When the bank is subject to stress tests, it begins to care about losses in the bad state of the world in a very specific manner: in a manner dictated by the scenario proposed by the stress test model. The bad states of the world in the model is defined as a lower tail realization of the factor shock f, consistent with the practice of actual stress test. The expected loss of the stress test is given by $E[(w_0 - w_1(\theta))|f < \underline{\text{f}}]$, where $\underline{\text{f}}$ is the scenario of the stress test macroeconomic condition. Consistent with the stress test requirements, we assume that the bank must maintain some level of equity capital under the stressed scenario, i.e., we assume that the bank's losses in the stressed scenario is bounded by a multiple c of its current equity capital. This assumption is consistent with the idea that banks incur both explicit and implicit costs if they perform poorly on the stress tested scenario. For example, banks may be prohibited from paying dividend or may be required to raise additional equity if their projected value in the bad state of the world is too low compared to the equity they currently have. The cost can also come in the form of heightened regulatory scrutiny. The optimization problem with stress test is as follows:

$$\begin{aligned} \max_{\theta} \quad & \mu_\theta - w_0 \\ \text{s.t.} \quad & E[(w_0 - w_1(\theta))|f < \underline{\text{f}}] \leq ce \end{aligned} \tag{5}$$

The solution is given by the following condition:

$$s_1'(\theta_1 w_0) - s_2'((1-\theta_1)w_0) + (\beta_1 - \beta_2)\mu_f = \frac{\delta}{1+\delta}\sigma_f[\beta_1 - \beta_2]\frac{\phi(\underline{\text{f}})}{\Phi(\underline{\text{f}})} \tag{6}$$

δ is the shadow price of stress test constraint. Assume, without any loss of generality, that asset a_1 has a higher sensitivity to the macroeconomic factor on which banks are tested. Then $\beta_1 - \beta_2 > 0$, and the RHS of the above equation is positive. At the optimum point the unconstrained marginal return from investing in a_1 over a_2, namely $s_1'(\theta_1 w_0) - s_2'((1 - \theta_1)w_0) + (\beta_1 - \beta_2)\mu_f > 0$. Therefore, from the concavity of the skill functions, it follows that for banks will lower their investment in a_1. Further, the optimal θ_1 will be lower when the RHS is larger.

Commonality in Assets: Banks tilt their portfolio towards a_2, i.e., asset that looks attractive on stress test factor, by a larger amount under stress tests compared to their internal risk management decisions as long as the following condition holds:

$$\frac{\delta}{1+\delta}\sigma_f[\beta_1-\beta_2]\frac{\phi(\underline{\mathrm{f}})}{\Phi(\underline{\mathrm{f}})} > \frac{\lambda}{1+\lambda}\Phi^{-1}(1-\alpha)\frac{\partial\sqrt{\theta'\Omega_\theta\theta}}{\partial\theta} \tag{7}$$

Even if an asset (a_2 in the model) has very high overall volatility due to its exposure to the non-tested or hidden risk exposure, banks prefer it over the other asset with the stress test constraint. Thus, banks herd more towards a_2 is the following conditions hold: (i) the shadow price of the stress constraint (δ) is larger compared to the shadow price of bank's internal constraint (λ), (ii) factor volatility (σ_f) is high, (iii) the sensitivity to macroeconomic factor is relatively higher for a_1 as captured by $\beta_1 - \beta_2$, (iv) stress test scenario is too pessimistic, i.e., $\underline{\mathrm{f}}$ is smaller, and (v) the diversification benefit of a_2 from the overall risk perspective is relatively small.

To make further progress and to numerically estimate the level of commonality, we now need to specify the form of skill function and construct a precise measure of asset commonality. We do so in Appendix A using the cosine similarity in asset holdings for an economy populated with VaR constrained versus an economy with stress test constrained banks. Our numerical results provide three key insights. First, whether homogeneity increases under the stress tests or not depends critically on the relative importance of skill of banks and the risk-exposure of the assets. As shown in Figure A1c, if the factor volatility is sufficiently low, then banks may not tilt their portfolio towards the attractive asset (a_2) by a large enough amount to increase homogeneity in the system. Therefore, the impact of stress test on homogeneity in the system remains an open empirical question that we tackle in our paper. Second, Figure A1d shows that homogeneity increases when the stress test constraint is more binding. Therefore, we expect banks with higher explicit or implicit cost from the failure of stress tests to adjust their behavior more aggressively and become homogenous with the rest of the system. Third, as the stress test scenario becomes more pessimistic, homogeneity is likely to increase (Figure A1e).

We now empirically analyze whether the commonality has increased or not, and whether they are consistent with the predictions of our stylized model. In the model asset correlation and equity correlations are equivalent. In our empirical work, we begin with a measure of similarity in equity returns and follow it up by an analysis of cosine similarity across assets. Our model also guides us in constructing empirical tests that relate the cost of stress test to increase in homogeneity.

3 Data and summary statistics

Our main sample covers all publicly traded banks in the U.S. whose stocks are continuously traded over the entire sample period. These banks are covered in both the Bank Holding Company Call Report (FR Y-9C) and CRSP database. We complement the banking sample with data on non-financial firms that are covered in the CRSP database. We classify these firms into various industry groups based on Fama-French industry classification. Specially, firms belonging to the industry group "Insurance and Financial Trading" are classified as non-bank financial firms.

We classify banks into stress-tested or non-tested group based on the size criteria laid out by the DFA: banks above book asset value of $10 billion are classified in the tested group, whereas the rest are in the non-tested group. We require firms to be continuously traded between 1995 and 2020 to be included in the base sample over which we conduct majority of our tests.[4] In total, we have a sample of 50 stress-tested banks and 172 non-tested banks. Our sample of banks account for more than 80% of the entire banking sector assets.

[4] We also provide some results based on an extended sample that goes back till 1986. Our focus on post-1995 sample is due to the improved coverage of banks in the CRSP database after this period.

3.1 Measure of homogeneity

Our main measure of homogeneity across banks is their pair-wise correlation in equity return. At the beginning of every month, we compute the CAPM-adjusted idiosyncratic return for each firm, i.e., banks, non-bank financials, and non-financial firms, based on the past 12 months of data. Our focus on the CAPM-adjusted return allows us to compare and contrast bank equity return correlation over and above the equity correlation in other sectors of the economy due to common market-wide movement. However, our results are similar if we focus on total returns. Using equity returns allows us to analyze high-frequency (daily) data and document how bank exposure to systemic risk factors is changing over time.

Our second measure of homogeneity is the first principal component of CAPM-adjusted equity return across all banks. We measure the first principal component based on past one year's data using daily stock returns. We conduct the same exercise for non-bank financials and other industry groups separately. Therefore, the first PC gives us a measure of similarity within an industry group over time.

For our third measure of homogeneity, we use quarterly balance sheet data to compute a measure of distance in asset holdings across banks. An advantage of this measure is that it provides more direct evidence from banks' real decisions. However, this measure has some limitations since balance sheet data provides only aggregated information and assets within the same class, for example, different loans under the category of commercial and industrial loans, also differ in terms of their risk exposure. Further, these measures do not clearly capture off-balance sheet items, nor do they fully account for window dressing within a quarter. Therefore, we focus on market-based measures in our study. Besides these advantages, a market based measure is a more useful indicator of investors' belief and hence their likely action during a period of crisis.

Table 1 presents the summary statistics of our sample broken into three categories: Banks

(Panel A), non-bank Financial Firm (Panel B), and Non-financial Firms (Panel C) over 1995 – 2020. We compute the pairwise equity return correlation for all firms within a group (for example, for all banks in the banking group and so on) and report the summary statistics in the Table. The average pairwise correlation across banks is 0.13, with a median of 0.10. The average pairwise correlation for financial firms is 0.07, and 0.06 for the non-financial firms. Clearly, banking stocks exhibit higher correlation with each other than firms in any other group. In our empirical analysis, we focus on how the correlation has changed over time, especially for the stress-tested banks.

4 Results

4.1 Are bank equity return correlations increasing over time?

Figure 1 plots the correlation in equity return from 1986-2020 for banks as well as for non-bank financial firms. Each graph represents the average correlation in equity returns of a firm within a group to the rest of the firms within the group, i.e., the average of pairwise correlations for both groups. There was a modest but steady increase in pairwise correlation in bank equity returns since 1999, reaching a level of 0.10 before the onset of the crisis. During the crisis, the correlation increased further to a level of 0.13 and hovered around this level till 2013, the year of the enactment of the DFA. Since then, there has been a remarkable increase in this measure, reaching a level of 0.40 before the onset of the COVID-19 pandemic. Said differently, the sector specific equity correlations increased almost three-to-four folds in the decade following the DFA. In contrast there is no such pattern for the group of non-financial firms. These firms, typically comprising insurance companies, broker-dealers and independent lenders, are also subject to several shocks that affect the financial sector. But they do not face the same set of regulations. Hence this group provides a reasonable benchmark for our comparison.

It is reasonable to expect that correlation in equity returns for financial firms increased during the financial crisis as they all faced large shocks to their asset values and future income growth. In Figure 2 we narrow our focus to the period just after the financial crisis: from 2009-2019. It is evident from this figure that the increase in equity correlation is not a financial crisis phenomena. Rather it occurred mainly after the implementation of the DFA. Further, the non-financial firms follow a parallel trend before 2013, moving in tandem with the banks. However, the two groups diverge significantly after 2013.

We now contrast the evolution of pairwise correlation in several other industries over the same time period. We select 12 industry groups for this comparison. These 12 industry groups were selected based on the criterion that they have at least 50 unique continuously traded firms over the sample period. We require a minimum threshold for the number of firms in an industry to estimate a reliable measure of pairwise correlation within the industry group. Figure 3 shows that the pattern we document is specific to banks. None of the 12 industry groups we consider shows a pattern in correlation that is similar to the banking sector. Consider the software sector, for example. The pairwise correlation has remained steady at an average level of just below 0.10 during the entire period. Other industry groups show a similar pattern.

Table 2 presents formal regression results to assess the economic and statistical significance of these patterns. Specifically, we are interested in estimating the changes in pairwise correlation for banking stocks after the enactment of the DFA compared to the corresponding changes in firms in the other sectors. We compute the average monthly pairwise correlation for each sector separately, namely the banking industry, non-banking financial sector, and all other 12 industry groups, and estimate the following regression model with each industry-month data as a unique observation:

$$\overline{\rho_{i,t}} = \alpha_i + \beta_{pst} D_{pst} + \beta_{bnk} D_{bnk} + \gamma D_{pst} \times D_{bnk} + \epsilon_{i,t}$$

Here, $\overline{\rho_{i,t}}$ is the monthly pairwise correlation for sector (i.e., industry) i in month t. D_{pst} is a dummy variable that equals one for the years 2013 – 2020 and D_{bnk} is a dummy variable that equals one for the banking sector. The model includes sector fixed-effects (α_i). The interaction term measures the change in equity correlation for the banking sector in the post-DFA period as compared to before compared to the corresponding changes in the equity correlations of non-bank financials and non-financial sectors. We include all industry sectors in the regression analysis; however, our results remain similar if we restrict the sample to banks and non-bank financials only, consistent with Figure 3. As documented in Column (3) of Table 2, the banking sector experienced an increase of 19% in the average pairwise correlation after the DFA compared to the other sectors. The result is statistically significant at the 1% level. In terms of economic importance, the estimate shows almost 150% increase in equity correlation compared to the average level 0.13 of this variable for the entire sample of banks. Therefore, there has been a remarkable increase in homogeneity among banks over this time period, compared to other industries.

4.2 First Principal Component Analysis

We supplement the correlation results with a first principal component (PC) analysis. For each group of firms (banks, financials and non-financials) we compute the first principal component of their idiosyncratic equity return on a monthly basis based on daily equity return of the month. The first PC provides us with a measure of homogeneity within the sector. Figure 4 plots the evolution of the first PC for banks and non-bank financials. A stark pattern emerges from this plot. While the non-bank financials have a higher value of the first PC in the pre-2013 period, the pattern reverses afterwards. Post-2013, the first PC of bank stock returns crosses above the non-bank financial firms and stays at a higher level throughout the rest of the sample period. Table 3 documents the yearly values of first PC for banks, financials and non-financials averaged across 12 industries that we considered for the earlier analysis using pairwise correlation. The increase in the first PC for the banking sector in the post-2013 period is unique to them.

We formally test these assertions with the following regression model, estimated at the sector level using banks, non-banks as well as 12 non-financial sectors we used in our earlier analysis:

$$PCA_{i,t} = \alpha_i + \beta_{pst}D_{pst} + \beta_{bnk}D_{bnk} + \gamma D_{pst} \times D_{bnk} + \epsilon_{i,t}$$

Here, $PCA_{i,t}$ is the first principal component for banks, financial, or non-financial firms at month t. D_{pst} is a dummy variable that equals one for the years 2013 – 2020 and D_{bnk} is a dummy variable that equals one for the banking sector. Results are documented in Table 4. As shown in Column (4), the first PC explains 11.84% higher variation in idiosyncratic equity return for the banking group compared to the other groups. The estimate is economically large when we compare it to the pre-crisis level of the PC that is typically in the range of 5%-30% depending on the year. In sum, these figures and regression estimates show that the increase in return correlation during the 2013-219 period is unique to the banking sector, and the effects are economically large. We now investigate whether the increase is due to their desire to do well on annual stress tests.

4.3 Are there differences between stress- and non-stress-tested banks?

We break all banks into two groups: the stress-tested banks and the non-tested banks. We compute a measure of homogeneity within each group by computing the average pairwise correlation of each bank within the group. As shown in Figure 5, the distribution of the pairwise correlation for the stress-tested banks increased remarkably over time. We do not find such pattern for the non-tested banks. We estimate the following regression model to formally test the changes in homogeneity across stress-tested and non-tested banks, using bank-month level data:

$$\overline{\rho_t^i} = \alpha_i + \beta_{str} D_{str} + \beta_{pst} D_{pst} + \gamma D_{str} \times D_{pst} + Controls + \epsilon_{i,t}$$

$\overline{\rho_t^i}$ is the average pairwise correlation of bank i with all other banks in the respective group in month t, D_{str} equals 1 for a bank if its subject to stress-tests and is zero otherwise. D_{pst} equals 1 post 2013 and is zero otherwise. $\overline{\rho_t^i}$ is computed separately (i.e., within groups) for stress- and non-stress-tested banks. The model includes bank and year fixed effects to soak away variations caused by bank-specific risk culture or yearly aggregate trends in the economy. Stress tested banks are larger by definition. And large banks have different levels of equity capital, both due to the differences in their business models and difference in regulations they face. We control for the differences in bank size and leverage as control variables in the model.

Table 5 presents the results. Column (4) shows that the stress-tested banks have 0.0674 higher pairwise correlation in the post-DFA period compared to the corresponding difference for the non-tested banks. Compared to the sample average of 0.10 in pairwise correlation, this is an economically large effect. The results are statistically significant at the 1% level.

A potential concern with our regression analysis is that it does not capture the non-linear effects of bank size on risk-taking behavior. We address this concern by reporting the non-parametric distribution of correlation measure across two sets of banks over time: (a) large stress-tested banks, defined as banks with more than $50 billion in assets, and (b) all other stress tested banks. We report the distribution of pairwise correlation for each group for years 2004, 2009, 2014, and 2019 in Figure 6. Both groups of banks show a remarkable rightward shift (i.e., increase) in the distribution in 2014 and 2019, consistent with the formal regression analysis that the effect of stress tests on correlation is not explained away by the size of the bank.

4.4 Stress test or other macroeconomic changes

A concern with our interpretation that stress tests caused increased correlation among banks is that over this time period a number of important changes occurred in macroeconomic policy and other regulations. Specifically, the Federal Reserve Bank engaged in extensive quantitative easing after the global financial crisis. As the Fed's balance sheet size increased during this time period, institutions dependent on Fed policies could potentially become more correlated with each other due to their dependence on the Fed's policy actions. Our results show that the increase in correlation is unique to banks, and not present for non-bank financial firms that are also dependent on monetary policy decisions. More important, it is the subset of stress-tested banks that shows the most remarkable increase in equity correlations after the enactment of the DFA. Therefore, it is unlikely that our results are completely driven by the increasing importance of Fed's monetary policy decisions during this period. For that to be the case, stress-tested banks must be affected by these policies in a disproportionate manner and only after 2013. This is unlikely to be the case because the quantitative easing and the expansion of the Fed's balance sheet occurred right after the financial crisis of 2008-09. As we showed earlier, during the interim period of 2008 to 2013, banks and non-bank financial firms showed a parallel increase in commonality. It is only after the enactment of formal stress tests in 2013 that we find a divergence between stress-tested banks and the rest of the control sample.

We exploit an interesting feature of the stress test implementation to more directly address the endogeneity concern. In every stress test cycle, a bank can either pass the test unconditionally, pass with conditions or simply fail the test. If a bank does not pass the stress test, it has to make adequate plans for raising capital and it faces higher obstacles in paying out dividends. Therefore, failing a stress test provides an extra incentive to banks to change their business models in a manner that allows them to pass the subsequent tests. As shown in our theoretical model, homogeneity is likely to increase when the shadow price of stress test constraint is high. Failing a stress test provides such a variation in our sample. More important for our identification strategy, it is unlikely that the event of a bank's stress-test failure correlates with other unobserved shocks to banking regulation and monetary policy, and that too for the failed banks only.

Of the largest banks for whom the results are disclosed to the public, we have 8 banks in the sample that did not pass the test: six of them failed and two had a conditional pass. We create a variable D_{fal} that takes a value of one for years after the failure or conditional pass, and zero otherwise. We augment our base regression model of Table 5 to test whether the failed banks' correlation increased with the rest of the stress-tested banks after the failure or not. Thus the model is as follows:

$$\overline{\rho_t^i} = \alpha_i + \theta_t + \beta_{str} D_{str} + \beta_{pst} D_{pst} + \gamma D_{str} \times D_{pst} + \beta_{fal} D_{str} \times D_{fal} + Controls + \epsilon_{i,t}$$

Here, $\overline{\rho_t^i}$ is the average pairwise correlation of bank i in month t as defined earlier. All other variables and controls are as defined as above. In all regressions we include bank and year fixed effects. This regression model is similar to the base care regression model we had presented earlier, except for the additional interaction term $D_{str} \times D_{fal}$. This interaction term estimates the incremental change in similarity for a stress-tested bank after it failed the test. Each column in Table 8 shows the results for a separate specification. Columns (1) and (2) depict the results without any control variables, while columns (3) - (5) control for either the total book value of assets or leverage or both.

The coefficient of interest is β_{fal}. If this coefficient is positive and statistically significant, it indicates that banks that fail the stress test become more similar (as measured by their average pairwise equity return correlation with other stress-tested banks) post failure. The results indicate that the coefficient β_{fal} is always positive, with values of 0.0356 - 0.0426, and is statistically significant at the 5% level or better. Indeed, the magnitude of the coefficient, estimated to be 0.0391 in Column 5 with control for size and leverage, is economically meaningful when we compare it to the sample average of 0.13 for the pairwise correlation among banks. These results provide confidence in our interpretation that the increased correlation comes from a bank's desire to do well on the stress test.

4.5 Evidence from test results

We now use the disclosed stress test result itself to address whether increased correlation in bank stock returns is due to their incentives to perform well on the test. Naturally, we do not have the results for the non-tested banks; nor do we have it for the stress-tested banks that were not required to publicly disclose the results. Therefore, we limit it to the set of largest banks with publicly disclosed data on the Federal Reserve Bank's website. We compare whether their test results become similar over time. Although not conclusive, such an analysis is less susceptible to endogeneity concerns mentioned earlier as it allows us to directly look at the performance on the test.

The stress test results provide the minimum amount of capital that a tested bank would have under different sets of scenario. Scenarios are either the stressed state of the world or the severely stressed state of the world. Under each of these scenario, the test provides the minimum capital that the bank would have as defined by the Tier 1 Capital Ratio, Total Capital Ratio, and Tier 1 Leverage Ratio. We focus on the severely stressed scenario and ask whether these measures of capital ratios become increasingly similar over time.

If banks converge in terms of their risk-taking to look attractive on the stress-tested scenario, we expect the dispersion to narrow over time. In the first round of the DFA tests, 18 large banks were required to disclose their results. In 2019, some of these banks stopped disclosing their results due to a change in the disclosure threshold. Therefore, we follow these 18 banks from 2013 to 2018 and compute the standard deviation of the output of the test results for the same set of banks over time.

In Figure 7 plots the standard deviation of each of these measures. There is a stark decline in standard deviation of each one of these measures by 2018. In 2013, the standard deviation of the minimum Tier 1 Capital Ratio in adverse scenario was over 2% that steadily declined to just over 1% by 2018. In other words, banks' performance look increasingly similar over time, consistent with the argument of increased homogeneity over time. As they learn more about the model and the exposure of their assets to the tested factors, they seem to be increasingly moving in the same direction.

4.5.1 Method of Moments Estimation

The standard deviation of the test result provides a measure of conditional dispersion, conditional on a severely stressed state of the world. The primitive parameter of interest is the standard deviation of the portfolio values that banks have invested in over time. We use a method of moments estimator to uncover these parameters using two moment conditions. Suppose a bank has invested in a portfolio of assets such that its equity capital ratio y over the life of test horizon follows a distribution $f(y, \theta)$ with mean μ and standard deviation σ as the parameter θ .

The output of the severely stressed scenario is a realization from this distribution conditional on a bad state of the world, i.e., for every bank we get to see a realization from the tail of this distribution: $y_i | Severeley\_Stressed$ as in the optimization problem of equation 25 in the theory model. Therefore, the mean and the variance of the sample provide us with sample moments of the tail of this distribution. Under the assumption of normality and using the moments of a truncated normal distribution, the conditional mean of y can be expressed as follows:

$$E[y|Severely\_Stressed] = \mu + \sigma * c(\alpha) \quad (8)$$

$$Var[y|Severely\_Stressed] = \sigma^2[1 + c(\alpha) * \alpha - c(\alpha)^2] \quad (9)$$

$$where, c(\alpha) = -\phi(\alpha)/\Phi(\alpha) \quad (10)$$

$\phi(.)$ and $\Phi(.)$ represent the density and distribution function of a standard normal variable. α is the lower quantile of the distribution $f(.)$ that corresponds to the severely stressed scenario. For example, the severely stressed scenario may be measuring the return distribution in the bottom 0.5% or 1% of the tail. Since we do not have the exact correspondence between the scenario and the quantile, we present our results for various sensible measures of α such as bottom 0.5%, 1% or 5% of distribution. Our estimates are not sensitive to this choice.

The first two equation above provide us with two moment conditions from which we can recover the parameters of the underlying distribution. We estimate the model separately for the first half (2013-2015) and the second half (2016-2018) of the sample period and report the estimated values of σ for different quantile levels in Table 6. If banks are taking similar risk, we expect the estimate of σ to come down in the later period compared to the earlier period. Our estimates across all three measures of capital that the stress test results report and across all three assumed values of α support this claim. For example, consider Panel A of the Table that presents the results for a 0.5% tail distribution. The Tier 1 Capital ratio is distributed with a standard deviation of 6.93% in 2013-15 compared to 5.08% in the later period. In the later half of the sample, the standard deviation of the underlying distribution of bank's capital ratios from which the stress test results are drawn has come down for each measure. These estimates support the claim that the banks have become homogenous over time due to their desire to perform similarly on stress tests.

We now shed light on mechanism behind our key finding of increased homogeneity. Specifically, we ask two questions: (a) are banks responding similarly to factor shocks that enter the stress tests?, and (b) have their asset holdings and sources of income become similar since 2013?

4.6 Are banks responding similarly to shocks?

We first evaluate whether banks' exposure to risk factors used in stress tests have increased after the DFA. Risk factors and scenario used in the tests differ somewhat from year to year. However, the broad idea has remained similar: factors attempt to capture exposure to credit risk, mortgage markets, volatility, inflation, economic growth, and consumer expenditure. We choose the following six factors that are used in the stress test scenario: (i) the return on BBB-bond index, (ii) the level of VIX, (iii) 30-year mortgage rate, (iv) personal consumption expenditure, (v) consumer price index, and (vi) the Case-Shiller home price index. We pick these factors for two reasons: they represent some of the most commonly used factors in the stress test modeling, and we have a long time series of data available for these factors that allows us to conduct statistical analysis. For expositional simplicity, we refer to the first three factors as market-based factors, whereas the last three as macroeconomic factors. We do not include the level of aggregate stock market or the GDP growth rate since we are working with CAPM-adjusted idiosyncratic stock returns in our analysis.

We proceed in two steps. We first compute the sensitivity (β) of an individual bank's stock return to the chosen factor each month based on daily stock return data over the past 12 months. Once we have these β for each bank, we compute a measure of distance across them. This approach is consistent with our theoretical model where banks pick portfolios based on the assets' exposure to the factor. Correlated exposure to these factors should decrease the distance in these estimates across banks. Therefore, we compute the average absolute distance between banks' beta as our measure of similarity to these shocks.

To estimate the sensitivity to each factor, we first compute the innovation in the factor using the following AR-1 model:

$$f_t^i = \delta_i + \phi_i f_{t-1}^i + \epsilon_t^i$$

Our model allows us to parse out the predictable component of the factor allowing us to focus on the innovation in the measure as the variable of economic interest. We regress the bank's CAPM-adjusted equity return on the residual from this regression to measure their sensitivity to macroeconomic surprises, notably surprises that form the basis of stress test scenario.

We assess the effect of stress tests on the homogeneity in factor exposure using the same difference-in-difference regression design that we use in the rest of the paper. Panel A of Table 7 reports the results for these tests for the three market-based factors: return on BBB bonds, VIX, and the mortgage rate. Column (1) shows that the stress tested banks experienced a decrease of 0.2950 in the distance measure. Said differently, the sensitivity of individual bank's equity return to BBB bond return became similar for the stress tested banks after 2013. Similarly, the coefficient on the interaction term is negative and significant for VIX and mortgage rate as well. Therefore, the stress tested banks have become similar in their exposure to these shocks after the enactment of stress tests as per the DFA.

Panel B of Table 7 repeats this exercise for the three macroeconomic factors, namely personal consumption expenditure, consumer price index, and the Case-Shiller home price index. We find negative and statistically significant γ for two of these three factors. The coefficient is positive and insignificant for Case-Shiller index. Overall, these findings uncover risk exposure that banks are taking that results in higher homogeneity we document earlier with equity returns.

A key economic driver of increased homogeneity in our theoretical model is the volatility of factor exposure. Specifically, the model shows that the incentive to herd increases in the volatility of the stress tested factor. Due to the limited number of factors, we are not able to conduct a formal regression analysis to test this hypothesis. However, among all the factors we consider the VIX factor has the highest volatility as shown in Table A2. Therefore, we expect banks' exposure to the VIX factor to become more similar over time. We compute the mean absolute dispersion of beta for each risk factor in 2009 and 2019 as a measure of similarity and present the estimate in Table A2. Consistent with our earlier results, dispersion in risk exposure across banks came down for each of the six measures. But the largest decline (-77%) occurred in exposure to VIX, the risk factor with highest volatility.

4.7 Evidence from operating decisions

Our results so far relies on stock market based measure of similarity. If stress tested banks are taking correlated risks, we expect them to have similar operational results. Specifically, we expect them to hold similar assets as shown in the theoretical model. It then follows that they have similar sources of earnings. In this section, we examine homogeneity across banks in terms of these real decisions.

4.8 Do banks have similar sources of earnings?

We obtain data on each bank's quarterly income from the its FRY9-C report: We start by collecting data for all items reported in the FRY9C under the heading income. Any income item code, where more than half the number of observations is missing is dropped. All remaining categories are then used to construct the cosine measure of similarity. This breakdown provides us with a fairly accurate assessment of the broad risk categories that a bank earns its income from. For example, if a bank moves its activities from trading to lending, or lending to leasing, or lending to securitization, our breakdown would be able to capture such variation. However, we would not be able to detect changes that happen due to changes within a given class of earnings. Therefore, our analysis faces a higher hurdle in detecting correlations: we are only capturing correlations across these broad categories.

With this caveat in mind, we compute the cosine measure of similarity in bank's earnings from these sources scaled by the asset value. For each bank, we first create a vector of income sources by taking the ratio of respective earnings number to the book value of total assets. We then compute the average value of the cosine of the angle between this vector of each bank in a given group, stress-tested or non-tested, and all other banks in the same group. The measure of distance is simply one minus cosine similarity, which we also refer to as cosine distance. We refer to this measure as $\overline{Income^i}$. If banks become similar in their earnings sources, we expect $\overline{Income^i}$ to shrink towards zero. We estimate the following model to test whether stress-tested banks have become similar after the passage of the DFA:

$$\overline{Income_t^i} = \alpha_i + y_t + \beta_{str} D_{str} + \beta_{pst} D_{pst} + \gamma D_{str} \times D_{pst} + Controls + \epsilon_i \tag{11}$$

Results are provided in Table 9. Columns (1) and (2) provide the base case results with and without bank fixed effects. In the remaining Columns, we also control for the effect of bank size and leverage. As shown in Column (2), $\overline{Income^i}$ has shrunk for the stress-tested banks after the DFA compared to the non-tested banks over the same time period. A negative and significant γ coefficient of -0.0269 indicates the stress-tested banks derive income from similar sources after the DFA. Since cosine measure ranges from -1 to +1, the estimate is economically significant.The result remains similar when we control for leverage and assets in the remaining columns of the Table.

4.9 Do banks hold similar assets?

We repeat the exercise for distance in income with distance in asset holdings directly in line with the prediction of the theoretical model. We begin with the broadest category of asset definition and then narrow it down to more granular levels. Our first measure of distance $\overline{Asset^i}$ for bank i is based on one minus cosine similarity in assets across banks held in the following categories: cash, securities, federal funds sold, loans and leases, trading assets, premises and fixed assets, investments in real estate ventures, intangible assets, and other assets. The data come from the quarterly call reports of the bank holding company. We scale these numbers by the book value of total asset of the bank at the quarter end and compute the cosine distance in each asset category between bank i and the rest of the banks in the group, stress-tested or non-stress-tested. Thus, we measure the distance in asset holdings for bank i with all other banks in the group.

Estimation results are provided in Table 10. We find a negative and statistically significant coefficient on the interaction term $D_{str} \times D_{pst}$, indicating that after the stress tests, the tested banks' distance with others in the group decreases, i.e., these banks became homogeneous. The tested banks' cosine distance decreased by about 0.0178, which is economically significant.

A natural concern with the broadest asset category is that it misses out on granular variation in risk exposure within the same asset class. In our next test, we focus on a finer breakdown of loans made by the bank across the following categories: real estate, commercial loans, and personal loans. With these sub-categories of loans, we compute a measure of cosine distance using the same methodology as discussed above. The regression results are provided in Table A4. The estimated coefficient of -0.0565 in Column (1) of the Table shows that after the stress tests, the lending portfolio of banks have become similar. Going further granular, we break down the total amount of real estate loans into the following categories:

construction and land development, farmland, 1-4 family mortgages, multifamily residential mortgages, non-farm and non-residential properties. The results are reported in Column (2) of the Table. The estimated coefficient of -0.0219 shows that banks have become similar in their real estate holdings after the stress tests. Finally, we estimate homogeneity across securities that banks hold across the following categories: residential pass through securities, commercial pass through securities, residential mortgage-backed-securities, and commercial mortgage-backed-securities. As shown in Column (3) of Table A4, banks' security holdings have also become similar after the stress tests.

In sum, our results, both from the distance in income sources and asset holdings, are consistent with the view that banks are changing their portfolios in a manner that increases homogeneity in the system.

4.10 Risk exposure to uncorrelated factors

In the final part of the paper we directly show that banks increased their risk exposure to a factor that is orthogonal to the stress tested factors. Our econometric approach to constructing the orthogonal portfolio follows standard methods in asset pricing literature. Our 'mimicking portfolio approach' has been used by earlier papers such as Fama and MacBeth (1973), Chen, Roll, and Ross (1986), and Huberman, Kandel, and Stambaugh (1987). The construction of this factor is discussed below.

We begin by collecting time-series data for all U.S. macroeconomic and financial factors that have ever been mentioned as part of the stress test scenario over the years 2013-2020. From this list we keep data for only those variables for which monthly data is available throughout our sample period, resulting in a total of 12 time-series. These include the index of industrial production, the consumer price index, personal consumption expenditure, the unemployment rate, stock market volatility, mortgage rates, the yield to maturity on the

20-year Treasury bond, the yield to maturity on the 10-year Treasury note, the yield to maturity on the 3-month Treasury bill, the prime interest rate, the federal funds rate, and the total return index for BBB-rated bonds issued by nonfinancial corporations in the U.S. We discard other variables such as, the growth rate of U.S. gross domestic product, for which data is available at best quarterly.

Next, we use principal component analysis to extract and capture common variation in the first differences of these 12 monthly time-series for U.S. macroeconomic and financial data. The resulting first principal component represents a 'U.S. factor' and it explains about 80% of the variation in the first difference of the 12 monthly time-series over our entire sample. We then construct a traded mimicking portfolio that moves independently of (i.e., is orthogonal) to this U.S. macroeconomic and financial factor. For this, we utilize data for the 100 Fama-French portfolios sorted by market capitalization (size) and book-to-market. We solve (i.e., optimize) for weights for a traded mimicking portfolio that is a liner combination of the 100 Fama-French portfolios, so that the traded mimicking portfolio itself has zero correlation with the 'U.S. factor'.

With the data for the orthogonal traded mimicking portfolio in hand, for each bank in our sample, we estimate the beta of its returns to this orthogonal mimicking portfolio. Table 11 presents the results of a difference-in-differences regression using the empirical specification used earlier in the paper. After the implementation of the DFA, stress tested bank's exposure to this orthogonal factor increased significantly. Overall, the result confirms our earlier analyses that banks increases their risk exposure to factors that are less correlated with the stress tested factor.

5 Conclusion

We document a significant increase in commonality in risk exposure across banks after the implementation of the Dodd-Frank Act mandating stress tests for banks above a certain size threshold. These findings highlight an unintended consequence of the risk regulation: banks change their behavior to perform well on the same set of future scenario, which in turn makes the risk of collective failure high. Our results do not make any welfare claims; rather, the goal of our paper is to highlight an important potential cost of stress tests. Specifically, even if the probability of failure comes down as a result of the stress test regulation, the cost of failure is likely to be high since correlated risk exposure has increased. If a number of banks fail in the same state of the world, then the cost of fire-sale externality or distress resolution is likely to be high. These findings have implications for the design and implementation of financial regulation. For example, our analysis sheds light on the regulator's choice between an explicit ex-ante regulation that are susceptible to gaming versus ex-post discretion in dealing with failures (Greenwood, Stein, Hanson, and Sunderam (2017)). Similarly, our results suggest that explicit disclosure of the stress test model has a cost in terms of increased correlation in the system.

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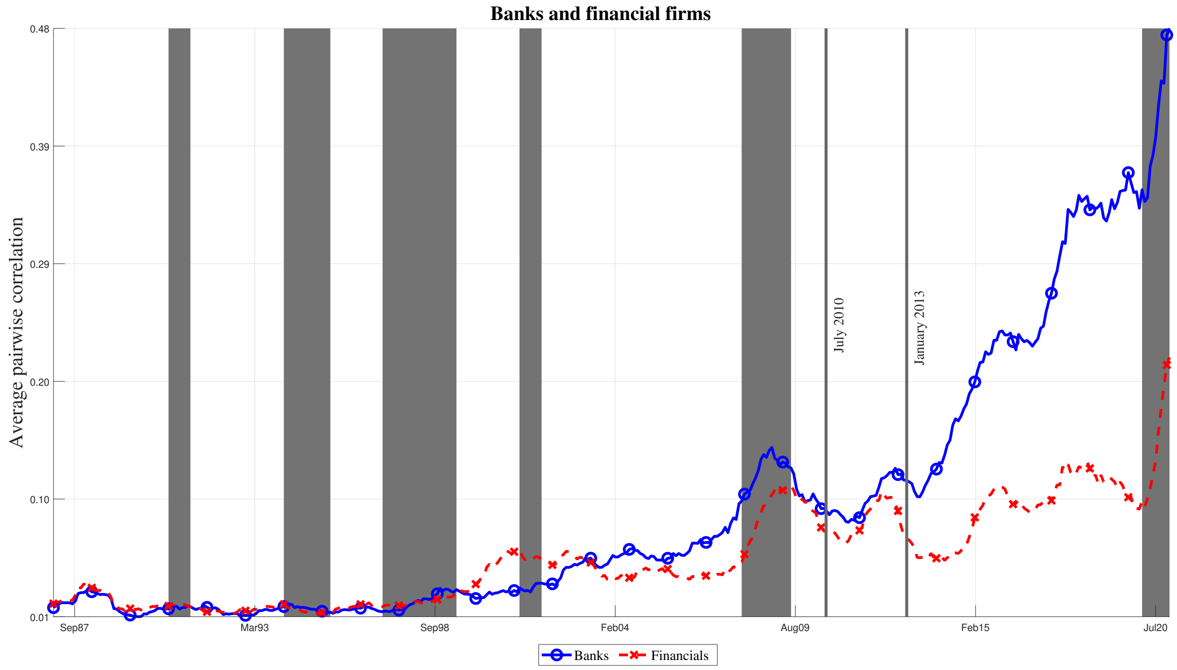


Figure 1: Equity return correlation for banks and financial firms: Long-term.

Notes: This figure plots the average pairwise correlation (12-month moving average) of daily idiosyncratic equity returns for banks (blue solid line) and financial firms (red dashed line). Idiosyncratic returns are computed using the one-factor CAPM model. Grey shaded regions are National Bureau of Economic Research (NBER) recessions. The NBER recession dates are published by the NBER Business Cycle Dating Committee. Daily data, 1986 – 2020.

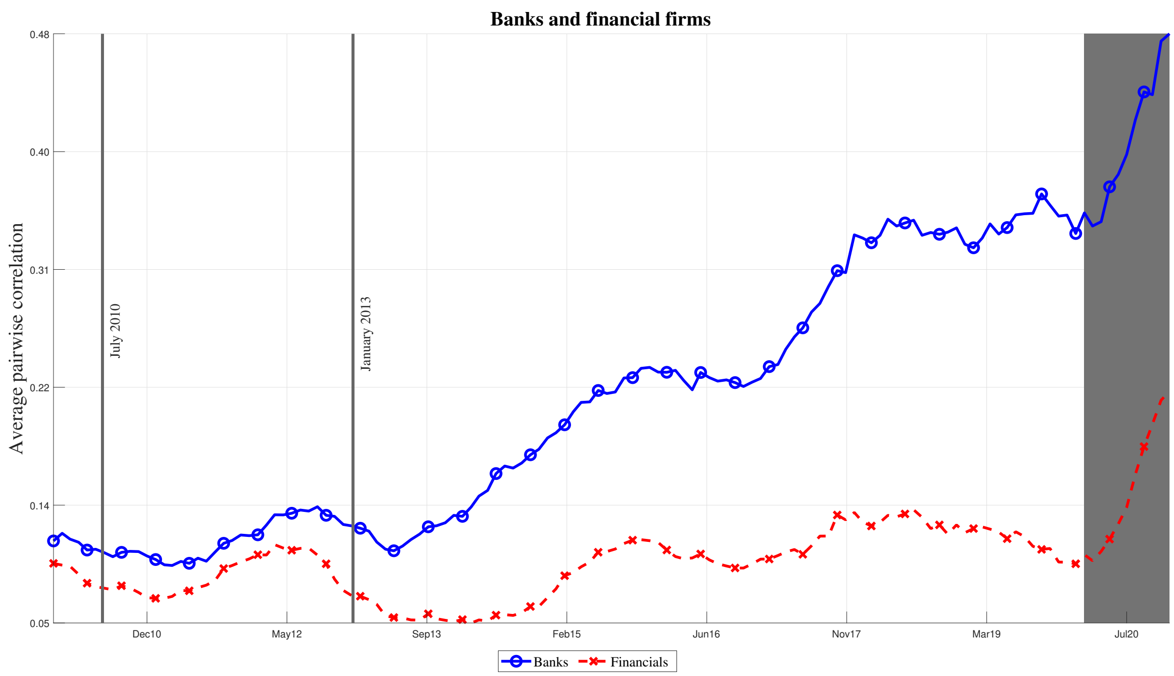


Figure 2: Equity return correlation for banks and financial firms.

Notes: This figure plots the average pairwise correlation (12-month moving average) of daily idiosyncratic equity returns for banks (blue solid line) and financial firms (red dashed line). Idiosyncratic returns are computed using the one-factor CAPM model. Grey shaded regions are National Bureau of Economic Research (NBER) recessions. The NBER recession dates are published by the NBER Business Cycle Dating Committee. Daily data, 2009 – 2020.

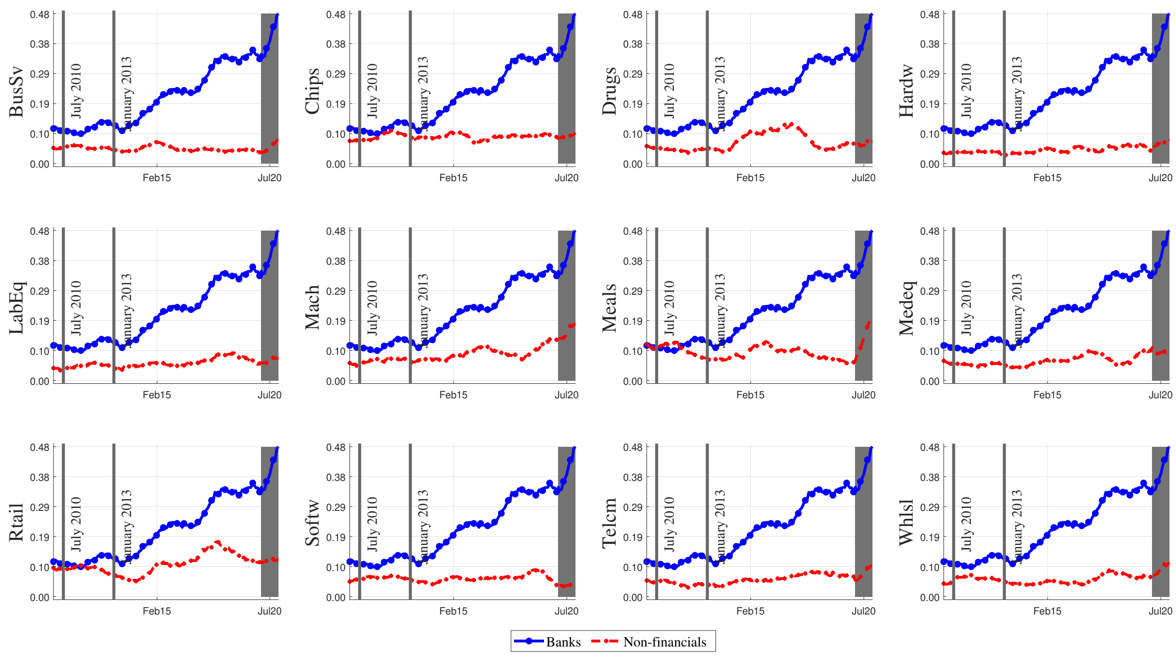


Figure 3: Equity return correlation for banks and nonfinancial firms.

Notes: This figure plots the average pairwise correlation (12-month moving average) of daily idiosyncratic equity returns for banks (blue solid line) and nonfinancial firms by industry (red dashed line). Idiosyncratic returns are computed using the one-factor CAPM model. Each panel depicts data for a separate industry. Industry definitions are from Kenneth French's website and include all industries with at least 50 firms available over the entire sample. Grey shaded regions are National Bureau of Economic Research (NBER) recessions. The NBER recession dates are published by the NBER Business Cycle Dating Committee. Daily data, 2009 – 2020.

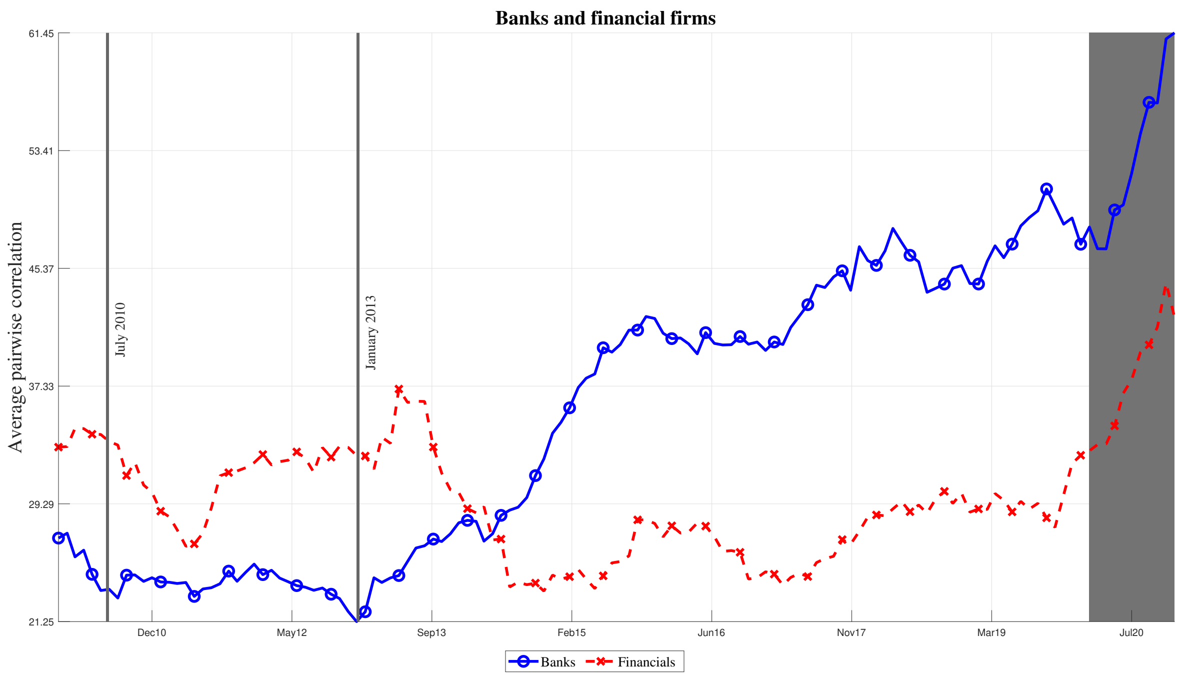


Figure 4: Principal component for banks and financial firms.

Notes: This figure plots the percentage of variation explained by the first principal component extracted from the idiosyncratic equity returns for banks (blue solid line) and financial firms (red dashed line). Idiosyncratic returns are computed using the one-factor CAPM model. Grey shaded regions are National Bureau of Economic Research (NBER) recessions. The NBER recession dates are published by the NBER Business Cycle Dating Committee. Monthly data, 2009 – 2020.

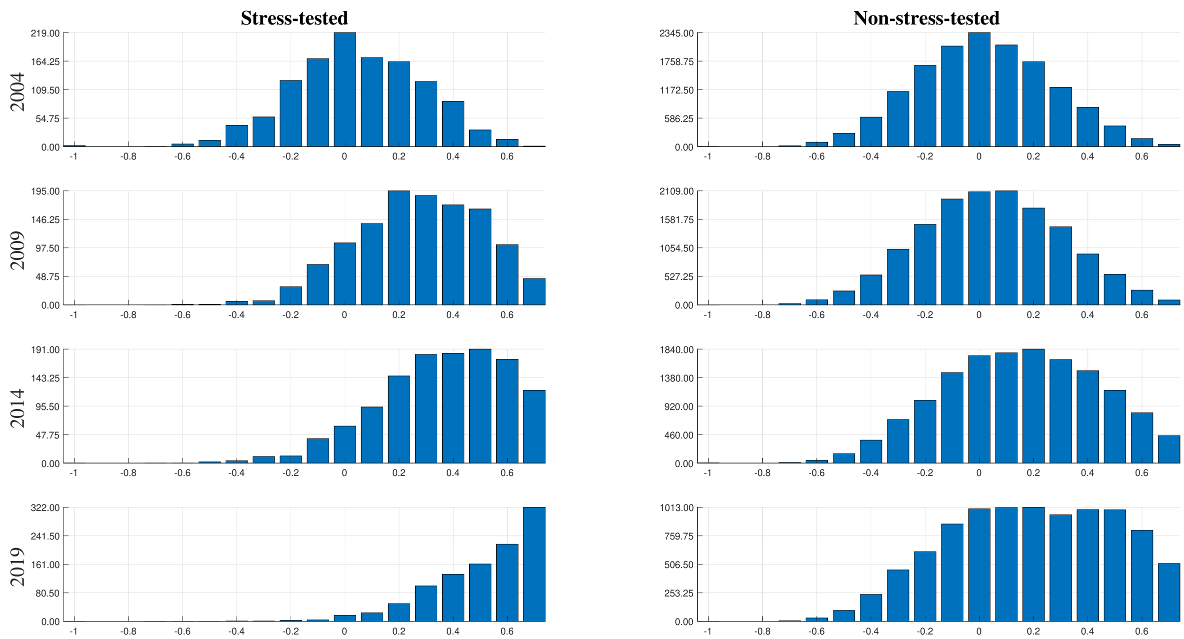


Figure 5: Distribution of pairwise equity return correlations: Stress-tested and Non-stress-tested banks.

Notes: This figure plots the distribution of pairwise daily idiosyncratic equity returns correlations for stress and non-stress tested banks. Idiosyncratic returns are computed using the one-factor CAPM model. The first and second columns depict data for stress and non-stress tested banks, respectively. Each row depicts data for December for a different year. Thus, the first row plots data for December 2004. Daily data, 2004, 2009, 2014, and 2019.

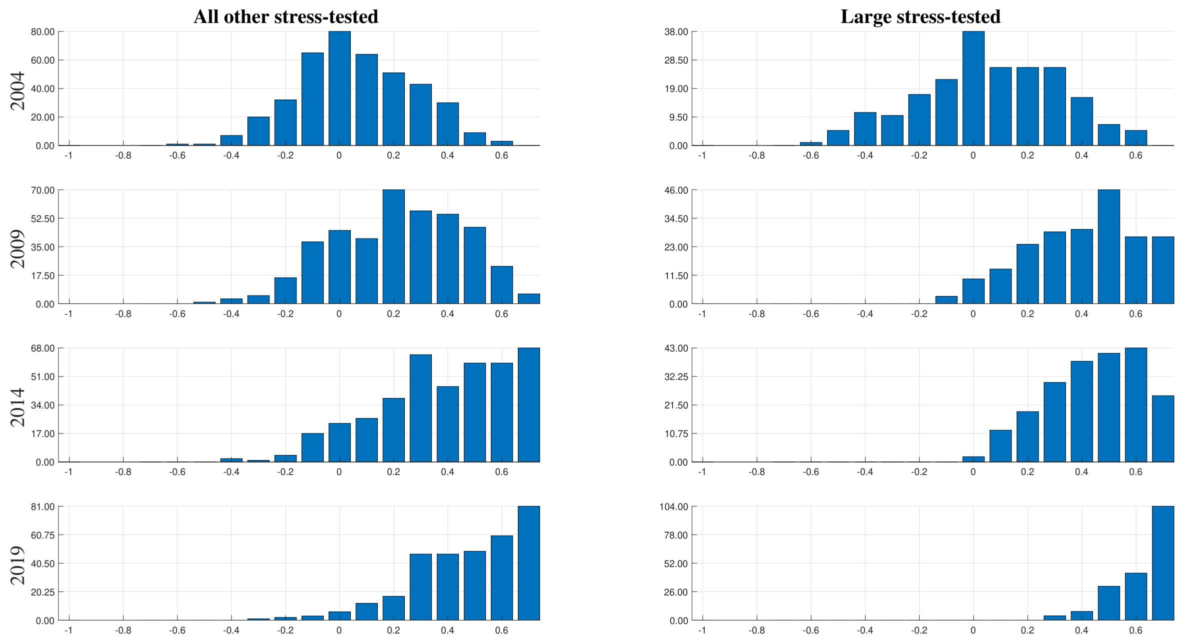


Figure 6: Distribution of pairwise equity return correlations: Large and all other stress-tested banks.

Notes: This figure plots the distribution of pairwise daily idiosyncratic equity returns correlations for large and all other stress tested banks. Idiosyncratic returns are computed using the one-factor CAPM model. The first and second columns depict data for all other and large stress-tested banks, respectively. Large banks are those that are required to participate in the Dodd-Frank Act Stress Test conducted by the Federal Reserve Board. Each row depicts data for December for a different year. Thus, the first row plots data for December 2004. Daily data, 2004, 2009, 2014, and 2019.

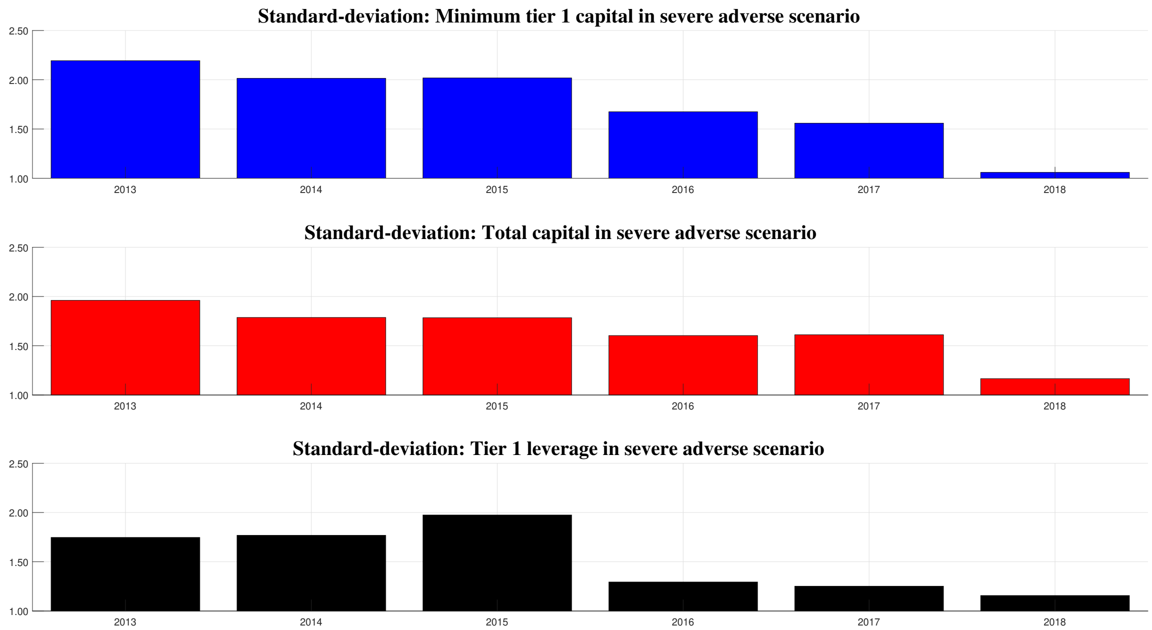


Figure 7: Evidence from DFA tests.

Notes: The figure plots the standard deviation of the three measures of capital that the stress tests measures over 2013 – 2018. The sample is the 18 banks that were subjected to the Dodd-Frank Act Stress Tests conducted by the Federal Reserve Board in 2013. The three measures of capital are the minimum tier 1 capital in severe adverse scenario (top panel), the total capital in severe adverse scenario (middle panel), and the tier 1 leverage in severe adverse scenario (bottom panel).

Table 1: Summary statistics.

Notes: This table shows the summary statistics for banks, financial, and non-financial firms. The first column indicates the variable for which summary statistics are computed. Summary statistics are computed for annual returns, annual volatility, market capitalization, and the average pairwise correlation. Columns 2 - 7 report the mean, standard deviation, minimum, 25^{th}-percentile, 50^{th}-percentile, 75^{th}-percentile, and maximum values. Panels A, B, and C report the summary statistics for banks, financial, and non-financial firms, respectively. Daily data, 1995 – 2020.

	Mean	σ	Min	25^{th}	Median	75^{th}	Max
Panel A: Banks							
Ret	16.34	17.06	-17.75	4.47	13.32	28.63	54.52
σ	0.39	0.16	0.24	0.28	0.34	0.42	0.82
Mktcap	5.53	2.65	1.00	3.93	4.87	7.28	11.28
Pairwise ρ	0.13	0.12	0.01	0.03	0.10	0.19	0.48
Panel B: Financial firms							
Ret	19.41	16.19	-10.41	8.21	20.68	27.58	44.67
σ	0.45	0.16	0.29	0.32	0.39	0.52	0.90
Mktcap	8.43	5.39	2.25	4.73	6.84	11.07	20.96
Pairwise ρ	0.07	0.05	0.01	0.04	0.07	0.10	0.22
Panel C: Nonfinancial firms							
Ret	23.71	27.24	-38.40	7.25	22.81	37.73	84.32
σ	0.59	0.17	0.38	0.46	0.54	0.70	1.02
Mktcap	8.06	5.73	1.85	4.67	6.13	10.10	25.31
Pairwise ρ	0.06	0.03	0.02	0.04	0.06	0.08	0.12

Table 2: Average pairwise correlation: Banks vs. Non-banks

Notes: This table shows the estimated coefficients for the regression:

$$\rho_{i,t} = \alpha_i + \beta_{pst} D_{pst} + \beta_{bnk} D_{bnk} + \gamma D_{pst} \times D_{bnk} + \epsilon_t$$

Here, $\rho_{i,t}$ is the average monthly pairwise correlation for banks, financial, or non-financial firms at time t. D_{pst} is a dummy variable that equals one for the years 2013 – 2020 and D_{bnk} is a dummy variable that equals one for banks. Average monthly pairwise correlations are computed using daily idiosyncratic equity returns for banks, financial, and non-financial firms. For nonfinancial firms, industry definitions are from Kenneth French's website and include all industries with at least 50 firms available over the entire sample. Idiosyncratic returns are computed using the one-factor CAPM model. The first two columns use data for only banks and financial firms and the last two columns use data for banks, financial, and non-financial firms. The numbers in parenthesis are the standard errors. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels, respectively. Monthly data, 1995 – 2020.

Coefficient	(1)		(2)		(3)		(4)	
β_{pst}	0.0601***	(0.0085)	0.2666***	(0.0145)	0.0327***	(0.0014)	0.1117***	(0.0042)
β_{bnk}	0.0074	(0.0067)	0.0074	(0.0046)	0.0035***	(0.0038)	0.0350***	(0.0033)
γ	0.1659***	(0.0120)	0.1659***	(0.0083)	0.1933***	(0.0054)	0.1929***	(0.0048)
R^2	0.5815		0.7993		0.4755		0.5827	
Year fixed effects	*No*		*Yes*		*No*		*Yes*	
Industry fixed effects	*No*		*No*		*Yes*		*Yes*	

Table 3: Principal component analysis.

Notes: This table shows the percentage of variation explained by the first principal component extracted from daily idiosyncratic equity returns for banks, financial, and non-financial firms. For nonfinancial firms, we first compute the percentage variation explained by the first principal component in each industry and then the average across all industries. Industry definitions are from Kenneth French's website and include all industries with at least 50 firms available over the entire sample. Idiosyncratic returns are computed using the one-factor CAPM model. Percentage variation explained is computed for each year from 1995 to 2020 and for the post-crisis (2010 – 2012) and post-Dodd-Frank (2013 – 2020) periods. Daily data, 1995 – 2020.

Years	$Banks$	$Financial$	$Non-financial$
1995	7.81	20.57	28.66
1996	7.60	13.60	24.68
1997	4.53	9.32	24.07
1998	6.34	8.38	25.65
1999	6.55	9.18	20.87
2000	13.38	16.05	21.52
2001	9.54	15.95	26.68
2002	11.32	26.61	26.63
2003	14.52	27.98	28.51
2004	12.36	9.75	27.48
2005	11.94	12.11	27.15
2006	17.03	11.58	27.62
2007	28.92	22.12	25.52
2008	30.62	27.55	24.47
2009	22.42	21.21	32.50
2010	13.14	20.71	25.50
2011	15.16	30.19	24.91
2012	12.93	30.59	26.19
2013	16.15	20.67	26.22
2014	31.53	14.39	28.15
2015	37.16	14.86	24.64
2016	38.16	14.45	31.60
2017	46.03	15.25	32.20
2018	42.96	19.10	31.56
2019	45.66	26.73	32.11
2020	61.96	23.79	35.07
2010 − 2012	12.87	26.09	24.10
2013 − 2020	46.46	15.19	31.58

Table 4: First principal components of equity returns

Notes: This table shows the estimated coefficients for the regression:

$$PCA_{i,t} = \alpha_i + \beta_{pst}D_{pst} + \beta_{bnk}D_{bnk} + \gamma D_{pst} \times D_{bnk} + \epsilon_t$$

Here, $PCA_{i,t}$ is the percentage of variation explained by the first principal component extracted from daily idiosyncratic equity returns for banks, financial, or non-financial firms at time t. $D_{pst}t$ is a dummy variable that equals one for the years 2013 – 2020 and D_{bnk} is a dummy variable that equals one for banks. Principal components are computed each month using daily idiosyncratic equity returns for banks, financial, and non-financial firms. For nonfinancial firms, industry definitions are from Kenneth French's website and include all industries with at least 50 firms available over the entire sample. Idiosyncratic returns are computed using the one-factor CAPM model. The first two columns use data for only banks and financial firms and the last two columns use data for banks, financial, and non-financial firms. The numbers in parenthesis are the standard errors. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels, respectively. Monthly data, 1995 – 2020.

Coefficient	(1)		(2)		(3)		(4)	
β_{pst}	1.6381	(1.1720)	18.0637***	(2.4226)	10.9431***	(0.5509)	16.5762***	(1.6932)
β_{bnk}	-7.1395***	(0.9194)	-7.1395***	(0.7734)	-41.9815***	(1.4432)	-41.9815***	(1.3784)
γ	21.1460***	(1.6575)	21.1460***	(1.3942)	11.8409***	(2.0611)	11.8409***	(1.9686)
R^2	0.3773		0.5594		0.5557		0.5947	
Year fixed effects	*No*		*Yes*		*No*		*Yes*	
Industry fixed effects	*No*		*No*		*Yes*		*Yes*	

Table 5: Average pairwise correlation: Stress Tested vs. Other Banks.

Notes: This Table shows the estimated coefficients for the following regression:

$$\overline{\rho^i} = \alpha_i + \beta_{str}D_{str} + \beta_{pst}D_{pst} + \gamma D_{str} \times D_{pst} + Controls + \epsilon_i$$

Here, $\overline{\rho^i}$ is the average pairwise correlation of bank i with all other banks, D_{str} equals 1 for a bank if its subject to stress-tests and is zero otherwise. D_{pst} equals 1 post 2013 and is zero otherwise. $\overline{\rho^i}$ is computed separately (i.e., within groups) for stress- and non-stress-tested banks. Each column reports the results for a different specification. The numbers in parenthesis are standard errors. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using clustered errors at the firm level. Monthly data, 1995 – 2020.

	(1)		(2)		(3)		(4)	
β_{str}	0.1304***	(0.0082)	–	–	–	–	–	
β_{pst}	0.1885***	(0.0078)	0.1885***	(0.0078)	0.0918***	(0.0065)	0.3334***	(0.0206)
γ	0.1014***	(0.0117)	0.1015***	(0.0117)	0.0780***	(0.0120)	0.0674***	(0.0100)
Assts					0.1005***	(0.0039)	0.0409***	(0.0065)
Levrg					-0.0031**	(0.0014)	-0.0026**	(0.0012)
R^2	0.3772		0.3772		0.4908		0.5632	
N	64,458		64,458		51,890		51,890	
Bank fixed effects	*No*		*Yes*		*Yes*		*Yes*	
Year fixed effects	*No*		*No*		*No*		*Yes*	

Table 6: GMM Estimation Results

Notes: This table presents the parameter estimates from the GMM estimation model. Estimates of the standard deviation of the minimum values of the respective capital ratios are presented in the Table. The standard errors of the estimates are presented in the bracket below each estimate. The quantile value (α) assumed to correspond to the severely stressed scenario is presented at the top of each Panel.

Panel A: α=0.5%		
Capital Measure	Early (σ)	Late (σ)
Tier 1 Capital Ratio	6.93	5.08
	(0.78)	(0.50)
Total Capital Ratio	6.22	5.12
	(0.62)	(0.38)
Tier 1 Leverage Ratio	6.08	4.26
	(0.43)	(0.58)
Panel B: α=1%		
Capital Measure	Early (σ)	Late (σ)
Tier 1 Capital Ratio	6.53	4.78
	(0.73)	(0.47)
Total Capital Ratio	5.86	4.82
	(0.59)	(0.36)
Tier 1 Leverage Ratio	5.73	4.01
	(0.41)	(0.54)
Panel C: α=5%		
Capital Measure	Early (σ)	Late (σ)
Tier 1 Capital Ratio	5.46	4.00
	(0.61)	(0.40)
Total Capital Ratio	4.91	4.03
	(0.49)	(0.30)
Tier 1 Leverage Ratio	4.79	3.36
	(0.34)	(0.46)

Table 7: Sensitivity to bond and stock market factors

Notes: This Table shows the estimated coefficients for the following regression:

$$\overline{\beta^i} = \alpha_i + \beta_{str} D_{str} + \beta_{pst} D_{pst} + \gamma D_{str} \times D_{pst} + Controls + \epsilon_i$$

Here, $\overline{\beta^i}$ is the average absolute distance between the β for bank i and the βs for all other banks on shocks to the total return on an index of BBB-rated corporate bonds (Column 1, Panel A), CBOE volatility index (Column 2, Panel A),the thirty-year fixed mortgage rate (Column 3, Panel A), personal consumption expenditure (Column 1, Panel B), consumer price index (Column 2, Panel B), and the Case-Shiller home price index (Column 3, Panel B). D_{str} equals 1 for a bank if its subject to stress-tests and is zero otherwise. D_{pst} equals 1 post 2013 and is zero otherwise. $\overline{\beta^i}$ is computed separately (i.e., within groups) for stress- and non-stress-tested banks. Each column reports the results for a different specification. The numbers in parenthesis are standard errors. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using clustered errors at the firm level. Monthly data, 1995 – 2020.

Panel A	(BBB)		(VIX)		(Mortgage rate)	
β_{pst}	0.1405***	(0.0801)	-0.0252***	(0.0080)	1.3324**	(0.6228)
γ	-0.2950***	(0.0474)	-0.0198***	(0.0039)	-0.7824*	(0.4225)
$Assts$	-0.1268***	(0.0426)	0.0052*	(0.0038)	-0.6130*	(0.3577)
$Levrg$	-0.0109*	(0.0057)	0.0006	(0.0005)	-0.1035**	(0.0522)
R^2	0.1695		0.4192		0.2370	
N	25,077		25,077		25,077	
Bank fixed effects	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	

Panel B	(Consumption)		(CPI)		(Case-Shiller)	
β_{pst}	-0.5155	(0.3543)	-2.1744***	(0.5899)	-3.1072***	(0.5487)
γ	-0.6228***	(0.1595)	-0.6241***	(0.2407)	0.2661	(0.1831)
$Assts$	-0.2784*	(0.1639)	-0.4358	(0.2745)	-0.3070	(0.2572)
$Levrg$	-0.0156	(0.0245)	-0.0316	(0.0235)	-0.0175	(0.0233)
R^2	0.3116		0.3635		0.4507	
N	25,077		25,077		25,077	
Bank fixed effects	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	

Table 8: Post stress-test failure correlation.

Notes: This Table shows the estimated coefficients for the following regression:

$$\overline{\rho^i} = \alpha + \theta_t + \beta_{fal} D_{fal} + \beta_{str} D_{str} + \beta_{pst} D_{pst} + \gamma D_{str} \times D_{pst} + Controls + \epsilon_i$$

Here, $\overline{\rho^i}$ is the average pairwise correlation of bank i with all other banks, D_{fal} equals 1 for a bank if its subject to stress-tests and after it failed its first stress and is zero otherwise. D_{str} equals 1 for a bank if its subject to stress-tests and is zero otherwise. D_{pst} equals 1 post 2013 and is zero otherwise. Each column reports the results for a different specification. The numbers in parenthesis are standard errors. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using clustered errors at the firm level. Monthly data, 1995 – 2020.

	(1)		(2)		(3)		(4)		(5)	
β_{fal}	0.0414***	(0.0170)	0.0392**	(0.0173)	0.0426***	(0.0153)	0.0356**	(0.0173)	0.0391***	(0.0154)
β_{str}	0.1173***	(0.0111)	–	–	–	–	–	–	–	–
β_{pst}	0.4368***	(0.0103)	0.4370***	(0.0104)	0.3448***	(0.0203)	0.4304***	(0.0106)	0.3393***	(0.0203)
γ	0.0733***	(0.0111)	0.0735***	(0.0111)	0.0731***	(0.0109)	0.0735***	(0.0110)	0.0731***	(0.0107)
$Assts$					0.0402***	(0.0066)			0.0398***	(0.0065)
$Levrg$							-0.0027**	(0.0013)	-0.0026**	(0.0012)
R^2	0.5530		0.5530		0.5599		0.5564		0.5631	
N	51,890		51,890		51,890		51,890		51,890	
Bank Fixed effects	No		Yes		Yes		Yes		Yes	
Year Fixed effects	Yes		Yes		Yes		Yes		Yes	

Table 9: Difference in difference: Cosine similarity in income.

Notes: This Table shows the estimated coefficients for the following regression:

$$\overline{Income^i} = \alpha + \beta_{str} D_{str} + \beta_{pst} D_{pst} + \gamma D_{str} \times D_{pst} + Controls + \epsilon_i$$

Here, $\overline{Income^i}$ is one minus the average cosine measure of similarity for income sources for bank i to all other banks. D_{str} equals 1 for a bank if its subject to stress-tests and is zero otherwise. D_{pst} equals 1 post 2013 and is zero otherwise. $\overline{Income^i}$ is computed separately (i.e., within groups) for stress- and non-stress-tested banks. Each column reports the results for a different specification. The numbers in parenthesis are standard errors. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using clustered errors at the firm level. Quarterly data, 1995 – 2020.

	(1)		(2)		(3)		(4)		(5)	
β_{str}	0.0387***	(0.0095)	–	–	–	–	–	–	–	–
β_{pst}	-0.0262***	(0.0044)	-0.0262***	(0.0044)	-0.0392***	(0.0105)	-0.0253***	(0.0040)	-0.0384***	(0.0101)
γ	-0.0270***	(0.0052)	-0.0269***	(0.0052)	-0.0262***	(0.0052)	-0.0271***	(0.0051)	-0.0264***	(0.0051)
$Assts$					0.0078*	(0.0044)			0.0079*	(0.0044)
$Levrg$							0.0004	(0.0004)	0.0004	(0.0004)
R^2	0.2711		0.2711		0.2765		0.2730		0.2785	
N	14,216		14,216		14,216		14,216		14,216	
Bank fixed effects	No		Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes		Yes	

Table 10: Difference in difference: Cosine similarity in assets.

Notes: This Table shows the estimated coefficients for the following regression:

$$\overline{Asset^i} = \alpha + \beta_{str} D_{str} + \beta_{pst} D_{pst} + \gamma D_{str} \times D_{pst} + Controls + \epsilon_i$$

Here, $\overline{Asset^i}$ is one minus the average cosine measure of similarity for asset portfolio for bank i to all other banks. D_{str} equals 1 for a bank if its subject to stress-tests and is zero otherwise. D_{pst} equals 1 post 2013 and is zero otherwise. $\overline{Asset^i}$ is computed separately (i.e., within groups) for stress- and non-stress-tested banks. Each column reports the results for a different specification. The numbers in parenthesis are standard errors. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using clustered errors at the firm level. Quarterly data, 1995 – 2020.

	(1)		(2)		(3)		(4)		(5)	
β_{str}	0.0048	(0.0133)	–	–	–	–	–	–	–	–
β_{pst}	0.0304***	(0.0094)	0.0304***	(0.0095)	0.0259	(0.0184)	0.0337***	(0.0098)	0.0287	(0.0187)
γ	-0.0173**	(0.0069)	-0.0174**	(0.0069)	-0.0171**	(0.0070)	-0.0181**	(0.0068)	-0.0178**	(0.0079)
$Assts$					0.0027	(0.0095)			0.0030	(0.0084)
$Levrg$							0.0014***	(0.0004)	0.0014***	(0.0005)
R^2	0.1417		0.1417		0.1418		0.1457		0.1458	
N	14,235		14,235		14,235		14,235		14,235	
Bank fixed effects	*No*		*Yes*		*Yes*		*Yes*		*Yes*	
Year fixed effects	*No*		*Yes*		*Yes*		*Yes*		*Yes*	

Table 11: Sensitivity to a risk factor orthogonal to U.S. macroeconomic risk.

Notes: This Table shows the estimated coefficients for the following regression:

$$\beta^i = \alpha_i + \beta_{str} D_{str} + \beta_{pst} D_{pst} + \gamma D_{str} \times D_{pst} + Controls + \epsilon_i$$

Here, β^i is the β for bank i on a risk-factor that is orthogonal to U.S. macroeconomic risk. To construct this factor, we begin with the twelve time-series for U.S. macroeconomic and financial factors that are part of the Federal Reserve Board's stress test scenario for which monthly data is available. These factors include, for example, the index of industrial production, consumer price index, consumption expenditure, mortgage rate, yield spreads, etc. We compute for first principal component of monthly changes in these twelve macroeconomic series. We compute the loadings for the first principal component extracted from the monthly changes in these twelve macroeconomic series. We then, use data for the hundred Fama-French portfolios sorted by market capitalization (size) and book-to-market, to solve (optimize) for weights for a mimicking portfolio that is orthogonal, that is has zero correlation with this first principal component. For each bank in our sample, we estimate the β for its returns to this orthogonal risk factor. D_{str} equals 1 for a bank if its subject to stress-tests and is zero otherwise. D_{pst} equals 1 post 2013 and is zero otherwise. Each column reports the results for a different specification. The numbers in parenthesis are standard errors. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using clustered errors at the firm level. Monthly data, 1995 – 2020.

	(1)		(2)		(3)		(4)		(5)	
β_{str}	-0.0023***	(0.0004)	–	–	–	–	–	–	–	–
β_{pst}	0.0029***	(0.0003)	0.0029***	(0.0003)	0.0040***	(0.0006)	0.0032***	(0.0003)	-0.0044***	(0.0006)
γ	0.0012***	(0.0004)	0.0012***	(0.0004)	0.0011***	(0.0003)	0.0012***	(0.0004)	0.0011***	(0.0003)
$Assts$					-0.0007**	(0.0003)			-0.0007**	(0.0003)
$Levrg$							0.0008	(0.0005) *	0.0008**	(0.0004)
R^2	0.4356		0.4356		0.4403		0.4382		0.4434	
N	25,077		25,077		25,077		25,077		25,077	
Bank fixed effects	No		Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes		Yes	

Appendices

A Theoretical Model

We assume complete markets and consider the portfolio selection problem of a bank i that has access to two risky assets indexed by $a \in \{1, 2\}$. Investments are made at $t = 0$ and payoffs are realized at $t = 1$. The assets deliver the following returns to a market investor for every unit of investment:

$$\tilde{r_a^i} = \beta_a \tilde{f} + \epsilon_a \tag{12}$$

β_a captures the sensitivity of the asset a's returns to a macroeconomic risk factor $\tilde{f} \sim N(\mu_f, \sigma_f^2)$. This is the factor that enters the stress test model, as we discuss later in the section. ϵ_a are shocks uncorrelated to the macroeconomic factor, either hidden to the regulator or simply not a part of the stress testing scenario. We assume that and $\epsilon_a \sim N(0, \sigma_a^2)$ for asset a, and $corr(\epsilon_1, \epsilon_2) = \rho$.

The bank has some specific technology in screening and monitoring the two assets, allowing it to earn some return in excess of the return available to the market investors. The technology or the skill varies with $\{bank, asset\}$ pair, consistent with the idea that banks specialize in different markets and products. Differences in relative skills leads to heterogeneity of asset holdings across banks even in the absence of any regulation or market frictions. We assume that bank $i's$ skill in asset a, for a level of investment I, is given by $s_a^i(I)$ such that $s_a^{'i}(I) \geq 0$ and $s_a^{''i}(I) \leq 0$, i.e., the skill function is an increasing and concave function of the amount of investment a bank makes in an asset.

Therefore, for I units of investment in assets $a \in \{1, 2\}$ at $t = 0$, bank $i's$ gross payoffs at $t = 1$ is given by the following:

$$\tilde{X_a^i}(I) = s_a^i(I) + (1 + \beta_a \tilde{f} + \epsilon_a)I \tag{13}$$

The bank has w_0 of initial wealth, comprising of $e\%$ of equity capital and the remainder of debt. It picks a portfolio $\theta = [\theta_1, \theta_2]$at $t = 0$. Hence at time $t = 1$, the bank receives the following random payoff:

$$\tilde{w_1}(\theta) = s_1(\theta_1 w_0) + (1 + \beta_1 \tilde{f} + \epsilon_1)\theta_1 w_0 + s_2((1 - \theta_1)w_0) + (1 + \beta_2 \tilde{f} + \epsilon_2)((1 - \theta_1)w_0). \tag{14}$$

Asset holdings without any constraints: We first solve for the bank's optimal portfolio holding in the absence of any risk-management constraints, internal or external, to get a frictionless benchmark. In an unconstrained world, the bank maximizes the expected net present value of its investments as given below:

$$\max_{\theta_1} \quad E_t[w_1(\theta_1) - w_0] = s_1(\theta_1 w_0) + s_2((1 - \theta_1)w_0) + (\beta_1 \theta_1 w_0 + \beta_2(1 - \theta_1)w_0)\mu_f. \tag{15}$$

Concavity of the skill functions ensures that the second order condition for maxima is satisfied. Therefore, the optimal asset holding is given by the following first order condition:

$$s_1'(\theta_1 w_0) + \beta_1 \mu_f = s_2'((1-\theta_1)w_0) + \beta_2 \mu_f \tag{16}$$

At the optimum point the marginal benefit from investments are equated across the two assets. As expected, the bank tilts its investment in favor of the asset in which it has more skill. For example, if the risk premium were equal across the two assets (i.e., either $\mu_f = 0$ or $\beta_1 = \beta_2$), then for a bank with higher skill in asset a_1, we have $s_1'(I) \geq s_2'(I), \forall I$. Therefore the FOC condition holds at $\theta_1 \geq 0.5$. The reverse holds if the bank is better skilled at managing a_2. Thus, the bank picks a portfolio that is weighted in favor of the asset in which it has higher skill, and the weight varies with a bank's skill differential across the two assets.

Asset holdings with bank's internal risk-management: The frictionless benchmark provides an interesting starting point; however, it is not a realistic benchmark. Even in the absence of regulatory constraints, a bank is likely to care about the risk of its portfolio. We therefore solve for the portfolio choice problem when banks care about risk-management even in the absence of any stress tests. Frictions such as bankruptcy costs (Smith and Stulz, 1984), financial distress costs (Purnanandam, 2008), or costly external financing (Froot et al. 1993) provide motivations for managing the downside risk of a bank. In practice, banks often maintain their own internal risk controls and make use of tools such as Value-at-Risk or impose limits on positions. Motivated by these theoretical models and practical considerations, we now solve for a bank's portfolio choice problem when it cares about its Value-at-Risk (VaR), a popular risk-management tool in the industry. Later, we solve for the bank's problem when faced with stress test based risk constraint and compare the optimal asset holdings across these two scenarios to derive insights into how banks are likely to change their asset holdings once they are subject to stress tests.

Let μ_θ and Ω_θ be the expected return and the variance-covariance matrix of portfolio $[\theta_1,\theta_2]$. Denoting by $VaR(\theta)$ the Value-at-Risk for portfolio choice θ at a significance level α, we get the following:

$$P_t[w_0 - w_1(\theta) \geq VaR(\theta)] = \alpha$$

$$\implies P_t[\frac{w_1 - \mu_\theta}{\sqrt{\theta'\Omega_\theta\theta}} \leq \frac{w_0 - Var(\theta) - \mu_\theta)}{\sqrt{\theta'\Omega_\theta\theta}}] = \alpha \tag{17}$$

$$\implies P_t[Z \leq \frac{w_0 - Var(\theta) - \mu_\theta}{\sqrt{\theta'\Omega_\theta\theta}}] = \alpha \tag{18}$$

$$\implies \Phi^{-1}(\alpha) = \frac{w_0 - Var(\theta) - \mu_\theta}{\sqrt{\theta'\Omega_\theta\theta}} \tag{19}$$

$$\implies Var(\theta) = w_0 - \mu_\theta + \sqrt{\theta'\Omega_\theta\theta}\Phi^{-1}(1-\alpha) \tag{20}$$

As expected, the VaR number is lower for a portfolio that has higher expected return (μ_θ) and lower risk ($\theta'\Omega_\theta\theta$). We assume that the bank faces an internal constraint to keep the VaR level of its chosen portfolio (θ), derived above, below some multiple k of its equity capital. Now the bank solves the following constrained optimization problem:

$$\begin{aligned} \max_{\theta} \quad & \mu_\theta - w_0 \\ \text{s.t.} \quad & VaR(\theta) \leq ke \end{aligned} \tag{21}$$

The Lagrangian can be written as follows:

$$\mu_\theta - w_0 + \lambda\{ke - (w_0 - \mu_\theta + \sqrt{\theta'\Omega_\theta\theta}\Phi^{-1}(1-\alpha))\} \tag{22}$$

And the solution is characterized by the following first order condition:

$$\frac{\partial \mu_\theta}{\partial \theta} = \frac{\lambda}{1+\lambda}\Phi^{-1}(1-\alpha)\frac{\partial\sqrt{\theta'\Omega_\theta\theta}}{\partial\theta} \tag{23}$$

In the frictionless benchmark derived in equation 16, the bank equated marginal benefits of investment across the two assets at the optimal point. With internal risk-management concerns, the bank is willing to sacrifice some investment in assets with higher skill for the diversification benefit the lower skill asset provides. The precise amount of adjustment to the optimal asset mix depends on the exact specification of the skill functions, the riskiness of the portfolio, and the tightness of the VaR constraint. Equation 23 can be expanded into the following intuitive equation:

$$s_1'(\theta_1 w_0) - s_2'((1-\theta_1)w_0) + (\beta_1 - \beta_2)\mu_f = \frac{\lambda}{1+\lambda}\Phi^{-1}(1-\alpha)\frac{\partial\sqrt{\theta'\Omega_\theta\theta}}{\partial\theta_1} \tag{24}$$

The left hand side of the above equation is the marginal benefit of investing an extra unit in a_1 compared to the same investment in a_2. In the unconstrained optimization, this marginal benefit was set to zero. With the risk-management concerns in place, the bank also takes into account the additional risk the marginal investment in asset one presents to the overall portfolio. The right hand side of the equation captures that effect. Suppose a bank has superior skill in a_1. If a unit of additional investment in a_1 increases the contribution to the bank's VaR, as captured by the RHS of the first order condition, then at the optimal point, we have $s_1'(\theta_1 w_0) - s_2'((1-\theta_1)w_0) + (\beta_1 - \beta_2)\mu_f > 0$. From the concavity of the skill functions, it follows that the optimal level of θ_1 is lower than the unconstrained case where $s_1'(\theta_1 w_0) - s_2'((1-\theta_1)w_0) + (\beta_1 - \beta_2)\mu_f = 0$. Therefore, compared to the unconstrained case, banks are willing to trade off their skill in a_1 with the diversification benefit provided by a_2. As they move their holdings towards a_2, they are likely to become similar to each other compared to the case where they simply maximized their returns on skill. Specifically, banks pick their optimal asset mix based on the skill they have and the variance-covariance structure of the asset payoffs they face. Asset commonality in the economy will be a function of skill distribution across banks and the variance-covariance structure. We provide numerical results for asset commonality in an economy where banks differ in their skill endowment after presenting the model with stress test constraint.

Asset holdings with stress test: When the bank is subject to stress tests, it begins to care about losses in the bad state of the world in a very specific manner: in a manner dictated by the scenario proposed by the stress test model. The bad states of the world in the model is defined as a lower tail realization of the factor shock f, consistent with the practice of actual stress test. The expected loss of the stress test is given by $E[(w_0 - w_1(\theta))|f < \underline{\text{f}}]$, where $\underline{\text{f}}$ is the scenario of the stress test macroeconomic condition. Consistent with the stress test requirements, we assume that the bank must maintain some level of equity capital under the stressed scenario, i.e., we assume that the bank's losses in the stressed scenario is bounded by a multiple c of its current equity capital. The multiple can be one, corresponding to a constraint that losses should not exceed the current level of equity capital. A lower multiple (say 0.5 of current equity capital) corresponds to a scenario where the losses cannot be allowed to be more than 50% of the current capital. Thus, c measures the tightness of the stress test capital requirement.

This assumption is consistent with the actual practice, where banks incur both explicit and implicit costs if they perform poorly on the stress tested scenario. For example, banks ability to pay dividends depend on the result of these tests. They may need to raise additional equity if their projected value in the bad state of the world is too low compared to the equity they currently have. The cost can also come in the form of heightened regulatory scrutiny in case of shortfall or the ability to pay larger dividends in case of surplus. We leave these frictions un-modeled in the paper.

The optimization problem with stress test is as follows:

$$\begin{aligned} \max_{\theta} \quad & \mu_\theta - w_0 \\ \text{s.t.} \quad & E[(w_0 - w_1(\theta))|f < \underline{\text{f}}] \leq ce \end{aligned} \tag{25}$$

The Lagrangian is given by the following:

$$\max_{\theta} \quad \mu_\theta - w_0 + \delta\{ce - E[(w_0 - w_1(\theta))|f < \underline{\text{f}}]\} \tag{26}$$

$$\begin{aligned} \max_{\theta_1} \quad & s_1(\theta_1 w_0) + s_2((1-\theta_1)w_0) + (\beta_1\theta_1 w_0 + \beta_2(1-\theta_1)w_0)\mu_f \\ +\delta\{ce + (s_1(\theta_1 w_0) &+ s_2((1-\theta_1)w_0)) + w_0(\beta_1\theta_1 + \beta_2(1-\theta_1))(\mu_f - \sigma_f \frac{\phi(\underline{\text{f}})}{\Phi(\underline{\text{f}})})\} \end{aligned} \tag{27}$$

where $\phi(.)$ and $\Phi(.)$ stand for the pdf and the cdf, respectively, of a standard normal random variable. The FOC is given by the following:

$$s_1'(\theta_1 w_0) - s_2'((1-\theta_1)w_0) + (\beta_1 - \beta_2)\mu_f = \frac{\delta}{1+\delta}\sigma_f[\beta_1 - \beta_2]\frac{\phi(f)}{\Phi(f)} \tag{28}$$

Assume, without any loss of generality, that asset a_1 has a higher sensitivity to the macroeconomic factor on which banks are tested. Then $\beta_1 - \beta_2 > 0$, and the RHS of the above equation is positive. At the optimum point the unconstrained marginal return from investing in a_1 over a_2, namely $s'_1(\theta_1 w_0) - s'_2((1-\theta_1)w_0) + (\beta_1 - \beta_2)\mu_f > 0$. Therefore, from the concavity of the skill functions, it follows that for banks will lower their investment in a_1. Further, the optimal θ_1 will be lower when the RHS is larger. Therefore, banks are more likely to shift towards asset with lower sensitivity to f if: (i) the volatility of the factor (σ_f) is higher, (ii) the shadow price of stress test or the cost of poor performance on the test (δ) is higher, (iii) the difference in asset's sensitivity to the macroeconomic factor ($\beta_1 - \beta_2$) is higher, and (iv) the stress test scenario is stricter, i.e., $\underline{f}$ is lower.

Commonality in Assets: Comparing equation 29 with the corresponding optimal solution under internal risk-management constraint characterized in equation 24, it is easy to see that the deviation from the first-best asset holding choice will be larger under the stress test scenario compared to the internal risk-management scenario if the following condition holds:

$$\frac{\delta}{1+\delta}\sigma_f[\beta_1 - \beta_2]\frac{\phi(\underline{f})}{\Phi(\underline{f})} > \frac{\lambda}{1+\lambda}\Phi^{-1}(1-\alpha)\frac{\partial\sqrt{\theta'\Omega_\theta\theta}}{\partial\theta} \tag{29}$$

As long as this condition holds, banks shift a larger amount of their investment into the relatively attractive asset on stress test, namely a_2, under the stress test scenario compared to their internal model. Even if an asset (a_2 in the model) has very high overall volatility, banks prefer it over the other asset as long as it helps the bank lower its losses in the stressed scenario. Thus, banks herd more towards a_2 is the following conditions hold: (i) the shadow price of the stress constraint (δ) is larger compared to the shadow price of bank's internal constraint (λ), (ii) factor volatility (σ_f) is high, (iii) the sensitivity to macroeconomic factor is relatively higher for a_1 as captured by $\beta_1 - \beta_2$, (iv) stress test scenario is too pessimistic, i.e., $\underline{f}$ is smaller, and (v) the diversification benefits of a_2 are relatively smaller.

To make further progress and to numerically estimate the level of commonality, we now need to specify the form of skill function and construct a precise measure of asset commonality. While our results so far holds for all skill functions that are increasing and concave, for further analysis we assume the following form of skill function for bank-asset pair $\{b, a\}$:

$$s_b^a(x) = 1 - e^{-\lambda_a^b x} \tag{30}$$

λ_a^b captures the level of skill bank b has in asset a. We simulate an economy where this parameter is randomly generated from a uniform distribution and then solve for optimal asset holdings across a_1 and a_2 for every bank in the economy. Based on the optimal portfolio choice of each bank, we compute a measure of asset commonality based on the cosine measure of similarity as defined below for bank i and j:

$$cos_{ij} = \frac{(\theta_1^i * \theta_1^j) + ((1-\theta_1^i) * (1-\theta_1^j))}{\sqrt{(\theta_1^i)^2 + (1-\theta_1^i)^2} * \sqrt{(\theta_1^j)^2 + (1-\theta_1^j)^2}} \tag{31}$$

We restrict portfolio weights between zero and one, disallowing short sales. However, this restriction is not crucial for our key results. The parameters that we use for the base case is provided in Table A1.

Numerical Results: In our first analysis, we solve for optimal portfolio holding for three scenario: (a) the unconstrained or frictionless benchmark, (b) internal model based choice, and (c) stress test model based choice. Before presenting the results on asset commonality, we present the percentage of investment in a_2, the asset that is attractive from the viewpoint of stress tests, in Figure A1a for various levels of factor volatility. As factor volatility increases, banks shift relatively higher proportion of their asset to a_2. Optimal investment in a_2 is higher than the frictionless benchmark even for the internal model due to the diversification benefit it provides. However, with stress tests, the asset becomes really attractive and the bank invests a significantly higher share of its wealth into a_2, an asset in which it has lower skill. As the volatility increases, risk management concerns become stronger and the bank invests more in a_2; however, the relative distance between the internal model and stress test based model gets larger with the increase in factor volatility. The result shows that the attractiveness of herding into safer asset is higher when the factor is riskier.

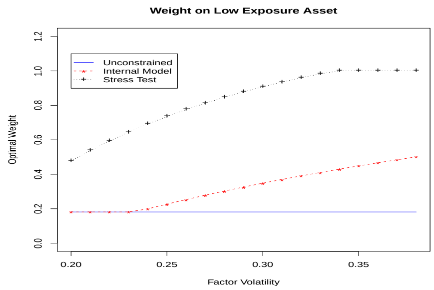
Another key parameter of the model is the level of equity capital the bank has and its behavior as a function of this parameter. Figure A1b plots the optimal investment in a_2 as a function of the level of equity capital. The difference across the three models is especially higher when the bank has lower levels of equity capital, i.e., when the shadow price of capital constraint is more binding. At sufficiently higher levels of capital, the constrained optimization gets closer to the frictionless benchmark, as expected.

We now measure cosine similarity across banks in an economy populated with VaR-constrained banks with an economy populated with banks with stress test requirements. We simulate 1,000 banks that vary in their respective skills in a_1 and a_2. Skill function for a_1, i.e., λ_1, is drawn from a uniform distribution $U_1 \sim [0, 1]$, and λ_2 is given by $g \times \lambda_1$ for each draw of λ_1. g is again drawn from $U_2 \sim [0, 2]$. As a result about half the banks in the economy are more skilled in a_1 (i.e., $g < 1$) and the remaining ones are more skilled in a_2.

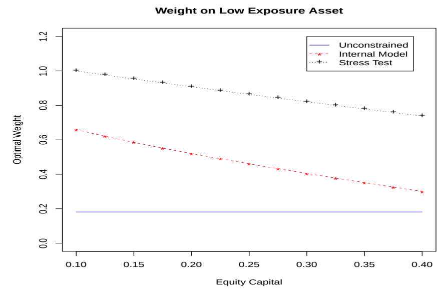
We show two key results: (a) one focused on how similarity changes as the factor volatility goes up, and (b) how similarity changes when the stress test becomes more stringent. In Figure A1c we show the changes in asset commonality across the two economies when the variance of the factor risk goes up. To do so, we fix the overall variance of a_1 and a_2 at 36% and 4%, respectively and gradually change the proportion of the asset's variance explained by the factor shock while keeping the overall variance the same. This allows us to compare asset commonality while holding the overall risk in the economy constant. The model is calibrated with the base case parameters provided in Table A1. As shown in Figure A1c, when factor variance is relatively small, asset commonality is lower with stress tests. At these levels of factor risk, banks find it optimal to not deviate too much from their optimal portfolio based on their skill parameters. Only when the factor variance goes up beyond a threshold, the banks shift their assets more aggressively to the safer asset and commonality increases as compared to the VaR-based economy.

In our second analysis, we focus on the stringency of the stress test regulation. Two parameters in the model dictate how stringent these tests are: (a) parameter c that governs the maximum allowable loss in the bad state of the world, and (c) parameter $\underline{f}$ that governs how severe the adverse scenario are. We first vary the level of allowable loss (c) in the bad state of the world and compute cosine similarity across the two economies. Results are presented in Figure A1d. As the stress test requirements become more stringent, i.e., when allowable losses are smaller, asset homogeneity increases. Figure A1e repeats the experiment for the severity of the tested scenario. Lower values of $\underline{f}$ indicate more adverse scenario, for example the severely adverse scenario of stress tests correspond to a much lower tail of the distribution of $\underline{f}$ compared to the corresponding number for the adverse scenario. We find that the homogeneity is higher when $\underline{f}$, i.e., when regulators test based on stringent criteria.

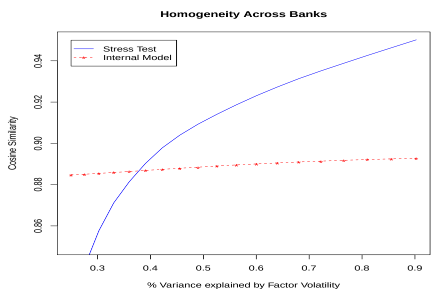
Overall, our model shows that the changes in asset commonality is likely to be higher when the factor volatility is higher and the stress test constraints are more binding. We now empirically analyze whether the commonality has increased or not, and whether they are consistent with the predictions of our stylized model. In the model asset correlation and equity correlations are equivalent. In our empirical work, we begin with a measure of similarity in equity returns and follow it up by an analysis of cosine similarity across assets. Our model also guides us in constructing empirical tests that relate the cost of stress test to increase in homogeneity.



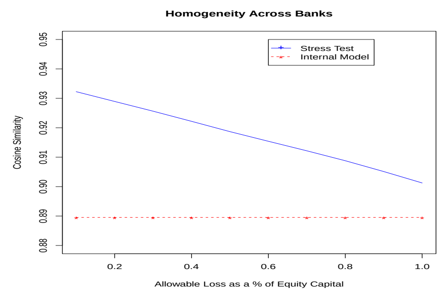
(a) Portfolio Choice and Factor Volatility



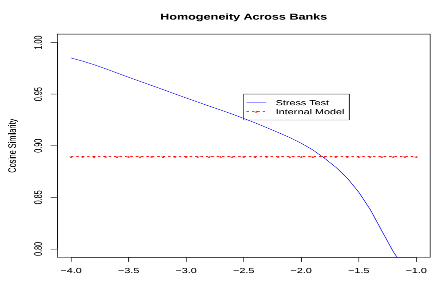
(b) Portfolio Choice and Capitalization



(c) Cosine Similarity and Factor Volatility



(d) Cosine Similarity and Stress Test Stringency: Maximum Allowable Loss



(e) Cosine Similarity and Stress Test Stringency: Severity of scenario

Notes: Figure A1a plots the fraction of investment in assets with low exposure to stress test factor as the volatility of the tested factor changes. Figure A1b plots the fraction of investment in assets with low exposure to stress test factor as the capitalization ratio of the bank changes. Figure A1c, A1d, and A1e plot the average cosine similarity across banks in the economy as the volatility of the macroeconomic factor changes, the maximum allowable losses in the bad state changes, and the severity of the test scenario changes.

Table A1: Model Parameters: Base Case

Notes: This table presents the parameters for the base case of simulation exercise.

w_0	initial wealth	1.00
e	equity capital	0.20
c	stress test capital constraint	1.00
k	internal model capital constraint	1.00
α	VaR significance level	0.025
$\underline{f}$	stress test scenario level	-2.325
λ_1	skill parameter in a_1	0.50
λ_2	skill parameter in a_2	0.40
β_1	factor risk of a_1	1.50
β_2	factor risk of a_2	0.50
σ_1	idiosyncratic risk of a_1	0.20
σ_2	idiosyncratic risk of a_2	0.10
ρ	asset correlation	0.50
μ_f	risk-premium	0.04
σ_f	factor volatility	0.30

Table A2: Mean absolute deviation of betas.

Notes:
This table shows the dispersion (mean absolute deviations) in factor loadings (i.e., factor betas) for various bond market, stock market, and macroeconomic factors. These include the total return on an index of BBB-rated corporate bonds, the change in stock market volatility (VIX), the change in mortgage rates, the change in personal consumption expenditure, the change in consumer price index, and the change in the Case-Shilller house price index. The first row reports the annualized volatility for the 6 factors. The second and third row report the mean absolute deviations in the betas for the 6 factors for stress-tested banks in 2009 and 2019, respectively. In all cases, the dispersions are normalized by the cross-sectional mean of the betas. The last row reports the percentage change in the dispersion from 2009 to 2019.

	BBB	VIX	Mortgage rate	Consumption	CPI	Case-Shiller
Volatility	0.0469	0.5688	0.0086	0.0309	0.0196	0.0097
MAD (2009)	1.16	2.55	1.95	0.53	0.31	0.66
MAD (2019)	0.79	0.57	1.28	0.38	0.21	0.35
Change	-0.3190	-0.7765	-0.3436	-0.2830	-0.3226	-0.4697

Table A3: Summary statistics - Distance measures.

Notes: This table shows the summary statistics for one minus the average cosine similarity measures between income sources, assets, loans, real-estate loans, and securities portfolio for the cross-section of banks. For instance, to computed the cosine similarity measure for income, for each bank, i, we collect quarterly data on the dollar income from loans, leases, securitization, trading, repurchase agreements, fiduciary, brokerage, investment banking, insurance, and venture capital activities etc. For each quarter, we compute the average cosine measure of similarity for bank i with all other remaining banks. Distance measures are computed separately for stress- and non-stress-tested banks. The first column indicates the variable for which summary statistics are computed. Columns 2 - 7 report the mean, standard deviation, minimum, 25^{th}-percentile, 50^{th}-percentile, 75^{th}-percentile, and maximum values. Quarterly data, 1995 – 2020.

	Mean	σ	Min	25^{th}	Median	75^{th}	Max
Income	0.0461	0.0501	0.0119	0.0244	0.0337	0.0503	0.6830
Assets	0.1035	0.1027	0.0220	0.0514	0.0797	0.1040	0.9460
Loans	0.1384	0.1078	0.0447	0.0843	0.1029	0.1422	0.9725
RE loans	0.1966	0.1183	0.0379	0.1253	0.1745	0.2431	0.9598
Securities	0.5212	0.1577	0.0829	0.4156	0.4989	0.6070	0.9944

Table A4: Difference in difference: Cosine similarity in loans, real estate loans, securities.

Notes: This Table shows the estimated coefficients for the following regression:

$$\overline{Y^i} = \alpha + \beta_{str} D_{str} + \beta_{pst} D_{pst} + \gamma D_{str} \times D_{pst} + Controls + \epsilon_i$$

Here, $\overline{Y^i}$ is one minus the average cosine measure of similarity for loan, real estate loan, and securities portfolio for bank i to all other banks. D_{str} equals 1 for a bank if its subject to stress-tests and is zero otherwise. D_{pst} equals 1 post 2013 and is zero otherwise. $\overline{Loans^i}$ is computed separately (i.e., within groups) for stress- and non-stress-tested banks. Each column reports the results for a different dependent variable. The numbers in parenthesis are standard errors. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using clustered errors at the firm level. Quarterly data, 1995 – 2020.

	(Loans)		(Real estate)		(Securities)	
β_{pst}	0.0559**	(0.0279)	0.1589***	(0.0216)	0.1837***	(0.0235)
γ	-0.0565***	(0.0140)	-0.0219*	(0.0131)	-0.0396***	(0.0146)
$Assts$	-0.0306***	(0.0101)	-0.0207***	(0.0081)	-0.0135	(0.0106)
$Levrg$	-0.0003	(0.0004)	-0.0005	(0.0004)	0.0002	(0.0006)
R^2	0.0827		0.4041		0.3158	
N	15,100		11,949		17,166	
Bank fixed effects	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	