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"Bias and the Efficacy of Stress Test Disclosures"

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BIAS AND THE EFFICACY OF STRESS TEST DISCLOSURES

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Abstract. We investigate bias in the Federal Reserve's stress test disclosures for the Comprehensive Capital Analysis and Reviews (CCAR) between 2012 and 2017. Using the market response to the report, we develop and estimate a model of biased disclosure that incorporates a regulator's trade-off between market discipline and short-term stability. We find that disclosed capital ratios are biased upwards to prop up systemically important banks, but downwards to discipline poorly capitalized banks. This bias has real consequences for bank behavior – propped-up banks are less likely to subsequently improve their capital ratios, either by increasing equity or reducing risk-weighted assets.

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Key words and phrases. regulatory disclosure, stress tests, CCAR, financial institutions.

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1. Introduction

In the wake of the recent financial crisis, the U.S. Federal Reserve (the Fed) began conducting assessments of the largest U.S. financial institutions to determine if these firms had sufficient capital buffers to withstand financial market turmoil in the future. The Fed justified the tests, along with public disclosure of their results, as a vehicle to enhance transparency and improve market discipline (Tarullo [2010]; Bernanke [2013]; Powell [2018]).[1] In the years following the crisis, these stress tests and their accompanying disclosures have become important components of the supervisory toolkit. As the Fed's use of stress tests has become more prominent and public disclosures surrounding these tests have expanded, practitioners, regulators, and academics have become concerned with the effects of these disclosures on market outcomes. On one hand, "disclosure of test results is beneficial because it promotes financial stability. However, in promoting financial stability, such disclosures may exacerbate bank-specific inefficiencies" (Goldstein and Sapra [2014]).

When conducting stress tests, the Fed is privy to private information about bank fundamentals, which it acquires via on-site representatives at each bank, the banks' own risk models, and required capital distribution plans. Public disclosure of this information is a potentially powerful tool to shape market beliefs due to the importance of coordination in financial markets (Morris and Shin [2002]). To reduce asymmetric information between banks and their stakeholders, who can then exercise discipline on the banks' behavior, the Fed has an incentive to disclose this private information as a part of the stress tests. To maintain short-term stability and the solvency of the financial system, the Fed has a conflicting incentive to retain some of this private information (Goldstein and Sapra [2014], Shapiro and Skeie [2015]). Because the regulator may want a struggling bank to survive, or for a

[1]Specifically, Bernanke motivated the use of stress test disclosures as "provid[ing] anxious investors with something they craved: credible information about prospective losses at banks. Supervisors' public disclosure of the stress test results helped restore confidence in the banking system and enabled its successful recapitalization." Further, "the disclosure of stress-test results, which increased investor confidence during the crisis, can also strengthen market discipline in normal times" (Bernanke [2013]). Current Fed Chair Powell states "The post-crisis framework remains novel and unfamiliar [. . .] As a result, transparency and accountability around financial stability tools present particular challenges [. . .] The framework is still evolving, and we will need to be open to making changes and to new ways to enhance transparency and accountability" (Powell [2018]).

strong bank to raise more capital—with the goal of averting future crises—these conflicting incentives may lead to upward or downward bias in the reports.

We examine the effects of regulatory disclosure in light of the fact that the Fed may design stress test disclosures to achieve its strategic objectives.[2] While the Fed maintains that its objective in publicly disclosing stress test results is to improve market discipline, it must weigh this objective against its duty to protect the stability of the financial system and reduce systemic risk.[3] We find evidence of bias in the Fed's stress test disclosures from the Comprehensive Capital Analysis and Reviews (CCAR) between 2012 and 2017. Overall, our findings are consistent with the Fed dynamically adjusting its supervisory toolkit in response to a tradeoff between the systemic risk and capitalization of the financial system. However, we also find that designing stress tests to balance these two objectives has natural consequences: disciplining poorly capitalized banks leads to improved capitalization, but propping up systemically important banks allows these banks to avoid increasing their capital.

We incorporate the Fed's conflicting incentives and ability to bias reports in a model of biased disclosure based on Fischer and Verrecchia [2000]. Because reduced form methods cannot uncover the Fed's bank-specific policy stance and do not account for the equilibrium behavior of the Fed and the market, we estimate this model structurally using capital market responses to CCAR reports. This uncovers the market's perception of bias for each bank. We then take the estimated bias from the model and investigate whether it is associated with bank characteristics and outcomes consistent with the Fed's tradeoff.

When the Fed makes an announcement, the market rationally updates its beliefs about bank quality – we use this update to uncover the market's beliefs about the Fed's stance

[2] In his autobiography, Bernanke alluded to the fact that the Fed behaves strategically in its disclosures: "In congressional testimony immediately after Lehman's collapse, Paulson and I were deliberately quite vague when discussing whether we could have saved Lehman [. . .] we had agreed in advance to be vague because we were intensely concerned that acknowledging our inability to save Lehman would hurt market confidence and increase pressure on other vulnerable firms" (Bernanke [2015]). Moreover, financial journalists mention the "black-box" nature of the stress tests (https://www.americanbanker.com/opinion/jpmorgan-changes-var-model-again-but-its-still-a-black-box; https://www.theatlantic.com/magazine/archive/2013/01/whats-inside-americas-banks/309196/). As the New York Times notes on August 19, 2013, "By making its expectations clearer, the Fed could sacrifice some of the unpredictability that could keep the banks on their toes when they apply the tests." (https://dealbook.nytimes.com/2013/08/19/banks-were-not-tough-enough-on-themselves-in-stress-tests-fed-says/)

[3] See, for example, the Fed's mission statement (http://www.federalreserve.gov/aboutthefed/mission.htm).

with respect to each bank.[4] Following the logic of Fischer and Verrecchia [2000], if the market posterior is more negative than would be expected given the CCAR report, we infer an upward, or propping-up bias for that bank. If the market is skeptical of good news from the Fed about a particular bank, for example, it will underreact to the news. However, if the market posterior is more positive than would be expected given the report, we infer a downward, or disciplining bias.

Once we have estimated bias for each report, we examine potential determinants in cross-sectional regressions. Given its objectives, the Fed may be concerned with whether the bank is systemically important or is poorly capitalized. Following the literature, we use bank size as a proxy for systemic risk (Bord, Ivashina, and Taliaferro [2017], Acharya, Pedersen, Philippon, and Richardson [2017], Billio, Getmansky, Lo, and Pelizzon [2012], Sedunov [2016]). We supplement this with direct measures of systemic risk, CoVaR (Adrian and Brunnermeier [2016]) and SRISK (Brownlees and Engle [2016], as well as bank age (Duchin and Sosyura [2014]) and pre-crisis bank profitability, which Meiselman, Nagel, and Purnanandam [2018] argue is a bank-specific measure of systematic tail risk exposure in bad times. To study time consistency in Fed policy, we construct a measure based on the allocation of Troubled Asset Relief Program (TARP) funds to each bank in our sample.

Given the bank capital and liquidity requirements of recent regulation, we study both Tier 1 capital ratios and bank liquidity ratios as determinants of bias in the stress test reports (Basel Committee [2010], Gatev, Schuermann, and Strahan [2009], Diamond and Dybvig [1983], Diamond and Rajan [2005], Cifuentes, Ferrucci, and Shin [2005]). We also study two other components of the CAMELS rating system. To investigate the quality of bank assets as a potential determinant, we construct measures based on asset quality, charge-offs, and the

[4] We show that the disclosures of stress test results are significant information events for banks by documenting abnormal stock returns and volume around the disclosures. These abnormal returns are significantly associated with CCAR reports (see also Morgan, Peristiani, and Savino [2014], Candelon and Sy [2015], and Flannery, Hirtle, and Kovner [2015]). This result is consistent with the findings of Petrella and Resti [2013], who show that the disclosure of 2011 European Union stress test results were considered relevant by investors and also the findings of Peristiani, Morgan, and Savino [2010] that stress tests provide the market new information about the size of capital needs among weaker banks.

riskiness of the banks' investment portfolios (Duchin and Sosyura [2014]). Finally, we measure bank profitability using return on equity (ROE). Together, these measures capture both risk-based distinctions for assets and liabilities, overall solvency, liquidity, and performance.

Bias follows systematic patterns with respect to these policy-relevant bank characteristics. Consistent with the short-term stability objective, we find evidence that reports are more likely to be propped up for the largest and most systemically important banks in the sample. We also find evidence of time consistency in the Fed's supervisory objectives – banks allocated a higher fraction of TARP funds were more likely to receive propping up bias. This is consistent with Brown and Dinç [2011], which finds evidence that regulatory intervention favors larger banks when the banking system is weak. Similarly, Duchin and Sosyura [2012] find that banks with more capital and higher earnings received less capital under the Troubled Asset Relief Program while larger banks received more. However, consistent with the market discipline objective, we also find relatively negative bias for banks with low Tier 1 capital ratios, low liquidity, poorly performing assets, and high earnings (Meiselman et al. [2018]).

To investigate the consequences of bias, we look at subsequent bank behavior. As stated in the 2012 CCAR,[5] the Fed is concerned with banks' plans regarding overall capitalization, including equity issuance and dividends. One reason that the Fed might have a disciplining stance towards a bank is to encourage the bank to improve its financial position by increasing its Tier 1 capital ratio, which the bank could accomplish by raising equity, cutting dividends, or changing the risk profile of its assets.

We find that bias in stress test reports has real consequences for subsequent bank behavior. Banks that receive more positive bias in their reports improve their capital ratios relatively less following the CCAR. This occurs through increases in risk-weighted assets and decreases in equity, which is brought on by a lower likelihood of cutting payout, issuing equity, or increasing profitability. Specifically, a one standard deviation increase in bias is associated with a 16.5 percentage point lower likelihood of issuing equity and 5.4 percentage point lower

[5]See the 2012 CCAR press release: http://www.federalreserve.gov/newsevents/press/bcreg/20120313a.htm.

likelihood of cutting dividends. These findings are consistent with Duchin and Sosyura [2014], which shows that banks take on more risk after receiving approval for government assistance.

The estimation of our structural model depends on the relationship between the CCAR report and the market's reaction. One may be concerned that our estimates of bias capture more than just the Fed's stance toward each bank. For example, the CCAR report produces quantitative and qualitative results for each bank, but our model restricts the market from conditioning on the qualitative component. However, our results on the Fed's stance are robust to controlling for the market response to the CCAR report as well as the quantitative component itself, which together should capture all information revealed by the Fed to the market at the time of the CCAR report. This finding suggests that bias is incrementally important for bank behavior.

We also investigate whether required capital plan adjustments are driving our findings, both by controlling for the adjustment and excluding banks that have adjusted plans, and demonstrate that our results are robust in these specifications. Because our estimates are based on variation in the market response to CCAR disclosures, they may similarly capture the contemporaneous release of unrelated corporate news by stress-tested banks. In subsample analysis, we present additional evidence that our findings are not driven by the small subset of banks that have contemporaneous news releases.

Our flexibile model-driven approach allows for heterogeneity in Fed strategies with respect to all banks. We present alternative specifications for the model, showing that our results are not driven simply by the form of the game played between the Fed and the market. Finally, markets could react differently to news releases about certain banks. We investigate earnings announcements as alternative event dates that are not related to the Fed. Our falsification tests show that the bias we uncover is not related to market reactions surrounding earnings announcements, illustrating that what we uncover is specific to the Fed, as opposed to more generally news-specific.

1.1. **Related Literature.** We draw upon the literature examining strategic information flows. While this work typically considers information that flows from a firm to its investors, many of the insights gleaned from this work apply in our setting where information flows from a regulator to investors. One line of research in this area considers an entity's decision to voluntarily disclose privately held information to external parties (see Verrecchia [1983], Dye [1985]; and Jung and Kwon [1988] for examples; see Stocken [2012], for a review). The sender's report is restricted to be truthful, although the sender may withhold information. This research identifies factors the entity might consider when choosing to disclose information and examines how the report is interpreted and used by the receivers. Another branch of research, which is more relevant to our question, examines conditions under which strategic biases emerge and affect market outcomes. Early work in this area (e.g., Narayanan [1985]; and Stein [1989]) shows that when users of a report have rational expectations and perfect knowledge of the reporting entity's objective, then the users perfectly back out any bias included in the report. Any bias contained in a report, therefore, does not affect outcomes. Subsequent work demonstrates that if receivers are not perfectly informed about the sender's reporting objective, then bias in a report can affect market outcomes because receivers are not able to perfectly filter out the bias and discern the truth (e.g., Dye [1988]; Fischer and Verrecchia [2000]). This latter case is most applicable to our setting where investors are not likely to have a complete understanding of the regulator's reporting objectives.

This paper also draws upon and contributes to the literature examining regulatory disclosure in banking.[6] A common theme in the literature is that increased transparency enhances market discipline and improves allocation efficiency. Barth, Caprio, and Levine [2004] examine regulation fostering information disclosure and the monitoring of banks. Their findings suggest that policies that encourage accurate information disclosure work best to promote bank development, performance, and stability. Bischof and Daske [2013] show that the timing and content of regulatory disclosure impacts the voluntary disclosure of banks about their sovereign debt. Bouvard, Chaigneau, and Motta [2015] examine a setting in which transparency on the part of the regulator unnecessarily exposes lower-quality banks to runs. Goldstein and Leitner [2018] study the optimal disclosure policy of a regulator who has

[6]See Goldstein and Sapra [2014] for a review of the trade-offs related to transparency in financial systems.

information about banks' ability to overcome future liquidity shocks. They find that full disclosure is not optimal because it destroys risk sharing opportunities as in Hirshleifer [1971]. Bond and Goldstein [2015] show that disclosure by the regulator might harm the regulator's ability to learn from the market. Consequently, the regulator may choose to withhold information when learning from the market is beneficial. Along those same lines, Prescott [2008] shows that too much information disclosure by a bank regulator decreases the amount of information the regulator can gather about banks. Burkart, Gromb, and Panunzi [1997] and Gigler, Kanodia, Sapra, and Venugopalan [2014] demonstrate that regulatory disclosure may undermine the ex-ante incentives of bank managers (see also Ben-Porath, Dekel, and Lipman [2017]). This finding is supported by Shahhosseini [2015] and Cheng, Subramanyam, and Zhang [2010], who show empirically that firms subject to increased transparency behave myopically. Morrison and White [2013] show that a regulator's commitment to transparency improves confidence ex ante but impedes the regulator's ability to stem panics ex post.

The literature on bank regulatory disclosure has emphasized the consequences of the regulator choosing to disclose or withhold information altogether. The usual trade-off examined in the analysis is the trade-off between promoting market discipline while maintaining the stability of the banking sector (see Shapiro and Skeie [2015] as an additional example). Our paper considers a related trade-off, but focuses on how the trade-off influences the regulator's decision to bias its public reports once the decision to disclose has been made. This analysis is appropriate in light of the fact that, in connection with a mandate in the Dodd-Frank Wall Street Reform and Consumer Protection Act that stress test results must be disclosed publicly, the Fed has been committed to providing public reports of CCAR results since the 2012 test.

We also believe that this paper contributes to the literature that studies strategic disclosure by individual banks by studying the regulator's disclosure decision. This literature suggests that banks respond to the incentives created by minimum capital requirements when disclosing the riskiness of their assets and liabilities (Begley, Purnanandam, and Zheng [2017], Huizinga and Laeven [2012], Plosser and Santos [2014], and Skinner [2008]). In contrast, our paper makes direct inferences about the Fed's objective function when applying discretion to its own financial reports about individual banks.

1.2. **Outline of the Paper.** The remaining sections of the paper proceed as follows. Section 2 provides institutional background. Section 3 outlines the model and empirical identification. Section 4 discusses the determinants and consequences of bias, Section 5 investigates the robustness of the results to alternative estimation procedures and specifications, and Section 6 concludes.

2. Institutional Background and Data

Financial institutions have been subject to increased regulatory scrutiny since the inception of the financial crisis in 2008. One of the first formal manifestations of this scrutiny was the Supervisory Capital Assessment Program (SCAP), which began in February of 2009. This program involved a comprehensive assessment of capital adequacy of the 19 largest bank holding companies (BHCs) by the Federal Reserve and other bank supervisors. The specific goal was to measure how much additional capital buffer would be necessary to ensure that BHCs met regulatory minimum capital levels even in the event of a particularly adverse macroeconomic scenario. The methodology for this program was described in a white paper released on April 24, 2009, and was followed by detailed public disclosures on loss rates across different assets for each BHC, along with the resulting necessary capital buffers. These disclosures revealed that total losses at the 19 firms in the program could reach $600B through 2010 in the adverse scenario investigated. The result of the SCAP was a requirement that these banks raise $185B in aggregate new Tier 1 capital.

The bank supervisory process evolved into the Comprehensive Capital Analysis and Review (CCAR), announced by the Federal Reserve on November 17, 2010, though the 2011 version (which took place in March of 2011) did not involve public disclosure of the results. As of the 2012 CCAR, the Federal Reserve publicly discloses the results of its review. These reviews have evolved somewhat over time but have retained a similar structure and purpose. The first three CCARs involved all U.S. domiciled BHCs with assets of at least $50B, which initially covered the same 19 BHCs as the 2009 SCAP, though coverage expanded significantly in 2014.

The CCAR program works as follows. Banks submit annual capital plans to the Federal Reserve that detail their planned capital actions, such as dividend payments and any issuance or repurchase of equity. The capital plans include projections on sources and uses of capital over the following nine quarters under two different scenarios - expected or baseline, and stressed economic conditions. The Fed assesses these plans for the reasonableness of the embedded assumptions to determine whether or not the BHC has the ability to maintain capital ratios above regulatory minimums under the adverse scenario. BHCs are constrained by the Fed's assessment in the sense that the Fed may object and allow the BHC to make only approved capital distributions. If the Fed objects, either because stressed capital would become too low or because it lacks confidence in the banks governance procedures surrounding capital plans, the BHC must resubmit the plan.

As part of this process, the Fed publicly discloses the results of its own stress scenarios projections. The stress scenario is disclosed in advance and is meant to capture particularly adverse macroeconomic conditions, involving increased unemployment, recession and a significant retrenchment in consumer and business borrowing and ability to repay existing debt. The stress scenario projection estimates net income for each BHC, including both revenues and expected losses on different assets, then adds the effects of the banks' proposed capital plans to calculate the implied change in regulatory capital ratios. The projections are quite conservative in the sense that they assume the use of capital plans under banks' baseline scenario; hence, the calculations don't allow BHCs to adjust their capital plans as and when the stress scenario becomes more likely. Note that the projections vary across banks only because of the inputs to the calculation - they do not assume any differences in behavior. This means that the Fed's disclosed capital ratios are likely to be much different from banks' own projections.

The adverse scenario investigated in these reviews typically results in significant drops in these post-stress capital ratios for the BHCs in the program. For example, the original

CCAR in 2012 projected $534B in total losses. There were large differences across banks based primarily on their asset portfolios, as well as different risk characteristics within those portfolios. The net effect was a decline in BHCs' aggregate Tier 1 capital ratio from 10.1% to 6.3% by the end of the review horizon (the fourth quarter of 2013).

2.1. **Data.** Financial statement and daily stock prices and returns data for financial institutions come from Compustat, bank holding company regulatory filings, and CRSP. We use the post-stress ratios that come from the adverse scenario in annual CCAR reports. Federal Reserve CCAR reports are filed March of each year between 2012 and 2015 and in June of 2016 and 2017.[7] Table 1 shows summary statistics for several bank fundamentals, the post-stress ratios of the CCAR reports and the market reaction to these disclosures, and various systemic risk measures. Whereas the average Tier 1 capital ratio for these banks is 12.5%, the average post-stress Tier 1 capital ratio in the stress test adverse scenario is 7.6%, and the Fed requires an adjusted capital plan in 15.8% of tests. Banks had average ROE of 2.4% during the period, which is approximately half of their average pre-crisis ROE of 4.6%.

We investigate whether the CCAR report is informative to market perceptions about bank value and riskiness. Figure 1 shows returns for the banks in the CCAR program around the public disclosure of capital ratios, averaged across banks and aggregated across the six CCARs in our sample. The three day announcement return is significantly different from zero and is 1.8% on average, suggesting that on net, the market believes the information in CCARs to be positive. Figure 2 shows trading volume for the same sample around CCARs and is also indicative of the importance of the event, with a significant increase in volume around the average CCAR disclosure.

3. Model and Estimation

In this section, we build a structural model that interprets the market reaction to the Fed's stress test disclosures in order to uncover any latent bias, up or down, in these disclosures. In Section 4, we investigate the determinants and consequences of this bias. With this

[7]2012 is the first year the Fed began consistently disclosing the results of these tests.

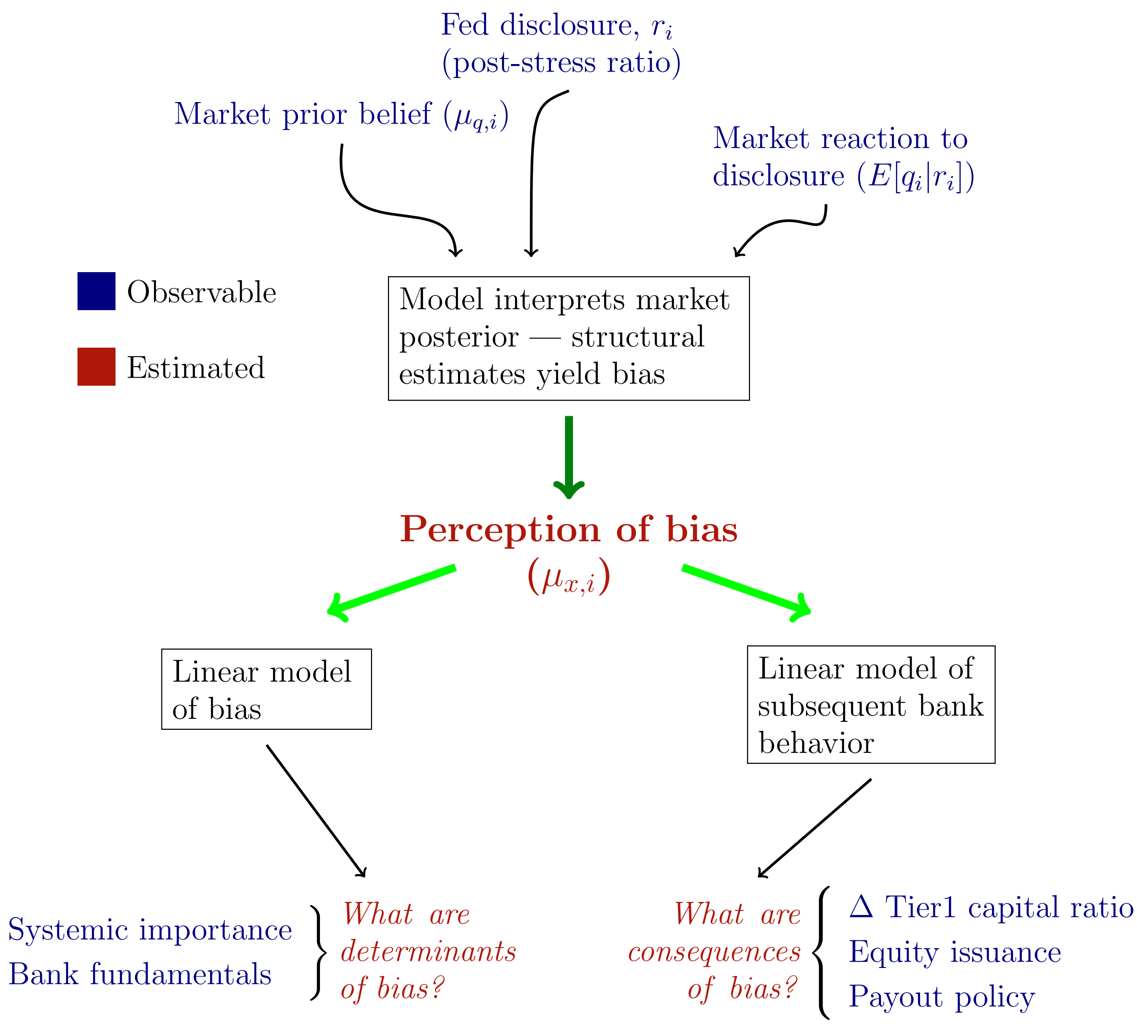
goal in mind, we pursue a flexibile model-driven approach that allows the Fed to tailor its strategy to particular banks, such as through a dependence on bank performance. A more reduced form approach might be simpler, but would require much stronger assumptions. It also might misinterpret equilibrium play by the Fed and the market as bias. Our approach allows for the Fed to play bank-specific strategies. We show that our results are robust to these different modeling choices in Section 5. This ensures that our findings are driven by the intuition we describe below, as opposed to model misspecification.

The following figure provides an overview of our estimation method. The model uses the market's prior belief about bank value, the Fed's quantitative disclosure, and the market's response to this disclosure as inputs. Using these inputs, the model yields the bias in this disclosure for each stress tested bank in each year.

3.1. **Model.** Since bias is not directly observable, we must rely on the market's perception of bias for our empirical tests. We can infer bias because the market has a belief about the desire of the Fed to bias signals and adjusts its responses to the reports accordingly. In other words, we observe the regulator's report as well as the market's beliefs immediately before and after the disclosures are made. The way the market updates its beliefs in response to the report tells us how much and in what direction the Fed was likely to have biased the report. Intuitively, we infer positive bias if the post-stress ratio from the adverse scenario is higher than the market posterior. The basic idea, which we develop formally below, is that if the market is skeptical of good news from the Fed about a particular bank, for example, it will underreact to the news. Conversely, we infer negative bias if the CCAR report is lower than the market posterior. A timeline summarizing the updating process by the market is provided in the figure below.

We formalize this intuition with a model of biased disclosure based on Fischer and Verrecchia [2000] that explicitly allows us to interpret the market posterior to infer bias. We consider a one period reporting game with a bank regulator and a market concerned with assessing the fiscal condition of a bank. The regulator is tasked with privately evaluating the

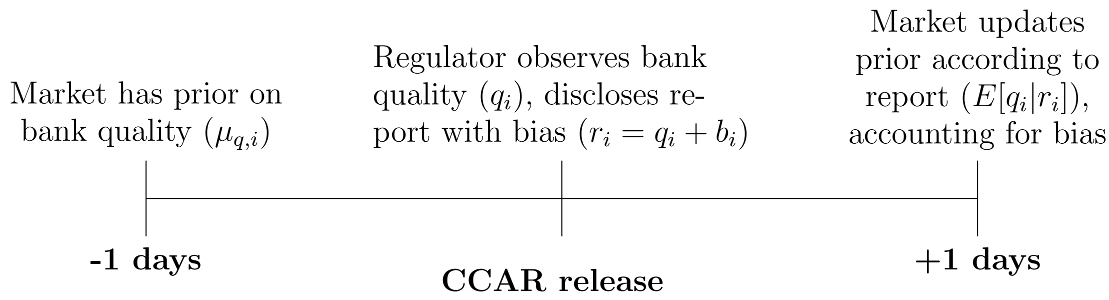
Estimation Method



condition of the bank and providing a public report of its findings to the market. More formally, the regulator privately observes the quality of a bank, denoted $\tilde{q}$, where the market's priors for $\tilde{q}$ are normally distributed with mean μ_q and variance σ_q^2, and this distribution is common knowledge. After observing realized bank quality, the regulator provides a report, r, to the market, which then updates its belief about the condition of the bank.

The regulator is assumed to have some discretion over the report and can use that discretion to disclose a level of bank quality that is different from what it actually observes. In our setting, this may reflect either the Fed applying bias to the disclosures, or implementing a test that produces biased information. For example, if the Fed anticipates that a specific

Market-Regulator Timeline



scenario would have particularly deleterious outcomes for banks it cares about, it may underweight such scenarios in the stress test. Conditional on the regulator observing quality of $\tilde{q} = q$, the regulator's report, r, equals $q + b$, where b is the bias the regulator introduces into the report.

When determining the level of bias to include in the report, the regulator considers two objectives. On one hand, the regulator seeks to influence the market's short-term perception of bank quality. For example, the regulator may choose to overstate the quality of a bank in order to prevent a run or to encourage lending from other banks. Another possibility is that the regulator may understate quality as a way of encouraging a particular bank to raise more capital. On the other hand, the regulator desires to promote market efficiency (in the sense that the market belief reflects the underlying fundamentals), and to maintain its credibility and ability to regulate in the future.[8] Thus, while the regulator may derive benefits from introducing bias in the report, the regulator also incurs a cost associated with the bias. With these ideas in mind, we characterize the regulator's objective function by the expression

$$xE[\tilde{q}|r] - \frac{cb^2}{2}, \tag{1}$$

[8]The Fed in principle has other goals that may affect its regulatory behavior, but are likely less significant in this setting, such as promoting maximum sustainable employment and price stability.

where x is the realization of a stochastic parameter, $\tilde{x}$, that determines the direction and extent to which the regulator desires to bias the bank's report, $E[\tilde{q}|r]$ is the market's expectation of bank quality conditioned upon the regulator's report, $\frac{cb^2}{2}$ represents the cost of bias to the regulator, and c is simply a cost parameter. In other words, for a given realization of $\tilde{x} = x$, the regulator seeks to maximize $xE[\tilde{q}|r]$ subject to the cost of including bias in the report as a means of achieving its objective.

We assume the regulator's desire to bias the bank's report ($\tilde{x}$) is determined by specific characteristics of the bank. That is, $\tilde{x}$ is determined by publicly observable characteristics (such as the bank's size, leverage, and liquidity) and characteristics that are privately observable to the regulator regarding the bank's systemic importance and how the regulator would benefit if the market's assessment of the bank's quality were different from the realized value. To motivate our our empirical analysis, we assume $\tilde{x}$ satisfies the following criterion relating to characteristics of the bank in question:

$$\tilde{x} = \arg\max_{\dot{x}} \; -\left(\dot{x} - \beta_{Pub}\tilde{X}_{Pub} - \beta_{Priv}\tilde{X}_{Priv}\right)^2$$

which implies

$$\tilde{x} = \beta_{Pub}\tilde{X}_{Pub} + \beta_{Priv}\tilde{X}_{Priv}, \tag{2}$$

where $\tilde{X}_{Pub} = X_{Pub}$ is a vector of publicly observable characteristics and $\tilde{X}_{Priv} = X_{Priv}$ is a vector of characteristics observable only to the regulator. As the market observes $\tilde{X}_{Pub} = X_{Pub}$ and can compute the value $\beta_{Pub}\tilde{X}_{Pub}$, but does not observe $\tilde{X}_{Priv} = X_{Priv}$ and cannot compute $\beta_{Priv}\tilde{X}_{Priv}$, we denote $\beta_{Pub}\tilde{X}_{Pub}$ as μ_x and $\beta_{Priv}\tilde{X}_{Priv}$ as η. Restating, we represent $\tilde{x}$ from the market's perspective as $\tilde{x} = \mu_x + \eta$. We additionally assume that η has a normal distribution with mean 0 and variance σ_x^2. Thus, $\tilde{x}$ has a normal distribution with mean μ_x and variance σ_x^2.

We interpret the mean of this distribution, μ_x, as the market's perception of bias for a given bank or the Fed's stance toward the bank. Our empirical analysis focuses on the determinants and consequences of this perception of bias. Examining the determinants of μ_x

provides us with an understanding of the factors the Fed considers when deciding whether to bias the reported results for a particular bank. In addition, examining whether μ_x influences the subsequent behavior of banks allows us to assess whether the Fed's stance and the bias it applies are important for a bank's understanding of what regulatory actions the Fed may take in the future.

To facilitate robustness analysis of our empirical tests and to make sure that our results are not driven by economic features of the disclosure game, or by functional form, we explicitly allow for dependence between the regulator's desire to bias a report and the actual realization of bank quality. This is important because the Fed is potentially more or less likely to bias a signal when the realization of the bank's quality is extremal in the direction of the Fed's desire to bias. For instance, it is plausible that the Fed will benefit less from adding positive bias to a report when the realized quality of a bank is high to begin with. We incorporate this notion into our analysis by including dependence between the regulator's preference to bias ($\tilde{x}$) and a bank's realized level of quality ($\tilde{q}$). Specifically, we assume the joint distribution of $(\tilde{q}, \tilde{x})$ is bivariate normal with correlation $\rho_{q,x}$. In robustness tests, we assess the sensitivity of our empirical findings to different assumptions regarding the relationship between bias and the bank's realized quality, and find that our results are not dependent on this economic features of the model.[9]

To summarize the model, the regulator privately observes realized bank quality (q) and issues a (potentially) biased report of quality to the market ($r = q + b$). In determining the amount of bias to include in the report, the regulator trades off the benefit of altering the market's belief through the use of bias ($xE[\tilde{q}|r]$) and the cost of including bias in the report ($\frac{cb^2}{2}$). The regulator's benefit from including bias is determined by realized x and the sensitivity of the market's belief to the report. The market, in turn, forms its posterior belief about bank quality ($E[\tilde{q}|r]$) consistently with the report and an imperfect but rational assessment of the direction and extent to which the regulator has biased the report, which is based on the market's perception of bias, μ_x.

[9] For our main analysis we assume $\rho_{q,x} = -\frac{1}{2}$, but we also conduct analyses assuming $\rho_{q,x} = 0$ and $\rho_{q,x} = \frac{1}{2}$ and show that our results remain unchanged (see Table 7).

In equilibrium, the regulator's choice of bias, $b(q,x)$, maximizes the regulator's objective, and the market's updated expectation of quality, $E[\tilde{q}|r]$, must be consistent with the report. Additionally, since the regulator's choice of bias anticipates the sensitivity of the market's belief to the report and the market's sensitivity, in turn, depends on an assessment of how the regulator is likely to have biased the report, we require the regulator's conjecture about market sensitivity and the market's conjecture about the regulator's biasing strategy to coincide.

We construct an equilibrium in which the regulator's choice of bias is a linear function of realized x and the market's update is a linear function of the report r. Details of the derivation of this equilibrium are provided in Appendix A. In equilibrium, the regulator chooses bias $b(q,x) = \frac{\beta}{c}x$, making the report

$$r = q + \frac{\beta}{c}x, \tag{3}$$

and the market's expectation of bank quality given the report

$$E[\tilde{q}|r] = \beta r + \alpha, \tag{4}$$

where β reflects the sensitivity of the market's belief to the report and α represents the market's prior on bank quality as well as an adjustment for the expected bias. More specifically, the solutions to the model components α and β are given by

$$\beta = \frac{\sigma_q^2 + \left(\frac{\beta}{c}\right)\rho_{q,x}\sigma_q\sigma_x}{\sigma_q^2 + \left(\frac{\beta}{c}\right)^2\sigma_x^2 + 2\left(\frac{\beta}{c}\right)\rho_{q,x}\sigma_q\sigma_x} \qquad \alpha = \mu_q(1-\beta) - \frac{\beta^2}{c}\mu_x.$$

(See Appendix A for proof.) Intuitively, the market's sensitivity to the report, β, is determined by the prior uncertainty surrounding bank quality (σ_q^2) and the uncertainty about the regulator's reporting objective (σ_x^2). Note that β is different for each firm due to the fact that σ_q should vary across firms. It is easy to see that if $\rho_{q,x} = 0$, the market's sensitivity to the report increases with the ex ante uncertainty about bank quality (σ_q^2). This sensitivity increases with uncertainty about bank quality because the regulator's report becomes relatively more informative when the market has less information to begin with. Additionally, the market's sensitivity to the report decreases with uncertainty about the reporting objective (σ_x^2). Note that in the extreme case when the regulator's reporting objective is known perfectly by the market ($\sigma_x^2 = 0$), the market can perfectly anticipate and unravel any bias so that realized quality can be fully recovered from the report. In this case, the market's belief is perfectly sensitive to the regulator's report ($\beta = 1$) and the regulator's attempt to sway the market through the use of bias is fruitless (despite being costly).[10]

Additional insight necessary to use this model for identification can be gleaned by rewriting the market's updated belief in the following manner:

$$E[q|r] = \underbrace{\mu_q}_{\text{prior}} + \underbrace{\beta(r - \mu_q)}_{\text{update}} - \underbrace{\beta\left(\frac{\beta}{c}\mu_x\right)}_{\text{adjustment for expected bias}} . \tag{5}$$

The first term on the RHS of Equation (5) is simply the market's unconditional expectation of bank quality. The second term signifies what the update would be if the report were taken at face value. The remaining term represents the adjustment made to the update due to the market's knowledge of the regulator's desire and ability to bias the report. Note that the term $\frac{\beta}{c}\mu_x$ denotes the amount of bias the market anticipates the regulator to include in the report. Since the market has an imperfect understanding of the regulator's objective, the anticipated level of bias will differ from the actual amount of bias in the report and the market's adjustment for bias will be imperfect.

3.2. **Estimation.** We are interested in structurally estimating this equation using data, for which we need a measure of the market's expectation of bank quality both before and after the report, and the report itself. For the market's expectation of bank quality, we use price-to-book and the post-stress ratio from the adverse scenario in the Fed CCAR reports.[11]

[10]In robustness tests, discussed in Section 4.1, we assess the sensitivity of our empirical results to different assumptions about σ_x^2.

[11]Note that since post-stress ratios are capital ratios, they are not on the same scale as price-to-book ratios. Therefore, we standardize post-stress ratios over the entire sample period to have the same mean and standard deviation of price to book. We otherwise avoid any ad hoc restrictions on the relationship between price-to-book ratios and post-stress ratios (i.e., the market's valuation model). Any affine function mapping the Fed's report into price-to-book space preserves the ordinal information as in our standardized measure of bias. See Table 7 for results that use only ordinal variation in bias. Note that if this function changes over time, time series comparisons of average bias are uninformative. So that we are not misled by such changes,

We directly solve for the Fed's desire to bias from the equilibrium conditions described above using the observable market prior (price-to-book at the end of the day, before the Fed's report) and market reaction (price-to-book at the end of the day, after the Fed's report), and the Fed's disclosure (in price-to-book terms). Formally, for a given bank i we measure the market's perception of (bank specific) bias, $\mu_{x,i}$, in the following manner. We note that for a given bank i, an expression for $\mu_{x,i}$ is provided by rearranging the market's equilibrium updating Equation (5):

$$E[q_i|r_i] = \mu_{q,i} + \beta_i(r_i - \mu_{q,i}) - \frac{\beta^2}{c}\mu_{x,i}$$

$$\Longleftrightarrow$$

$$\mu_{x,i} = -\frac{c}{\beta_i^2}\left[(E[q_i|r_i] - \mu_{q,i}) - \beta_i(r_i - \mu_{q,i})\right], \tag{6}$$

making our estimating equation,

$$Bias_{i,t} = -\frac{c}{\beta_i^2}[(PB_{i,t+1} - PB_{i,t-1}) - \beta_i(FedReport_{i,t} - PB_{i,t-1})] \tag{7}$$

where i and t signify bank and day, respectively, and β_i is the bank-specific equilibrium sensitivity of the market's belief to the report, as discussed above and in Appendix A.[12] $PB_{i,t}$ is price-to-book for bank i where price is measured at the close on day t and book values are from the most recent quarterly report, $FedReport_{i,t}$ is the standardized post-stress ratio from the adverse scenario of the CCAR report, standardized so that the population of post-stress ratios has the same mean and standard deviation as the population of price to book ratios, and c is the marginal cost of biasing the report. Note that prices for price to book are at close on day $t-1$, the day before the release of the CCAR report, and at close on day $t+1$, the day after the release of the CCAR report.

Essentially, this estimating equation uses the model to interpret the relationship between the market update ($PB_{i,t+1} - PB_{i,t-1}$) and the post-stress report update ($FedReport_{i,t} -$

in our determinants and consequences tests, we include year fixed effects to eliminate time series variation in the functional mapping.

[12]In our empirical tests, we define $Bias_{i,t}$ as the market's perception of bias, $\mu_{x,i}$.

$PB_{i,t-1}$), as potential bias. This equation formalizes the intuition connecting systematic underreactions and overreactions, to bias. For example, an "underreaction" by the market would mean that the first term would be less than the second term, indicating positive bias. This would be consistent with the market being skeptical of good news from the Fed about that particular bank.

Equation (7) is just identified, for the Fed's bias, $\mu_{x,i}$, for each bank. We normalize $c = 1$, without loss of generality, while $\sigma_{q,i}$, the standard deviation of bank quality in the model, is set equal to the standard deviation in price-to-book data over the period 2003-2006 (pre-crisis). The Fed and market are engaged in a signaling game. We wish to eliminate simple signaling strategies and responses as potential explanations for any of our findings, so we model a more general setting that allows for more flexibility in these strategies. This means that we calibrate some of the paramaters of the model in our main analysis, later relaxing these assumptions to show that our findings cannot be driven simply by equilibrium play by the Fed and the market.

Thusly, in our main analysis we assume that $\sigma_{x,i}$, the level of uncertainty over the stance of the Fed with respect to a particular bank, is a concave function of $\sigma_{q,i}$ in order that uncertainty over this is related to uncertainty with respect to the bank in general ($\sigma_{x,i} = \sigma_{q,i}^{0.8}$), but does not grow at as fast a rate. We also assume $\rho_{q,x}$ is the same for all banks and is equal to -0.5. This provides the intuition that if a bank were to do particularly well, the Fed would be less likely to further ratchet up the signal with favorable bias. Additionally, negative correlation between bias and quality would lead the Fed to be less likely to discipline, or bias downward a signal, when the bank has a particularly negative realization. Including this feature in the model allows us to exclude such reasonable considerations as mechanical drivers of our results. As we show in Table 7, our results remain qualitatively unchanged with various modeling and parameter choices.[13] None of these alternatives meaningfully change our results, which removes systematic elements of the reporting game as an explanation for our findings.

[13]While our estimates are robust to a range of choices of $\rho_{q,x}$ across banks, we find higher average levels of bias with positive $\rho_{q,x}$, meaning our assumption that the correlation is negative is likely conservative.

4. Determinants and Consequences of Bias

In this section, we have three main objectives. First, we analyze the distribution of bias derived from our model estimates. Second, we investigate the relationship between our estimated bank-specific bias and bank characteristics that are related to the policy objectives of the stress tests. Third, we analyze the post-CCAR decisions of banks to see whether banks are influenced by the regulator's actions, in particular along the key margin of capital ratios. Our analysis is motivated, in part, by a statement issued on November 17, 2010 by the Federal Reserve regarding the purpose of CCAR reports. The summary stated its guidelines to provide "a common, conservative approach to ensure that these bank holding companies hold adequate capital to maintain ready access to funding, continue operations and meet their obligations to creditors and counterparties, and continue to serve as intermediaries, even under adverse conditions."[14]

4.1. **Bias Estimates.** Figure 3 presents a histogram of the distribution of estimated bias for the years 2012 to 2017. Figure 4 presents density plots for estimated bias, splitting the sample into early tests from 2012, 2013, and 2014 and the late tests in 2015, 2016, and 2017. This figure shows that estimated bias is higher in the earlier tests and in an untabulated test, we find that the estimated bias is about one third of a standard deviation higher in the first half of our sample compared to the second half. This result is statistically significant at the 10% level.

We appeal to several theoretical and practical rationales for this downward trend in the average level of bias during our sample period. Many choices made by the Fed before 2015 were in support of the financial system, such as the use of quantitative easing and maintaining low interest rates. It thus seems unlikely that, in the early iterations of the CCAR, the Fed would have engaged in disciplining behavior as this could have undermined its overall strategy. As Morris and Shin [2002] point out, public disclosure has a strong impact on market beliefs, due to its effect on coordination (runs, etc.). These effects are likely to be

[14] "Revised Temporary Addendum to SR Letter 09-4: Dividend Increases and Other Capital Distributions for the 19 Supervisory Capital Assessment Program Bank Holding Companies." November 17, 2010. Available at http://www.federalreserve.gov/boarddocs/srletters/2009/SR0904_Addendum.pdf.

large relative to those of the implicit and private negotiation between banks and the Fed over capital plans, a part of stress testing regulation and potentially an alternative venue for disciplining banks. Further, unemployment in the months leading up to the first few CCAR reports was still comparatively high (8.4% and 7.9% in 2012 and 2013, respectively). Fed officials have stressed the need for moderation in policy (Williams [2013]), meaning that despite relative improvements in the health of the financial system, the Fed may have been unwilling early on to quickly shift its policy stance. A final potential rationale for this disciplining trend in bias relates to the fact that the banks in the CCAR were raising substantial capital in the first half of our sample period. All else equal, if the Fed wants banks to hold more capital, it may have an incentive to facilitate capital raising by making banks look healthier through more positive CCAR reports, on average.[15]

In the tests that follow, we look to cross-sectional variation in bias to understand its determinants and consequences. This variation in bias across banks does not depend on the average level of bias, and so is independent of any time series trends. Therefore, we can be assured that it reflects the regulator's bank-specific objectives rather than confounds related to aggregate changes in bank quality, the stress test scenario, macroeconomic conditions, or the Fed's objective.

Note that in our estimation procedure, we did not assume any within bank persistence in bias. We instead allow for bias to flexibly vary both across banks, and across years for the same bank, and so in principle could have found that bank-specific bias changes significantly from year to year. In fact, we find that the Fed's stance toward a particular bank is quite persistent. We find that the within bank correlation of estimated bias across years is 0.87. Having not imposed stationary biases within bank, this high correlation provides substantial evidence for the plausibility of our conclusions since one would expect the regulator's view of a particular bank to be relatively stable over time. In fact, we find that bias is more

[15]This idea is analogous to companies' window-dressing before raising capital (Rangan [1998]; Louis [2004]; DuCharme, Malatesta, and Sefcik [2004]). If the Fed's objective was to aid banks in capital raising, whether they achieve this objective or not depends on both their intended consequences for banks as well as unintended incentives that these disclosures may provide.

persistent than its components, the CCAR report itself, and the market response to the CCAR.[16]

4.2. **Determinants.** We begin our cross-sectional determinants investigation in Table 2. Our empirical model for the determinants of bias involves regressing estimated bias on our hypothesized determinants. Due to data limitations, these tests include a sample of 120 bank-year observations.[17] Our preferred specification is as follows:

$$Bias_{i,t} = \alpha + \beta X_{i,t-1} + u_t + \varepsilon_{i,t} \tag{6}$$

where $Bias_{i,t}$ is our estimate of bank-level bias, and $X_{i,t-1}$ is a bank characteristic, measured one quarter prior to CCAR release. We include year fixed effects, u_t, to focus identifying variation on the cross-section of banks for a given stress test scenario, and calculate standard errors that are robust to heteroskedasticity. For ease of economic inference and consistency across variables and specifications, we standardize each of these variables.

Our restrictions on biasing behavior follow from several strands of the banking literature that highlight bank characteristics of importance to regulators. In light of the recent financial crisis and resulting popularity of terminology like "too big to fail", we incorporate $Size$ to explore size heterogeneity, even among the large banks selected into the CCAR. With this measure, we intend to capture cross-sectional variation in systemic importance (Laeven, Ratnovski, and Tong [2014]), following the literature that links bank size to the transmission of financial shocks (Bord et al. [2017]) and to popular measures of systemic risk (Adrian and Brunnermeier [2016], Acharya et al. [2017], Billio et al. [2012], and Sedunov [2016]). We supplement these measures with two popular systemic risk measures: $SRISK$ and $CoVaR$. $TARP$ allows us to study whether the Fed's stance toward any banks is consistent over time and across supervisory tools, and we include $Pre\text{-}CrisisROE$ following policy proposals

[16]In Table 8, we show that directly controlling for CCAR or the market response does not change our inferences.

[17]For example, as Ally did not have a stock price during a subset of this period, we exclude it from our tests because we cannot estimate its bias. These and related data restrictions eliminate 32 bank-year observations.

based on the premise that bank profitability is indicative of risk-taking. These measures focus on the systemic importance of individual banks and, in particular, the contribution of individual banks to crisis severity conditional on a crisis occurring.

We also investigate whether measures of stability, or failure propensity, based on bank balance sheet strength and performance impact the Fed's stance toward banks in the cross-section. We follow capital and liquidity regulation and include $Tier\,1\,Capital$ and $Liquidity$, the ratio of cash to total deposits, since these regulatory measures are linked to bank stability (Gatev et al. [2009]). In light of Diamond and Dybvig [1983], we view bank liquidity as a measure of bank risk with regulatory importance that is potentially distinct from solvency. $Charge\text{-}offs$, $Asset\,Quality$, and ROE capture asset quality and profitability, and $LowRisk$ captures the ex ante riskiness of bank investment securities. Along with the measures of systemic importance, these measures capture banks' contributions to both the propensity and severity of banking crises.

The results in Table 2 suggest that poorly capitalized banks, banks with low liquidity, and banks with poorly performing or ex ante risky assets are disciplined, on average. That is, their stress scenario capital ratio is reduced. Poorly capitalized banks are potentially harmed by bias in that their true downside riskiness is not reflected in the CCAR stress test reports—their closeness to insolvency is exaggerated. Columns (1) through (6) of Table 2 show univariate relationships between $Bias$ and these determinants, and column (7) presents a multivariate setting. The results from the multivariate setting are consistent with the univariate relationships. Poorly capitalized banks are disciplined, as are banks with low liquidity and poorly performing assets. As all of the determinants are standardized, it is evident from the coefficient estimates that variation in performance variables—$Charge\text{-}offs$ and ROE—explain the most variation in $Bias$. However, even after controlling for performance and asset quality, bank solvency and liquidity remain statistically significant determinants of $Bias$. A one standard deviation decrease in Tier 1 capital ratios is associated with a 0.15 to 0.20 standard deviation decrease in $Bias$.

We continue our cross-sectional determinants investigation in Table 3, and introduce several determinants that reflect the systemic importance of the institution: $Size_{i,t-1}$, total assets, $SRISK_i$, the capital shortfall of bank i conditional on a severe market decline in 2007 (Brownlees and Engle [2016]), $CoVaR_i$, the value at risk of the financial system conditional on bank i being under distress in 2007 (Adrian and Brunnermeier [2016]), Age_i, the number of years since the founding year of bank i, $TARP_i$, the fraction of TARP funding allocated to bank i, and $Pre\text{-}CrisisROE_i$, bank i's ROE in 2006 (Meiselman et al. [2018]).

The results in Table 3 suggest that large, systemically important banks are propped up—their stress scenario capital ratio is increased. That is, systemically important banks benefit from bias in that their true downside riskiness is not fully reflected in the CCAR stress test reports. This result holds for alternative measures of systemic importance, including $Size$, $SRISK$, and $CoVaR$. In light of evidence that political factors play a role in bank regulation (Duchin and Sosyura [2012]), one may be concerned that the Fed props up large banks not because they are systemically important, but because large banks exert political influence. In the multivariate test presented in column (6), we show that simply adding another measure of systemic importance flips the sign and eliminates the statistical significance of bank size as a $Bias$ determinant. This evidence is consistent with systemic risk, not political influence explaining the relationship between bank size and the Fed's stance. We investigate whether the Fed's stance toward banks is consistent across the allocation of TARP funds and $Bias$. Banks that were allocated one standard deviation more TARP funds had, on average, 0.22 standard deviations higher $Bias$. We also find evidence that young banks and banks with high pre-crisis return on equity received lower $Bias$, on average. This evidence is consistent with the Fed taking a disciplining stance toward innovative banks that participated in risky activities before the financial crisis. With the exception of size, the statistical significance and economic magnitudes of the systemic determinants are quantitatively similar when all six variables are included in the column (7) regression, suggesting that these determinants have distinct effects. This confirms that size was picking up systemic importance.

4.3. **Consequences.** We examine the consequences of bias by modeling changes in subsequent bank behavior as linear functions of our measure. Because banks may adjust at different rates in response to the CCAR, we measure changes in bank behavior in the quarters following the CCAR report. We place these restrictions on bank behavior by separately running regressions of the form,

$$Y_{i,t+\tau} = \alpha + \beta_1 Bias_{i,t} + u_t + v_i + \varepsilon_{i,t} \tag{7}$$

where $Y_{i,t+\tau}$ is a measure of bank behavior in each of the quarters following the stress test in quarter t and preceding the subsequent test (i.e., such that τ ranges from 1 to 5).[18] u_t and v_i are year and bank fixed effects, respectively. We include year fixed effects to focus identification on cross-sectional variation in the Fed's stance to stress tested banks, and we include specifications with bank fixed effects to focus on within bank variation in behavior conditional on the Fed's changing stance toward the bank. We present robust standard errors that are clustered at the bank level.

We investigate the consequences of bias in three ways. First, we study whether propped up banks subsequently increase Tier 1 capital ratios. We measure changes in bank capitalization using $\Delta Tier\,1\,Capital_{i,t+\tau}$, the year-over-year change in Tier 1 capital ratios in quarter $t+\tau$, and with $1[\uparrow Tier\ 1\ Capital_{i,t+\tau}]$, an indicator that equals one if the bank increased its Tier 1 capital ratio in quarter $t+\tau$ and zero otherwise. Second, we decompose the effect on Tier 1 capital ratios into the effect on Tier 1 capital components, including $\Delta \ln RWA$, the natural log of total risk-weighted assets, $\Delta \ln Equity$, the natural log of common equity, and $\Delta \ln TotalAssets$, the natural log of total assets. Including both risk-weighted and unweighted total assets allows us to disentangle the change in risk-weighted assets into asset growth and asset allocation components. Third, we study the discrete actions that banks may take to raise equity in response to the bias. We study whether banks cut payout, issue equity, or increase profitability following the stress tests. $1[\downarrow Dividend_{i,t+\tau}]$ is an indicator that equals

[18]In 2016, the Fed started disclosing CCAR results in June rather than March, so the 2015 CCAR report has five quarters rather than four. Our findings are robust to excluding the second calendar quarter of 2016, which immediately preceded the disclosure of the 2016 CCAR.

one if bank i cuts dividends in quarter $t+\tau$, and $1[\downarrow Repurchases]$ is an indicator that equals one if bank i cuts repurchases in quarter $t+\tau$. $1[Equity\,Issuance_{i,t+\tau}]$ is an indicator that equals one if bank i's dollar volume of equity issuance during quarter $t+\tau$ is in the top quartile of equity issuance and zero otherwise.[19] Finally, $1[\uparrow ROE]$ is an indicator that equals one if bank i's return on equity increased in quarter $t+\tau$ and zero otherwise.

We next turn to an investigation of the consequences of bias on the margins identified by the Fed as goals of the stress tests. The results in Tables 4, 5, and 6 explore subsequent changes in bank behavior conditional on the estimated bias. These tests include a sample of 343 bank-quarter observations because we allow the change in bank behavior to manifest in the quarters following the CCAR report for each stress test.

Table 4 explores the cross-sectional variation in changes in Tier 1 capital ratios on bias. Our preferred specification, which is presented in column (2) and includes bank and year fixed effects, shows that banks that were propped up by the regulator by one additional standard deviation increased their capital ratio by 0.34 standard deviations less than other banks. This difference in capital ratio changes is an order of magnitude larger than the average change in Tier 1 capital ratios in our sample, suggesting that bias has an economically large negative impact on capital-raising. Columns (3) and (4) present estimates with an indicator variable that equals one if bank i increased its Tier 1 capital ratio in quarter t and zero otherwise. These estimates corroborate the continuous measure in columns (1) and (2). One additional standard deviation of *Bias* is associated with a 16.0 percentage point reduction in the probability of increasing the Tier 1 capital ratio.

Table 5 explores the cross-sectional variation in changes in the primary components of Tier 1 capital ratios on bias. These components include risk-weighted assets and equity. Because risk-weighted assets may change due to changes in total assets or changes in asset allocation across risk weight categories, we investigate the relationship between *Bias* and asset growth as well. Our preferred specifications include bank and year fixed effects, and are presented in columns (2), (4), and (6). We measure continuous changes in these Tier 1 capital ratio

[19] We calculate the dollar volume of equity issuance by multiplying common shares issued by share price as reported in Compustat.

components using year-over-year differences in the natural log of the underlying measure. Our preferred estimates suggest that a one standard deviation increase in bias is associated with a 3.1% increase in risk-weighted assets, a 1.5% decrease in equity, and no statistically significant change in total assets. This evidence suggests that relative to disciplined banks, propped up banks created riskier asset allocations and decreased equity.

To further investigate the discrete choices that banks make to raise equity following the stress tests, in Table 6, we test whether propped up banks are more or less likely to cut dividends or repurchases, issue equity, or improve their return on equity. All of these specifications include bank and year fixed effects, and are comparable to our preferred specifications in Tables 4 and 5. We find that a one standard deviation increase in *Bias* is associated with a 5.4 percentage point decrease in the propensity to cut dividends, a 8.2 percentage point decrease in the propensity to cut repurchases, a 16.5 percentage point decrease in the propensity to issue equity, and a 20.7 percentage point decrease in the propensity to raise profitability. Among these, only the repurchases estimate is not statistically significant at the 1% level, though it is consistent in direction and magnitude with the dividends estimate. Together, the estimates in Tables 4, 5, and 6 suggest that propped up banks were less likely to improve their capital positions than disciplined banks, both through asset allocation and equity raising activities.

5. Robustness

5.1. **Estimation Robustness.** In Section 3, we used a structural model to uncover any latent bias in the Fed's stress test disclosures and we investigated the determinants and consequences of this bias in Section 4. We incorporated flexibility in the modeling approach to allow for potential heterogeneity in strategies by the Fed across banks. We also construct a placebo measure of bias based on non-information event days and run tests on that measure to rule out model restrictions as an explanation for our findings. These tests also allow us to rule out the possibility that our results are driven by within bank persistence in daily returns. To further show that our findings are not driven by elements of the reporting game, we explore robustness of our results to relaxing the model restrictions themselves. Finally, we rescale the bias we uncover to show that our results are in fact driven by the cross-section as opposed to specific outliers in the data.

We first investigate the determinants and consequences of bias, but replace bias with *placebo bias* estimated on days that do not have earnings announcements, 8-K filings, or the CCAR itself. To estimate placebo bias, we follow the same procedure as before but replace the return around the CCAR announcement with non-event day returns, producing additional observations for all non-event days. In the determinants specification presented in Panel A of Table 7, this sample includes 24,570 bank-day observations. We control for estimated bias and bias inputs and cluster standard errors at the bank level. In the consequences specification presented in Panel B of Table 7, this sample includes 18,814 bank-day observations. We find no significant results except for $Charge\text{-}offs$, which has a negative and statistically significant relationship with *Placebo bias* at the 10% level. However, the economic magnitude of the relationship is an order of magnitude smaller than the relationship between $Charge\text{-}offs$ and $Bias$. Overall, this illustrates that our results critically depend on the interaction between the CCAR report and the market response thereto.

We next explore relaxation of model restrictions. We re-estimate the model using several alternative assumptions and present these findings in Table 7. In our main analysis, we allow for the Fed's strategy to be responsive to each bank. Calibrating $\rho_{q,x} = -0.5$ has a moderating effect on the Fed's strategy. It implies that the Fed will be less likely to bias downward if the bank does particularly poorly in the tests, and less likely to bias upward if the bank does particularly well. We re-estimate our model setting $\rho_{q,x} = 0$ and $\rho_{q,x} = 0.5$; these alternatives result in greater absolute bias on average—because we remove the moderating influence on the Fed's policy—but do not change our main findings.

In our main analysis, we model uncertainty surrounding the Fed's stance toward a particular bank as being a concave function of underlying bank uncertainty. In alternative specifications, we use a linear function, $\sigma_x = \sigma_q$, or a convex function, $\sigma_x = \sigma_q^{1.2}$, leaving our results qualitatively unchanged, as does assuming exogenously less uncertainty about the

Fed's objective ($\sigma_x = 0.25\sigma_q^{0.8}$). Therefore, our inferences are not dependent on these particular assumptions about functional form, and therefore our overall findings are not dependent on any specific ways in which the reporting game might be played.

Finally, to demonstrate that our findings are not driven by measurement choices for $Bias$, we present three alternative measures. Whether we use $Percentiles$, which is the percentile rank of $Bias$, $Indicator$, an indicator for above median $Bias$, or $Rank$, the cross-sectional rank of $Bias$ (by year), we find results that are similar in economic and statistical significance to our baseline findings. These results, presented in the last three rows of Panels A and B of Table 7, illustrate that our findings are not driven by outliers or particular distributional properties of $Bias$ that may be influenced by specific empirical assumptions. The $Bias$ rank results, in particular, show that ordinal bias contains enough relevant information to identify determinants of the Fed's stance and subsequent bank behavior.

5.2. **Information Robustness.** One may be concerned that our results are driven by coincident events or by the informational inputs to the model. We address this issue in several ways. First, we explore the sensitivity of our results to sample exclusions based on contemporaneous news releases or capital plan adjustments. We also investigate the robustness of our findings to controlling for the inputs to our structural model and whether the Fed intervened to negotiate an adjusted capital plan with the bank. Our results could reflect heterogeneity in the way the market updates to news releases about individual banks. To address this final concern, we construct a falsification test that applies our method to bank earnings announcements.

Our sample exclusion tests focus on two potential measurement concerns with inputs to our structural model. The market reaction to CCAR releases is an important input to our model, so any contemporaneous information releases that are unrelated to the stress tests but may correlate with the determinants and consequences we study could bias our estimates. Our first sample exclusion focuses on stress tested banks that have an unrelated 8-K filing within the three day event window that we use to calculate the market reaction to the CCAR release.[20] As shown in Table 8, accounting for alternative news generates quantitatively similar findings in both the determinants (Panel A) and consequences (Panel B) tests. The second sample exclusion focuses on cases in which the Fed intervenes and negotiates an adjusted capital plan with the bank. Our findings are economically and statistically similar to our baseline findings under this sample exclusion as well, suggesting that *Bias* is not simply picking up the market's beliefs about Fed interventions.

Because our structural model combines the level of the post-stress ratio from the adverse scenario and the market's reaction to this information to uncover potential bias in each bank's report, one may be concerned that our results are driven not by bias but rather directly by these model inputs. In Table 8, we investigate whether alternative sources of information (the post-stress ratio, adjusted capital plans, and market reactions to the release of CCAR reports) moderate the relationships between estimated bias and its determinants and between estimated bias and subsequent bank behavior. For both the determinants and consequences of *Bias*, tests that control for any combination of these factors yield quantitatively similar results. This alleviates the concern that our results could be explained by the direct information and return consequences of the CCAR report, rather than purely the bias component. Because the market response to the CCAR report should reflect all information transmitted to the market, the effect of bias is incremental to the Fed's signals contained in the qualitative component of the CCAR report and the market's anticipation of interventions related to this qualitative component. These results also mitigate concerns that our estimates of the bias reflect disagreement between the market and the Fed's private beliefs. If this were the case, we would not expect to find a significant relationship between the Fed's stance and subsequent bank behavior, especially after controlling for the CCAR report and the market's response.[21]

[20]For example, the day after the CCAR announcement in 2013, PNC announced that its CFO was retiring.

[21]Moreover, a simple disagreement story would not predict a significant market reaction to the CCAR announcement in the first place. This is because, without new information, the market would not update its beliefs.

Another potential concern is that our results are driven by the way in which markets respond to information disclosures about specific banks. Insofar as the market responds differentially to disclosures about each bank, and especially if these differences are correlated with our key observable bank characteristics, then our bias should be related to market returns surrounding other information announcements. Table 9 regresses three-day cumulative market-adjusted returns around earnings announcements on estimated bias as a falsification test. We use cumulative returns surrounding each of the four quarterly earnings announcements for each bank-year in our sample. If our results were coming from either systematic differences in how markets perceive disclosure about different banks, or from manipulation by bank managers themselves, we would expect to see a positive correlation between the response to these alternative information events, earnings announcements, and our estimated bias. The results in Table 9 show that this is not the case, and so diminish systematic misinterpretation of disclosure by markets as an explanation for our findings on the determinants of bias. Further, these results suggest that it is unlikely that what we interpret as the Fed's bias is in fact bias on the part of the bank, because one would expect the bank to face similar incentives to manipulate its disclosures around earnings announcements as it would around the CCAR.

6. Conclusion

This paper develops a framework for estimating bias in public disclosures using market reactions. We study stress test disclosures following the 2007-2008 financial crisis, and estimate the Fed's bias arising from its conflicting objectives to promote short-term stability of the financial system and discipline banks. We examine the reactions in capital markets to these disclosures, and find evidence of significant price and volume responses associated with CCAR reports. These findings show that the disclosures are indeed informative. We use this information to uncover bank-specific bias from a structural model, and find evidence of a propping up bias, on average, for the most systemically important institutions and a disciplining bias, on average, for poorly capitalized banks. Propped up banks subsequently raise less capital than disciplined banks, suggesting that the bias in stress test disclosures has real consequences for bank behavior.

Our findings suggest that regulators are concerned with more than just providing accurate information to improve market discipline and price efficiency (Tarullo [2010], Bernanke [2013]). Furthermore, our evidence is consistent with a motive to shape bank behavior through the disclosures themselves, and that in fact, this discretion is a key channel through which the stress tests influenced bank behavior. These inferences have implications for the interpretation of other regulatory disclosures. For example, in light of the nuanced interactions between national and supranational regulators, studying biases in European stress test disclosures may provide a rich setting in which to explore the political economy of financial sector regulation.

Appendix A. Derivation of the Equilibrium

A.1. **Defining the Equilibrium.** In equilibrium, the bias function for the regulator $b(q, x)$ and the market's belief $E[\tilde{q}|r]$ must satisfy the following conditions:

(1) The regulator's choice of bias for each realization $\{q, x\}$, $b(q, x)$, must solve its optimization problem given its conjecture as to how the market responds to the report:

$$b(e, x) = \arg\max_b x\hat{E}[\tilde{q}|r](r = q + b) - \frac{cb^2}{2},$$

where $\hat{E}[\tilde{q}|r]$ is the regulator's conjecture about the market's belief function.

(2) The market expectation of quality must equal the expectation of bank quality, $\tilde{q}$, based on a report $r = q + b$ and a conjecture about the bias strategy for each regulator type (i.e. the bias choice conditional upon the realizations of $\tilde{q}$ and $\tilde{x}$):

$$E[\tilde{q}|r] = E[\tilde{q}|r; \hat{b}(q, x)],$$

where $\hat{b}(q, x)$ is the market's conjecture about the regulator's bias function.

(3) Both the regulator's and the market's conjectures must be rational in the sense that they are fulfilled, that is:

$$\hat{b}(q, x) = b(q, x) \ \ \forall\{q, x\}$$

and

$$\hat{E}[\tilde{q}|r] = E[\tilde{q}|r] \ \ \forall r.$$

A.2. **Linear Equilibrium Conditions.** We construct an equilibrium of the form

$$b(q, x) = \lambda_q q + \lambda_x x + \delta,$$

and

$$E[\tilde{q}|r] = \beta r + \alpha.$$

A.2.1. *Regulator's Problem:* The regulator conjectures that the market expectation of bank quality based on a report r is:

$$\hat{E}[\tilde{q}|r] = \hat{\beta} r + \hat{\alpha}$$
$$\hat{E}[\tilde{q}|r] = \hat{\beta} q + \hat{\beta} b + \hat{\alpha}.$$

Thus, the regulator's objective function can be written as

$$x[\hat{\beta} q + \hat{\beta} b + \hat{\alpha}] - \frac{cb^2}{2}.$$

The optimal bias is given by the first-order condition, which yields:

$$b(q, x) = \frac{\hat{\beta}}{c} x$$

for all $\{q, x\}$. This implies that the regulator's bias is a linear function of the form $b(q, x) = \lambda_q q + \lambda_x x + \delta$, where $\lambda_q = 0$, $\lambda_x = \hat{\beta} c$, and $\delta = 0$.

A.2.2. *Market Belief Function:* Assume a conjectured bias function of the form $\hat{b}(q, x) = \hat{\lambda}_x x$. Given the conjectured bias function, the joint distribution of $(q, r = q + \hat{\lambda}_x x)$ is bivariate normal with the following parameters: μ_q, σ_q^2, $\mu_r = \hat{\lambda}_x \mu_x + \mu_q$, and $\sigma_r^2 = \sigma_q^2 + \hat{\lambda}_x^2 \sigma_x^2 + 2\hat{\lambda}_x \rho_{q,x} \sigma_q \sigma_x$, where

$$\rho_{q,r} = \frac{\sigma_q^2 + \hat{\lambda}_x \rho_{q,x} \sigma_q \sigma_x}{\sigma_q \sigma_r} = \frac{\sigma_q^2 + \hat{\lambda}_x \rho_{q,x} \sigma_q \sigma_x}{\sigma_q (\sigma_q^2 + \hat{\lambda}_x^2 \sigma_x^2 + 2\hat{\lambda}_x \rho_{q,x} \sigma_q \sigma_x)^{\frac{1}{2}}}.$$

Thus, the market expectation of the bank's quality conditional on the report is:

$$E[\tilde{q}|r] = \mu_q + \rho_{q,r} \frac{\sigma_q}{\sigma_r}(r - \mu_r).$$

$$E[\tilde{q}|r] = \mu_q + \left(\frac{\sigma_q^2 + \hat{\lambda}_x \rho_{q,x} \sigma_q \sigma_x}{\sigma_q^2 + \hat{\lambda}_x^2 \sigma_x^2 + 2\hat{\lambda}_x \rho_{q,x} \sigma_q \sigma_x} \right) (r - (\hat{\lambda}_x \mu_x + \mu_q)).$$

$$E[\tilde{q}|r] = \mu_q - \left(\frac{\sigma_q^2 + \hat{\lambda}_x \rho_{q,x} \sigma_q \sigma_x}{\sigma_q^2 + \hat{\lambda}_x^2 \sigma_x^2 + 2\hat{\lambda}_x \rho_{q,x} \sigma_q \sigma_x} \right) (\hat{\lambda}_x \mu_x + \mu_q) + \left(\frac{\sigma_q^2 + \hat{\lambda}_x \rho_{q,x} \sigma_q \sigma_x}{\sigma_q^2 + \hat{\lambda}_x^2 \sigma_x^2 + 2\hat{\lambda}_x \rho_{q,x} \sigma_q \sigma_x} \right) r.$$

So the market expectation of bank quality is a linear function of the report:
$E[q|r] = \alpha + \beta r$ where

$$\alpha = \mu_q - \beta(\hat{\lambda}_x \mu_x + \mu_q) \quad \text{and} \qquad \beta = \frac{\sigma_q^2 + \hat{\lambda}_x \rho_{q,x} \sigma_q \sigma_x}{\sigma_q^2 + \hat{\lambda}_x^2 \sigma_x^2 + 2\hat{\lambda}_x \rho_{q,x} \sigma_q \sigma_x}.$$

A.2.3. *Regulator and Market Conjectures:* In equilibrium, the conjectures must be rational, which implies that $\hat{\lambda}_x = \frac{\beta}{c}$ and $\hat{\beta} = \beta$.

A.3. **Equilibrium Solution.** Summarizing, we have $r = q + \frac{\hat{\beta}}{c} x$, $E[q|r] = \alpha + \beta r$, $\alpha = \mu_q - \beta(\hat{\lambda}_x \mu_x + \mu_q)$, $\beta = \frac{\sigma_q^2 + \hat{\lambda}_x \rho_{q,x} \sigma_q \sigma_x}{\sigma_q^2 + \hat{\lambda}_x^2 \sigma_x^2 + 2\hat{\lambda}_x \rho_{q,x} \sigma_q \sigma_x}$, $\hat{\lambda}_x = \frac{\beta}{c}$, and $\hat{\beta} = \beta$.

Combining the equations provides:

$$\beta = \frac{\sigma_q^2 + (\frac{\beta}{c}) \rho_{q,x} \sigma_q \sigma_x}{\sigma_q^2 + (\frac{\beta}{c})^2 \sigma_x^2 + 2(\frac{\beta}{c}) \rho_{q,x} \sigma_q \sigma_x}.$$

Rearranging yields:

$$\beta^3 \sigma_x^2 + 2\beta^2 \rho_{q,x} \sigma_q \sigma_x c + \beta \left(\sigma_q^2 c^2 - \rho_{q,x} \sigma_q \sigma_x c \right) - \sigma_q^2 c^2 = 0$$

Solving the third-order polynomial equation results in one up to three equilibria. □

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Figure 1. Information Content of CCAR: Market-Adjusted Returns

This figure presents an event study plot of daily market-adjusted returns surrounding CCAR announcements between 2012 and 2017 for all banks in our sample. The lines represent fitted local polynomials that smooth returns in the 10 days before and after CCAR announcements, respectively. The shaded regions on either side of the lines represent the 90% confidence interval in the average cumulative market-adjusted return.

Figure 2. Information Content of CCAR: Trading Volume

This figure presents an event study plot of the natural log of daily trading volume surrounding CCAR announcements between 2012 and 2017 for all of the banks in our sample. The lines represent fitted local polynomials that smoothes daily trading volume in the 10 days before and after the CCAR announcements, respectively. The shaded regions on either side of the lines represent the 90% confidence interval in the average trading volume.

Table 2. Financial Determinants of *Bias*

This table presents fixed effects regressions of the financial determinants of bias for the 2012 to 2017 stress tests. *Tier1Capital* is the Tier 1 Capital ratio. *Liquidity* is cash divided by total deposits. *LowRisk* is the fraction of assets invested in Treasury securities. *Charge-offs* is the fraction of assets charged off during the quarter. *Asset Quality* is negative one times the fraction of total loans that are 90 days past due. *ROE* is net income divided by total equity. All measures are standardized for ease of economic inference. Robust standard errors are reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	*Bias*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier1Capital	0.199**						0.141*
	(0.089)						(0.077)
Liquidity		0.169***					0.097***
		(0.057)					(0.037)
LowRisk			0.096***				0.021
			(0.022)				(0.024)
Charge-offs				-1.156***			-1.142***
				(0.405)			(0.361)
Asset Quality					0.083		0.029
					(0.060)		(0.059)
ROE						-0.819***	-1.023***
						(0.079)	(0.115)
Fixed effects:							
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.1455	0.1537	0.1278	0.1957	0.1075	0.5114	0.5849
Obs.	120						

Table 3. Systematic Importance Determinants of *Bias*

This table presents fixed effects regressions of the systematic importance determinants of bias for the 2012 to 2017 stress tests. *Size* is the natural log of total assets. *Age* is the number of years since the bank was founded. $SRISK$ is the conditional capital shortfall measure of systemic risk as in Brownlees and Engle [2016], and $CoVaR$ is the value at risk of the financial system conditional on an institution being under distress relative to its median state as in Adrian and Brunnermeier [2016]. $TARP$ is the fraction of TARP funds allocated to the bank during the 2007-2008 financial crisis. $Pre-Crisis\ ROE$ is the return on equity of the bank in 2006, which captures bank risk-taking as argued in Meiselman et al. [2018]. All measures are standardized for ease of economic inference. Robust standard errors are reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	*Bias*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Size	0.203***						-0.056
	(0.064)						(0.119)
$SRISK$		0.312***					0.301***
		(0.050)					(0.083)
$CoVaR$			0.290***				0.179***
			(0.069)				(0.048)
Age				-0.411***			-0.483***
				(0.099)			(0.097)
$TARP$					0.218***		0.171*
					(0.058)		(0.094)
Pre-Crisis ROE						-0.283***	-0.115
						(0.103)	(0.088)
Fixed effects:							
$Year$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.1645	0.2272	0.1278	0.2882	0.1715	0.1943	0.5327
Obs.	128						

Table 4. The Consequences of *Bias* for Tier 1 Capital

This table presents fixed effects regressions of $\Delta Tier\,1\,Capital_{i,t}$ and $1[\uparrow Tier1Capital]$ on $Bias$. $\Delta Tier\,1\,Capital_{i,t}$ is the year-over-year change in the standardized Tier 1 Capital ratio, and $1[\uparrow Tier1Capital]$ is an indicator that equals one if the bank increased its Tier 1 Capital ratio this quarter and zero otherwise. $Bias$ is standardized for ease of economic inference. Robust standard errors are clustered by bank and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	$\Delta Tier1Capital$		$1[\uparrow Tier1Capital]$	
	(1)	(2)	(3)	(4)
$Bias$	-0.082**	-0.337***	-0.057**	-0.160***
	(0.041)	(0.130)	(0.027)	(0.044)
Fixed effects:				
$Bank$	No	Yes	No	Yes
$Year$	Yes	Yes	Yes	Yes
R^2	0.0035	0.0082	0.0694	0.1696
Obs.	343			

Table 5. The Consequences of *Bias* for Tier 1 Capital Components

This table presents fixed effects regressions of $\Delta\ln RWA$, $\Delta\ln Equity$, and $\Delta\ln TotalAssets$ on *Bias*. These dependent variables correspond to year-over-year changes in risk-weighted assets, equity, and total assets, respectively. *Bias* is standardized for ease of economic inference. Robust standard errors are clustered by bank and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	$\Delta\ln RWA$		$\Delta\ln Equity$		$\Delta\ln TotalAssets$	
	(1)	(2)	(3)	(4)	(5)	(6)
Bias	0.009*	0.031**	-0.001	-0.015*	0.002	0.006
	(0.005)	(0.015)	(0.002)	(0.008)	(0.004)	(0.015)
Fixed effects:						
Bank	No	Yes	No	Yes	No	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0023	0.0056	0.0213	0.0260	0.0057	0.0110
Obs.	343					

Table 6. The Consequences of *Bias* for Equity Raising

This table presents fixed effects regressions of $1[\downarrow Dividend]$, $1[\downarrow Repurchases]$, $1[Equity\ Issuance]$, and $1[\uparrow ROE]$ on *Bias*. Each dependent variable is an indicator that reflects the quarterly change in the underlying corporate policy. *Bias* is standardized for ease of economic inference. Robust standard errors are clustered by bank and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	$1[\downarrow Dividend]$	$1[\downarrow Repurchases]$	$1[Equity\ Issuance]$	$1[\uparrow ROE]$
	(1)	(2)	(3)	(4)
Bias	-0.054***	-0.082	-0.165***	-0.207***
	(0.014)	(0.060)	(0.048)	(0.059)
Fixed effects:				
Bank	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
R^2	0.0769	0.1685	0.7247	0.3524
Obs.	343			

Table 7. Estimation Robustness

Panel A of this table presents estimation robustness tests of the main results on the determinants of bias. Column (1) reports the coefficient on $Tier1Capital$, column (2) reports the coefficient on $Liquidity$, column (3) reports the coefficient on $LowRisk$, column (4) reports the coefficient on $Charge\text{-}offs$, column (5) reports the coefficient on $Asset\ Quality$, column (6) reports the coefficient on ROE, and column (7) reports the coefficient on $Size$. All regression variables are standardized for economic inference. *Baseline* estimates correspond to those presented in Tables 2 and 3. *Placebo* estimates correspond to a placebo measure of bias that we estimate for all non-event dates during the sample period (i.e., not reflecting CCAR news). All subsequent rows reflect alternative estimation procedures that compare to our baseline estimates. In the model robustness rows, $\rho_{q,x} = 0$ and $\rho_{q,x} = 0.5$ present results in which bias is estimated using alternative calibrations of the correlation between uncertainty over bank quality and the Fed's desire to bias (baseline specification is $\rho_{q,x} = -0.5$). σ_x at 25%, convex σ_x and linear σ_x calibrate the Fed's desire to bias to $0.25\sigma_q^{0.8}$, $\sigma_q^{1.2}$, and σ_q, respectively (the baseline specification is $\sigma_x = \sigma_q^{0.8}$). We investigate alternative functional forms for $Bias$ in the $Percentiles$ and $Indicator$ rows. These correspond to a percentile ranking and median split of $Bias$, respectively. $Rank$ is the within year rank of $Bias$. Panel B presents analogous results on the consequences of $Bias$, where column (1) reports the coefficient on $\Delta Tier1Capital$, column (2) reports the coefficient on $1[\uparrow Tier1Capital]$, and *Baseline* estimates correspond to those presented in Table 4. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Determinants

Independent variable:	$Tier1Capital$	$Liquidity$	$LowRisk$	$Charge\text{-}offs$	$Asset\ Quality$	ROE	$Size$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Baseline	0.199**	0.169***	0.096***	-1.156***	0.083	-0.819***	0.203***
Placebo	0.003	-0.066	-0.025	-0.063*	0.022*	0.002	-0.043
Model robustness:							
$\rho_{q,x} = 0$	0.197**	0.183***	0.103***	-1.129***	0.105*	-0.806***	0.187***
$\rho_{q,x} = 0.5$	0.197**	0.183***	0.103***	-1.124***	0.104*	-0.805***	0.187***
$\sigma_x(\cdot) = 25\%$	0.197**	0.182***	0.104***	-1.132***	0.097	-0.804***	0.190***
convex $\sigma_x(\cdot)$	0.185**	0.177***	0.101***	-1.163***	0.086	-0.812***	0.193***
linear $\sigma_x(\cdot)$	0.193**	0.181***	0.103***	-1.136***	0.095	-0.806***	0.190***
Alternative $Bias$ measures:							
Percentiles	6.718***	5.062***	3.263***	-23.731**	5.359***	-21.218***	5.348***
Indicator	0.068*	0.043*	0.026*	-0.290*	0.108	-0.293***	0.068*
Rank	-1.457**	-1.110**	-0.990***	4.915**	-1.345***	5.069***	-1.800***

Panel B. Consequences

Dependent variable:	$\Delta Tier1Capital$	$1[\uparrow Tier1Capital]$
	(1)	(2)
Baseline	-0.337***	-0.160***
Placebo	0.176	-0.001
Model robustness:		
$\rho_{q,x} = 0$	-0.300***	-0.129***
$\rho_{q,x} = 0.5$	-0.302***	-0.129***
$\sigma_x(\cdot) = 25\%$	-0.296***	-0.125***
convex $\sigma_x(\cdot)$	-0.316***	-0.125***
linear $sigma_x(\cdot)$	-0.306***	-0.126***
Alternative *Bias* measures:		
Percentiles	-0.010***	-0.005***
Indicator	-0.452**	-0.098*
Rank	-0.024*	-0.006

Table 8. Information Robustness

Panel A of this table presents robustness tests of the main results on the determinants of bias. Column (1) reports the coefficient on $Tier1Capital$, column (2) reports the coefficient on $Liquidity$, column (3) reports the coefficient on $LowRisk$, column (4) reports the coefficient on $Charge\text{-}offs$, column (5) reports the coefficient on *Asset Quality*, column (6) reports the coefficient on ROE, and column (7) reports the coefficient on $Size$. All regression variables are standardized for economic inference. *Baseline* estimates correspond to those presented in Tables 2 and 3. *Other events* estimates exclude bank-year observations in which the bank disclosed an unrelated 8-K filing within the three day CCAR announcement window. *Adjusted capital plan* estimates exclude bank-year observations in which the bank had to adjust its capital plan in response to Fed intervention. Rows that include lists of control variables incrementally control for key inputs to our structural model. *T1Cap-Adv.* is the difference between the bank's Tier 1 Capital ratio and the reported Tier 1 Capital ratio in the CCAR adverse scenario. *CCAR Adj.* is an indicator that equals one if the bank had to adjust its capital plan in response to Fed intervention and zero otherwise. $CMAR$ is the cumulative market-adjusted return around the CCAR report. Panel B presents analogous results on the consequences of $Bias$, where column (1) reports the coefficient on $\Delta Tier1Capital$, column (2) reports the coefficient on $1[\uparrow Tier1Capital]$, and *Baseline* estimates correspond to those presented in Table 4. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Determinants

Independent variable:	$Tier1Capital$	$Liquidity$	$LowRisk$	$Charge\text{-}offs$	*Asset Quality*	ROE	$Size$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Baseline	0.199**	0.169***	0.096***	-1.156***	0.083	-0.819***	0.203***
Sample exclusions:							
Other events	0.197**	0.172***	0.095***	-1.500***	0.076	-0.878***	0.238***
Adjusted capital plan	0.145	0.370***	0.100***	-0.729	0.142***	-0.983***	0.206***
Controls:							
T1Cap-Adv.	0.262***	0.102***	0.083***	-0.770	0.090	-1.055***	0.037
CCAR Adj.	0.186**	0.174***	0.095***	-1.064***	0.083	-0.808***	0.219***
$CMAR$	0.199**	0.169***	0.098***	-1.168***	0.084	-0.819***	0.202***
T1Cap-Adv., *CCAR Adj.*	0.262***	0.104***	0.082***	-0.775	0.088	-1.092***	0.043
T1Cap-Adv., $CMAR$	0.261***	0.100***	0.086***	-0.773	0.104	-1.078***	0.027
CCAR Adj., $CMAR$	0.186***	0.174***	0.096***	-1.076***	0.084	-0.809***	0.219***
T1Cap-Adv., *CCAR Adj.*, $CMAR$	0.261***	0.103***	0.085***	-0.777	0.101	-1.125***	0.032

Panel B. Consequences

Dependent variable:	$\Delta Tier1Capital$	$1[\uparrow Tier1Capital]$
	(1)	(2)
Baseline	-0.337***	-0.160***
Sample exclusions:		
Other events	-0.293**	-0.189***
Adjusted capital plan	-0.313**	-0.154**
Controls:		
T1Cap-Adv.	-0.721***	-0.070***
CCAR Adj.	-0.348***	-0.162***
CMAR	-0.355**	-0.171***
T1Cap-Adv., CCAR Adj.	-0.719***	-0.246***
T1Cap-Adv., CMAR	-0.724***	-0.254***
CCAR Adj., CMAR	-0.372**	-0.176***
T1Cap-Adv., CCAR Adj., CMAR	-0.723***	-0.253***

Table 9. Falsification

This table presents fixed effects regressions of the market reaction to earnings news on estimated bias. To measure the market reaction to earnings news, we construct $EAret_{i,t}^{3\,day}$, the three day cumulative market-adjusted return around the earnings announcement, and its absolute value, $|EAret_{i,t}^{3\,day}|$, for quarterly earnings announcements of stress-tested banks during our sample period. Returns are measured in percentage points, and $Bias$ is standardized for ease of economic inference. Robust standard errors are clustered by bank and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	$EAret^{3\text{ day}}$		$\lvert EAret^{3\text{ day}}\rvert$	
	(1)	(2)	(3)	(4)
$Bias$	-0.435	-0.529	-0.241	-0.078
	(0.356)	(0.415)	(0.283)	(0.316)
Input controls:	No	Yes	No	Yes
Fixed effects:				
$Bank$	Yes	Yes	Yes	Yes
$Year$	Yes	Yes	Yes	Yes
R^2	0.0722	0.0738	0.1441	0.1544
Obs.	460			

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