Bank Stress Test Disclosures, Private Information Production, and Price Informativeness *

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Abstract

From 2015-2017, banks holding $10-$50 billion in assets were required to disclose a portion of the results of company-run stress tests mandated by the Dodd-Frank Act of 2010. While these disclosures were intended to increase bank transparency and promote financial system stability, recent theory models suggest that increased regulatory disclosure may have the unintended consequence of discouraging private information production and reducing the informativeness of equity prices. We find that the disclosure of stress test results by treatment banks is associated with reduced analyst following of approximately 5%, driven primarily by the loss of seasoned analysts. We also find that earnings forecasts of analysts that continue to follow these banks exhibit decreased dispersion and contain less firm-specific information. Further, we find that, post-disclosure, bank equity prices become more synchronous with the entire stock market, indicating that their prices become less informative. Taken together, our results suggest an unintended consequence of stress test disclosures. Because equity prices can be informative to bank regulators, our study suggests that stress test disclosures can, paradoxically, reduce the information available to bank regulators, which could negatively affect financial system stability.

Keywords: Stress test, disclosure, market efficiency
JEL-Classification: G14, G28.

1 Introduction

Since the financial crisis of 2007-2009, stress tests have become an important element of bank supervision in the United States. The goal of conducting stress tests is to assess banks' ability to withstand economic shocks, allowing supervisors to discipline the bank's behavior and promote economic stability.[1] A key question regarding stress tests is the extent to which results should be made public. On the one hand, disclosing these results could potentially enhance market discipline and increase confidence in the supervisory process (Goldstein and Sapra, 2013). Furthermore, because market participants have the ability to synthesize and incorporate information from many different sources into prices (Hayek, 1945; Grossman, 1976; Roll, 1984), releasing supervisory information to the public may enhance the informativeness of prices and provide new, valuable information to the regulator.

On the other hand, as detailed in Goldstein and Sapra (2013), there are potential costs associated with increased regulatory disclosure. Most notably, recent theoretical models suggest that more disclosure does not unambiguously lead to greater production of private information and more informative prices.[2] These models caution that releasing additional information into the market may reduce the incentives of traders to produce private information and encourage them instead to rely on public information (Morris and Shin, 2002). This

[1]Existing studies have indicated that capital inadequacy can lead to reduced bank lending (Bernanke et al., 1991; Bolton and Freixas, 2006; Beatty and Liao, 2011), deleveraging via asset sales potentially at fire sale prices (Hanson et al., 2011), increased risk-shifting incentives (Acharya et al., 2016), decreased probability of survival , competitive position, and market share (Berger and Bouwman, 2013), and increased borrowing costs and decreased availability of credit (Afonso et al., 2011; Kashyap and Stein, 1995, 2000)

[2]Goldstein and Sapra (2013) also discuss two additional costs of disclosure: 1) Disclosure may harm the operation of the interbank market and the provision of risk-sharing in this market, as modeled by Dang et al. (2017)), and 2) Disclosure may impact the incentives of bank managers and lead them to make myopic actions to pass the test or act in their own self-interest (see Beatty and Liao (2014) and Bushman (2016) for further discussions).

could ultimately lead to less informative market prices, potentially impeding the ability of regulators to use market prices as a supervisory tool (Bond et al., 2010; Bond and Goldstein, 2015; Goldstein and Yang, 2019). The extent to which stress test disclosures promote or discourage private information production remains an open empirical question.

From 2015-2017, under provisions updating the Dodd-Frank Act of 2010, all savings and loan holding companies, bank holding companies (BHCs), and complex financial institutions with capitalized assets of $10 to $50 billion were required to generate and disclose the results of *company-run* stress tests estimated under a set of "severely adverse" economic conditions set forth by the Federal Reserve. Meanwhile, the Federal Reserve had been conducting stress tests and disclosing the results for banks with greater than $100 billion in assets since 2013 and greater than $50 billion in assets since 2014, and banks with assets less than $10 billion were never required to conduct stress tests.

We use this setting to examine two questions. First, how does the public release of stress test results affect the production of private information? Second, how does revealing stress test information affect the overall price informativeness of the disclosing banks? To the best of our knowledge, this paper is the first to examine the impact that these company-reported stress test disclosures have on capital markets. Further, the existing empirical literature examining stress test disclosures is void of a study focusing on price informativeness. Given anecdotal and analytical evidence that market prices are an important determinant of government actions and policies,[3] this is an important link to understand.

We begin our analysis by examining whether these new self-reported disclosures provided the

[3]See both the discussion and theory model presented in Bond and Goldstein (2015).

market with new information by examining their stock market reactions.[4] One benefit of our setting, compared to previous empirical studies examining other U.S. or European stress test disclosures, is that banks disclosing their company-run DFAST results self-reported them on different days.[5] The staggered nature of this disclosure provides identification and helps us directly quantify the stock market price responses to these disclosures.[6] For each bank, we calculate the three-day cumulative market-adjusted excess returns and three-day absolute market-adjusted excess returns. As discussed in Flannery et al. (2017), absolute cumulative abnormal returns may be a better metric for analyzing the information content of stress test disclosures, since both large negative and positive announcement effects are consistent with stress test results conveying new information. Consistent with stress tests conveying new information to the market, We find that absolute market-adjusted excess returns are positive and significant 2.81% while cumulative returns are not significantly different from 0.

Next, we focus on the impact these company-run DFAST disclosures have on the production of private information. We conduct a difference-in-difference analysis, comparing disclosing banks with assets between the $10 billion and $50 billion disclosure threshold to non-disclosing banks with assets under $10 billion, allowing us to examine the direct impact of this disclosure. Existing theory models suggest that the impact of increased disclosure on

[4]While our paper is the first to examine the impact that the self-reported Dodd Frank Act Stress Test (DFAST) disclosures had on banks with assets $10-$50 billion, other papers have empirically examined stock market reactions to other U.S. or European stress test announcements and found mixed results regarding the extent to which their content was informative (Petrella and Resti, 2013; Morgan et al., 2014; Candelon and Sy, 2015; Bird et al., 2015; Flannery et al., 2017; Fernandes et al., 2020)

[5]In comparison, the results of the stress tests that the Federal Reserve conducts (SCAP, CCAR, DFAST for large banks) are released on a single day.

[6]As Goldstein and Leitner (2018) point out, one of the empirical challenges that researchers face is that initial stress test disclosures are often coupled with confounding events, such as other government regulations. In contrast, our sample period spans 2015-2017, which Flannery et al. (2017) refer to as a relatively "benign" banking environment. This "benign" banking environment is actually a strength of our study because it helps to alleviate the concern that confounding events are driving our findings.

the amount of private information market participants produce is an empirical question. For example, the model proposed in Bond and Goldstein (2015) suggests that if the regulator discloses information about issues that investors are researching, that may induce investors to acquire less information on their own. However, disclosing information about matters that investors cannot research may spur them to produce more information.[7]

While it is difficult to directly observe the amount and quality of information that market participants produce, we begin by examining how stress test disclosures affect the number of analysts making earnings forecasts. We find that the number of analysts making earnings forecasts drops by about one analyst, on average, for treated banks after initiation of stress test disclosures. We decompose the number of analysts following the firm into analysts that are new to making earnings forecasts ("rookies") and seasoned analysts with prior forecast experience. We find that, post-2015, the reduction in analyst following is almost entirely driven by the loss of seasoned analysts, while there is no meaningful difference in the number of "rookie" analysts.

We next examine how stress test disclosures affected properties of analysts' forecasts, specifically the mean forecast error and dispersion. Barron et al. (1998) develop a framework that decomposes analyst forecasts into information known only to individual analysts and information common to all analysts. In their framework, as the amount of private information analysts produce increases, the dispersion of forecasts increases. Consistent with a decrease in private information production, we find a decrease in forecast dispersion but no change in

[7]Other theoretical models are discussed in greater detail in Section 2.1. For example, McNichols and Trueman (1994) suggest that increased disclosure leads to greater private information production, while Morris and Shin (2002); Angeletos and Pavan (2007); Bond and Goldstein (2015); Goldstein and Yang (2019) suggest that market participants may be less likely to produce their own.

forecast accuracy for treated banks in the disclosure period.

We expand on this finding by implementing two additional proxies for information production. First, following Barron et al. (1998), we create a more sophisticated measure of the amount of idiosyncratic bank information contained in analyst forecasts. The model uses forecast errors and dispersion to decompose analysts' forecasts into common and idiosyncratic information and quantify the content of such types of information. We also calculate the deviation of analysts' forecasts from time-series predictions as a second measure of private information production. Consistent with stress test disclosures discouraging private information production, both measures indicate that, post-disclosure, analysts' forecasts contain less idiosyncratic information.

To measure the firm-specific information contained within a bank's stock price, we calculate the R^2 from a modified index-model regression.[8] Durnev et al. (2003) find future earnings explain share prices more for lower R^2 firms and conclude that it is a good measure of share price accuracy, and a number of other studies have implemented R^2 as a proxy for idiosyncratic information.[9] We find that company-run stress test disclosures are negatively associated with idiosyncratic information, indicating that bank stock prices are less informative in the disclosure period.

While increased disclosure is often viewed as a panacea, we find an unintended consequence of stress test disclosures in the form of a decrease in private information production, ultimately leading to less informative prices. Our paper contributes to the literature by providing

[8]Within this regression framework, a lower R^2 indicates a lower ability for market-wide news to explain stock returns. Thus, bank returns are driven more by bank-specific information.

[9]For example, see Durnev et al. (2004), Jin and Myers (2006), and Hutton et al. (2009)

empirical evidence on negative externalities associated with releasing regulatory information to the public by way of decreased private information production and price informativeness. Despite existing theory models generating predictions pertaining to the effect regulatory disclosures have on price informativeness, to the best of our knowledge, we are the first paper to test these predictions empirically. From a policy standpoint, our results suggest that stress test disclosures could inhibit bank supervision to the extent that regulators learn from bank equity prices. In this respect, our paper suggests that regulators should be cautious with regard to the amount and type of stress test information that they require banks to publicly disclose.

Our paper proceeds as follows. We present an over overview of U.S. stress tests as well as the related literature in Section 2. We discuss our related literature as well as background information regarding stress tests in Section 2 and develop our hypotheses in Section 3. Subsequently, we outline our data, variables of interest, and empirical design in Section 4 and present our results in Section 5. In Section 6, we conclude.

2 Background

2.1 Related Literature on Cost and Benefits of Stress Test Disclosure

The economic consequences of mandatory disclosure have been extensively debated (Healy and Palepu, 2001; Shleifer and Wolfenzon, 2002). While some studies document benefits to mandatory disclosure in securities,[10] others are more circumspect (see Leuz and Wysocki (2016) for survey evidence). Within the mandatory disclosure literature, we contribute to growing number of studies focusing on the impact bank stress test disclosures have on financial system stability. Recently, a small but growing body of theoretical models identify the mechanisms through which stress test disclosures may lead to negative market consequences, and paper empirically tests some of the mechanisms outlined in these theories.

Both policymakers and academics have acknowledged that one of the primary intended benefits of disclosing regulatory information to market participants is market discipline.[11] This disclosure gives market participants better insights into banks' risk exposures and promotes the incorporation of this information into stock prices, which reflect the aggregate information of many different market participants (Hayek, 1945; Grossman, 1976; Roll, 1984). Thus, banks should become more accountable to both supervisors and investors. This ultimately increases economic stability by facilitating the monitoring and disciplining of banks' risk taking and reducing the chances that unexpected events will cause major systemic disruptions. As Goldstein and Sapra (2013) discuss, many proponents of disclosing stress test results link the most recent financial crisis to bank opacity. These proponents argue that if banks had properly disclosed their risk-taking decisions, market discipline would have penalized banks for taking on excessive risks and ex-ante reduced their incentives to take such risks. [12]

[10]Healy and Palepu (2001) survey the existing literature and find that a number of studies have concluded that increased disclosure can be associated with improved stock liquidity and cost of capital reductions.

[11]Underscoring this idea is the fact that market discipline is one of three pillars of the Basel III international regulatory framework.

[12]Michael (2004) also discusses that during the Savings and Loan (S&L) Crisis of the 1980s and highlights that SLs were not using market prices to value their assets, which would have arguably provided market discipline by highlighting the problem to outsiders much earlier.

A second benefit of disclosing regulatory information that goes hand-in-hand with market discipline is the ability of the regulator to gather information about bank safety and soundness from the prices of bank securities. As Gary Stern, the former President of the Federal Bank of Minneapolis, explained, "Raw market prices are nearly free to supervisors. This characteristic seems particularly important given that supervisory resources are limited and are diminishing in comparison to the complexity of large banking organizations."[13] Traders have incentives to quickly gather, generate, and trade on information in order to reap their own monetary profits, and as a result, regulators can benefit from this information production. By monitoring the prices of banks' securities in real time, regulators can quickly identify concerns regarding bank risk taking and/or solvency and take appropriate disciplinary action. The academic literature has established that market prices influence government actions (Feldman and Schmidt, 2003; Krainer and Lopez, 2004; Furlong et al., 2006), and policy proposals call for bank supervisors to even make *greater* use of market prices (Evanoff and Wall, 2004; Herring, 2004).

However, recent theoretical models suggest that a potential cost of increased regulatory disclosure is that it discourages private information production under two broad scenarios. First, by releasing more information into the market, traders that had already been generating that information may lose some of their competitive advantage and therefore realize fewer gains from trading. As a result, market participants have less incentive to produce private information (Bond and Goldstein, 2015; Gao and Liang, 2013). Second, if regulators release more information, traders may become increasingly reliant on public information and

[13]http://www.minneapolisfed.org/pubs/region/01-09/stern.cfm

produce less of their own (Morris and Shin, 2002; Angeletos and Pavan, 2007),[14] ultimately crowding out private information in market prices.

In extreme cases, placing excessive weight on public information may lead to a coordination problem between traders, whereby market participants overreact to bad news, which can compromise stability, create suboptimal bank runs, or prevent efficient runs (He and Manela, 2016; Chen and Hasan, 2006).[15] Thus, the theory literature outlines a variety of reasons market participants may reduce their production of private information in response to increased disclosures, ultimately making market prices less informative and adversely affecting the ability of regulators to learn from them (Bond et al., 2010; Bond and Goldstein, 2015; Goldstein and Yang, 2019).

This paper is most closely related to theoretical models demonstrating the "dark side" of stress test disclosure. Despite the fact that there is a large literature surrounding the impact of stress test disclosures around the world, to the best of our knowledge, we are the first empirical paper to examine how stress test disclosures affect price informativeness. Understanding the effect of stress test disclosures is important given costs of producing such disclosures and the existing anecdotal and academic evidence that indicates that policymakers learn from prices. Furthermore, we are only the second paper to empirically examine the production of private information after stress test disclosures.[16]

[14] In Bond and Goldstein (2015), the regulator can release different types of information. The model suggests that if the regulator discloses information about issues that investors are researching, that may induce investors to acquire less information on their own, but disclosing information about matters that investors cannot research may spur them to produce more information.

[15] The model proposed by Bouvard et al. (2015) suggests that releasing bank-specific information can enhance stability during crisis times but impede it during normal times. Morrison and White (2013) shows that regulatory transparency improves confidence ex ante but impedes regulators' ability to stem panics ex post.

[16] Our results are opposite to Flannery et al. (2017), which focuses on the consequences of large BHC stress

2.2 Stress Testing Background

Before the financial crisis, stress testing was viewed as one of many risk management tools and was not yet a major component of bank supervisory programs (Hirtle and Lehnert, 2015). However, in the aftermath of the financial crisis, national authorities turned to bank stress tests as a credible means of both assessing the health of banks and communicating it to the public. As part of the 2009 Supervisory Capital Assessment Program (SCAP), the first stress tests were administered to 19 of the largest U.S.-owned BHC's with more than $100 billion in order to ensure that these banks had sufficient capital to withstand adverse macroeconomic conditions (Hirtle and Lehnert, 2015). Later, supervisors began to implement coordinated stress testing into a larger group of banks through the implementation of the Comprehensive Capital Analysis and Review (CCAR) in 2011 and the Dodd-Frank Act stress testing (DFAST) provisions first implemented in 2013.

The Dodd-Frank Wall Street Reform and Consumer Protection Act ("Dodd-Frank" Act), enacted on July 21, 2010, required the Federal Reserve to generate stress test results each year under three supervisory scenarios: baseline, adverse, and severely adverse for all banks with more than $50 billion in assets. The severely adverse scenario includes trajectories for 26 variables, including 14 variables that capture economic activity, asset prices, and interest rates in the U.S. economy and financial markets, plus three variables in each of four countries or country blocks.[17] The Federal Reserve adopted rules implementing these requirements and their public disclosures of the adverse and severely adverse scenarios in October 12,

test disclosures made by the Federal Reserve.

[17]Real GDP growth, inflation and the U.S./foreign currency exchange rate are reported for the Euro area, the United Kingdom, developing Asia, and Japan.

2012,[18] though they allowed for a phase-in period for this regulation. This amendment also added the requirement that all regulated financial companies, including BHCs, with $10 - $50 billion in capitalized assets must disclose their own bank-calculated estimates under the severely adverse scenario. The first public DFAST results were released on March 7, 2013, and they disclosed the results of the severely adverse case scenario for 18 of the banks subjects to SCAP.[19] The 2014 DFAST disclosure, which took place on March 20, 2014, released both the adverse and severely adverse case scenarios for 30 U.S.-owned BHC's with greater than $50 billion in assets. BHCs with assets of $10-$50 billion conducted their own stress tests, and starting in 2015, they self-reported their severely adverse case scenarios either on their own websites or by filing a Form 8-K with the Securities and Exchange Commission.

While our paper focuses on DFAST, the Federal Reserve also has a complementary stress test program, CCAR. One of the primary goals of CCAR is to evaluate each BHC's ability to maintain adequate capital after taking its planned capital actions. During the financial crisis, many large BHCs had significantly reduced (or suspended) dividend payments (Hirtle, 2014), and once the turmoil surrounding the crisis had passed, there was a desire to resume these programs. The Federal Reserve implemented CCAR in 2011 to provide a framework to determine whether the largest and most complex 19 BHCs had sufficient capital to resume these distributions (Board of Governors of the Federal Reserve System, 2011). CCAR also provides a framework and tools for the Federal Reserve to annually assess a BHC's internal capital positions and planning processes, including the governance over their capital planning process, its policy governing capital actions, such as dividends, repurchases, and share

[18]See 77 FR 62380 (October 12, 2012).

[19]Lehman Brothers was not included.

issuances, and its bank-run stress test projections under the Federal Reserve's baseline, adverse, and severely adverse scenarios, as well as under two bank-determined scenarios (Hirtle and Lehnert, 2015). Starting in 2014, 30 BHCs with assets greater than $50 billion participated in CCAR, which was the same population participating in DFAST, and the results of CCAR are publicly disclosed every year.

The supervisory stress results for CCAR are very closely linked to the DFAST projections. Both tests include the same banks and both based on the same baseline, adverse, and severely adverse scenarios outlined by the Federal Reserve. They also include the same projections of the balance sheet, risk-weighted assets, and net income. However, they differ in their assumptions about the BHCs actions affecting capital. Under CCAR, each BHC specifies their own intended capital plan, including dividends and share repurchases. In contrast, DFAST uses stylized assumptions specified in the Dodd-Frank Act, which are based on historical dividend levels for each BHC and set share repurchases and share issuance at zero, except for issuances associated with employee compensation (Board of Governors of the Federal Reserve System, 2015a,b).

On February 3, 2017, Dodd-Frank was amended such that banks with assets less than $50 billion capitalized assets were no longer required to report their company-run DFAST results after their November 2017 releases. According to the same amendment, banks with assets less than $250 billion were no longer subject to annual DFAST or CCAR examinations, though banks with capitalized assets of $100-$250 will still be tested periodically.[20]. Appendix B gives a breakdown of banks that are stress tested each year under each type of stress test.

[20]See 82 Fed. Reg. 9308 (February 3, 2017)

3 Hypothesis Development

As discussed in Section 2.1, it has been widely established that the mandatory disclosures have the ability to impact capital markets in meaningful ways. There are a number of channels through which stress test disclosures may impact private information production and price informativeness. To further clarify this relationship, we develop two hypotheses in this section.

Market participants, including analysts, have greater incentives to produce private information when they have the ability to profit from that information, such as through either demand for their services or gains from trades (McNichols and Trueman, 1994; Healy and Palepu, 2001). It is possible that the disclosure of stress test results could attract analysts who believe that they can profit from a superior ability to analyze and interpret stress test data. However, recent theory models suggest that a potential cost of increased regulatory disclosure is that it discourages private information production under two broad scenarios. First, by preempting traders' information advantage from information acquisition, disclosure could reduce private information production (Gao and Liang, 2013; Bond and Goldstein, 2015). Second, if regulators release more information, traders may become increasingly reliant on public information and produce less of their own (Morris and Shin, 2002; Angeletos and Pavan, 2007), ultimately crowding out private information production. Thus, the effect stress test disclosures have on private information production is an empirical question, which leads us to our first null Hypothesis:

H1: Company-run stress test disclosures do not affect analyst private information production.

Aside from the aggregate level of private information produced, recent theory models have suggested that mandatory disclosure can affect the *type* of private information produced, which my affect the informativeness of prices. In both Gao and Liang (2013) and Goldstein and Yang (2019), price informativeness is a function of two types of information. The first type of information is the type that an agent (such as a regulator or manager) knows, while the second is one where the agent is trying to gain information. In Gao and Liang (2013), the two types of information are positively correlated. Thus, the decrease in private information produced by market participants mentioned above ultimately leads to prices becoming less informative. However, in Goldstein and Yang (2019), the two types of information are substitutes. Under certain circumstances, when the agent releases more information pertaining to the known factor, market participants produce more information pertaining to the unknown factor. This leads to market prices being more informative along the dimension of the unknown factor.

Empirically, we can observe *overall* equity price informativeness but not the *relative* measures of informativeness pertaining to each type of information presented within these models. Thus, our hypothesis development has an additional level of complexity, since our measure of overall equity informativeness will only capture the net effect of all types of information produced.

Within the Gao and Liang (2013), where the two types of information are complements, an increase (decrease) in the production of one type of information will only magnify the overall effect on price informativeness. However, within the Goldstein and Yang (2019) framework, if a decrease (increase) in the production of one type of information is greater (less than) than the production of the other, the overall effect may be negative (positive). Thus, the overall effect stress test disclosures have on overall price informativeness is an empirical question, which forms our second null Hypothesis 2:

H2: Company-run stress test disclosures do not affect price informativeness.

4 Data and Empirical Design

4.1 Data

We obtain quarterly bank-level variables from the Federal Reserve's quarterly Consolidated Financial Statements (FR Y-9C) from 2011-2017 and daily equity prices from the Center for Research in Security Prices (CRSP). We acquire analyst forecast data from the Institutional Brokers' Estimate System (IBES) and actual earnings from SP Global Market Intelligence. We hand-collect company-run stress test disclosures, including their release dates, from bank websites, Form 8-K Securities and Exchange (SEC) filings, and SP Global Market Intelligence.

4.1.1 Analyst Forecasts

We obtain quarterly analyst earnings forecasts and actual earnings data from the IBES Summary History file over the period 2011-2017. Analysts often update their earnings forecasts prior to earnings announcement, resulting in multiple earnings forecasts per analyst for a given earnings period. Our coarsest measure of private information production is the total number of analyst forecasts within a given earnings period, allowing for forecast revisions, *EPS_FCSTNUM*. A greater number of analysts following a firm may lead to greater firm-level private information production, and analysts that make updates more frequently may be doing so based on the information they produce. We also calculate the number of analysts providing earnings forecasts, *EPS_ANALYSTS* and decompose this variable into the number of analysts making forecasts for the first time, *ROOKIE_FCST*, and those that had previously made forecasts, *SEASONED_FCST*.

From there, we retain the most recent earnings forecast for each analyst within a given earnings period and gather the mean and standard deviation of these forecasts (*EPS_MEAN* and *EPS_SD*) as well as the realized EPS, *EPS_ACTUAL*. Using these data, we calculate analyst earnings forecast dispersion and forecast error, *EPS_DISPERSION* and *EPS_FE* for banks that have at least two analysts making forecasts, so our sample size is slightly reduced.

Forecast dispersion represents the consensus among analysts regarding future firm prospects (see Imhoff Jr and Lobo (1992)). As indicated in Equation 1, quarterly *EPS_DISPERSION* is calculated by taking the ratio of the standard deviation of the quarterly EPS forecasts divided by the price at the end of the previous quarter:

$$EPS\_DISPERSION_{b,q} = \frac{EPS\_SD_{b,q}}{Price_{b,q-1}} \tag{1}$$

We also calculate EPS forecast error, EPS_FE, as the absolute value of the difference between the mean analyst EPS forecast and the actual EPS normalized by price at the end of the previous quarter, as shown in Equation 2:

$$EPS\_FE_{b,q} = \frac{\mid EPS\_MEAN_{b,q-1} - EPS\_ACTUAL_{q} \mid}{Price_{b,q-1}} \tag{2}$$

We report summary statistics for our full sample of banks with assets less than $50 billion in Table 1. While the mean number of analysts making quarterly EPS forecasts in our sample is 5.425, bigger banks have greater analyst following. For example, pre-2015, banks with less than $10 billion in assets have an average of approximately 4.9370 analysts making forecasts. This is less than half of the analyst following that banks with assets between $10-$50 billion have (13.0890 analysts).

4.1.2 Private Information Measures

While it is difficult to directly observe the amount of private, firm-specific information that analysts produce, we follow the methodology in Barron et al. (1998) to estimate the amount of firm-specific information in analysts' forecasts. Barron et al. (1998) decompose analysts' information environment into two components, common and idiosyncratic information, and develop a proxy for the precision of idiosyncratic information in analysts' forecasts. The intuition behind the measure is that forecast dispersion reflects idiosyncratic information among individual analysts, while the squared error of the consensus mean forecast primarily reflects the precision of the information that is common among all analysts. The precision of idiosyncratic information in analysts' forecasts utilizing earnings per share estimates is reflected in Equation 3:

$$EPS\_PRIV\_INFO1_{b,q} = \frac{(EPS\_SD_q)^2}{(((1 - 1/EPS\_ANALYSTS_{b,q}) \times EPS\_SD_{b,q}{}^2) + EPS\_SE_{b,q})^2} \tag{3}$$

where *EPS_SE* denotes the squared mean forecast error. Greater values of *EPS_PRIV_INFO1* indicate a higher degree of idiosyncratic information in the analysts' forecasts, which is a reflection of greater analyst private information production. *EPS_PRIV_INFO1* is increasing in dispersion, *EPS_SD*, and the number of analysts making forecasts, *EPS_ANALYSTS*, but decreasing in the uncertainty surrounding common information, *EPS_SE*.

We also incorporate a second measure of private information, which is the deviation of analysts' forecasts from time-series predictions. Previous literature has shown that analyst forecasts predicting earnings are typically superior to time-series models (Brown et al., 1987), presumably because analysts incorporate information beyond historical financial information in making their forecasts. The magnitude of the deviation of the analysts' forecast from a time-series prediction will reflect the information incorporated into forecasts beyond the time-series estimate. We incorporate a seasonal random walk and compute this measure in Equation 4:

$$EPS\_PRIV\_INFO2_{b,q} = \frac{|EPS\_MEAN_{b,q} - EPS\_ACTUAL_{b,q-4}|}{Price_{b,q-1}} \quad (4)$$

To mitigate concerns that this measure is affected by acquisitions, we restrict our sample to banks that had asset growth rates of less than 20% over the last year. We present the summary statistics for these variables in Table 1.

4.1.3 Price Informativeness

Roll (1984) finds that only a small portion of price movements can be explained by contemporaneous public news and speculates that traders acting on nonpublic firm-specific information could be driving returns. Subsequently, a number of papers have examined the relation between information and stock price dynamics, focusing on the R^2 from a modified index-model regression to measure stock price informativeness (Morck et al., 2000; Durnev et al., 2003, 2004; Jin and Myers, 2006; Hutton et al., 2009). Within our setting, a lower R^2 indicates a lower ability for market-wide news to explain stock returns. This means that there is a greater degree of bank-specific information available, and therefore, prices are more informative. We follow the literature and compute a measure of quarterly R^2, *QuarterlyRSQ*, from a modified index-model regression framework shown in Equation 5

$$r_{b,q} = \alpha + \beta_1 r_{m,q-1} + \beta_2 r_{m,q} + \beta_3 r_{m,q+1} + \gamma_1 r_{i,q-1} + \gamma_2 r_{i,q} + \gamma_3 r_{i,q+1} + \epsilon_{b,q} \quad (5)$$

where $r_{b,q}$, $r_{m,q}$, and $r_{i,q}$ are excess returns of the stock, the market, and the stock's industry during quarter q. Since R^2 ranges from 0 to 1, 1-R^2 is a measure of firm-specific volatility or lack of market synchronicity. We follow the literature (Morck et al., 2000; Hutton et al., 2009) in estimating the amount of idiosyncratic information in prices, *IDIOSYN*, using a logistic transformation of $QuarterlyRSQ$, as shown in Equation 6:

$$IDIOSYN_{b,q} = ln(\frac{1 - QuarterlyRSQ_{b,q}}{QuarterlyRSQ_{b,q}}) \tag{6}$$

where higher values of *IDIOSYN* indicates a greater amount of stock price informativeness.

4.1.4 Control Variables

Following prior literature, we control for a number of bank-level variables constructed using FR Y-9C reports. These variables include size, calculated as the natural logarithm of total bank assets (*LNASSETS*), market value of equity (MVE), calculated as the number of shares outstanding multiplied by price, market-to-book value of equity (MTB), calculated as the book value of equity divided by the market value of equity, and bank capital ($CAPITAL$), calculated as the book value of equity divided by total assets. We also control for net charge-offs (NCO), measured as the average net charge-offs over the last four quarters normalized by total loans from the previous quarter.

When examining stock price informativeness, we follow Hutton et al. (2009) and add three additional controls to account for a stock's skewness, volatility, and kurtosis over a calendar year. Additional information regarding the calculation of these variables can be found in Appendix B, and summary statistics are in Table 1.

4.2 Empirical Design

We test our main hypotheses using a difference-in-differences approach that compares changes in the variables of interest before versus after the release of company-run DFAST disclosures for treated (i.e., disclosing) banks compared to control (i.e., unaffected) banks.

As discussed in Section 2.2, the Federal Reserve had been conducting Dodd-Frank Act Stress Tests on banks with assets of more than \$100 billion (\$50 billion) and disclosed the results of both their adverse and severely adverse scenarios starting in 2012 (2013). The Act was later updated such that all banks holding assets of \$10-\$50 billion were required to conduct company-run stress tests and publicly disclose the results for the severely adverse scenario starting in 2015. In our primary analysis, we compare the treatment banks disclosing company-run stress tests to a control group that was never required to conduct or disclose any DFAST results.[21]

We define a variable, DISCLOSE, that is an indicator variable that takes a value of 1 for the years 2015 to 2017 and zero otherwise, and a second indicator variable, *TREAT*, that takes a value of 1 for banks with assets of \$10-\$50 billion. Our main specification is a single-stage, bank-level regression as indicated by Equation 7:

$$\begin{aligned} DEPENDENT\_VARIABLE_{b,q} = \alpha_b + \gamma_q + \beta_1' \, DISCLOSE_{b,q} \times TREAT_{b,q} + \\ \beta_2' \, BANK\_CONTROLS_{b,q-1} + \epsilon_{b,q} \end{aligned} \tag{7}$$

[21] In robustness tests mentioned in Section 5.5, we show that our results are qualitatively similar when we use large BHCs with total assets greater than \$50 billion where the Federal Reserve released DFAST results as a control group.

where for a bank b in quarter q, α_b represents bank fixed effects and γ_q denotes year-quarter fixed effects. Because the bank and year-quarter fixed effects subsume the direct effects from *TREAT* and *POST*, respectively, they are omitted from the specifications. The bank fixed effects control for all time-invariant heteroteneity across banks, while the bank-quarter fixed effects remove overall time trends. *BANK_ CONTROLS* is a vector of time-varying bank controls that include log assets (*LNASSETS*), charge-offs (*NCO*), market value of equity (*MVE*), market-to-book (*MTB*), and *CAPITAL*, which are discussed in Section 4.1.4 and defined in Appendix B. We cluster our standard errors by year-quarter, though they are robust to clustering by firm.

In our primary analysis, we present our results for the full sample of banks with assets less than $50 billion. We summarize the pre-period characteristics for both treated and control banks in Table 2. Table 2 shows the pre-period characteristics for the full sample of banks with assets under $50 billion. For the treated and control samples, we show the mean, median, and number of observations for each variable of interest along with the difference in means, test statistic for the two-tailed difference in means test, along with the significance level associated with the two-tailed test for the difference in means. It's important to acknwoledge that our treatment group is one that surpasses the size threshold of $10 billion. Therefore, we should not be surprised that the treatment and control group vary along dimensions that correlate with size.

In Figure 1, we plot the yearly average number of analysts for both treated and control firms in order to show the validity of the parallel trends assumption necessary for a difference-in-difference analysis. The vertical line in the figure is drawn at the year 2014 to indicate the final year before the company-run DFAST disclosures were initiated. Pre-2015, the number of analysts for both the treated and control groups appear approximately parallel. Meanwhile, starting in 2015, the rate at which the disclosing banks lose analysts starts decreasing at a more rapid rate than the control group.

5 Empirical Results

5.1 Information Content of Disclosures

First, we examine whether company-run stress test disclosures contained information that was new to the market. A number of other papers examining the release of stress test information in Europe or for Federal Reserve-conducted stress tests conducted on large U.S. BHCs (both SCAP and CCAR) have largely concluded that these disclosures conveyed new information to market participants (Petrella and Resti, 2013; Morgan et al., 2014; Candelon and Sy, 2015; Bird et al., 2015; Flannery et al., 2017; Fernandes et al., 2020). The Federal Reserve releases SCAP and DFAST BHC results in a single day, raising concerns that a confounding event or other regulatory announcement drives these results, as discussed in Goldstein and Leitner (2018). However, each \$10-\$50 billion bank that was required to perform a company-run (DFAST) stress disclosed the results on different days. The staggered nature of these disclosures helps alleviate this concern.

We first examine three-day cumulative abnormal returns around all DFAST disclosure dates, including both company-run and Federal Reserve-conducted stress tests,[22] and present the

[22]When stress test disclosures are unavailable through 8-K filings, 8-K filings, or S&P Global Market

results in Table 3. In Row 1, we present the results of the full sample of all stress test disclosures, including both company-run and those conducted by the Federal Reserve. We report excess cumulative abnormal returns (CAR) as adjusted by the CRSP value-weighted index (Column 2) or using DGTW adjustments (Column 4). We also present the results for subsamples of only company-run DFAST disclosures (Row 2), only Federal Reserve DFAST disclosures (Row 3), only the first release of company-run stress test disclosures (Row 4), and only subsequent releases of company-run stress test disclosures (Row 5). While fewer banks are included in the Federal Reserve-conducted stress tests, there are more disclosures and corresponding announcement dates because these banks typically release DFAST disclosures twice each year, one annual and one midyear report. We find that for all subsamples, the number of CARS with positive and negative abnormal returns is approximately equal (Columns 3 and 5). As discussed by Flannery et al. (2017), stress test releases can convey either positive or negative information, which means comparing CARs to zero may not be an appropriate comparison. Thus, while excess and DGTW-adjusted CARs are not significantly different from zero for any of our sub-samples, this does not necessarily indicate that there is no new information being conveyed to the market. Following Flannery et al. (2017), we compute the absolute value of our excess and DGTW-adjusted CARs and report the results in Columns 6 and 7. We find evidence that the absolute value of CARs are positive and significant, indicating that they did convey new information to the market.

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intelligence, we contacted the bank's investor relations departments directly using the contact information whenever it is available. In many cases, we received responses, but for some banks that we believe were stress tested, we are unable to discover the dates of the stress test releases, so this small number of banks is omitted from these CAR tests.

5.2 Analyst Following, Forecast Error, and Dispersion

As discussed in Section 3, market participants, such analysts, have greater incentives to produce private information when they have the ability to profit from that information, such as through gains from trades or increased demand for their services. However, stress test disclosures could reduce analysts' advantage generating private information by making more information available to the public. Thus, the effect of stress test disclosures on analyst following is unclear ex ante. In this section, we analyze the impact that company-run stress test disclosures have on the number of analysts making EPS forecasts and present the results in Table 4.

The coefficient on the interaction term $DISCLOSE \times TREAT$ is negative and significant. This is consistent with the initiation of company-run stress test disclosures leading to a decline in analyst following for treated banks relative to control banks. The results in Column 1 indicates that, on average, treated banks lose about 0.81 analysts making a quarterly EPS forecasts in the disclosure period. In terms of economic significance, this represents a reduction in analyst following of approximately 5% from the pre-disclosure-period treated firm average of 16.4481 analysts. This result contrasts the findings in Flannery et al. (2017), who find an increase in analyst following after the Federal Reserve started disclosing stress test results for large banks through either CCAR or SCAP. In Column 2, we find that on average, analysts make more infrequent forecasts post-disclosure, suggesting that either there is less information available for them to use in their forecasts or that they are producing less private information.

Next, we decompose the number of analysts into analysts making forecasts for the first time, "rookie" analysts, and "seasoned" analysts that had made previous forecasts, and we show the results in Table 5. In Column 1, the negative interaction term indicates that the reduction of analysts is driven almost entirely by disclosing firms losing more seasoned analysts, who could have acquired more firm-specific knowledge over time. Furthermore, the results in column 3 indicates that the stress test disclosures did not significantly impact the level of rookie analysts. The results from Tables 4 and 5 indicate that banks releasing DFAST disclosures were able to retain fewer seasoned analysts than the group of control banks that did not have such disclosure requirements.[23] These naïeve measures of information production: number of analysts making forecasts, number of forecasts, number of seasoned analysts making forecasts suggest that these DFAST disclosures are associated with a decrease in bank-level private information production by analysts.

The theory model presented in Barron et al. (1998) allows us to use analyst forecasts to examine whether these company-run DFAST disclosures increased the amount and precision of common information available to all analysts. The model assumes that analysts receive two signals: one common to all market participants and a second private one. Within their model, if analysts are producing more private information, they are more dispersed. In Table 6, we find that company-run DFAST disclosures are associated with no statistically significant change forecast errors, though analyst forecasts are less dispersed. In the next section, we continue to follow the framework outlined in Barron et al. (1998) to use the properties of analyst forecasts in order to examine how stress test disclosures affect the amount of private, bank-specific information that is contained in these forecasts, allowing us

[23] Alternatively, the results presented in Table 5 are robust if we decompose the number of analysts following a bank into rookie (seasoned) analysts that have made forecasts for less (more) than one year.

to determine whether the increase in analyst forecast accuracy and consensus is driven by an increase in common or private information.

5.3 Analyst Private Information Production

Analyst forecasts are a function of both public and privately produced information, and existing theory models have indicated that despite providing more public information, increased disclosures could make market participants less likely to produce their own information (Morris and Shin, 2002; Angeletos and Pavan, 2007; Bond and Goldstein, 2015; Goldstein and Yang, 2019). We first follow Barron et al. (1998) to calculate a measure of the level of idiosyncratic earnings information contained in analysts' forecasts and also analyze our second private information measure, the magnitude of the deviation of the analysts' forecast from a time-series prediction. Both the construction and intuition behind these variables is in Section 4.1.2, and we present the results in Table 7. Column 1 examines *EPS_PRIV_INFO1* and indicates that the coefficient on the interaction term $DISCLOSE \times TREAT$ is negative and significant, indicating that analysts produced less idiosyncratic information related to earnings for treated banks post-disclosure. Our results are consistent when we analyze the time-series measure of private information, *EPS_PRIV_INFO2* as indicated by Columns 2. This suggests that post-disclosure, the increase in analyst accuracy and consensus shown in Table 6 is *not* not by analysts incorporating *more* bank-specific information into forecasts but *less*, consistent with both analyst herding and Barron et al. (1998).

Taken together, our evidence analyzing analyst following, forecast error and dispersion, and more sophisticated measures of private information production rejects null Hypothesis 2.

That is, the results presented in Table 4 - Table 7 suggest that company-run stress tests lead to a decrease in analyst private information production.

5.4 Price Informativeness

In this section, we examine how company-run stress test disclosures affect the overall informativeness of market prices. As discussed in Section 2.1, regulators need to make decisions, such as whether to bail out a bank, in real time and can acquire real-time information about bank performance and solvency from market prices rather than waiting for updated accounting information included in quarterly regulatory filings. The theory model presented in Goldstein and Yang (2019) shows conditions under which a regulator can strategically disclose information in such a way as to affect the informativeness of prices via its impact on private information production. Within this model, there are two types information: one type that is known to a regulator and a second type of information that the regulator cares to learn about. Market participants can exert their resources towards producing information pertaining to either type of information (or both). If the regulator has precise information about the known type but would like to acquire more information about the other, the regulator can release information pertaining to the known type so the market participants can direct their efforts towards producing information pertaining to the second type of information which the regulator is trying to learn. As a result, since market participants direct their efforts to producing more of the second type of information information, prices become better reflections of the unknown type of information, and the regulator can learn more from market prices along the dimension by which it cares to learn.

While this model is related to our setting, there are some notable differences. First, individual banks are both running and disclosing their stress tests results, opposed to the regulator, who is gaining information from equity prices in order to make policy decisions. It is unclear whether the regulator has precise information pertaining to the bank's response to the severely adverse scenario. If the regulator's information is precise, the model suggests that the regulator can strategically disclose stress test information regarding the known type of information so market participants produce more information regarding other bank attributes that the regulator desires knowledge. Thus it is possible that, even if stress test disclosures discourage private information production regarding the risks in the loan portfolio, this decrease in private information could be offset by an increase in private information production on other dimensions. Empirically, it is difficult to decompose price informativeness as it pertains to the tw different types of information in the model, though we can measure the degree to which an individual stock price covaries with the broader market, as reflected in *IDIOSYN*. Thus, *IDIOSYN* is a measure of overall stock price informativeness, which is a function of all types of information impounded into prices.

Since this is an overall measure of stock price informativeness, it is a function of the information impounded into prices that is generated by the stress test disclosures as well as all other types of information that are not easily observable or quantifiable. Thus, the overall informativeness of stock prices will be a function of the impact the stress test disclosures directly had on the production of information, as well as the information market participants produce pertaining to all other types of information. Consistent with the model, to the extent that stress test disclosures release earnings-related information, the results presented in

Table 4 and Table 7 indicate that stress test disclosures discourage analysts from producing this type of information.

However, it is difficult for us to analyze information analysts produce pertaining to other types of information, such as bank competition. Furthermore, analysts are just one type of market participant that is producing information, and overall stock price informativeness could decrease (increase) if the reduction in private information produced by all market participants pertaining to stress tests exceeds (is less than) any increase in other privately produced information.

We analyze stock price informativeness utilizing the same empirical framework presented in Equation 7, though we follow Hutton et al. (2009) and add additional yearly stock price controls, as reflected in Equation 8.

$$
\begin{aligned}
IDIOSYN_{b,q} = \alpha_b + \gamma_q + \beta_1' \, DISCLOSE_{b,q} \times TREAT_{b,q} + \\
\beta_2' \, BANK\_CONTROLS_{b,q-1} + \beta_3' \, STOCK\_CONTROLS_{b,y-1} + \epsilon_{b,q} \quad (8)
\end{aligned}
$$

The bank level-controls are identical to those presented in Equation 7 with the addition of controls for volatility, skewness, and kurtosis that are computed over the previous year. We present the results in Table 8. The effect of $DISCLOSE \times TREAT$ is negative and statistically significant. This indicates that post-disclosure, price informativeness has decreased for treated banks relative to control banks.

One interpretation of this result is that any reduction in privately produced information related to stress tests by all market participants exceeds any increase in privately produced information pertaining to other types of information. Despite these disclosures reducing information asymmetry between the regulator and market participants, the regulator is ultimately able to infer less information from market prices. If the regulator is trying to make policy decisions based on the overall informativeness of prices, these disclosures ultimately hinder its ability gain such information.

5.5 Additional Analysis: Comparison to Fed-DFAST Banks

Our previous analysis has compared our treated banks that were required to disclose company-run stress tests to a group of banks that was never required to make such disclosures. In this analysis, we compare a set of treated banks to a set of control banks where the Federal Reserve both conducted and released DFAST results. We limit our treated sample to banks with assets exceeding $15 billion to facilitate comparison, though these results are also consistent when examining all banks with assets over $25 billion. As discussed in Section 2.2, the Federal Reserve conducted and disclosed the adverse and severely adverse scenario DFAST results for banks with assets above $100 billion in 2013 (19 banks) and those with assets greater than $50 billion in 2014 (30 banks), so we limit our sample to 2014-2017. This analysis has two shortcomings. First, our pre-period is very short, and second, both treatment and control groups are very small. We contine to define treated banks as those that made company-run DFAST disclosures.

Nonetheless, the results presented in Table 9 are qualitatively consistent with our previous analysis. This sample is over 85% smaller than the sample used for our primary analysis, which leads to a substantial reduction in power. While the results are mostly consistent with our previous analysis, not all coefficients demonstrate statistical significance. When treated banks start disclosing company-run DFAST results, they have fewer analysts making forecasts, and forecast errors and dispersion both decrease. Furthermore, both proxies for private information indicate that analysts are producing less private information, and analyst forecasts contain less private, firm-specific idiosyncratic information.

6 Conclusion

Our paper empirically examines some of the costs and benefits associated with the disclosure of company-run DFAST results. One of the most established benefits of releasing supervisory information to market participants is the enhanced ability for market participants to provide market discipline. In contrast, recent papers have highlighted a negative consequence of releasing more regulatory information and caution that market participants may become more reliant on public information as opposed to producing their own potentially valuable private information. We find that these disclosures provide new information to market participants. This could reduce information asymmetry between market participants and disclosing banks, facilitating more effective market discipline. However, we also find evidence that stress test disclosures are associated with a reduction in analysts following and decrease in the private, bank-specific information that analysts produce.

Further, we find that, post-disclosure, equity prices become less informative. This suggests that any increase in private information produced by market participants unrelated to the company-run DFAST disclosures does not surpass the decline in private information production caused by these disclosures. In this respect, if a regulator is attempting to garner greater information from equity prices, our paper suggests that regulators should exercise caution in releasing supervisory information, as this can reduce private information production and overall price informativeness.

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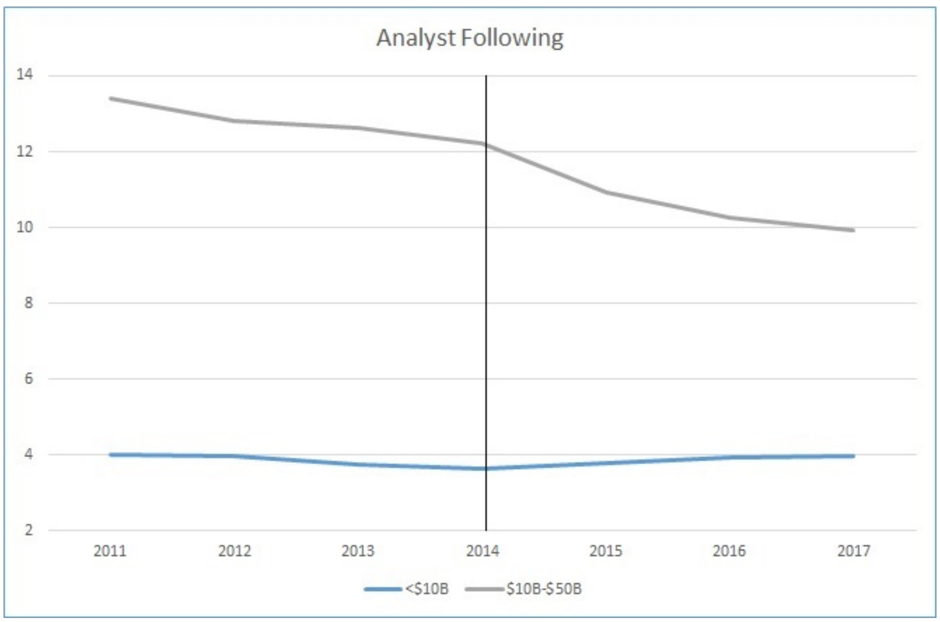
Figure 1. Trends in Analyst Following
This table compares analyst following each year for treated banks that are required to both administer and disclose DFAST results and control banks that never needed to conduct such stress tests.



Banks holding assets less than $50 billion

Table 1. Summary Statistics
This table shows the summary statistics for the key variables of interest defined in Appendix B. For each variable, we show the mean, standard deviation, 25th percentile, median, 75th percentile, maximum value, and number of observations in Columns 1-8, respectively, for the full sample of banks with assets less than $50 billion. Our sample period spans 2011-2017.

	(1) Mean	(2) SD	(3) Min	(4) P25	(5) Med	(6) P75	(7) Max	(8) N
EPS_ANALYSTS	7.0010	5.5453	1.0000	3.0000	6.0000	10.0000	34.0000	6,769
SEASONED_FCST	6.8475	5.3625	0.0000	3.0000	5.0000	9.0000	33.0000	6,769
ROOKIE_FCST	0.3775	0.6531	0.0000	0.0000	0.0000	1.0000	5.0000	6,769
EPS_FCSTNUM	7.2980	5.7762	1.0000	3.0000	6.0000	10.0000	42.0000	6,769
EPS_FE	0.0110	0.0447	0.0000	0.0006	0.0015	0.0037	0.3440	6,513
EPS_DISPERSION	0.0069	0.0282	0.0000	0.0006	0.0011	0.0024	0.2137	5,941
EPS_PRIVINFO1	0.0039	0.0150	0.0000	0.0002	0.0005	0.0017	0.1274	5,848
EPS_PRIVINFO2	0.0347	0.1652	0.0000	0.0009	0.0023	0.0060	1.2647	6,427
IDIOSYN	1.0687	1.3306	-2.0947	0.1761	0.8125	1.7330	7.7041	6,758
NCO	0.0017	0.0025	-0.0003	0.0002	0.0006	0.0021	0.0136	6,769
LNASSETS	15.1354	1.0616	13.0757	14.2657	15.0183	15.8955	17.7491	6,769
MTB	1.1679	0.4775	0.1987	0.8766	1.1494	1.4084	2.9872	6,769
CAPITAL	0.1106	0.0291	0.0445	0.0926	0.1070	0.1247	0.2521	6,769
SIGMA	0.0232	0.0141	0.0064	0.0142	0.0176	0.0269	0.1251	6,737
SKEW	0.2411	0.7095	-4.0293	-0.0668	0.1647	0.4818	7.8608	6,733
KURTOSIS	3.4607	5.7450	-0.4423	1.1346	1.9986	3.4696	119.7090	6,733

Table 2. Pre-Period Comparisons

This table compares pre-regulation characteristics between treated and control banks for the sample of banks with assets less than $50 billion over the 2011-2014 period. For a given variable, the mean, median, and number of observations are presented for treated (Columns 1-3) or control (Columns 4-6). We also report the difference in means, test statistic associated with the two-tailed difference in means test, and significance level in Columns 7-9. All variable definitions are defined in Appendix B Significance is denoted by * p <0.10, ** p < 0.05, and *** p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Treated ($10-$50 billion)			Control (< $50 billion)			Difference in Means		
	Mean	Med	N	Mean	Med	N	diff	t-stat	significance
EPS_ANALYSTS	16.4481	16.0000	703	6.0492	5.0000	2,967	10.399	58.830	***
SEASONED_FCST	15.9090	16.0000	703	5.9343	5.0000	2,967	9.975	58.311	***
ROOKIE_FCST	0.7881	1.0000	703	0.3482	0.0000	2,967	0.440	15.437	***
EPS_FCSTNUM	17.0939	17.0000	703	6.3148	5.0000	2,967	10.779	57.835	***
EPS_FE	0.0099	0.0011	703	0.0182	0.0023	2,876	-0.008	-3.440	***
EPS_DISPERSION	0.0080	0.0012	703	0.0111	0.0017	2,967	-0.003	-2.132	**
EPS_PRIVINFO1	0.0063	0.0009	703	0.0052	0.0006	2,876	0.001	1.475	
EPS_PRIVINFO2	0.0503	0.0021	702	0.0563	0.0034	2,881	-0.006	-0.598	
IDIOSYN	0.2459	0.2249	703	1.0692	0.7748	2,956	-0.823	-15.119	***
NCO	0.0023	0.0011	703	0.0025	0.0014	2,967	0.000	-1.223	
LNASSETS	16.7343	16.6880	703	14.7665	14.7721	2,967	1.968	71.854	***
MTB	1.2162	1.1171	703	1.0614	1.0460	2,967	0.155	7.856	***
CAPITAL	0.1169	0.1101	703	0.1079	0.1048	2,967	0.009	7.216	***
SIGMA	0.0229	0.0186	703	0.0277	0.0235	2,947	-0.005	-7.662	***
SKEW	0.0477	0.0385	703	0.3106	0.2195	2,947	-0.263	-9.502	***
KURTOSIS	2.7631	1.9805	703	3.5792	2.2016	2,947	-0.816	-3.827	***

Table 3. Return Results

This table presents the results for three-day excess and DGTW-adjusted cumulative abnormal returns around stress test disclosure dates. Column 1 shows the number of stress test disclosures, and Column 2 shows the excess returns as measured as the three day cumulative abnormal returns relative to the CRSP value-weighted index, while Column 4 shows the DGTW-adjusted returns. Columns 3 (and 5) indicate the number of positive and negative instances of abnormal excess (DGTW) returns. Columns 6 and 7 show the absolute value of the CRSP value-weighted and DGTW three-day cumulative abnormal returns. We report the results for disclosure dates for all stress tested banks (Federal Reserve and non-Federal Reserve DFAST disclosures) in Row 1 along with sub-samples consisting of Non-Federal Reserve DFAST disclosures (Row 2), Federal Reserve DFAST disclosures (Row 3), the first release of the non-Federal Reserve DFAST disclosures (Row 4), and subsequent releases for non-Federal Reserve DFAST disclosures (Row 5). Our sample period spans 2011-2017, and t-statistics are in parentheses. Significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Three-day CAR				Three-day |CAR|	
	N	CRSP Value-Weighted	Pos / Neg	DGTW	Pos / Neg	CRSP Value-Weighted	DGTW
All Banks	408	0.0006	213 / 195	-0.0009	210 / 198	0.0281	0.0263
		(0.51)		(-0.82)		(30.51)***	(30.50)***
Non-Fed DFAST	138	0.0023	78 / 60	0.0007	76 / 62	0.0276	0.0263
		(1.29)		(0.41)		(16.88)***	(18.17)***
Fed DFAST	270	-0.0003	135 / 135	-0.0017	134 / 136	0.0284	0.0263
		(-0.19)		(-1.29)		(25.43)***	(24.48)***
First Release (Non-Fed)	52	0.0024	31 / 21	0.0004	30 / 22	0.0222	0.0216
		(1.03)		(0.17)		(11.29)***	(13.92)***
Subsequent Releases (Non-Fed)	86	0.0022	47 / 39	0.0009	46 / 40	0.0309	0.0292
		(0.90)		(0.37)		(13.56)***	(14.07)***

Table 4. Number of Analysts Making Forecasts and Total Analyst Forecasts

This table reports the OLS regression results where the dependent variable is the number of analysts making Earnings Per Share forecasts (*EPS_ANALYSTS*) in Columns 1-2 or the total number of analyst forecasts (*EPS_FCSTNUM*) for banks with assets of less than $50 billion. *TREAT* is an indicator variable that takes a value of 1 if the bank has assets between $10-$50 billion and is therefore required to conduct a company-run stress test and disclose the results. Our sample period spans 2011-2017, and the *DISCLOSE* variable is an indicator variable that takes a value of 1 during the years 2015-2017, and $DISCLOSE \times TREAT$ is the interaction between the *DISCLOSE* and *TREAT* variables. Firm and year-quarter fixed effects are included in all regressions, and these fixed effects subsume the direct effects of *TREAT* and *POST*, which are omitted. All other variable definitions are defined in Appendix B. Standard errors are adjusted for cluster effects at the bank level. Robust t-statistics are in parentheses. Significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	(1) EPS_ANALYSTS	(2) EPS_FCSTNUM
DISCLOSE x TREAT	-0.8130	-0.7670
	(-2.07)**	(-2.05)**
LNASSETS	2.3008	2.2310
	(5.53)***	(5.26)***
NCO	-14.5046	-15.4160
	(-0.48)	(-0.51)
MVE	-0.0000	-0.0000
	(-2.11)**	(-1.99)**
MTB	0.0271	-0.0099
	(0.09)	(-0.03)
CAPITAL	8.4666	9.5439
	(1.60)	(1.78)*
Year-Quarter FE	Yes	Yes
Bank FE	Yes	Yes
Observations	6,769	6,769
R-squared	0.9320	0.9361

Table 5. Number of Seasoned and Rookie Analysts

This table reports the OLS regression results where the dependent variable is either the number of seasoned (*SEASONED_FCST*) or "rookie" (*ROOKIE_FCST*) analysts making Earnings Per Share forecasts for banks with assets of less than $50 billion. *TREAT* is an indicator variable that takes a value of 1 if the bank has assets between $10-$50 billion and is therefore required to conduct a company-run stress test and disclose the results. Our sample period spans 2011-2017, and the *DISCLOSE* variable is an indicator variable that takes a value of 1 during the years 2015-2017, and $DISCLOSE \times TREAT$ is the interaction between the *DISCLOSE* and *TREAT* variables. Firm and year-quarter fixed effects are included in all regressions, and these fixed effects subsume the direct effects of *TREAT* and *POST*, which are omitted. All other variable definitions are defined in Appendix B. Standard errors are adjusted for cluster effects at the bank level. Robust t-statistics are in parentheses. Significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	(1) SEASONED_FCST	(2) ROOKIE_FCST
DISCLOSE x TREAT	-0.7142	-0.0466
	(-2.00)**	(-0.80)
LNASSETS	2.0973	0.1630
	(5.27)***	(2.96)***
NCO	-8.8292	-4.1489
	(-0.30)	(-0.90)
MVE	-0.0000	-0.0000
	(-2.08)**	(-0.90)
MTB	0.0047	-0.0504
	(0.02)	(-1.15)
CAPITAL	8.1882	0.7367
	(1.66)*	(0.97)
Year-Quarter FE	Yes	Yes
Bank FE	Yes	Yes
Observations	6,769	6,769
R-squared	0.9270	0.1713

Table 6. Analyst Forecast Error and Dispersion

This table reports the OLS regression results where the dependent variables are analyst Earnings Per Share Forecast Error and Dispersion (*EPS_FE* and *EPS_DISPERSION*. We examine banks with assets less than $50 billion. *TREAT* is an indicator variable that takes a value of 1 if the bank has assets between $10-$50 billion and is therefore required to conduct a company-run stress test and disclose the results. Our sample period spans 2011-2017, and the *DISCLOSE* variable is an indicator variable that takes a value of 1 during the years 2015-2017, and $DISCLOSE \times TREAT$ is the interaction between the *DISCLOSE* and *TREAT* variables. Firm and year-quarter fixed effects are included in all regressions, and these fixed effects subsume the direct effects of *TREAT* and *POST*, which are omitted. All other variable definitions are defined in Appendix B. Standard errors are adjusted for cluster effects at the bank level. Robust t-statistics are in parentheses. Significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	(1) EPS_FE	(2) EPS_DISPERSION
DISCLOSE x TREAT	-0.0049	-0.0053
	(-1.62)	(-2.76)***
LNASSETS	0.0208	-0.0002
	(2.53)**	(-0.53)
NCO	4.9766	0.0104
	(4.77)***	(1.78)*
MVE	0.0000	0.0000
	(2.72)***	(1.90)*
MTB	-0.0230	-0.0153
	(-4.04)***	(-4.57)***
CAPITAL	-0.6008	-0.4061
	(-4.55)***	(-4.19)***
Year-Quarter FE	Yes	Yes
Bank FE	Yes	Yes
Observations	5,848	5,941
R-squared	0.5920	0.6425

Table 7. Private Information Production

This table reports the OLS regression results where the dependent variable the amount of private firm-specific information produced by analysts as measured through earnings per share forecasts using either the methodology of Barron et al. (1998), *EPS_PRIVATE_INFO1*, or time-series predictions using a seasonal random walk, *EPS_PRIVATE_INFO2*, for banks with assets less than $50 billion. *TREAT* is an indicator variable that takes a value of 1 if the bank has assets between $10-$50 billion and is therefore required to conduct a company-run stress test and disclose the results. Our sample period spans 2011-2017, and the *DISCLOSE* variable is an indicator variable that takes a value of 1 during the years 2015-2017, and $DISCLOSE \times TREAT$ is the interaction between the *DISCLOSE* and *TREAT* variables. Firm and quarter fixed effects are included in all regressions, and these fixed effects subsume the direct effects of *TREAT* and *POST*, which are omitted. All other variable definitions are defined in Appendix B. Standard errors are adjusted for cluster effects at the bank level. Robust t-statistics are in parentheses. Significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	(1) EPS_PRIV_INFO1	(2) EPS_PRIV_INFO2
DISCLOSE x TREAT	-0.0033	-0.0197
	(-2.70)***	(-1.71)*
DISCLOSE	0.0029	-0.0013
	(2.12)**	(-0.11)
TREAT	0.0029	0.0119
	(1.83)*	(0.90)
LNASSETS	0.0057	0.0445
	(2.11)**	(1.30)
NCO	1.8730	26.5566
	(5.22)***	(4.38)***
MVE	0.0000	0.0000
	(1.16)	(0.88)
MTB	-0.0071	-0.0266
	(-3.55)***	(-1.12)
CAPITAL	-0.1597	-1.1831
	(-3.99)***	(-2.90)***
Year-Quarter FE	Yes	Yes
Bank FE	Yes	Yes
Observations	5,848	4,357
R-squared	0.3573	0.5177

Table 8. Market Synchronicity

This table reports the OLS regression results where the dependent variable is the degree of idiosynchratic information in stock returns (*IDIOSYN*), where higher values mean that a bank's returns are less synchronous with the market and thus are driven by more idiosyncratic information. Following Hutton et al. (2009), *IDIOSYN* is calculated as $\ln(\frac{1-QuarterlyRSQ}{QuarterlyRSQ})$, where *QuarterlyRSQ* is alculated as the coefficient of determination from a regression of firm excess returns on market and industry excess returns, where the model is defined as $r_q = \alpha + \beta_1 r_{m,q-1} + \beta_2 r_{m,q} + \beta_3 r_{m,q+1} + \gamma_1 r_{i,q-1} + \gamma_2 r_{i,q} + \gamma_3 r_{i,q+1} + \epsilon_q$ where r_q, $r_{m,q}$, and $r_{i,q}$ are excess returns of the stock, the market, and the stock's industry during quarter q. Our sample contains banks with assets less than $50 billion. The variable *TREAT* is an indicator variable that takes a value of 1 if the bank has assets between $10-$50 billion and is therefore required to conduct a company-run stress test and disclose the results. Our sample period spans 2011-2017, and the *DISCLOSE* variable is an indicator variable that takes a value of 1 during the years 2015-2017, and $DISCLOSE \times TREAT$ is the interaction between the *DISCLOSE* and *TREAT* variables. Firm and quarter fixed effects are included in all regressions, and these fixed effects subsume the direct effects of *TREAT* and *POST*, which are omitted. All other variable definitions are defined in Appendix B. Standard errors are adjusted for cluster effects at the bank level. Robust t-statistics are in parentheses. Significance is denoted by * p <0.10, ** p < 0.05, and *** p<0.01.

	(1) IDIOSYN
DISCLOSE x TREAT	-0.2698
	(-4.09)***
LNASSETS	26.7145
	(2.75)***
NCO	0.0000
	(3.37)***
MVE	-0.2029
	(-2.48)**
MTB	-0.7867
	(-9.15)***
CAPITAL	1.1052
	(0.81)
VOLATILITY	-0.1168
	(-0.04)
SKEW	-0.0180
	(-0.82)
KURTOSIS	-0.0011
	(-0.38)
Year-Quarter FE	Yes
Bank FE	Yes
Observations	6,733
R-squared	0.7231

Table 9. Large Banks as the Control Group

This table reports the OLS regression results where the dependent variables are the number of analysts making earnings per share forecasts (*EPS_ANALYSTS*), the total number of analyst forecasts (*EPS_FCSTNUM*), number of seasoned (*SEASONED_FCST*) or "rookie" (*ROOKIE_FCST*) analysts making Earnings Per Share forecasts, along with analyst earnings earnings per share forecast error (*EPS_FE*), dispersion (*EPS_DISPERSION*), the amount of private firm-specific information produced by analysts as measured through earnings per share forecasts using either the methodology of Barron et al. (1998), *EPS_PRIVATE_INFO1*, or time-series predictions using a seasonal random walk, *EPS_PRIVATE_INFO2*, and synchronicity with the market (*IDIOSYN*) for banks with assets greater than $15 billion. *TREAT* is an indicator variable that takes a value of 1 if the bank has assets between $25-$50 billion and is therefore required to conduct a company-run stress test and disclose the results. Our sample period spans 2013-2017, and the *DISCLOSE* variable is an indicator variable that takes a value of 1 during the years 2015-2017, and $DISCLOSE \times TREAT$ is the interaction between the *DISCLOSE* and *TREAT* variables. Firm and year-quarter fixed effects are included in all regressions, and other variable definitions are defined in Appendix B. Standard errors are adjusted for cluster effects at the bank level. Robust t-statistics are in parentheses. Significance is denoted by * p <0.10, ** p < 0.05, and *** p<0.01.

	(1) EPS_ANALYSTS	(2) EPS_FCSTNUM	(3) SEASONED_FCST	(4) ROOKIE_FCST	(5) EPS_FE	(6) EPS_DISPERSION	(7) EPS_PRIV_INFO1	(8) EPS_PRIV_INFO2	(9) IDIOSYN
DISCLOSE x TREAT	-0.5824	-0.2590	-0.3044	0.0631	0.0002	-0.0004	-0.0003	-0.0030	-0.1735
	(-0.81)	(-0.36)	(-0.43)	(0.59)	(0.79)	(-1.29)	(-0.15)	(-1.82)*	(-2.51)**
LNASSETS	3.7913	3.4836	3.5009	-0.1711	-0.0013	-0.0000	-0.0024	0.0059	36.7920
	(3.68)***	(3.24)***	(3.50)***	(-0.75)	(-1.14)	(-0.66)	(-0.76)	(1.99)**	(1.90)*
NCO	-140.5611	-100.9468	-132.8024	14.0929	0.4089	0.0004	1.6522	2.3421	-0.0000
	(-0.70)	(-0.50)	(-0.74)	(0.40)	(0.88)	(0.80)	(1.22)	(1.61)	(-1.01)
MVE	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.8481	-0.0000	0.0000	-0.0247
	(-0.14)	(-0.21)	(-0.22)	(-0.02)	(-0.36)	(1.89)*	(-0.08)	(0.66)	(-0.25)
MTB	-1.4497	-1.4147	-1.2244	-0.1733	-0.0018	-0.0000	-0.0003	-0.0007	-0.4987
	(-2.31)**	(-2.33)**	(-2.10)**	(-1.14)	(-3.20)***	(-0.15)	(-0.19)	(-0.32)	(-3.63)***
CAPITAL	-14.9631	-15.0745	-16.8092	0.2802	-0.0044	-0.0013	-0.0321	0.0643	1.5911
	(-1.02)	(-1.05)	(-1.24)	(0.11)	(-0.38)	(-2.17)**	(-0.85)	(1.66)	(0.72)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,492	1,492	1,492	1,492	1,484	1,484	1,484	1,279	1,487
R-squared	0.9551	0.9589	0.9513	0.1842	0.2898	0.4238	0.4907	0.1722	0.6669

A Stress Test History

This table reports the assets size reporting threshold for each type of stress test along with the number of banks stress tested by year.

	SCAP		CCAR		Federal-Reserve DFAST		Company-run DFAST	
	Asset threshold	Banks	Asset threshold	Banks	Asset threshold	Banks	Asset threshold	Banks
2009	>$100 billion	19						
2010								
2011			>$100 billion	19				
2012			>$100 billion	19				
2013			>$100 billion	18	>$100 billion	18		
2014			>$50 billion	30	>$50 billion	30		
2015			>$50 billion	31	>$50 billion	31	$10-$50 billion	51
2016			>$50 billion	33	>$50 billion	33	$10-$50 billion	54
2017			>$50 billion	33	>$50 billion	33	$10-$50 billion	58

B Variable Descriptions

Variable	Definition	Source
CAPITAL	Book value of equity (bhck3210) divided by total bank assets (bhck2170)	Y-9C
DISCLOSE	*DISCLOSE* is an indicator variable that takes a value of 1 during the years 2015-2017	
EPS_ACTUAL	Actual earnings per share	S&P Global Market Intelligence
EPS_ANALYSTS	Number of analysts providing earnings per share forecasts	IBES
EPS_DISPERSION	Standard deviation of analyst earnings per share forecasts normalized by share price at the end of the previous quarter	IBES
EPS_FCSTNUM	Total number of quarterly analyst earnings per share forecasts, allowing for analyst forecast revisions	IBES
EPS_FE	Earnings per share forecast error is the absolute value of the difference between the mean analyst earnings per share forecast and the actual earnings per share normalized by price at the end of the previous quarter, calculated as $\frac{\lvert EPS\_MEAN_{b,q-1} - EPS\_ACTUAL_{b,q}\rvert}{Price_{b,q-1}}$	IBES
EPS_MEAN	Average earnings per share forecast across all analysts	IBES
EPS_PRIV_INFO1	Following Barron et al. (1998), this variable measures the precision of idiosyncratic information in analysts' earnings per share forecasts, calculated as $\frac{(EPS\_SD_q)^2}{(((1-1/EPS\_ANALYSTS_{b,q}) \times EPS\_SD_{b,q}{}^2) + EPS\_SE_q)^2}$	IBES
EPS_PRIV_INFO2	The magnitude of the deviation of the average analysts' forecast from a time-series prediction based on a seasonal random walk normalized by price at the end of the previous quarter, calculated as $\frac{\lvert EPS\_MEAN_{b,q} - EPS\_ACTUAL_{b,q-4}\rvert}{Price_{b,q-1}}$	IBES
EPS_SD	Standard deviation of the consensus mean earnings per share forecast	IBES
EPS_SE	Squared error of the consensus mean earnings per share forecast, calculated as the square of the difference between *EPS_MEAN* and *EPS_ACTUAL*	IBES
IDIOSYN	This variable indicates the degree of idiosyncratic information in a firm's stock returns. Following Hutton et al. (2009), it is calculated as $\ln(\frac{1-QuarterlyRSQ_{b,q}}{QuarterlyRSQ_{b,q}})$	CRSP
KURTOSIS	Kurtosis of daily returns over the calendar year	CRSP
MTB	Market value of equity divided by book value of equity (bhck3210), where market value of equity is calculated as shares outstanding (shrout) multiplied by price (prc)	Y-9C and CRSP
MVE	Market value of equity is calculated as shares outstanding multiplied by price	Y-9C and CRSP

NCO	Average net charge-offs, calculated as gross charge-offs (bhck4635) minus recoveries (bhck4605), over the trailing four quarters normalized by last quarter's total loans	Y-9C
QuarterlyRSQ	Calculated as the coefficient of determination from a regression of firm excess returns on market and industry excess returns, where the model is defined as $r_{b,q} = \alpha + \beta_1 r_{m,q-1} + \beta_2 r_{m,q} + \beta_3 r_{m,q+1} + \gamma_1 r_{i,q-1} + \gamma_2 r_{i,q} + \gamma_3 r_{i,q+1} + \epsilon_q$ where r_q, $r_{m,q}$, and $r_{i,q}$ are excess returns of the stock, the market, and the stock's industry during quarter q.	CRSP
ROOKIE_FCST	Number of "rookie" analysts making forecast where a "rookie" is considered an analyst that has never made a previous earnings forecast at the same bank	IBES
SEASONED_FCST	Number of seasoned analysts making forecast where a seasoned analyst is considered an analyst that has previously made an earnings forecast at the same bank	IBES
SKEW	Skewness of daily returns over the calendar year	CRSP
TOTAL_ASSETS	Total bank assets (bhck2170)	Y-9C
TREAT	*TREAT* is an indicator variable that takes a value of 1 if the bank has assets between \$10-\$50 billion and is therefor required to conduct a company-run stress test and disclose the results.	
VOLATILITY	Standard deviation of daily returns over the calendar year	CRSP