STRESS TESTS, FINANCIAL MARKETS, AND BANK RUNS IN THE MODERN ERA:

An Empirical and Theoretical Analysis

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Abstract

In recent years, the banking system has (1) undergone major changes in the stress test regulatory framework and (2) weathered a bank run crisis not seen since 2008. This thesis examines these two aspects from empirical and theoretical perspectives, respectively. First, I empirically analyze whether 2018 regulatory changes to Dodd-Frank supervisory stress testing rules — the Federal Reserve's main oversight tool — created significant changes in idiosyncratic risk and significant new market information around stress test results disclosure dates. I find the idiosyncratic risk of bank stock returns is significantly different for certain banks, and, critically, market reactions to stress test results disclosures may not reflect this change in idiosyncratic risk. This suggests current stress tests may not fully reflect banking system risks. Second, I modify and solve a model of demand deposit contracts in the context of social media and deposit insurance. I find the probability of a bank run increases and decreases in these two factors, respectively. Policymakers should carefully consider the implications of stress test reforms, social media, and deposit insurance as they chart a path forward to safeguard the banking system.

Part 1: The Effect of Dodd-Frank Rollback on Financial Markets

Introduction

> *For example, the agencies are considering whether to apply the proposed new rule to banks with assets over $100 billion. This consideration has certainly been influenced by the recent experience with three bank failures of institutions with assets between $100 billion and $250 billion. If we had any doubt that the failure of banks in this size category can have financial stability consequences, that has been answered by recent experience.*
>
> *FDIC Chairman Martin J. Gruenberg [on the Basel III Endgame](), June 2023*

In the last year, financial markets and the banking system experienced turbulence not seen since the 2008 crisis. Given that stress tests emerged as the Federal Reserve's primary assessment for examining the health of the banking system after the 2008 crisis, a natural question is whether the 2018 weakening of the Fed's stress test practices increased the risk of financial instability. That three financial institutions failed with assets in the $100 billion to $250 billion range suggests there are real risks to financial stability for banks of this size. <u>I hypothesize that less burdensome stress-testing regulation for banks post-2018, which freed up cash previously allocated for reserve capital for stress tests, would lead to heterogeneity in the kinds of investment decisions banks make. Assuming markets price that heterogeneity efficiently, it would appear as idiosyncratic risk, measured by the error term of a regression of those banks' stock returns on the S&P 500 and a custom bank index, and new market information, measured by the absolute value of cumulative abnormal return.</u> I test this hypothesis on three sets of banks using 2018 data and 2019 data: those stress tested both before and after the regulation change (10 banks), those not stress tested in either year (3 banks), and those stress tested before the regulation change but not after (9 banks). 2018 was the last year before the change in stress test disclosure rules, but February 5, 2019 was when the Fed announced the new regulation's frequency of stress testing for Category IV banks. 2019 was the first year the new rules were implemented. For a given set of banks, I compare the regression coefficients (including the error term) from the regression that uses pre-February 5, 2019 data and the regression that uses post-February 5, 2019 data by performing a t-test for significance. I also compare the 2018 and 2019 CAR values using a t-test for significance.

Table 1: Sets of Banks		
Stress Tested Before and After Regulation Changed	**Not Stress Tested Before Or After Regulation Change**	**Stress Tested Before But Not After Regulation Change**
1. Bank of America 2. Citigroup 3. Goldman Sachs 4. JPMorgan Chase 5. Morgan Stanley 6. Wells Fargo 7. BNY Mellon 8. Capital One 9. PNC Financial Services Group 10. US Bancorp	1. Charles Schwab 2. Comerica 3. Truist Financial	1. Ally Financial 2. American Express 3. Citizens Financial Group 4. Discover Financial Services 5. Fifth Third Bancorp 6. Huntington Bancshares 7. KeyCorp 8. M&T Bank 9. Regions Financial

Thus, in this paper, I consider if supervisory stress test results disclosures created significant idiosyncratic risk in a 2-factor model of bank stock returns and significant new market information after Congress changed the supervision requirements in 2018. First, I find the idiosyncratic risk of bank stock returns is significantly different for the first and third sets of banks. Second, I find the 2018 stress test changes did not create significant new market information around test results disclosure dates. This suggests current stress tests are not fully reflective of banking system risks.

In May 2018, Congress passed the bipartisan Economic Growth, Regulatory Relief, and Consumer Protection Act. The law weakened company-run and supervisory stress testing rules as prescribed in the 2010 Dodd-Frank Act for small and midsize banks, those with assets between \$100 billion and \$250 billion, by subjecting them to supervisory stress tests every two years instead of annually. The “year off” from stress testing permits small and midsize banks to make investment decisions, such as lending, with the capital they would have previously allocated as a buffer for the stress tests. The law also lowered the number of required supervisory stress test scenarios from three to two. Thus, the law modified the eligibility, frequency, and scenarios of supervisory stress tests.

In March 2023, the U.S. banking system underwent a real stress test. SVB's collapse motivates a fundamental question for the banking system at large: did the 2018 rollback of stress testing rules for small and midsize banks increase risk in the banking system?

The appendix contains various figures.

Background

A. Historical Overview

Following the Global Financial Crisis, Congress passed the Dodd-Frank Act of 2010. Among other reforms, Dodd-Frank prescribed stress tests for financial institutions with over $10 billion in assets. The Dodd-Frank Act Stress Tests (DFAST) assessed the impact of forward-looking economic shocks on capital ratios and banks' ability to absorb losses. Three main scenarios were used: baseline, adverse, and severely adverse. For example, the scenarios have included unemployment spiking to 10 percent and commercial real estate prices plummeting 40 percent. The stress tests proved to be effective. In prepared remarks at a financial stability conference in 2013, then-Chair of the Federal Reserve Ben Bernanke said, "The resilience of the U.S. banking system has greatly improved since then [2009], and the more intensive use and greater sophistication of supervisory stress testing, as well as supervisors' increased emphasis on the effectiveness of banks' own capital planning processes, deserve some credit for that improvement."

Dodd-Frank defined two categories of "covered" institutions: those with $10 - $50 billion in assets, and those above $50 billion in assets. The law required banks with over $50 billion in assets to undergo annual supervisory stress testing and all banks with over $10 billion in assets to submit the results of annual company-run stress tests to the Fed. As described in the Fed website, "In conducting the supervisory stress tests, the Federal Reserve projects balance sheets, RWAs, net income, and resulting post-stress capital levels and regulatory capital ratios over a nine-quarter 'planning horizon,' generally using a set of capital action assumptions prescribed in the Dodd-Frank Act stress test rules." Similarly, the company-run stress tests "use the same planning horizon, capital action assumptions, and scenarios as those used in the supervisory stress test."

The 2018 law, among other reforms, amended the classification of "covered" institutions, frequency of supervisory and company-run stress tests, and number of scenarios. The law revised the classification of covered institutions into four categories based primarily on asset size and risk to the financial system. Generally speaking, the classifications are as follows: Category I is U.S. globally systemically important banks (G-SIBs); Category II is banks with more than $700 billion in assets; Category III is banks with more than $250 billion in assets; Category IV is banks with $100 billion to $250 billion in assets. In 2019, the Fed and federal banking agencies finalized rules for supervision standards for the four categories.

This paper focuses on the rules changes for Category IV banks. Whereas previously all banks over $50 billion in assets underwent annual supervisory stress tests, now only those above $250 billion in assets continue undergoing annual supervisory stress tests. Those between $100 to $250 billion in assets are subject to "periodic" supervisory stress tests, but the 2018 law did not define the precise frequency of "periodic." Instead, the Fed announced on February 5, 2019 that it determined "periodic" to mean every two years. This effectively exempted small and midsize banks, those between $100 to $250 billion, from annual stress tests—roughly one-third less participated than the 2017 stress tests. Banks below $250 billion in assets were also exempt from company-run stress tests, raised from the $10 billion threshold. Finally, the law reduced the number of required stress test scenarios from three to two, eliminating the "adverse" scenario and maintaining the "baseline" and "severely adverse" scenarios.

B. Brief Literature Review

Previous literature shows stress tests are a critical tool in conducting oversight of the banking sector. Herring and Schuermann discuss how stress tests identified banks with capital challenges and improved public confidence in the banking system by requiring banks to raise capital. They also discuss the objectives of stress testing which provide the underpinnings for why we consider the structure of stress tests as part of this study. This structure includes the test scenarios, risks to be tested, which banks to test, test result disclosure rules, etc. They also acknowledge that stress tests are far from perfect, and face challenges ranging from cyber to the implications of shocks. Some have called for strengthening stress testing rules to cover a wider range of risks, include feedback effects between banks and the real economy, be expanded to more institutions, and be streamlined globally (such as the Basel III capital framework).

Goldstein and Sapra show that stress test results disclosure may limit market information generation. However, this paper relies on the methodology in Flannery, which shows that stress test results disclosures as an event study are associated with significantly higher absolute abnormal returns. They use several measures of market response to stress test announcements, such as cumulative abnormal returns. They also show that net market information generation is not limited by stress test results disclosures, which is fundamental to this paper's methodology. They also find that companies with more leverage and risk are more affected by stress test results disclosure information. These results emphasize the importance of market information generation, and how stress tests results disclosure can have real effects on market signals.

Methodology

There are two components to this study. First, I determine whether 2018 changes to the supervisory stress testing rules created significant idiosyncratic risk. Recall I separate banks into one of three sets of banks: those stress tested both before and after the regulation change (10 banks), those not stress tested in either year (3 banks), and those stress tested before the regulation change but not after (9 banks). There is no overlap between any of the three sets (they are all pairwise disjoint). The Fed's announcement date of the new frequency for Category IV banks was February 5, 2019. In order to capture sufficient data but not so much that other monthly Fed announcements could affect bank stock market returns, I use an event window of one month prior to the announcement date to one month after: January 5, 2019 to February 4, 2019 and February 5, 2019 to March 5, 2019.

I construct a two-factor ordinary least-squares (OLS) regression model that aims to track a bank's stock returns as closely as possible. The first factor is the S&P 500 daily market returns. I access them using the yfinance package in Python, which pulls data from Yahoo! Finance. The second factor is a custom bank index I create as follows: for a given bank on a given day, compute the average of the daily returns of all other banks in that set of banks. Thus, each bank each day has its own custom bank index value that its own daily returns (dependent variable) can be regressed against as one factor in the two-factor model. For each bank, I run two regressions: one for the one month window before the announcement date and a second regression for the one month window after the announcement date.

The two-factor OLS regression model is the following for bank stock i:

$$y_{i,t} = \beta_i * marketReturn_t + bankIndexCoeff_i * bankIndexReturn_{i,t} + \epsilon_i$$

Where $y_{i,t}$ is bank i's true daily return on day t, $marketReturn_t$ is the daily S&P 500 market return on day t, $bankIndexReturn_{i,t}$ is the custom bank index value for bank i on day t, and the OLS function determines the three optimal coefficient values i.e. for β_i, $bankIndexCoeff_i$, and ϵ_i.

Thus, for each $y_{i,t}$, there is an error: the difference between the true daily return and the estimated return derived from the regression above. Figure 1 plots these errors for the three sets of banks. For each bank stock in a set of banks, that stock's idiosyncratic risk is the standard deviation of the errors over the time window. Thus, I want the idiosyncratic risk $\sigma_{\epsilon_i,N}$ for bank stock i for a period of N days. $\bar{\epsilon}_{i,N}$ is the mean error for stock i over the N days. In this case, I compute the idiosyncratic risk for a period of one month (say N_1 days) before the announcement date and another idiosyncratic risk for a period of one month (say N_2 days) after the announcement date. Suppose $\epsilon_{i,n}$ is the error for stock i on day n of the month, $n \in \{1, 2, \ldots, N_j\}$, $j \in \{1, 2\}$. Then:

$$\sigma_{\epsilon_i,N_1} = \sqrt{\frac{1}{N_1}\sum_{n=1}^{N_1}(\epsilon_{i,n} - \bar{\epsilon}_{i,N_1})^2},$$

$$\sigma_{\epsilon_i,N_2} = \sqrt{\frac{1}{N_2}\sum_{n=1}^{N_2}(\epsilon_{i,n} - \bar{\epsilon}_{i,N_2})^2}$$

In a slight abuse of language, I consider the idiosyncratic risk for a stock i to be a regression coefficient. So there are four regression coefficients. To determine if there was a significant change in the regression coefficients before and after the Fed's announcement date, I perform a t-test on the four regression coefficients using the OLS output coefficient values. Figure 2 contains the results of the t-test for three sets of banks.

The second component of this study is to quantify unexpected changes in stock prices at the date of the stress test results disclosure. I rely on a similar methodology as done in Flannery. I measure the market reaction to DFAST results disclosures for each date, June 21, 2018 (before the regulatory change) and June 21, 2019 (after the regulatory change). For each date, I use the absolute value of cumulative abnormal returns, denoted as |CAR|, as the primary measure for market information generated over an event window around the results disclosure date. I exclude banks subject to mergers and acquisitions or that are subsidiaries of foreign firms. For each disclosure date, I calculate the average of the |CAR| values from each bank tested.

I measure the normal return using the true daily stock returns. The abnormal return is the normal return minus the expected return as if the event never happened. I measure the expected return using the 2-factor regression model constructed above. The event day t is the first trading day after the stress test result disclosure. For a given date and firm, the abnormal return is summed over the event window [t - 1, t + 1] to get the cumulative abnormal returns (CAR). I use the absolute value of the CAR for a given firm because it is a direction-neutral measure: it considers positive or negative information as a market reaction. Finally, I take the average of each firm i's |CAR|, denoted $|CAR|_i$ for a total of J firms:

$$|CAR| = \frac{1}{J}\sum_{i=1}^{J} |CAR_i|$$

Finally, for each set of banks, I perform a t-test between the June 2018 and June 2019 CAR values for banks in that set. Figure 3 shows the result of the t-tests.

Results and Discussion

Figures 1.1 and 1.3 are the most important: they show significance at the 0.01 and 0.1 levels, respectively, that the idiosyncratic risk of bank stock returns is significantly different before vs. after the Fed's February 5, 2019 announcement of the two-year stress testing cycle for

Category IV banks. The result for Figure 1.3 is the most revealing. It is also consistent with my hypothesis: that lifting stress-testing regulation requiring higher capital requirements for banks to undergo stress testing means banks can use the capital to make a variety of investment decisions with a range of risks, known as heterogeneity. Assuming markets price that heterogeneity efficiently, it would appear as idiosyncratic risk, measured by the error term of a regression of those banks' stock returns on the S&P 500 and a bank index, and new market information, measured by the absolute value of cumulative abnormal return. The main finding is that the Figure 1.3 result suggests the 2018 reforms would significantly change the level of risk posed by banks that otherwise underwent annual stress testing rather than biennial stress testing. Because the CAR t-test for this set of banks is non-significant, it suggests the market viewed the easing of regulation as a potential source of a change in idiosyncratic risk around the announcement date (February 2019) but did not believe this significant change in idiosyncratic risk was reflected in market reactions to stress tests results disclosures from June 2018 to June 2019. This is significant because one of the primary objectives of the stress testing framework is to assess the risks that banks pose to the financial system as a result of their investment decisions. But since that risk is not fully reflected in the market reactions to stress tests results disclosures—as the result here suggests—then Congress and the Fed cannot rely so heavily on current stress tests to assess the health of the banking system; they need to find another way to unearth that risk potential (new stress tests scenarios, regulatory reforms, etc). The potentially large downside of missing a significant change in banking system risk levels could very well exceed the cost of supervisory oversight. I also consider why the stress tests results disclosure dates may not create new market information below for the CAR results.

The result for Figure 1.1 is surprising because the 2018 reforms left regulatory requirements for the largest banks largely intact, all the more so at a low significance level of 0.01. A possible explanation is markets reacted positively (i.e. less uncertainty) to the Fed's not attempting a change in regulation for the largest banks (and the most systemically important) in their February 2019 announcement. While markets may respond with less uncertainty to less bank regulation, due to the systemic importance of these largest banks, the reverse dynamic may be occurring here. The graph of errors in Figure 1 appears to have less volatility in the error rates post-February 5, 2019 announcement, which would support this explanation.

The result for Figure 1.2 makes sense: banks not involved with the stress testing framework before and after the 2018 rules change shouldn't see significant changes in their idiosyncratic risk, at least not due to the rules change.

The |CAR| is the regression output variable indicating market information. Figure 3 below shows the t-tests for each set of banks' |CAR| values. There is no p-value less than the 0.01, 0.05, or 0.1 levels. Therefore, I fail to reject the null hypothesis that the 2018 stress test rules change did not create significant new market information for DFAST tests. I consider three reasons why no significant market information was created: Generally, the event window did not capture it, there was no real information effect due to stress tests functioning as health indicators for the banking industry, there was no real information effect due to stress tests being less meaningful, and the regression model (used to find the expected return) was unable to discern a market reaction.

First, the rules change created real information, but market reaction to the stress test results during the event window may have been dampened by prior public knowledge of the Fed's implementation of the rules change. The Fed followed a multi-year process of publicly revealing and finalizing their approach to implementing the 2018 rules change, well in advance of the stress test results disclosure dates. Thus, any information that could have been revealed by changes in market information levels during the event window was already known to investors.

Second, there was no real information effect. Investors might have assumed non-stress tested banks with similar businesses as larger, stress tested banks would have similar stress test results anyway. Research shows stress test results produce information about the state of the banking industry more broadly, including for non-stress tested banks. That suggests investors did not believe the 2018 rules change significantly curtailed their ability to assess the health of the banking system, so no significant market information was created.

Third, there was no real information effect because stress test results are simply not as meaningful when smaller banks are excluded. Suppose investors believe that big banks are generally better-capitalized, stronger, and better-managed than small and midsize banks. Then they might believe that big banks can withstand stress test scenarios better than smaller lenders that may be more vulnerable to market shocks. Thus, how meaningful is a stress test if you don't test the most vulnerable banks? Investors may shrug at the rules change since there is limited information value in unsurprising annual announcements of all big banks passing the stress tests.

Finally, the regression model may not have uncovered a real information effect. The sample size of the data is limited, and a two-factor model cannot perfectly capture bank returns.

Implications for Policymakers, Future Research

The March 2023 banking crisis underscored the need for sound policy to address weaknesses in the banking system. The crisis required an immediate response from the President, Treasury, FDIC, and close monitoring from Congress to ensure it did not trigger a financial contagion. By taking the extraordinary step of protecting the 89 percent of deposits uninsured by the FDIC—over $150 billion—regulators sought to reduce the risk of contagion and stabilize the banking system.

Two future research questions stem from this kind of heavy-handed government response: how should we think about the moral hazard relating to the response to the March 2023 crisis? One might suppose such interference reduces the incentive of banks to manage risks well. Furthermore, if the FDIC effectively insures all or much more than the $250,000 limit in deposits, it opens the door to asking what a deposit insurance limit even means. Practically, one is asking what the optimal level of deposit insurance is, a tricky economics question. Perhaps a phenomenon of "too small to fail" has taken root since the government fears even a small bank failing could trigger depositors in small banks across the country to panic and increase the risk of contagion, inciting a crisis in the banking system. We are reminded of the fragility of the financial system and the real risks that banks and regulators must manage responsibly.

As a consequence, it is very much in policymakers' interest to enact guardrails to prevent such (potentially catastrophic) crises from happening, from higher capital requirements to stronger lending and liquidity guidelines. The main finding of this paper—that the 2018 reforms would significantly change the idiosyncratic risk posed by banks that switched from an annual to a two-year testing cycle—suggests policymakers should take stock of the potential unintended consequences of new reforms before enacting them. The 2018 Dodd-Frank rollback was strongly bipartisan in a polarized time and supported by the banking industry; yet that may not be a sufficient bar to justify the reform.

In contrast, as alluded to in the last section, if there is a limited or nonexistent real information effect, the Fed may believe they implemented the 2018 stress test changes smoothly—i.e. without suddenly affecting production of market information at result disclosure dates. The results may provide the Fed with more room to make changes to the stress testing framework without shocking the markets. That could mean the Fed has some additional leeway to manage the banking system. But that would not diminish the role of Congress; instead, it bolsters the importance of close cooperation between lawmakers and central bankers. For example, the Fed can add interest rate risk, such as short-term interest rate spikes, to the stress tests scenarios. More broadly, as the Fed seeks to re-examine proposed Basel III endgame reforms, such as requiring more capital to be held against unrealized losses for banks with over $100 billion in assets, policymakers have less reason to fear significant market reactions. Note that if the regression model is simply unable to identify changes in market information, then these consequences cannot be supported.

Conclusion

In this section, I empirically analyze whether 2018 changes to DFAST supervisory stress testing rules created significant idiosyncratic risk and new market information around stress test results disclosure dates. I run a 2-factor OLS regression design on the February 5, 2019 announcement as prescribed by the 2018 rules change. Remarkably, I find evidence that the 2018 reforms would change the level of risk posed by banks that otherwise underwent annual stress testing rather than biennial stress testing. Combined with the insignificant changes in CAR values from June 2018 to June 2019, this result suggests the market viewed the new two-year stress test cycle as a potential source of a change in idiosyncratic risk but did not believe this significant change in idiosyncratic risk was reflected in market reactions to stress tests results disclosures from June 2018 to June 2019. Policymakers ought to consider these nuances before major regulatory changes to our banking system.

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Part 2: The Effect of Social Media and Deposit Insurance on Bank Runs

Introduction

"No matter how strong capital and liquidity supervision are, if a bank has an overwhelming run that's spurred by social media so that it's seeing deposits flee at that pace, a bank can be put in danger of failing."

Treasury Secretary Janet Yellen before the Senate Finance Committee, March 2023

A Nobel prize-winning model by Diamond and Dybvig (1983) provides a basic framework to understand how bank runs cause financial crises. They show that banks offer demand deposit contracts, which create liquid claims on illiquid assets, as a form of risk sharing. As a result, investors with sudden, early liquidity needs can participate in long-term investments. The main drawback of demand deposit contracts is they expose banks to panic-based bank runs. This is when depositors believe other depositors will withdraw their deposits, so they too rush to withdraw their deposits, hoping they can withdraw before the bank fails. The bank supplies cash for the withdrawals by liquidating long-term investments unless it runs out of liquidity, in which case the bank fails.

This paper is inspired by the collapse of Silicon Valley Bank (SVB), but does not analyze its specifics. Instead, I observe a particular feature affecting the collapse — social media — and incorporate it into a generalized model of bank runs based on the Diamond-Dybvig model. While the mechanics of SVB's collapse function like a classic bank run, the rapid spread of information on Twitter surrounding the solvency of the bank and users purported intention to withdraw (Cookson et al. (2023)) suggests the network effects of social media and high levels of uninsured deposits may affect the probability of bank run. Communication has been shown to be a crucial factor in precipitating a bank run and previous literature shows the effectiveness of deposit insurance in preventing runs (Diamond and Dybvig (1983), Angeletos and Werning (2006)).

Here, I modify a model based on Diamond and Dybvig (1983) and Goldstein and Pauzner (2005) to investigate how social media — a relatively new form of communication — and deposit insurance may affect the probability of a bank run. I use the unique equilibrium modification presented in Goldstein and Pauzner (2005) to address the multiple equilibria challenge in Diamond and Dybvig (1983). The modification rests on the assumptions that the economy's fundamentals are stochastic, investors observe slightly noisy private signals, and one-sided strategic complementarities exist instead of global strategic complementarities. I solve the model using the global games method as presented in Morris and Shin (1998) and Carlsson and Van Damme (1993), allowing us to obtain a unique equilibrium and basic comparative statics. The unique threshold equilibrium enables us to calculate the probability of a bank run in the contexts of social media and deposit insurance.

Motivation

In just two days in March 2023, Silicon Valley Bank became the largest bank to collapse since the 2008 crisis and the second-largest to fail in U.S. history. Depositors, primarily firms in the technology industry, withdrew $42 billion from the 16th largest bank in a matter of mere hours. On Friday, March 10, regulators seized SVB and moved swiftly to ensure all deposits would be available Monday morning. By taking the extraordinary step of protecting the 89 percent of deposits uninsured by the FDIC — over $150 billion — regulators sought to reduce the risk of contagion and stabilize the banking system.

The collapse of SVB is remarkable in a number of ways. First, the depositors were a sophisticated and fickle group. They coordinated closely over social media and, as expected of startups, were sensitive to sudden liquidity needs. Second, unlike the 2008 crisis where some financial institutions held complex financial instruments and risk exposure, SVB's investments were relatively straightforward. They were concentrated in commonly-held government debt securities and faced the conventional risk of interest rate hikes, which caused the value to tumble. Third, SVB engaged in the maturity transformations expected of banks. While SVB maintained a unique (and not diversified) depositor base and better internal risk management and outside oversight would have been welcome, the relatively straightforward nature of the bank's investments, risk exposure, and lending activities prompts the question of whether depositors communicating on social media can increase the risk of a bank run. Furthermore, SVB's high level of uninsured deposits suggests that depositors may have been particularly sensitive to tremors regarding the solvency of the bank.

Appearing before the Senate Finance Committee on March 16, Treasury Secretary Janet Yellen acknowledged this very risk: “No matter how strong capital and liquidity supervision are, if a bank has an overwhelming run that’s spurred by social media so that it’s seeing deposits flee at that pace, a bank can be put in danger of failing.” Recent empirical evidence supports Secretary Yellen’s assertion, finding that social media amplifies bank run risk factors (Cookson et al. (2023)).

Literature Review: Diamond-Dybvig Model with Private Signals and Unique Equilibrium

I introduce the famous Diamond-Dybvig model with private signals and unique equilibrium, which includes the global games technique from Morris and Shin and Carlsson and Van Damme and the unique equilibrium modification from Goldstein and Pauzner.

First, I show the Diamond and Dybvig (1983), henceforth DD, model with multiple equilibria (no private signals). There are three periods, (0, 1, 2), one good, and a continuum [0, 1] of agents. Each agent is born at period 0 with an endowment of 1. Consumption only occurs in period 1 or 2, denoted by c_1 and c_2, respectively. There are two types of agents, i.i.d., privately revealed to agents at the beginning of period 1: impatient agents of probability λ and patient agents of probability $1-\lambda$. Impatient agents enjoy utility $u(c_1)$ and patient agents enjoy utility $u(c_1 + c_2)$. u is increasing, twice differentiable, and $u(0) = 0$. 1 unit of input at period 0 generates 1 unit of output at period 1 or R units at period 2 with probability $p(\theta)$, where θ is the fundamental of the economy and R is the return of a long-term project. θ is uniformly distributed over [0, 1], revealed in period 2, and $p(\theta)$ is increasing in θ. This makes sense because the higher the fundamental higher, the chance of a successful long-term project returning R is higher. Banks offer short-term payment $r_1 > 1$ to every agent who behaves impatiently, i.e. demands early withdrawal at $t = 1$. Let $n > \lambda$ be the fraction of agents, patient and impatient, who demand early withdrawal. When an agent demands early withdrawal, the bank liquidates long-term projects to pay for it. If the bank follows a sequential service constraint, it pays r_1 agents demanding early withdrawal by such liquidation. Then patient agents have the following incentive constraint to wait until $t = 2$ to withdraw:

$$u(r_1) < E_\theta[p(\theta)]u\left(\frac{1-nr_1}{1-n}R\right) \tag{1}$$

If too many agents demand early withdrawal and the bank runs out of resources, it goes bankrupt and the remaining agents get 0. The following payoff matrix for patient agents helps them decide whether to demand early withdrawal in t = 1 or wait until t = 2:

Period	$nr_1 < 1$	$nr_1 \geq 1$
1	r_1	$\begin{cases} r_1, & \text{prob } \frac{1}{nr_1} \\ 0, & \text{prob } 1-\frac{1}{nr_1} \end{cases}$
2	$\begin{cases} \frac{(1-nr_1)}{1-n}R, & \text{prob } p(\theta) \\ 0, & \text{prob } 1-p(\theta) \end{cases}$	0

Let 1 be the money the bank can pay to investors in t = 1. Then if each agent demanding early withdrawal demands r_1, the total demanded is nr_1. If $nr_1 < 1$, the bank has sufficient funds to pay r_1 to all agents who withdraw in t = 1. If $nr_1 \geq 1$, then the bank does not have sufficient funds to pay all agents who demand early withdrawal. Following the sequential service constraint, a run occurs: agents receive r_1 with probability $\frac{1}{nr_1}$ and nothing with probability $1-\frac{1}{nr_1}$ because the bank ran out of resources (bankrupt). Assuming our incentive constraint holds, there are at least two Nash equilibria (DD). The good, "no run" equilibrium is when n = λ, so only impatient agents withdraw early (they have no choice but to withdraw early). No patient agents run: running would award them $u(r_1)$ while waiting would award them $E_\theta[p(\theta)]u(\frac{1-nr_1}{1-n}R)$. By the incentive constraint, waiting is preferred to running, so patient agents do not run. The bad, "run" equilibrium is when n = 1, so all agents, patient and impatient, run. If everyone else is running, the bank runs out of resources, so a patient agent will also run because they would rather receive $u(r_1)$ with some probability than be guaranteed 0 by waiting. This is a panic-based run, which occurs due to the self-fulling belief that other depositors will run.

Second, I modify DD to find a unique equilibrium value and calculate the probability of a bank run. The downside of the DD model is it does not determine which equilibrium is more likely to occur. To address this challenge, I follow the approach in Goldstein and Pauzner (2005), henceforth GP, where the economy's fundamentals uniquely determine if a bank run occurs. I assume a lack of common knowledge, i.e. agents do not know the economy's fundamentals, but agents observe slightly noisy signals of the economy's fundamentals. Thus there is imperfect information. A bank run occurs if and only if the fundamentals are less than a threshold value. Suppose at t = 1 agent i receives a private signal of the fundamentals, denoted $\theta_i = \theta + \epsilon_i$, where ϵ_i is uniformly distributed between $-\epsilon$ and ϵ. The higher the signal, the higher the probability the long-term investment returns R, and the lower the incentive to run. Importantly, I assume there exist global strategic complementarities: an agent's incentive to take an action strictly increases with the number of other agents taking that same action. Agents observe imperfect signals, so they must observe other agents' actions to help determine their optimal action. However, DD does not satisfy the global strategic complementarities assumption: an agent's incentive to run is highest when the bank runs out of resources, not when everyone runs. Thus, I rely on GP, which shows that the uniqueness result applies with one-sided strategic complementarities.

I find the unique threshold equilibrium θ^* at which a patient agent is indifferent between running and not running. To solve the model, I take the limit as ϵ approaches zero.

$$\int_{\lambda}^{1/r_1} u(r_1)dn + \int_{1/r_1}^{1} \frac{1}{nr_1}u(r_1)dn = \int_{\lambda}^{1/r_1} p(\theta^*)u\left(\frac{(1-nr_1)}{1-n}R\right)dn \tag{2}$$

So θ^* is:

$$\lim_{\epsilon\to 0}\theta^* = p^{-1}\left(\frac{u(r_1)(1-\lambda r_1 + ln(r_1))}{r_1\int_{\lambda}^{1/r_1} u\left(\frac{(1-nr_1)}{1-n}R\right)dn}\right) \tag{3}$$

Thus, patient agents run if their signal is below the threshold θ^* and don't run otherwise. An example implication is θ^* is increasing in r_1, increasing the likelihood of a bank run.

Intuitively, if the payment r_1 is greater in period 1, then there is a greater incentive for patient agents to withdraw in period 1.

I capture this result below.

Proposition 1: The model with noisy signals has a unique threshold equilibrium θ^* where patient agents run only if they observe a signal below θ^* and otherwise do not run.

Model with Social Media

I consider how social media may affect the probability of a bank run. Cookson et al. (2023) empirically shows that social media amplifies bank run risk by increasing the share of uninsured deposits that run. In the case of SVB, the network effects of social media were powerful due to founders and venture capital investors participating in closely-connected social media networks on Twitter, where posts are public and speed of communication is high. Many tweets consisted of investors urging startup depositors to withdraw their money as soon as possible. Let the value gained by depositors on social media be the "information premium" that is harder to learn outside of social media. Functionally, this information can be considered as a type of signal. Each depositor (representative agent) has access to the same social media platforms, and while much social media content is public, each depositor has a slightly different social media feed and thus observes the information premium through their private signal θ_i. As a result, social media is a mechanism of learning (updating): depositors read other depositors' intention to run and troubles regarding a bank's solvency, so they worry they could lose their money.

The agent's utility is the same as before, but with an additional utility function of the "information premium" of social media. All agents observe the same signal and utility function. Let $g_{t,n}(\gamma\theta_i)$ be a monotonically increasing concave function where $g(0) = 0$ and $\gamma < -1$. γ is a network effect constant urging depositors to withdraw. I include n, the share of agents running, and t, denoting time from the first Tweet encouraging early withdrawal to when the bank runs out of resources, because the intensity of the Twitter conversation increases as the bank runs out of resources and bank stock losses climb, thereby increasing the incentive to run and utility of the information.

I set up the indifference condition, slightly modified from the previous case. I solve using the same global games technique for a unique threshold equilibrium θ^{SM}.

$$\int_{\lambda}^{1/r_1} u(r_1)dn + \int_{1/r_1}^{1} \frac{1}{nr_1}u(r_1)dn + \left(1 - \frac{1}{r_1}\right) g_{t,n}(\gamma\theta_i) = \int_{\lambda}^{1/r_1} p(\theta^{SM})u\left(\frac{(1-nr_1)}{1-n}R\right) dn \quad (4)$$

So θ^{SM} is:

$$\lim_{\epsilon \to 0} \theta^{SM} = p^{-1}\left(\frac{u(r_1)(1 - \lambda r_1 + ln(r_1)) + (r_1 - 1)\, g_{t,n}(\gamma\theta_i)}{r_1 \int_{\lambda}^{1/r_1} u\left(\frac{(1-nr_1)}{1-n}R\right) dn}\right) \quad (5)$$

The difference between θ^* and θ^{SM} is the additional term $(r_1 - 1)\, g_{t,n}$ in the numerator of $p-1$. The payoff matrix is unchanged. By definition from Section 2, $r_1 > 1$ so $r_1 - 1$ is strictly positive. Next, $g_{t,n}(\gamma\theta_i) < 0$ so the additional term is strictly negative, so the argument to $p-1$ is smaller than in Section 1. From Section 2, $p(\theta)$ is an increasing function so $p-1$ is a decreasing function. Thus, a smaller argument to $p-1$ yields a bigger critical value, so $\theta^{SM} > \theta^*$. This means if agents use social media, they will worry that the bank will run out of resources and are more likely to run on the bank, and by Proposition 1, the probability of a bank run will be higher. Said another way, the threshold above which a patient agent would wait is higher, so they are more likely to run on the bank in the context of social media.

Proposition 2: The model with social media has a unique threshold equilibrium $\theta^{SM} > \theta^*$ where patient agents run only if they observe a signal below θ^{SM} and otherwise do not run.

Model with Deposit Insurance

I consider how deposit insurance can change a depositor's willingness to run on a bank. Our setup is the basic model of DD with private signals and a unique threshold equilibrium. Suppose that the government supplies deposit insurance s, where those who are patient until period 2 receive s, except when the bank's long-term investment yields return R. In the case of the exception, when only impatient agents run, patient agents receive s if the long-term investment fails. Excluding the exception, if the bank cannot pay s, the government will pay the remaining amount such that the depositor receives a total of s. Let s be a random variable distributed between 0 and $\overline{S}$ according to density function f(s) and distribution function F(s). The realization of s is perfectly observable to all agents in period 1. The bank pays r_1 in period 1 until it runs out of resources, and pays s or $u\left(\frac{(1-nr_1)}{1-n}R\right)$ in period 2. The following payoff matrix helps patient agents decide whether to demand early withdrawal in t = 1 or wait until t = 2.

If n = 1 (everyone runs), a patient depositor weakly prefers early withdrawal when:

Period	$nr_1 < 1$	$nr_1 \geq 1$
1	r_1	$\begin{cases} r_1, & \text{prob } \frac{1}{nr_1} \\ 0, & \text{prob } 1-\frac{1}{nr_1} \end{cases}$
2	$\begin{cases} \frac{(1-nr_1)}{1-n}R, & \text{prob } p(\theta) \\ s, & \text{prob } 1-p(\theta) \end{cases}$	s

$$\frac{1}{r_1}u(r_1) + \left(1-\frac{1}{r_1}\right)u(0) \geq u(s) \tag{6}$$

Let s = S_1 be the deposit insurance when the above condition is binding. Then for s ∈ [0, S_1], there's a "run" equilibrium. If n = λ, only impatient agents withdraw early. A patient agent weakly prefers staying when:

$$r_1 \leq \frac{(1-\lambda r_1)}{1-\lambda}Rp(\theta) + s(1-p(\theta)) \tag{7}$$

Let s = S_2 be the deposit insurance when the above condition is binding. So S_2 is:

$$S_2 = \frac{r_1 - \frac{(1-\lambda r_1)}{1-\lambda} Rp(\theta)}{(1-p(\theta))} \tag{8}$$

Then for s $\in$ [S_2, $\overline{S}$], there is a "no run" equilibrium. For s $\in$ (S_1, S_2), there is a partial run equilibrium where a patient agent is indifferent between running and not running. Let n(s) be the proportion of depositors that withdraw early when deposit insurance is s. Then:

$$\frac{1}{n(s)r_1}u(r_1) + \left(1 - \frac{1}{n(s)r_1}\right)u(0) = u(s) \tag{9}$$

I compute the expected utility of a depositor under this setup:

$$\begin{aligned}
\mathbb{E}(u) &= \int_0^{S_1} \left[\frac{1}{r_1}u(r_1) + \left(1 - \frac{1}{r_1}\right)u(0)\right] f(s)ds + \int_{S_1}^{S_2} u(s)f(s)ds \\
&+ \int_{S_2}^{\overline{S}} \lambda u(r_1) + (1-\lambda)u\left[p(\theta)\frac{(1-nr_1)}{1-n}R + (1-p(\theta))s\right] f(s)ds \\
&= F(S_1)\left[\frac{1}{r_1}u(r_1) + \left(1 - \frac{1}{r_1}\right)u(0)\right] + \int_{S_1}^{S_2} u(s)f(s)ds \\
&+ \int_{S_2}^{\overline{S}} \lambda u(r_1) + (1-\lambda)u\left[p(\theta)\frac{(1-nr_1)}{1-n}R + (1-p(\theta))s\right] f(s)ds
\end{aligned} \tag{10}$$

which is increasing in s. The expected cost of the insurance to the government is:

$$\mathbb{E}(cost) = \int_{S_1}^{S_2} s\,(1-n(s))\,f(s)ds \tag{11}$$

When s ≤ S_1, the deposit insurance is not effective because all patient depositors run. This case would include the bad, "run" equilibrium when n = 1 and r_1 = 0 in Section 2 (n = 1 and s = 0 in this setup). Only when s ≥ S_2 does the insurance completely prevent a bank run. When s $\in$

(S_1, S_2), I prevent a partial run. Our conclusion is the effectiveness of preventing runs increases in s.

Proposition 3: The model with deposit insurance $s \in [0, \overline{S}]$ does not prevent runs below a critical value S_1 when $s \in [0, S_1]$, partially prevents runs when $s \in (S_1, S_2)$ and S_2 is a critical value, and completely prevents runs when $s \in [S_2, \overline{S}]$. Thus the effectiveness in preventing runs is increasing in s.

I consider how Proposition 3 can connect back to comparative statics. Because there is no deposit insurance in the original DD model, to avoid modifying its payoff matrix, I represent the expected utility of deposit insurance as the function h. h is a concave, monotonically increasing function such that h(0) = 0. Let h be a function of the deposit insurance limit $s \in [0, \overline{S}]$ distributed according to density function f(s) and distribution function F(s). I set up the indifference condition, slightly modified from the basic DD model. I solve using the same global games technique for a unique threshold equilibrium θ^{DI}.

$$\int_{\lambda}^{1/r_1} u(r_1)dn + \int_{1/r_1}^{1} \frac{1}{nr_1}u(r_1)dn + \left(1 - \frac{1}{r_1}\right) h(s) = \int_{\lambda}^{1/r_1} p(\theta^{DI})u\left(\frac{(1-nr_1)}{1-n}R\right) dn \qquad (12)$$

So θ^{DI} is:

$$\lim_{\epsilon \to 0} \theta^{DI} = p^{-1}\left(\frac{u(r_1)(1-\lambda r_1 + ln(r_1)) + (r_1 - 1)\, h(s)}{r_1 \int_{\lambda}^{1/r_1} u\left(\frac{(1-nr_1)}{1-n}R\right) dn}\right) \qquad (13)$$

The difference between θ^* and θ^{DI} is the additional term (r_1 − 1) h(s) in the numerator of p−1. The payoff matrix is unchanged. By definition from Section 2, $r_1 > 1$ so $r_1 - 1$ is strictly positive. For the sake of comparative statics, let $s \in (0, \overline{S}]$ (i.e. there is some non-zero level of deposit insurance). Then h(s) > 0, so the additional term is strictly positive and the argument to

p^{-1} is larger than in Section 1. From Section 2, $p(\theta)$ is an increasing function so p^{-1} is a decreasing function. Thus, a larger argument to p^{-1} yields a smaller critical value, so $\theta^{DI} < \theta^*$. This means if deposit insurance exists, agents are less worried they will lose their money and are less likely to run on the bank, and by Proposition 1, the probability of a bank run will be lower.

Proposition 4: The model with deposit insurance has a unique threshold equilibrium $\theta^{DI} < \theta^*$ where patient agents run only if they observe a signal below θ^{DI} and otherwise do not run.

Combining with Proposition 2, I observe $\theta^{DI} < \theta^* < \theta^{SM}$. I have shown that deposit insurance can make bank runs less likely, while social media can spur bank runs to be more likely. Given the crisis in the banking system this year, this contribution should be verified empirically as well. Further research could examine a combination of these two factors, such as how social media has changed our understanding of the optimal level of deposit insurance.

Conclusion

This paper introduces a relatively new means of communication, social media, since the 2008 bank failures and how it may affect the probability of a bank run. I also examine the mechanism of deposit insurance and its ability to stave off of a bank run over a range of values. First, I show the basic DD model with private signals and apply the global games technique from GP to solve for a unique threshold equilibrium. Next, I modify the aforementioned DD model in the context of social media. Social media functions as a type of private signal due to the "information premium" it offers its users, resulting in a mechanism of learning. The utility of social media is monotonically increasing in the private signal and the proportion of agents withdrawing early because as more agents withdraw, the bank runs out of resources, so the incentive to run increases. With a new threshold equilibrium in the social media context, I perform comparative statics and find social media increases the likelihood of a bank run. Third, I introduce the basic DD model with deposit insurance. I find the expected utility increases in the insurance amount and the precise ranges when the insurance is ineffective, partially effective, and completely effective at preventing runs. Comparative statics shows deposit insurance decreases the likelihood of a bank run. The interplay between these two factors captures some of the dynamics of SVB's collapse, and further research can empirically analyze the relative influence of each of them on agents' behavioral considerations of running. Policy makers may find analysis of optimal deposit insurance levels to be instructive, but it is nonetheless a difficult problem to solve.

A first-order question for future research is how the actions taken by the Federal Reserve, Treasury Department, and FDIC may present a moral hazard problem. What does a deposit insurance limit mean if the government effectively insures all (or a high percentage of) deposits? One might suppose it reduces the incentive of banks to manage risks well. Perhaps a phenomenon of "too small to fail" has taken root since the government fears even a small bank failing could trigger depositors in small banks across the country to panic and increase the risk of contagion, inciting a crisis in the banking system. This reminds one of the fragility of the financial system and the real risks that banks and regulators must manage responsibly.

Proofs

Proposition 1: I refer to the proof from the GP paper. I set up the same model and payoff matrix, and apply the global games technique to solve the model.

Proposition 2: Proof is built off of Proposition 1. The main assumption here is Proposition 1 is true. Our payoff matrix is unchanged. The indifference condition has an additional utility function term, which is concave and monotonically increasing. The utility function is a function of the private signal θi, and not the variables in the payoff matrix. Thus, it simply shifts the equilibrium but does not change the property of a unique threshold equilibrium.

Proposition 3: Proof relies on Proposition 1. I use the same technique of determining a "good" and "bad" equilibrium to solve the model. The key difference is s is a random variable so it is subject to a distribution of values over 0 to S. This feature is addressed by the bounds on s for "no run", "run", and partial run equilibria. The expected utility of a depositor is computed based on the bounds on s and the density function f(s).

Proposition 4: I rely on the assumption that the effectiveness in preventing runs increases in s as explained. Thus I have the concave, monotonically increasing function h(s). From here the proof is the same as Proposition 2, except h(s) instead of g.

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Appendix: Figures

Figure 1: Residual Errors for OLS Regression one month before the Fed's announcement of the two-year stress testing cycle (blue vertical dashed line) on February 5, 2019 to one month after the announcement.

Figure 1.1: For each bank (key indicates stock ticker), a two-sided t-test of standard deviation of these residual errors before and after the announcement showed significance, a surprising result since the announcement did not change the annual stress testing frequency for this group.

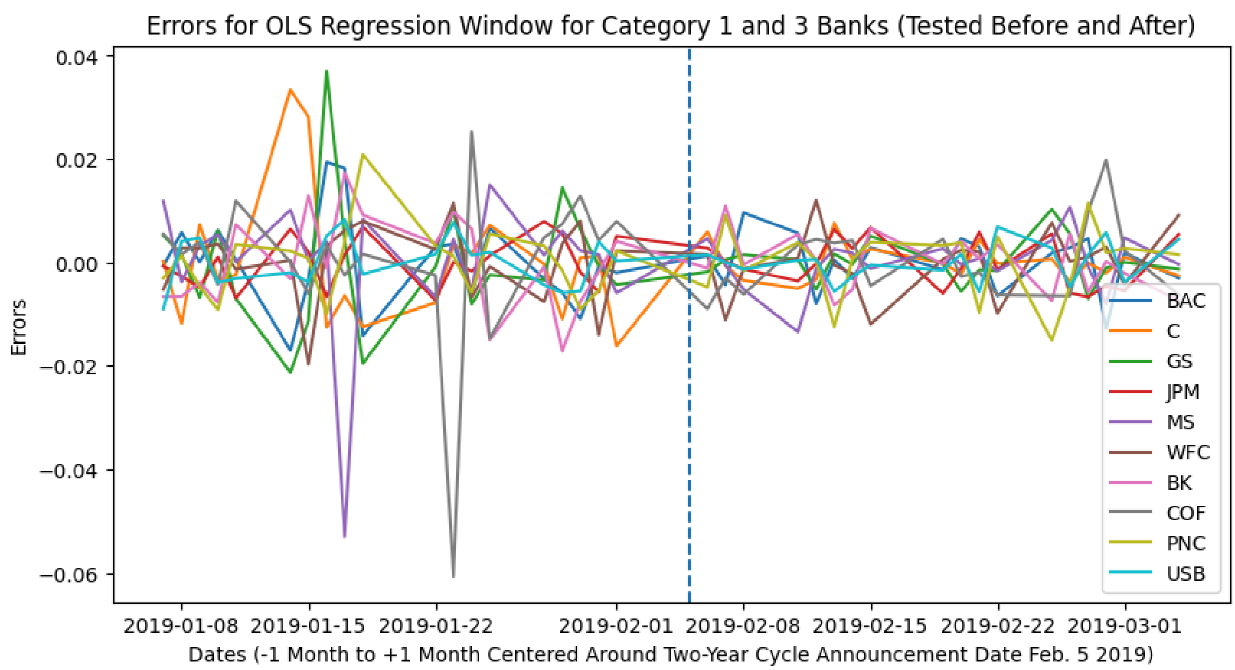

Figure 1.2: For each bank (key indicates stock ticker), a two-sided t-test of standard deviation of these residual errors before and after the announcement showed no significance, as expected since the announcement was not targeted at banks not participating in annual stress testing.

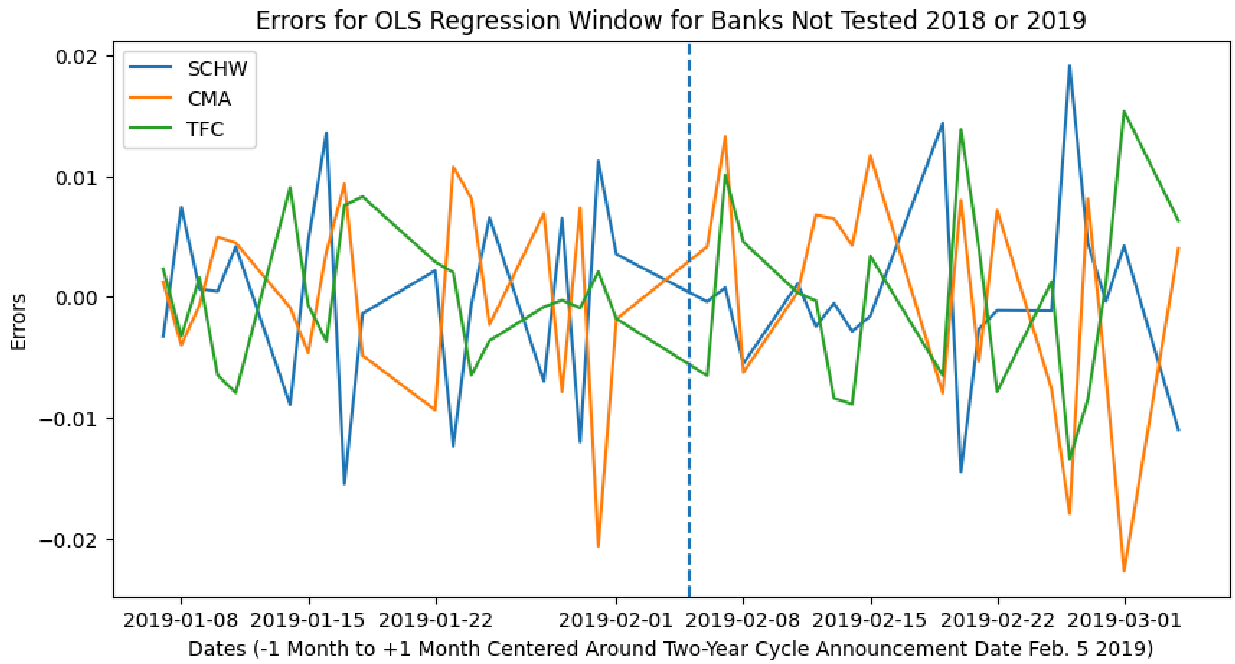

Figure 1.3: For each bank (key indicates stock ticker), a two-sided t-test of standard deviation of these residual errors before and after the announcement showed significance as expected since the announcement was targeted at this group of mid-size banks undergoing annual testing.

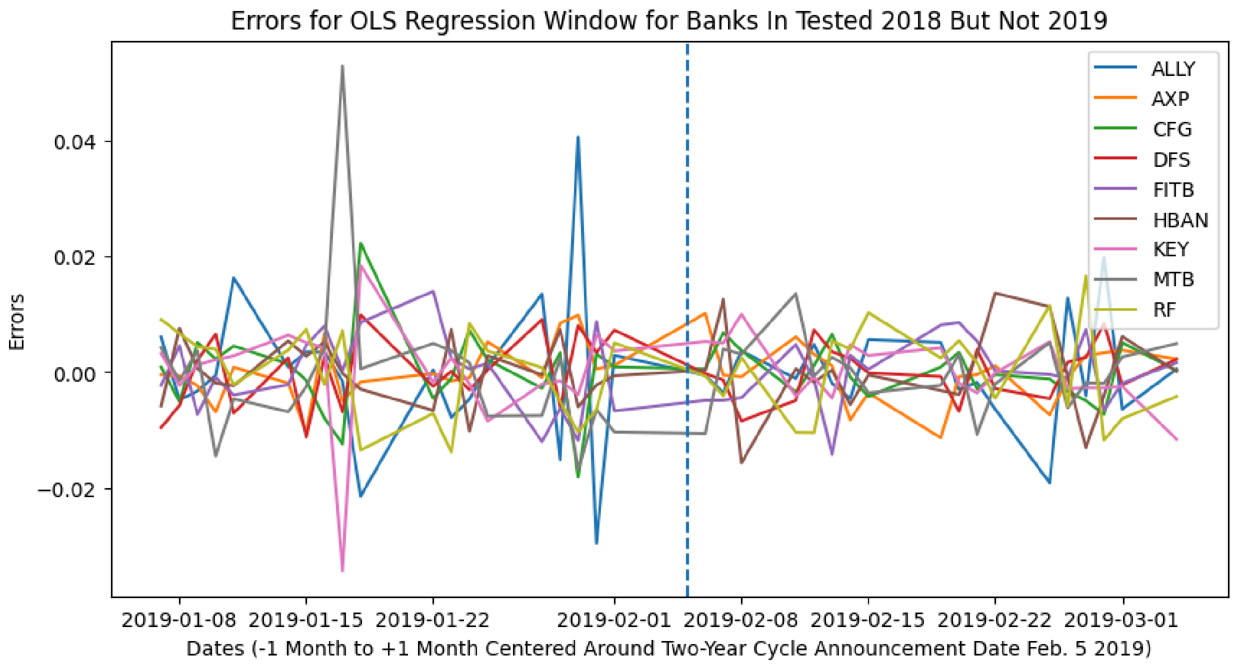

Figure 2: T-test P-Values For Regression.

Figure 2.1:

Coefficient	P-Value	Significant?
Error	0.773	No
Beta	0.713	No
Bank Index	0.976	No
Idiosyncratic Risk	0.00514	Yes at 0.01 level

Figure 2.2:

Coefficient	P-Value	Significant?
Error	0.766	No
Beta	0.877	No
Bank Index	0.924	No
Idiosyncratic Risk	0.267	No

Figure 2.3:

Coefficient	P-Value	Significant?
Error	0.684	No
Beta	0.921	No
Bank Index	0.578	No
Idiosyncratic Risk	0.059	Yes at 0.1 level

Figure 3: T-test P-Values For CAR Measure. All three sets of banks show no significant new market information created around test results disclosure dates for any group.

Bank Set Number	P-Value	Significant?
1	0.632	No
2	0.330	No
3	0.715	No