Stress Tests and Bank Opacity – A MIMIC Model[1]

Manvendra Tiwari[2]
University of Florida

September 20, 2021

JOB MARKET PAPER

Abstract

Banks are considered more opaque than non-financial firms due to the type of assets they own. Different measures of opacity have been used in the literature, but most of them are noisy proxies for the 'true opacity.' Searching for a better proxy for the 'true opacity' of banks, I propose a new approach based on the MIMIC model of Joreskog and Goldberger (1975). The model assumes that bank opacity is unobservable and latent, but there are several observable causes and indicators of opacity. The MIMIC model assumes that the latent opacity is caused by the type of bank assets (i.e., types of loans, trading assets, etc.) and banks' information environment (i.e., number of analysts covering banks and number of 8-K filings). In addition, several market microstructure variables are used as proxies are for indicators of opacity. Using the latent opacity computed using the MIMIC model and parametric and nonparametric regression discontinuity design ('RDD'), I study the impact of stress tests on the opacity of banks. We find that the opacity of mid-size banks (\$10B<Assets<\$50B) performing bank-run stress tests increased significantly for the period they were not required to disclose the results to the public. Therefore, stress testing without the disclosure of the results to the public may reduce market transparency.

Keywords: Opacity, MIMIC Model, Market Microstructure Variables, RDD, Stress Tests

---

[1] I am indebted to my advisors Mark Flannery, Mahendrarajah Nimalendran, and Nitish Kumar, for their encouragement, patience and guidance. I thank James Kolari (discussant), Giacomo Nocera (discussant), and the participants at the FMA Annual Meeting 2020, SFA Annual Meeting 2020, and IFABS 2019 Medellin conference for their helpful comments.

[2] Ph.D. Candidate in Finance at Warrington College of Business, University of Florida.

1 Introduction

The opacity of a firm can arise because of two main reasons: ‘operating opacity’ due to its complex business environment and ‘reporting opacity’ due to the firm’s low financial reporting quality (Tucker (2015)). The term firm opacity has been used extensively in the finance and accounting literature; however, it is not clearly defined. Further, firm opacity has also been defined and interpreted differently depending on the context in which it is used and discussed. On the one hand, information production by independent firms, i.e., credit rating agencies or research analysts, has been used to measure firm opacity. On the other hand, measures of accounting statement manipulations, i.e., loan loss provisions, accruals, etc., have been used for firm opacity. In this study, I consider bank opacity as a “latent” variable within a MIMIC (Multiple Indicators and Multiple Causes) framework. The model assumes that the opacity is caused by banks’ asset types and their information environment. The stock market microstructure variables are used as indicator variables. The estimated MIMIC model parameters and quarterly data on bank assets and microstructure variables, are used to construct quarterly bank opacity measures. The bank opacity measures together with a RDD framework are used to evaluate how changes in the information environment created by bank stress tests affect opacity. I find that the opacity of mid-size banks ($10B<Assets<$50B), which were required to perform bank-run stress tests, increased for the period they were not required to disclose the results to the public. The results have implications for policy regarding the transparency of stress tests.

It has been shown that firms are more opaque in countries with less developed financial systems and poorer corporate governance. Morck, Yeung, and Yu (2000) show that R^2 (where R^2 is a total unconditional variance due to the market variance) is higher in opaque countries with less developed financial systems and poorer corporate governance when stock returns are regressed on the market returns. They find that this stock return synchronicity is due to less respect for private property by the government in developing economies. Inadequate protection for property rights in these economies makes informed risk arbitrage unattractive. Jin and Myers (2006) use the measure of R^2 developed by Morck, Yeung, and Yu (2000) to show that imperfect protection for investors does not affect R^2 if the firm is completely transparent. Some degree of opaqueness is essential. Though, more opaqueness allows insiders to capture more cash flows in good scenarios; managers have to absorb downside risk in the bad scenarios since they hold a residual claim. Therefore, lack of transparency (or opacity) increases R^2 by shifting the firm-specific risk to managers. Outside investors replace unknown firm information in these countries with an expected value based on their information. Therefore, the firms' stock returns in these countries are more likely to reflect the market information than the firm-specific information and have higher R^2. In addition, Jin and Myers (2006) show that stocks with high R^2s (more opaque) are also more likely to crash or experience large negative returns.

Firms that operate in a similar legal and financial environment can have different opacities due to different disclosure requirements. Further, firms can be differentially opaque depending on the level of information revealed publicly or privately through trading, public disclosures including regulatory disclosures such as quarterly and annual filings, bank stress tests disclosure, earnings announcement, and reporting of insider trades. Private information channels include financial analyst coverage and informed investor trading. Financial analysts collect information from private and public sources, develop and disseminate information to investors, and allow investors to make more timely decisions regarding the firm's activity. Thus, firms maintain different information dissemination structures and different relations with the information intermediaries, leading to pervasive differences in the corporate opacity (Anderson, Duru, and Reeb (2009)). Several measures have been used as proxies for firm-level opacity for firms operating in similar legal and operating environments. The most common proxies are market microstructure measures (i.e., bid-ask spread, trading volume, and price impact, etc.), accounting-based measures (i.e., accruals, loan loss provisions, etc.), and analyst-based measures (number of analysts, analyst forecast error, etc.).

In addition to opacity due to different legal regimes and information environments, firms may also have different opacities due to their main business type. It has been widely believed that banks are more opaque than the other firms due to their type of assets. Borrowers use bank funding instead of public sources for their projects because they don't want to disclose their private information (Campbell and Kracaw (1980)). In addition to protecting this borrower's specific private information, banks also monitor these borrowers on behalf of the depositors and small investors (Diamond (1984) and Diamond (1996)). However, this intermediation process makes assets owned by banks extremely opaque for the investors. In addition, certain types of assets may be more opaque than other assets depending on the disclosures provided by the financial firms. Based on the above discussion, the causes and indicators of bank opacity are summarized in Figure 1.

Banks are much more regulated than non-banking firms to reduce the opacity of banking assets and information asymmetry. Also, banks are differently regulated depending on their sizes. For example, Comprehensive Capital Analysis and Review ('CCAR') and Stress Tests under the Dodd-Frank Wall Street Reform and Consumer Protection Act ('Dodd-Frank Act') are required for banks with assets more than a specific threshold due to them being more complex and considered too big to fail ('TBTF').

From the above discussion, we see that the 'true' opacity is unobserved (or latent), but there are many causes of opacity. Similarly, many proxies can be used as indicators of opacity. Therefore, measuring opacity is ideally suited for the Multiple Indicators Multiple Causes ('MIMIC') model developed by Joreskog and Goldberger (1975). In the proposed MIMIC model, first, I define asset opacity in terms of the banks' asset composition and information environment. Second, in estimating this latent asset opacity, I use several indicators based on market microstructure measures. MIMIC models are a special case of Structural Equation Models ('SEM'). Structural equation modeling has been extensively used to estimate causal models in psychology, sociology, education, and marketing but not in finance (Chang, Lee, and Lee (2009)). For example, Chang et al. used a MIMIC model to estimate the determinants of capital structure choice extending on the work of Titman and Wessels (1988). MIMIC models have been extensively used in economics to estimate the size of unobserved variables, i.e., shadow economies (Schneider and Enste (2000)). Maddala and Nimalendran (1996) discussed the appropriateness of the MIMIC model for estimating the coefficient of unobserved (or latent) variables. They also discuss the limitations of the MIMIC model. The main problem is the use of poor proxies as the instrumental variables, and they suggest caution in selecting too many indicator variables. The problems caused by poor instrument variables will not be revealed when every conceivable variable is included in the model.

The first round of supervisory stress tests, known as the Supervisory Capital Assessment Program (SCAP-2009), was conducted to the large U.S. bank holding companies ('BHCs') in early 2009, and results were disclosed on May 7, 2009. Post that, two rounds of Comprehensive Capital Analysis and Review ('CCAR') were conducted on large BHCs in 2011 and 2012. The process includes two related capital reviews of large BHCs from 2013 onwards - the Dodd-Frank Act stress tests ('DFAST') and CCAR. The Dodd-Frank Act requires two types of stress testing: (1) Stress tests conducted by the bank, known as 'bank-run stress tests,' and (2) stress tests conducted by the Federal Reserve Board ('Board') known as 'supervisory stress tests.' Therefore, in addition to supervisory stress tests, large BHCs were also conducting bank-run stress tests based on the scenarios provided by the regulator twice a year from 2013 onwards. Prior literature suggests that these stress tests provided new information to market participants (Morgan, Peristiani, and Savino (2014), Flannery, Hirtle, and Kovner (2017), Fernandes, Igan, and Pinheiro (2017)).

In addition to the stress testing of large BHCs, the Dodd-Frank Act also mandated that mid-size banks with assets between \$10 billion and \$50 billion conduct bank-run stress tests once a year from 2013 onwards. However, these banks were not required to undergo the supervisory stress tests conducted by the Board. In addition, these banks were exempted from disclosing the results to the public for the first round of bank-run stress tests in 2014.

Instead, they only disclosed these results to their respective regulator. The mid-size banks started disclosing the results of the bank-run stress tests to the public in addition to their regulator from 2015.

Most of the earlier work on the impact of the stress tests focused on the large banks (Assets>$50Bn). The non-disclosure of the 2014 stress test results to the public creates a "natural experiment" to investigate a subtlety that others have not previously evaluated. Using the MIMIC model, I can measure the opacity when: (1) information is created during a stress test, but the information is not available to market investors, (2) the same information is available to the market. Using this opportunity, I study the impact of the stress tests on the opacity of mid-size banks during the period when they were conducting the stress tests but not disclosing results to the public. Insiders would have been generating relevant information when conducting stress tests, but this information was not available to the public. In this paper, I examine the impact of stress tests on the opacity of mid-size banks ($10B<Assets<$50B) using the estimated latent opacity together with a regression discontinuity design ('RDD') approach. I find that the opacity of mid-size banks ($10B<Assets<$50B), which were required to perform bank-run stress tests, increased for the period they were not required to disclose the results to the public.

The rest of the paper is organized as follows. In section 2, I present a review of previous literature on the opacity of financial firms. Data and summary statistics are provided in Section 3. In Section 4, I propose a MIMIC model to predict opacity from the asset composition of banks, bank information environment, and market microstructure variables. Section 5 uses the predicted latent opacity to assess the impact of stress tests on the bank opacity after the enactment of the Dodd-Frank Act. Section 6 concludes.

2 Related Literature

An important reason for the strict regulation of the financial industry is based on the evidence that the industry creates opaque assets during intermediation and liquidity creation. Such opacity makes it difficult for investors, analysts, and market makers to value financial firms accurately. Financial intermediation theories suggest that the assets of financial firms are more opaque because of their nature. Studies by Campbell and Kracaw (1980), Berlin and Loeys (1988), and Diamond (1991) lead to the conclusion that bank loans are opaque. According to Campbell and Kracaw (1980), borrowers use financial intermediaries since they don't want to disclose private information to the public. Berlin and Loeys (1988) discuss how banks overcome the information asymmetry between borrowers and lenders by costly monitoring. Diamond (1991) highlights the difference in information asymmetry between borrowing directly (issuing a bond without monitoring) and borrowing through a bank that monitors to alleviate moral hazard. Borrowers with excellent credit ratings will choose to borrow directly, while borrowers with credit ratings towards the middle of the spectrum rely on bank loans. Using his monitoring model, Diamond also concludes that during periods of high interest rates or low future profitability, even higher-rated borrowers choose to borrow from banks. In all the asymmetric information models, it is assumed that bank insiders have more information than outsiders about bank loans.

Bank loans are a significant part of the banking assets. In addition, trading in securities is also an important banking asset. Even though it can be argued that trading securities are not that opaque, the trading positions are uncertain and change very frequently, making it difficult for outsiders to monitor. Moreover, the frequency at which banks trade in and out of these assets may make them a potential source of bank opacity. As Myers and Rajan (1998) state, trading is the 'dark side' of the liquidity of Banks. It is generally thought that firms with more liquid assets will find it easier to raise external finance due to the greater short-notice value of liquid assets. But greater asset liquidity also reduces the firm's ability to commit to a specific course of action. Consequently, greater asset liquidity can reduce the firm's ability to raise external finance in some circumstances. In addition, the banks are highly levered, which creates incentives for risk-shifting or asset substitution (Jensen and Meckling (1979)). This asset substitution can lead to investment in opaque assets and trading strategies, and which can increase the bank opacity.

The empirical evidence on the opacity of bank assets is mixed. Morgan (2002) looks at the rating disagreement between major bond-rating agencies for financial and non-financial firms by studying the split ratings between Moody's and Standard and Poor's on new bonds issued between 1983 and 1993. If a firm is entirely transparent, then the two rating agencies should reach the same conclusion regarding the default risk of the bonds issued by the firm. However, in opaque firms, rating agencies will evaluate default risk based on incomplete information leading to more rating disagreement. The pattern of disagreement between bond raters suggests that financial firms are inherently more opaque than other firms. The disagreement increases between raters as banks substitute loans and trading assets for securities. Cash also increases the disagreement between raters, while premises or banks' other fixed assets tend to reduce the disagreement. In a similar analysis, Iannotta (2006) confirms these results by investigating the disagreement between the split ratings on 2,473 bonds issued by the European firms during the 1993–2003 period. He shows that the opaqueness measured by the rating disagreement increases with financial assets, bank size, and capital ratio but decreases with bank fixed assets.

Flannery, Kwan, and Nimalendran (2004) empirically examine the difference in the opacity between banks and matched non-banking firms using microstructure properties and analysts' earnings forecasts during the 1990-1997 period and find that the banks are not unusually opaque compared to the non-banking firms. They find no statistically and economically significant differences between banks' and non-financial firms' microstructure properties for NYSE/AMEX traded firms. These banks' stocks resemble their control firms in trading activity, return volatility, and bid-ask spreads. In contrast, the (smaller) NASDAQ bank stocks trade much less frequently than a comparable non-bank, despite having comparable bid-ask spreads. These smaller banks also exhibit substantially lower return volatilities than non-banks, and on average, IBES analysts predict their earnings more accurately. The combination of low volatility and low earnings forecast error implies that market investors have good information about these banks. Thus, the assets of NASDAQ banks were not unusually opaque. They conclude that if the banks were intrinsically more opaque than the non-banking firms, the regulations and supervision might have reduced the opacity.

In a later study, Flannery, Kwan, and Nimalendran (2013) examine bank opacity during two financial crises and confirm that even though the evidence on the banks' relative opacity is mixed during normal times, it increases substantially during the financial crises. They also warn that this time-varying pattern of bank opacity is even more dangerous since it suggests a reduction in bank stability during crisis periods. Even though they found that asset composition affects opacity measures, they could not identify the specific asset classes causing this sensitivity. They also assert that a researcher's ability to find evidence that banking firms are opaque depends on the sample period examined.

Haggard and Howe (2012) establish a link between the firm's opacity and its stock price movements based on the theoretical model of Jin and Myers (2006). Jin and Myers (2006) define firm opacity as reduced firm-specific information available to outside investors and argue that opacity affects the division of risk-bearing between firm insiders and outside equity holders. Though more opaqueness allows insiders to capture more cash flow in good scenarios, managers have to absorb downside risk in the bad scenario since they hold a residual claim. For firms in opaque countries, outside investors replace unknown firm-specific information with the expected value based on their information. Therefore, they conclude that the firms' stock returns in the opaque countries are more likely to reflect the market information than the firm-specific information and have higher R^2. Using a sample of 243 Bank Holding Companies ('BHCs') for the period 1993-2002, Haggard and Howe (2012) provide evidence consistent with banks being more opaque (less transparent) than matching industrial firms. They also find that, while NASDAQ banks might be less opaque than banks traded on NYSE or AMEX, they are not less opaque than matching industrial firms, in contrast to Flannery, Kwan, and Nimalendran's conclusion. They also find that agricultural and consumer loans are more transparent than other types of loans made by banks.

Jones, Lee, and Yeager (2012) examine the financial instability and contagion effect due to banks opacity by measuring the impact of bank merger announcements for 2000-2006 on the valuation of banks that were not involved in mergers. They show that the announcements of bank mergers not only affect the stock prices of target banks, but the information in these announcements also leads to a revaluation of other banks – especially for those non-merger banks that have larger investments in opaque assets. This suggests that investors have difficulty assessing the value of banking assets and rely on merger valuations for better disclosure. In addition, they assess the impact of opacity on bank share price declines during the period Jan2007 to Jun2008 and find that non-merger banks that benefited most from merger activity in 2000–2006 experienced the largest declines in equity during the 2007 financial crisis. Thus, banks appear to have increased investments in opaque assets in response to the positive price signals around mergers, which exacerbated the eventual decline in equity.

Jones, Lee, and Yeager (2013) examine the effects of opacity on bank valuation and synchronicity in bank equity returns before the financial crisis (2000–2006). They find that investments in opaque assets are more profitable than investments in transparent assets, and taking profitability into account, have larger valuation discounts relative to transparent assets. The valuation discounts on opaque asset investments declined over the 2000–2006 period, followed by a sharp reversal in 2007. The decline coincides with a rise in bank equity share prices, a decrease in transparent asset holdings by banks, and greater return synchronicity – evidence consistent with a feedback effect. Jones, Lee, and Yeager (2013) provide two reasons why opacity hinders financial markets' ability to discipline bank risk-taking effectively and thereby create systemic risk. First, accounting for profitability and other factors that impact bank equity values, investments in opaque assets necessitate higher required rates of the market return. In a perfect world, markets correctly assess the risks associated with opaque assets, resulting in an efficient allocation of investments in opaque and transparent assets. However, banks are rewarded with higher equity values if markets do not sufficiently discount the risks embedded in opaque assets. This reward can set off a feedback effect that encourages other banks to increase their investments in opaque assets, resulting in a higher concentration of risk in the financial system (ex-post) than market participants realize. Second, they confirm findings from prior literature that bank investments in opaque assets create more systematic risk and reduce idiosyncratic risk. Opacity causes financial markets to become less information efficient. The resulting increase in price synchronicity raises the likelihood of systemic market failure from revaluations triggered by changes in outside investor perceptions about risk. They conclude that opacity of the banking assets matters since it reduces the effectiveness of market discipline.

Blau, Brough, and Griffith (2017) suggest that the opacity of banks might adversely influence the ability of outsiders to value banks, which may lead to less informational efficiency in the stock prices of banks. If banks are opaque due to opacity in the financial intermediation process, they argue that investors might have difficulty assessing the true value of the banks and, therefore, bank stock prices will be less efficient than non-bank stock prices. Using the Hou and Moskowitz (2005) measure of price delay, which captures the inefficiency of stock prices, they test and find evidence that opacity is positively related to price delay. Bank stocks have a markedly higher delay than similar non-bank stocks. After controlling for other factors that influence the level of price delay, banks experience price delays between 5.6% and 8.2% higher than the matched non-banks, suggesting that the differences are statistically significant and economically meaningful. Using market microstructure measures of liquidity on their sample of banks, they find that higher opacity (banks with higher bid-ask spreads, less trading activity, and larger Amihud's measure) directly contributes to higher levels of price delay.

Blau, Brough, and Griffith (2017) also use opaque asset structures to test whether bank opacity drives higher levels of price delay. Consistent with much of the theoretical research, they argue that bank loans are informationally opaque and find that the ratio of real estate loans to total assets and non-real estate loans to total assets is positively related to banks' price delay. Therefore, opacity (in the form of higher loan-to-asset ratios) creates an environment where bank stocks may be mispriced and have difficulty incorporating market-wide information. This higher level of delay is driven, in part, by market-based measures of informational opacity and the asset composition of the bank's balance sheet. Therefore, they conclude that bank opacity reduces the efficiency of financial markets.

Fosu et al. (2017) examine 402 U.S. BHCs over the period 1995–2013 and suggest that a high degree of opacity is associated with increased risk-taking and impairs bank stability. This effect is present even after controlling for observable and unobservable bank characteristics and other endogeneity problems. Moreover, the impact of opacity on banking stability is higher for periods of optimism than those of pessimism. Further, the opacity is more destabilizing in the periods before and during the 2007 financial crisis but not statistically robust post-crisis. They also find the negative effect of opacity on bank stability is accentuated by a higher degree of banking competition. In other words, while a higher degree of banking competition is associated with a less stable banking system, the effect is larger for highly opaque banks. Finally, they also show that the effect of opacity on bank risk-taking is conditional on bank business models. Specifically, higher dependence on non-deposit (wholesale) funding increase the risk-taking behavior of opaque banks, while diversification, in contrast, has a weak moderating effect. Therefore, the finding suggests that banks with highly diversified business models have an incentive to maintain a high level of transparency and relatively high risk-aversion.

Morgan, Peristiani, and Savino (2014) use standard event study techniques to investigate whether the first set of stress tests conducted by the Federal Reserve on 19 largest U.S. BHCs produced any useful information for the market. They find that the market largely deciphered on its own, which banks would have capital gaps before the stress test results were announced. But, stress tests revealed the size of the capital gap to the market, and the market used that information to revalue banks.

Flannery, Hirtle, and Kovner (2017) provide evidence that disclosing supervisory stress test results generates significant new information about stress-tested BHCs. They use two measures of information: the absolute value of affected BHCs' share price returns and abnormal trading volume. The new information appears to be most meaningful for more highly leveraged and riskier, more volatile BHCs. The initial stress tests conducted in 2009 had the largest effects on the stress-tested BHCs. Additional stress tests conducted until 2015 provided the market statistically significant information regarding significant abnormal volumes and returns and implied volatility changes. In addition, they find no evidence for negative welfare impacts from stress testing disclosures. Finally, stress-tested banks had more analysts whose earnings estimates were no less accurate than before stress testing was initiated.

Gounopoulosa, Höbeltb, and Papanikolaouc (2018) examine the impact of the stress tests on the opacity of banks using a unique dataset from 25 European countries. They use textual analysis to measure the effect of stress-tested banks' stress test disclosure sentiment and disclosure tone on market-based bank transparency attributes. They find that stress-tested banks improve their textual disclosure by stress text disclosure language, and the disclosure tone. Also, the quantitative disclosure behavior changes seem to affect the transparency process's evolution during stress periods. This improved disclosure seems to confuse market participants since the market-based transparency measures (i.e., bid-ask spread and analyst consensus) show less information asymmetry. Even though they don't claim any causal inference, they show a relationship between stress test language, textual disclosure tone, and market-based opacity measures.

3 Data and Summary Statistics

We use three data sources in this paper: NYSE Trade and Quote database ('TAQ') is used to calculate the market microstructure variables (i.e., volatility of returns, effective spread, price impact, etc.) for banking firms. In addition, balance sheet data for the BHCs and Commercial Banks have been taken from quarterly consolidated financial statements, i.e., Form FR Y-9C from Federal Reserve Board ('Board') and Call Reports from Federal Financial Institutions Examination Council ('FFIEC'). I use the Institutional Brokers' Estimate System ('IBES') database to compute the number of analysts covering banks. Finally, I use the WRDS SEC Analytics Suite to calculate the number of 8-K filings by the banks in each quarter.

3.1. Microstructure variables from TAQ

Using TAQ, I calculate daily market microstructure variables described below for all bank stocks available in the TAQ database from 2002 to 2016. In addition, I use second-level data from 2002-2012 and millisecond/nanosecond data from 2012-2016 and make the following adjustment to calculate microstructure variables.

For the period between 2002 to 2012, WRDS provides WRDS Consolidated Trades ('WCT') and National Best Bid & Offer ('NBBO') files. WCT files provide the midpoint of the Bid and Ask NBBO quotes for each trade with specified time lags (0, -1, -2, and -5 seconds) between quotes time and trade time to take care of lag in the trade timings. For this period, I use midpoints of the bid and ask quotes matched with a one-second lag to get the last available quote before the trade, as in Brogaard, Li, and Xia (2017). I use the Lee and Ready algorithm for identifying trade direction (Lee and Ready (1991)). Between 2012-2016, the millisecond/nanosecond NBBO files are not prepared by WRDS. The NBBO files for 2012-2016 are provided by the stock exchanges. The structure of NBBO files prepared for 2002-2012 by WRDS differs from the files provided by the stock exchanges for 2012-2016. The stock exchange NBBO files for 2012-2016 do not have complete NBBO history. When a quote arrives on the Consolidated Quote System that contains both a new best bid and best ask, it is stored only in the quotes files, and is not added to the stock exchange NBBO files. Therefore, I create NBBO files between 2012 and 2016 by including the missing NBBO quotes from the Quote file to the NBBO file provided by the Stock Exchange as suggested by WRDS.[3] This makes computed variables comparable across two periods.

I remove all trades and quotes before 9:35 AM and post 3:55 PM to avoid abnormal values during pre and post-market hours. Further, I drop quotes where best bid and best offer are negatives, the best bid is higher than the best ask, and the bid-ask spread is more than 10% of the midpoint of the bid and ask. I calculate Percent effective spread, Percent price impact, and turnover divided by total shares outstanding ('TOVER') daily for all bank stocks in the TAQ database.

Before creating quarterly averages from the daily market microstructure variables, I trim the variables on both ends at a 1% level at the daily frequency on each exchange to remove outliers. After that, I create a quarterly database from the daily microstructure variables by averaging daily values over a quarter. I dropped firms that had a low average share price (<\$2) and low trading volume (< 300 shares/day) over the quarter. Then, for each stock, I calculate the quarterly standard deviation of returns from the daily stock price return from CRSP. I have 113 banks listed on NYSE and 670 banks listed on NASDAQ during the sample period. In addition, 21 banks shifted listing from one exchange to the other exchange during the sample period. The definition of variables calculated using TAQ and CRSP to be used in the MIMIC model is provided below.

a) Percent effective spread (ES)

Percent effective spread has been calculated as $2D_k(P_k - M_k)/M_k$ at each second where P_k is the k^{th} trade price, D_k is an indicator variable that equals +1 if the k^{th} trade is a buy and -1 if the k^{th} trade is a sell and M_k is the midpoint of the NBBO quotes assigned

[3] https://wrds-www.wharton.upenn.edu/pages/support/support-articles/taq/millisecond-nbbo-dataset-history/

to the k^{th} trade by Lee-Ready Algorithm. Aggregated over daily, a stock's Percent effective spread is the volume-weighted average of Percent Effective Spread computed over all trades. In addition, I only calculate percent effective spreads if the trading price is in between or equal to the best bid or best ask.

b) Percent price impact (PI)

Percent price impact has been calculated as $2D_k(M_{k+5} - M_k)/M_{k,}$ where M_{k+5} is the midpoint five minutes after the midpoint M_k. The price impact is the permanent component of the effective spread. Aggregated over daily, the Percent Price Impact is the volume-weighted average of Percent Price Impact computed over all trades.

c) Standard Deviation of Returns (STD)

The standard deviation of returns has been calculated as the standard deviation of CRSP daily returns over the quarter.

d) Turnover (TOVER)

Trading activity is measured as the number of shares traded, divided by the average number of shares outstanding during the quarter.

e) Price Inverse (PINV)

The PINV is calculated as the inverse of the quarterly average share price.

f) Log Market Capitalization (LNMVEQ)

The LNMVEQ has been calculated as a natural log of the quarterly average market value of common equity. The daily market value of equity has been calculated by multiplying the closing share price with outstanding shares.

3.2. Bank Assets from Financial Statements

New York Federal Reserve provides PERMCO-RSSD links for the BHCs and Commercial Banks from June 20, 1986, to December 31, 2016.[4] I use these Banks as the base sample for Bank Stocks. For these Banks, I get quarterly financial assets from filings of

[4] (https://www.newyorkfed.org/research/banking_research/datasets.html)

Federal Reserve's Quarterly consolidated financial statements (FR Y-9C) for BHCs and 'Call Reports' (FFIEC 031, if the bank has both foreign and domestic offices, or FFIEC 041, if it has only domestic offices) for domestic, commercial banks. I have 742 unique BHCs and 32 unique Commercial Banks during the sample period.

Following Jones, Lee, and Yeager (2013), I divide banking assets into six broad categories:

1. COMREAL consists of commercial real estate loans.
2. RESREAL consists of residential real estate loans.
3. OTHLOAN are all other loans except real estate loans and mainly consist of consumer loans to individuals for households and other personal expenditures.
4. All trading assets have been included under TRADE category.
5. Transparent assets such as cash, federal funds sold, securities purchased under agreements to resell, federally guaranteed AFS and HTM securities have been included under TRANSP.
6. All remaining assets are termed as OTHOPAQ, which contains mostly opaque assets: mortgage-backed or asset-backed securities classified as available-for-sale (AFS) or held-to-maturity (HTM) that are not explicitly or implicitly guaranteed by a federal government-related entity, fixed assets, intangible assets, other assets, investment in an unconsolidated subsidiary, other real estate owned. The composition of these variables taken from FR Y-9C and call reports is given in Appendix A.

Other than the above six asset categories from the banks' balance sheet, following Hankins (2011), I also calculate the total derivatives exposure (TOTALDERIV) of the banks for the off-balance sheet items by combining the gross notional amount of derivatives used for either trading or hedging purposes. The derivative contracts included in TOTALDERIV are Interest rate contracts, Foreign exchange Contracts, Equity derivative Contracts, and Commodity and Other Contracts. In addition, I also calculate market-valued leverage (MVLEV) as the total book value liabilities plus the market value of common equity divided by the market value of common equity.

3.3. Number of analysts (IBES) and number of 8-K filings (EDGAR)

For the bank environment variables in the MIMIC model, I use two variables: the number of analysts covering the banks and the number of 8-K filings at the U.S. Securities and Exchange Commission (SEC) Edgar platform. Since it is difficult for the investors to analyze opaque firms, there will be a higher demand for analysts to cover those firms. Research suggests that analyst following increases with opacity. Barth, Kaszni, and McNichols (2002) find that analyst coverage is significantly greater for firms with larger R&D and advertising expenses relative to their peers. Lehavy, Li, and Merkley (2011) report that the analyst following and informativeness of their report increase for firms with less readable 10-K filings. Lobo, Song, and Stanford (2012) provide evidence that the analyst coverage increases as accruals quality decreases, consistent with analysts providing additional information for more opaque firms. But eventually, more analysts covering these firms should improve the firm's information environment and reduce the firm opacity. Therefore, we cannot conclusively say how the number of analysts covering the firm will impact the opacity in the equilibrium. But, the number of analysts should be an important factor in the firm's information environment. For each bank quarter, I calculate the number of analysts who covered the bank using the IBES database to include in the MIMIC model.

Additionally, using WRDS SEC Analytics Suite, I calculate the number of 8-K filings for each bank quarter. Firms provide a wide range of mandatory and voluntary updates using 8-K filings, i.e., business and operations, earnings forecasts and announcements, change in directors, etc. Since 8-K filings need to be filed for the most important updates of the public companies, they provide valuable information to the investors about what's happening with the firms. The firm that is going through a transformation and generating a lot of private information will likely make more 8-K filings during this period. In addition, a more opaque firm may file more 8-Ks to reduce information asymmetry. But again, the 8-K filings will provide additional information and can reduce the firm opacity when the firm is going through a complex structural process and a lot of information is being generated within the firm. Therefore, even though the number of 8-K filings will improve the firm information environment, it is difficult to conclude the direction.

3.4. Summary Statistics

Panel A of Table 1 reports summary statistics of microstructure variables for banks in the sample, and Panel B of Table 1 summarizes the quarterly bank assets. I provide summary statistics for the banks listed on NYSE and NASDAQ separately in both tables. We see from Panel A of Table 1 that the banks listed on NYSE are much larger compared to banks listed on NASDAQ. The average market capitalization of the banks listed on NYSE is $20 billion compared to $703 million for banks listed on NASDAQ. In addition, Effective Spread and Price Impact for NYSE listed banks (0.094% and 0.072%) are much smaller than the NASDAQ listed banks (0.70% and 0.185%). The daily standard deviation of returns (0.02) is in the same range for banks listed on both exchanges. The banks listed on NYSE trade around twice compared to banks listed on the NASDAQ. We also notice that even though the banks listed on the NYSE are much larger compared to NASDAQ banks, they have very similar market-valued leverage. As expected, NYSE banks are covered by more analysts compared to NASDAQ banks. Banks listed on the NYSE are covered by four times as many analysts as NASDAQ listed banks. Also, NYSE banks file more 8-K filings per quarter (average of 4.73) compared to banks listed on NASDAQ (average of 3.09).

From Panel B of Table 1, we see that the NYSE-listed banks have much larger asset sizes compared to NASDAQ-listed banks, similar to their market capitalization. NYSE-listed banks also have a very high level of Total Derivatives exposure in addition to a much larger asset size. The other noticeable point is that NASDAQ-listed banks have a very low level of trading assets comparatively.

4 Modeling Bank Asset Opacity using Multiple Indicators Multiple Causes (MIMIC) model

The 'true' bank opacity is unobservable, but there are many proxies used in literature to measure the bank opacity. Though the microstructure variables have been extensively used to measure firm opacity, many other factors influence opacity.

To model bank opacity as a latent variable, I propose a MIMIC model in which the bank asset opacity is influenced by the proportions of the different types of assets banks own and banks' information environment. Three market microstructure variables (Effective Spread, Price Impact, and Standard Deviation of Returns) are used as the indicator variables. Before I show the application of the MIMIC model in the current context, I describe the basic structure of the MIMIC model. The basic MIMIC model described below combines 'Regression with Latent Variable' and 'Multiple Indicators of a Latent Variable' as proposed by Greene (2002). It consists of two sets of equations.

Multiple Indicator Model (Measurement Model): $$\boldsymbol{y} = \boldsymbol{\beta} z^* + \varepsilon \tag{1}$$

Multiple Causes Model (Structural Model): $$z^* = \alpha' \boldsymbol{x} + u \tag{2}$$

In the model described by equation (1) and (2), $\boldsymbol{y}$ is a column vector of 'p' indicators of the single latent variable, z^*, and $\boldsymbol{x}$ is a vector of 'q' 'causes' of z^*. In this model, Eq. 1 is the measurement model for z^* and Eq. 2 is the structural model for the latent variable z^*. Eq. 1 can also be viewed as a confirmatory factor analysis model for the observable 'p' indicators with unique factor (z^*). In the structural model, it is assumed that the latent performance is caused by the vector of explanatory variables $\boldsymbol{x}$. Note that ε refers to the vector of zero mean (p×1) measurement error variables associated with the indicators, while u is a zero-mean scalar structural error that captures un-modeled variables affecting z^* and measurement errors associated with it. The measurement model relates each indicator variable to the latent performance and random measurement error term. The underlying assumption is that z^* and all the elements of ε are mutually unrelated. The reduced form of Eq. 1 and Eq. 2 gives a multivariate regression model.

$$\boldsymbol{y} = [\beta\alpha']\boldsymbol{x} + \boldsymbol{w} \tag{3}$$

$$\boldsymbol{Var}(\boldsymbol{y}) = \boldsymbol{\Sigma} = \boldsymbol{\beta\beta}' + \Theta^2 \tag{4}$$

where $\boldsymbol{w} = \beta u + \varepsilon$ and variance matrix of $\boldsymbol{y}$ is the sum of a rank one matrix, $\boldsymbol{\beta\beta}'$ and a diagonal matrix Θ^2. This is a multivariate regression with identical regressors. Estimation can be done using maximum likelihood, as described by Joreskog and Goldberger (1975), who also show that the estimator of z^* is given by:

$$\hat{z}^* = \frac{1}{\left(1 + \boldsymbol{\beta}\widehat{\Theta}^{-2}\hat{\boldsymbol{\beta}}\right)}(\boldsymbol{x}'\widehat{\boldsymbol{\alpha}} + \boldsymbol{y}'\widehat{\Theta}^{-2}\hat{\boldsymbol{\beta}}) \tag{5}$$

The MIMIC latent factor estimator, ($\hat{z}^*$) consists of two terms. The first term is the contribution by “causes” (a function of $\boldsymbol{x}$), while the second term comes from “indicators”, which are the factor scores of the factor analysis model. Identification of the MIMIC model requires that p (the number of $\boldsymbol{y}$ variables) is two or more, and k (the number of $\boldsymbol{x}$ variables) is one or more when we have one latent variable.

Other than estimating unobserved (or latent) variables, the MIMIC model also solves the problem of error-in-variables. Error-in-variables problems arise in finance from using incorrectly measured variables or the use of proxy variables for unobserved theoretical concepts, constructs, or latent variables. Maddala and Nimalendran (1996) show several approaches which can be employed to correct the errors-in-variables problem and obtain consistent estimates and standard errors. Since opacity is unobservable and proxy variables are used for unobserved variables, proxy variables can be considered as measuring the unobserved variable with measurement errors. The use of these proxy variables directly as regressor variables would lead to error-in-variables problems. However, if a single latent variable occurs in different equations as an explanatory variable, as in the case of the MIMIC model, then one can get consistent estimates of the coefficients of the unobserved variable. (Maddala and Nimalendran (1996)).

MIMIC Model of Bank Opacity

To apply the MIMIC model for bank asset opacity, I hypothesize that the opacity of bank assets is caused by the ratio of six major types of assets on the bank's balance sheet. The opaque assets will lead to higher asymmetric information and will result in an increase in adverse selection costs for market makers, which will have a positive effect on market microstructure variables, i.e., effective spread, price impact, and standard deviation of returns. Other than the bank assets, I use the number of analysts covering the stock and the number of 8-K filings as external causes for the opacity. As discussed earlier, it is difficult to predict the direction of impact of the number of analysts and the number of 8-K filings on the bank opacity ex-ante.

To estimate the latent "opacity", I use seven variables for the measurement model described by equations (6)-(8). Of these seven variables used in the measurement model, I consider three market microstructure variables (STD, ES, and PI) as indicator variables, which are influenced by the latent opacity. In addition, four other characteristics of the bank stock (LNMVEQ, TOVER, PINV, and MVLEV) and Exchange Dummy influence the three microstructure variables. The structural equation is based on six asset composition variables (COMREAL, RESREAL, OTHLOAN, TRADE, OTHOPAQ, and TOTALDERIV), and two market information variables (the number of analysts and number of 8-K filings), that drive the latent "opacity."

Based on Eq. 1 and Eq. 2, the bank asset opacity can be modeled using simultaneous equations in the following manner. The first three equations are the measurement model (equivalent to Eq. 1), while the last equation is the structural model (Eq. 2). In addition, I also control for market characteristics (Market Capitalization, Price, Turnover, and Market-Valued Leverage).

Measurement Model

$$STD_{it} = \alpha_1 + \gamma_1 Opacity_{it} + \delta_{11}(PINV_{it}) + \delta_{12}(LNMVEQ_{it}) + \delta_{13}(TOVER_{it}) + \delta_{14}(MVLEV_{it}) + \delta_{15}(Exchange\ Dummy) + \varepsilon_{1it} \tag{6}$$

$$ES_{it} = \alpha_2 + \gamma_2 Opacity_{it} + \delta_{21}(PINV_{it}) + \delta_{22}(LNMVEQ_{it}) + \delta_{23}(TOVER_{it}) + \delta_{24}(MVLEV_{it}) + \delta_{25}(Exchange\ Dummy) + \varepsilon_{2it} \tag{7}$$

$$PI_{it} = \alpha_3 + \gamma_3 Opacity_{it} + \delta_{31}(PINV_{it}) + \delta_{32}(LNMVEQ_{it}) + \delta_{33}(TOVER_{it}) + \delta_{34}(MVLEV_{it}) + \delta_{35}(Exchange\ Dummy) + \varepsilon_{3it} \tag{8}$$

Structural Model

$$\begin{aligned} Opacity_{it} = \alpha_4 &+ \beta_1(\text{COMREAL\_A}_{i,t-1}) + \beta_2(\text{RESREAL\_A}_{i,t-1}) \\ &+ \beta_3(\text{OTHLOAN\_A}_{i,t-1}) + \beta_4(\text{TRADE\_A}_{i,t-1}) \\ &+ \beta_5(\text{OTHOPAQ\_A}_{i,t-1}) + \beta_6(\text{TOTALDERIV\_A}_{i,t-1}) \\ &+ \beta_7(Ln(1 + Num_{Analyst})) + \beta_8(NUM\_8K) + \varepsilon_{4it} \end{aligned} \tag{9}$$

The graphical representation of the MIMIC model is shown in Figure 2. The trading characteristics of the stocks depend on the stock exchanges on which they trade. Therefore, I test whether the models differ for the NYSE and NASDAQ samples using a Wald test for equality of parameters. I find that $\chi^2(61) =$ 18543.34 when parameters are constrained, while for separate models where no parameters are constrained, I find that $\chi^2(32) = 836.02$.[5] The difference in chi-squared is 17707.32. The difference has 29 degrees of freedom and a p<0.01. Thus we can assume that a model with no invariance constraints does significantly better than a model in which all the parameters are constrained to be equal for both the exchanges. I estimate two versions of the MIMIC model – one with an exchange dummy and another with an exchange dummy along with its interaction terms with four variables in the measurement model (PINV, LNMVEQ, TOVER, and MVLEV). I find similar model estimates for both models. Therefore, to keep the model simple, I estimate the MIMIC model using an exchange dummy for the measurement equations.

The estimates for the proposed MIMIC model are shown in Table 2. I provide both unstandardized and standardized coefficients for the model parameters in columns 1 and 2

[5] The χ^2 statistics provided for the MIMIC models are without any clustering.

of Table 2, respectively. Unstandardized coefficients are model parameter estimates based on the raw data, while standardized coefficients are model parameter estimates based on the standardized data where all variables have unit variance. For MIMIC model estimates reported in Table 2, standard errors are clustered quarterly. I also provide standardized root mean squared residuals (SRMR) and the coefficient of determination (CD) in Table 2. SRMR is a measure of the fit of the model implied correlations to the sample correlation, on average. A value less than 0.08 is generally considered a good fit (Hu and Bentler (1999)). The model has a good fit based on the value of SRMR (0.012 from Table 2). The coefficient of determination is an overall summary of how well the model fits and is similar to R^2 for the whole model. A value close to one indicates a good fit. The model has a reasonable level of goodness of fit based on the coefficient of determination (0.938 from Table 2).

We see from the model estimated in Table 2 that the latent variable significantly affects the market microstructure variables: Standard deviation of returns, Effective Spread, and Price Impact. In addition, these three indicator variables are also significantly influenced by the other control variables included in the measurement model (PINV, LNMVEQ, TOVER, and MVLEV). The exchange dummy is also significant for all the three indicator variables and confirms the choice of its inclusion in the model. This confirms that the market microstructure variables are not only influenced by the firm opacity but also by the firm size, firm leverage, other trading variables, and exchange characteristics. If we look at the structural model equation estimates from Table 2, we find that the banks are more opaque when they own a higher fraction of the trading assets, other loans, and other opaque loans. While the number of analysts is not a significant contributor to the predicted opacity, more opaque banks file more 8-Ks with the SEC.

Based on the estimates of the MIMIC model, the conditional expected value of the latent "opacity" for each bank quarter is predicted using Eq. 5. The predicted values of the opacity are used in the subsequent analysis of changes in opacity for banks around stress tests.

Properties of Predicted Bank Opacity

In Panel A of Table 3, I provide the correlation of predicted opacity from the MIMIC model with three indicator variables (Effective Spread, Price Impact, and Standard Deviation of Returns). I find that the predicted opacity is much more correlated with Price Impact than Standard Deviation of Returns. The predicted opacity is least correlated with the Effective Spread. In Panel B of Table 3, I provide the correlation of predicted opacity with bank asset ratios and bank environment variables. The predicted opacity is not highly correlated with any single cause variable. But it is weakly correlated with Trading Assets, Other Loans, Total Derivatives, Number of analysts, and Number of 8-K filings.

In Figure 3, I also show how predicted opacity has evolved over time in the sample period in comparison with other indicator variables. From Figure 3, I similarly find that predicted opacity is much more correlated with Price Impact than Effective Spread or Standard Deviation of Returns in our sample period.

5 Impact of stress tests on bank opacity

5.1 Impact of Stress Tests on Mid-Size Banks (\$10Bn < Total Assets < \$50Bn)

In the wake of the 2008-09 financial crisis, Congress enacted the Dodd-Frank Act in 2010, which requires the Federal Reserve Board to conduct annual stress tests of all banks with total consolidated assets of more than \$50 billion ("large banks") as a part of an ongoing supervisory assessment. Large banks are required to undergo both bank-run and supervisory stress tests from 2013 onwards. The Federal Reserve and the large banks are required to publish the stress test results. But, the Dodd-Frank Act requires that banks with total consolidated assets between \$10 billion to \$50 billion ("mid-size banks") conduct only bank run-stress tests annually based on the scenarios provided by Federal Reserve. The mid-size banks were required to disclose the results of the bank-run annual stress tests by making them accessible to the public, for example, by publishing the results on the bank's website. The mid-size banks are not required to undergo supervisory stress tests. Banks with total consolidated assets less than \$10 billion ("small banks") are not required to perform any type of stress test. The Federal Reserve expects the large and mid-size banks to hold sufficient capital to continue lending to support real economic activity, even under adverse economic conditions. Stress testing helps the Federal Reserve measure whether a bank has enough capital to support its operations throughout periods of stress. The Federal Reserve used stress tests for large financial institutions with total assets of more than \$100 billion as a means to assess capital sufficiency during 2009-2012 using Supervisory Capital Assessment Program 2009 (SCAP-2009) and Comprehensive Capital Analysis and Review (CCAR) programs. Several studies have provided evidence that there is important new information in the stress tests disclosed to market participants. (Morgan, Peristiani, and Savino (2014), Flannery, Hirtle, and Kovner (2017), Fernandes, Igan, and Pinheiro (2017)). Most of these studies are based on the impact of stress tests on large banks.

In this paper, I focus on the mid-size banks and study how stress tests have affected the opacities of these banks. One important difference between the large banks and the mid-size banks is that large banks have to undergo supervisory stress tests while mid-size banks do not. The other interesting difference is that the mid-size banks were not required to disclose the results of the bank-run stress test to the public for the year 2014. The mid-size banks were required to submit their first bank-run stress tests to their primary regulator by March 31, 2014. But, these results were not required to be disclosed to the public. The mid-size banks were required to submit results of the next round of bank-run stress tests to the regulator by March 31, 2015, and disclose summary results to the public between Jun15-Jun30 2015. The non-disclosure of the 2014 stress test results to the public provides a "natural experiment" to investigate the impact of the information generated during stress tests on the bank opacity when these results were not available to the market investors.

I use a regression discontinuity design (RDD) with a discontinuity at \$10 billion of total assets to study the impact of stress tests on bank opacity. The following four model specifications are used to test for changes in bank opacity before and after a stress test.

$$M_{it} = \alpha + \beta_1(Stress\ Test) + \beta_2(log(\Delta Total\_Asset)) + \mu_{it} \tag{10}$$

$$\begin{aligned} M_{it} = \alpha + \beta_1(Stress\ Test) + \beta_2(log(\Delta Total\_Asset)) + \beta_3(\text{COMREAL\_A}_{it}) \\ + \beta_4(\text{RESREAL\_A}_{it}) + \beta_5(\text{OTHLOAN\_A}_{it}) + \beta_6(\text{TRADE\_A}_{it}) \\ + \beta_7(\text{OTHOPAQ\_A}_{it}) + \beta_8(\text{TOTALDERIV\_A}_{it}) \\ + \beta_9(Ln(1 + Num_{Analyst})) + \beta_{10}(NUM\_8K) + \mu_{it} \end{aligned} \tag{11}$$

$$\begin{aligned} M_{it} = \alpha + \beta_1(Stress\ Test) + \beta_2(log(\Delta Total\_Asset)) \\ + \beta_3(log(\Delta Total\_Asset) * Stress\ Test) + \mu_{it} \end{aligned} \tag{12}$$

$$\begin{aligned} M_{it} = \alpha + \beta_1(Stress\ Test) + \beta_2(log(\Delta Total\_Asset)) \\ + \beta_3(log(\Delta Total\_Asset) * Stress\ Test) + \beta_4(\text{COMREAL\_A}_{it}) \\ + \beta_5(\text{RESREAL\_A}_{it}) + \beta_6(\text{OTHLOAN\_A}_{it}) + \beta_7(\text{TRADE\_A}_{it}) \\ + \beta_8(\text{OTHOPAQ\_A}_{it}) + \beta_9(\text{TOTALDERIV\_A}_{it}) \\ + \beta_{10}(Ln(1 + Num_{Analyst})) + \beta_{11}(NUM\_8K) + \mu_{it} \end{aligned} \tag{13}$$

For the models (10)-(13), M_{it} is Opacity, effective spread, price impact, and standard deviation of returns. $\Delta Total\_Asset$ is Total Asset – Total Asset Cutoff ($10Bn), and $Stress\ Test$ is a dummy that equals 1 if a bank has total assets more than Total Asset Cutoff else 0.

Equations 10 and 11 assume that the banks across both sides of cutoff have a linear relationship between the dependent variable and the independent variables with a similar slope but different intercepts. Equations 12 and 13 also assume a linear relationship but different slopes and intercepts on both sides of the cutoff. I estimate equations (10)-(13), using ordinary least squares (OLS) for predicted opacity and indicator variables (Effective Spread, Price Impact, and Standard Deviation of Returns) for different time periods. I cluster standard errors at the bank level for these OLS regressions.

In addition, I also provide estimates of the model represented by Equation (10) using nonparametric kernel regressions. Nonparametric regression captures the nonlinearity of any function more accurately, allowing the data to determine the local shape of the conditional mean relationship (Blundell and Duncan (1998)). Nonparametric regression does not assume a linear relationship between the dependent and independent variables and allows the data to take the local shape of the conditional mean relationship. Epanechnikov kernel is used for Δ*Total_Asset* and Li–Racine kernel is used for the *Stress Test* dummy. I use 500 replications to compute the bootstrap standard errors and percentile confidence intervals for nonparametric regressions.

For the analysis in this section, I also plot two local polynomials for graphical representation of the discontinuity for two sets of banks (one with total assets less than cutoff and the other with total assets greater than cutoff) along with a 95% confidence interval for different periods. I provide this graphical representation for the predicted opacity and three indicator variables (Effective Spread, Price Impact, and Standard Deviation of Returns) for the different periods. For the nonparametric regression, I predict the dependent variables and then plot them with the total assets to show the discontinuity.

I study opacities of mid-size banks for three periods: (1) before the start of stress tests for these banks (Oct2011-Sep2012), (2) for the period when the results of the stress test were reported only to the regulator and not to the public (Sep2013-Mar2015) and (3) for the period when the results of the stress test were reported both to the regulator and the public (Jul2015-Jun2016). The middle period (Sep2013-Mar2015) can be used to study the impact of information generated by the bank insiders while that information is not available to the public.

I. Period before stress tests (Oct2011-Sep2012)

In Panel A of Table 4, we see that the coefficient for the "Stress Test" dummy is insignificant for all the four models (Eq. 10-13), where the predicted opacity is the dependent variable. Similarly, we find from Panel B and Panel D of Table 4 that the coefficient for the "Stress Test" dummy is insignificant for all the four models of Effective Spread and three models (Eq. 10, 12, and 13) of Standard Deviation of Returns. The coefficient for the "Stress Test" dummy is significant at 1% levels for the two models (Eq. 11 and 13) of Price Impact (Panel C of Table 4). In addition, from Panel E of Table

4, we see that the coefficient for the “Stress Test” dummy is insignificant for Predicted Opacity, Effective Spread, and Standard Deviation of Returns, while it is significant for Price Impact at 5% confidence level using nonparametric regression. The graphical representation of the discontinuity for this period is shown in Panel A and B of Figure 4. Thus before the stress tests, I find no evidence that mid-sized and small banks differ in their opacity.

II. The period during stress tests when results were not reported to the public (Sep 2013-Mar 2015)

From Panel A of Table 5, we see that the coefficient of the “Stress Test” dummy is significant for all the four models (Eq. 10-13) when predicted opacity is the dependent variable. The coefficient is significant at 5% confidence for model 1-3 (Eq. 10-12) and at 1% for model 4 (Eq. 13). But, the coefficient for the “Stress Test” dummy is insignificant for most of the models for Effective Spread, Price Impact, and Standard Deviation of Returns for this time period (Panel B, C, and D of Table 5). In addition, from Panel E of Table 5, we find that the coefficient for the “Stress Test” dummy is insignificant for Effective Spread, Price Impact, and Standard Deviation of Returns, while it is significant for Predicted Opacity at 1% confidence level using nonparametric regression. The graphical representation of the discontinuity for this period is shown in Panel A and B of Figure 5. Thus during the period when the mid-size banks were conducting the stress tests but not reporting the results to the public, I find that the opacity of mid-sized banks was higher than the small banks.

III. The period during stress tests when results were reported to the public (Jul2015-Jun2016)

From Panel A of Table 6, we see that the coefficient for the “Stress Test” dummy is insignificant for all the four models (Eq. 13-16) when predicted opacity is the dependent variable. Also, the coefficient for the “Stress Test” dummy is insignificant for Effective

Spread and Price Impact (Panel B and C of Table 6). But, from Panel D of Table 6, we find that the coefficient for the "Stress Test" dummy is significant for Standard Deviation of Returns for three models (Eq.10, 11, and 13) at a 5% confidence interval, while significant at 10% for one model (Eq. 12). In addition, the "Stress Test" dummy coefficient is insignificant for Predicted Opacity, while significant at more than 1% confidence level for Effective Spread, Price Impact, and Standard Deviation of Returns using nonparametric regression (Panel E of Table 6). The graphical representation of the discontinuity for this period is shown in Panel A and B of Figure 6. Thus during this period, when the mid-size banks reported the results of the stress tests to the public, I find no evidence that mid-sized banks and small banks differ in their opacity.

From the above discussion, we see that the opacity of the mid-size banks was higher than small banks during the period (Sep2013-Mar2015) when the mid-size banks carried out bank-run stress tests but did not report the results to the public. Further, the opacity of these banks dropped and was no longer different than small banks once the results of the stress test were made public for the period (Jul2015-Jun2016). However, I don't find a similar pattern for the other indicator variables, i.e., Effective Spread, Price Impact, and standard deviation of returns. In addition, I don't find evidence that the mid-sized and small banks were different in their opacity for the period before the start of the bank-run stress tests (Oct 2011-Sep 2012). I find similar results using nonparametric regressions for the three periods.

The opacity of the mid-size banks that conducted bank-run stress tests was higher than the small banks for the period when the results of the stress tests were not disclosed to the public. In contrast, the opacity of the mid-size banks conducting bank-run stress tests dropped and was no longer different than the small banks after they started disclosing the results of the stress tests to the public. Therefore, we can conclude that stress testing without disclosing the results to the market participants leads to increased bank opacity. I believe that the channel through which opacity increases for banks that conduct stress tests but do not reveal the results to the public is due to the firm's low financial reporting quality. Stress tests generate non-trivial private information, and if the results are not disclosed to the public, it can lead to a significant information asymmetry between bank insiders and the market participants leading to increased adverse selection problems and higher perceived firm opacity.

5.2 Impact of Stress Tests on Large Banks (Total Assets > $50Bn)

There is no exact similar period when the large banks with total assets greater than $50Bn have undergone the supervisory or bank-run stress tests, but the results were not disclosed to the public. Therefore, I study the impact of the stress test on the large banks a little differently. We know from the prior literature that the bank opacity varies over time, and it significantly increased during the 2008-09 financial crisis (Flannery, Kwan, and Nimalendran (2013)). Therefore, to study the banks on the boundary of $50 billion, I look for possible discontinuity using parametric and nonparametric RDD for three-time periods: (1) before the start of the financial crisis (Oct2005-Sep2007), (2) during the financial crisis but before the disclosure of 1st stress test (SCAP-2009) results (Oct2007-Mar2009) and (3) after few rounds of stress tests were disclosed (Oct2014-Sep2016). I follow a similar methodology as described in 5.1 for the mid-size banks to study the banks on the boundary of $50 billion. I use four linear RDD models represented in Eq. (10)-(13), where Δ*Total_Asset* is Total Asset – Total Asset Cutoff ($50Bn) and *Stress Test* is a dummy that equals 1 if a bank has total assets more than Total Asset Cutoff else 0. Similarly, I also provide nonparametric regression estimates for the base model illustrated in Eq. 10 for these three periods.

I. **Period before the financial crisis (Oct2005-Sep2007)**

In Panel A of Table 7, we see that the coefficient for the "Stress Test" dummy is insignificant for all the four models (Eq. 10-13), where the predicted opacity is the dependent variable. Similarly, we find that the coefficient for the "Stress Test" dummy is insignificant for all the four models of Effective Spread, Price Impact, and Standard Deviation of Returns from Panel B, C, and D of Table 7. In addition, from Panel E of Table 7, we see that the coefficient for the "Stress Test" dummy is insignificant for Predicted Opacity, Effective Spread, and Price Impact. But it is significant for Standard Deviation of Returns at 5% confidence level using nonparametric regression. The graphical representation of the discontinuity for this period is shown in Panel A and Panel B of Figure 7. Thus, before the financial crisis, I find no evidence that large and mid-size banks differed in their opacity.

II. The period during the financial crisis but before results of 1st stress test (SCAP-2009) were disclosed (Oct2007-Mar2009)

From Panel A of Table 8, we find that the coefficient for the "Stress Test" dummy is significant for three models when predicted opacity is the dependent variable. The coefficient is significant at 5% confidence for models 1, 2, and 4 (Eq. 10, 11, and 13), while insignificant for model 3 (Eq. 15). But, the coefficient for the "Stress Test" dummy is insignificant for most of the models for Effective Spread, Price Impact, and Standard Deviation of Returns (Panel B, C, and D of Table 8). In addition, from Panel E of Table 8, we see that the coefficient for the "Stress Test" dummy is insignificant for Effective Spread, Price Impact, and Standard Deviation of Returns. But it is significant for Predicted Opacity at a 5% confidence level using nonparametric regression. The graphical representation of the discontinuity for this period is shown in Panel A and Panel B of Figure 8. Thus, for the period during the financial crisis but before the 1st stress test (SCAP-2009) results were disclosed (Oct2007-Mar2009), I find that the opacity of large banks was higher than the mid-size banks.

III. The period after few rounds of stress test results was disclosed (Oct2014-Sep2016)

From Panel A of Table 9, we see that the coefficient for the "Stress Test" dummy is insignificant for all the four models (Eq. 10-13) when predicted opacity is the dependent variable. Also, the coefficient for the "Stress Test" dummy is insignificant for Effective

Spread, Price Impact, and Standard Deviation of Returns (Panel B, C, and D of Table 9). In addition, from Panel E of Table 9, we find that the "Stress Test" dummy coefficient is insignificant for Predicted Opacity, Price Impact, and Standard Deviation of Returns while significant at more than 5% confidence level for Effective Spread using nonparametric regression. The graphical representation of the discontinuity for this period is shown in Panel A and Panel B of Figure 9. Thus during this period, when the large banks have undergone few rounds of stress tests and the results of the stress tests were disclosed to the public, I again find no evidence that large banks and small banks differ in their opacity.

We didn't have an exact comparable period for the large banks when these banks were doing the stress tests, and the results were not disclosed to the public. For the large banks, we studied the predicted opacity in the crisis vs. non-crisis period. I find that during the financial crisis, but before the results of 1st stress test were disclosed to the public, the opacity of the large banks was higher than the opacity of the mid-size banks. But, the opacity of large banks was not statistically different than the mid-size banks before the financial crisis and after few rounds of stress tests. Therefore, we can conclude that the financial crisis increased the opacity of large banks disproportionately more than the opacity of the mid-size banks.

6 Conclusion

In the finance and accounting literature, firm opacity has been extensively used but seldom defined. Further, the firm opacity has been defined and interpreted differently depending on the context it has been discussed. Many proxies have been used to measure the firm opacity in the literature: the R^2 of stock return regressed on market return, accounting-based measures, market microstructure measures, analyst forecast errors, etc. But most of them are noisy proxies for the 'true opacity.' I propose a new approach based on the MIMIC model of Joreskog and Goldberger (1975) to measure opacity as a latent variable. The model assumes that bank opacity is unobservable, but there are several observable causes and indicators of opacity. In the MIMIC model, the latent opacity is caused by the bank assets (commercial real estate loans, residential real estate loans, consumer loans, trading assets, total derivative exposure, and other opaque assets) and the bank's information environment (number of analysts covering the bank and the number of 8-K filings). Different proxies for opacity are used as multiple indicators (effective spread, price impact, and stock return volatility).

We find that the opacity of the mid-size banks (\$10B<Assets<\$50B) was higher for the period when they carried out the stress tests but did not report results to the public, compared to the opacity of small banks (Assets<\$10B), which were not required to undergo any stress tests. However, once mid-size banks started to disclose their results to the public, there was no difference in the opacity of mid-size and small banks. Therefore, disclosure of the stress test results provided additional information to the market participants. The stress tests without public disclosure generate additional insider information that is not available to the public, causing increased adverse selection problems and costs. I also find that large banks' opacity was higher than the opacity of mid-size banks during the financial crisis and before disclosure of the 1st stress tests results.

Over the years, banks have become large, and their business models are increasingly complex. Therefore, the banking regulatory reforms place significant emphasis on disclosure and transparency. In the past, reforms have focused on larger banks, and little attention has been paid to smaller banks. This paper shows that the problem of the opacity of banking assets is not just limited to large banks. The opacity increased for mid-size banks that conducted bank-run stress tests but did not disclose the results to the public. Therefore, we can conclude that the stress tests generate valuable information about the banks, and non-disclosure of the stress test results to the public reduced the transparency of banks. Therefore, an activity producing private information without public disclosure may not be desirable for the financial stability of the banking system. In addition, the lack of public disclosure puts the investor at a trading disadvantage.

7 References

Anderson, Ronald C., Augustine Duru, and David M. Reeb, 2009, Founders, heirs, and corporate opacity in the United States, *Journal of Financial Economics*.

Barth, Mary E., Ron Kasznik and Maureen F. McNichols, 2002, Analyst Coverage and Intangible Assets, *Journal of Accounting Research.*

Berlin, Mitchell, and Jan Loeys, 1988, Bond Covenants and Delegated Monitoring, *The Journal of Finance* 43, 397–412.

Blau, Benjamin M., Tyler J. Brough, and Todd G. Griffith, 2017, Bank opacity and the efficiency of stock prices, *Journal of Banking and Finance*.

Brogaard, Jonathan, Dan Li, and Ying Xia, 2017, Stock liquidity and default risk, *Journal of Financial Economics* 124, 486–502.

Blundell, R., & Duncan, A. 1998, Kernel Regression in Empirical Microeconomics, *The Journal of Human Resources*, 33(1), 62–87.

Campbell, Tim S, and William a Kracaw, 1980, Information Production, Market Signalling, and the Theory of Financial Intermediation, *Journal of Finance*.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance*.
Chang, Chingfu, Alice C. Lee, Cheng F. Lee, 2009, Determinants of capital structure choice: A structural equation modeling approach, *The Quarterly Review of Economics and Finance*.

Dhaliwal, Dan S., Suresh Radhakrishnan, Albert Tsang, and Yong George Yang, 2012, Non-financial disclosure and analyst forecast accuracy: International evidence on corporate social responsibility disclosure, *Accounting Review*.

Diamond, Douglas W., 1984, Financial Intermediation and Delegated Monitoring, *The Review of Economic Studies*.

Diamond, Douglas W., 1984, Financial Intermediation as Delegated Monitoring: A Simple

Example, *Federal Reserve Bank of Richmond Research Publications*.

Diamond, Douglas W., 1991, Monitoring and Reputation: The Choice between Bank Loans and Directly Placed Debt, *Journal of Political Economy*.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics*.

Fernandes, Marcelo, Deniz Igan, and Marcelo Pinheiro, 2017, March madness in Wall Street: (What) does the market learn from stress tests?, *Journal of Banking and Finance*.

Flannery, Mark, Beverly Hirtle, and Anna Kovner, 2017, Evaluating the information in the federal reserve stress tests, *Journal of Financial Intermediation*.

Flannery, Mark J., Simon H. Kwan, and Mahendrarajah Nimalendran, 2013, The 2007-2009 financial crisis and bank opaqueness, *Journal of Financial Intermediation* 22, 55–84.

Flannery, Mark J, Simon H Kwan, and M Nimalendran, 2004, Market evidence on the opaqueness of banking firms' assets, *Journal of Financial Economics* 71, 419–460.

Fosu, Samuel, Collins G. Ntim, William Coffie, and Victor Murinde, 2017, Bank opacity and risk-taking: Evidence from analysts' forecasts, *Journal of Financial Stability*.

Gounopoulosa, Dimitrios, Höbeltb, Johannes, and Nikolaos I. Papanikolaouc, 2018, Transparency versus opacity: Are bank stress tests worthwhile?, *European Financial Management Association, Annual Meetings*

Greene, W.H., 2002, *Econometric Analysis Lancet*.

Gu, Feng, and Weimin Wan, 2005, Intangible assets, information complexity, and analysts' earnings forecasts, *Journal of Business Finance and Accounting*.

Haggard, K Stephen, and John S Howe, 2012, Are Banks Opaque ?, *International Review of Accounting Banking and Finance* 4, 51–72.

Hankins, Kristine, 2011, How Do Financial Firms Manage Risk? Unraveling the Interaction of Financial and Operational Hedging, *Management Science*.

Hou, Kewei, and Tobias J. Moskowitz, 2005, Market frictions, price delay, and the cross-section of expected returns, *Review of Financial Studies*.

Hu, Li Tze, and Peter M. Bentler, 1999, Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives, *Structural Equation Modeling*.

Iannotta, Giuliano, 2006, Testing for opaqueness in the European banking industry: Evidence from bond credit ratings, *Journal of Financial Services Research*.

Jensen, Michael C., and William H. Meckling, 1976, Theory of the Firm: Managerial Behavior, Agency Costs, and Ownership Structure, *Journal of Financial Economics*.

Jin, Li, and Stewart C. Myers, 2006, R^2 around the world: New theory and new tests, *Journal of Financial Economics* 79, 257–292.

Jones, Jeffrey S., Wayne Y. Lee, and Timothy J. Yeager, 2012, Opaque banks, price discovery, and financial instability, *Journal of Financial Intermediation*.

Jones, Jeffrey S., Wayne Y. Lee, and Timothy J. Yeager, 2013, Valuation and systemic risk consequences of bank opacity, *Journal of Banking and Finance* 37, 693–706.

Joreskog, Karl G., and Arthur S. Goldberger, 1975, Estimation of a Model with Multiple Indicators and Multiple Causes of a Single Latent Variable, *Journal of the American Statistical Association*.

Lee, Charles M C, and Mark J Ready, 1991, Inferring Trade Direction from Intraday Data, *The Journal of Finance*.

Lehavy, Reuven, Feng Li, Kenneth Merkley, 2011, The Effect of Annual Report Readability on Analyst Following and the Properties of Their Earnings Forecasts, *The Accounting Review.*

Madhavan, Ananth, 2000, Market microstructure: A survey, *Journal of Financial Markets*.
Maddala, G. S. and M. Nimalendran, (1996), 17 Errors-in-variables problems in financial

models, *Handbook of Statistics.*

Morck, Randall, Bernard Yeung, and Wayne Yu, 2000, The information content of stock markets: why do emerging markets have synchronous stock price movements?, *Journal of Financial Economics* 58, 215–260.

Morgan, Donald P., 2002, Rating banks: Risk and uncertainty in an opaque industry, *American Economic Review* 92, 874–888.

Morgan, Donald P., Stavros Peristiani, and Vanessa Savino, 2014, The information value of the stress test, *Journal of Money, Credit and Banking*.

Myers, Stewart C., and Raghuram G. Rajan, 1998, The paradox of liquidity, *Quarterly Journal of Economics*.

Schneider, Friedrich and Dominik H. Enste, 2000, Shadow Economies: Size, Causes, and Consequences, *Journal of Economic Literature.*

Titman, Sheridan, and Roberto Wessels, 1988, The Determinants of Capital Structure Choice, *The Journal of Finance.*

Tucker, Jennifer W., 2015, Firm Opacity, Analyst Forecasts, and Investor Reaction, *Working Paper.*

Appendices

Appendix A

Table: Definition of banking asset variables taken from FR Y-9C and call reports

Assets	Total Assets	BHCK2170
LOAN	Loan and leases, net	BHCK2122 – BHCK2123
COMREAL	Commercial real estate loans, net	BHDM1415 + BHDM1420 + BHDM1460 + BHDM1480
RESREAL	Residential real estate loans, net	BHDM1797 + BHDM5367 + BHDM5368
OTHLOAN	All other loans, net	LOAN - COMREAL - RESREAL
TRADE	Trading assets	BHCK3545
TRANSP	All transparent assets: cash, federal funds sold, securities purchased under agreements to resell, guaranteed AFS and HTM securities	BHCK0081 + BHCK0395 + BHCK0397 + BHDMB987 + BHCKB989 + BHCK1754 + BHCK1773 - (BHCK1709 + BHCK1733 + BHCKG320) - (BHCK1713 + BHCK1736 + BHCKG323) - (BHCKB838 + BHCKB842 + BHCKB846 + BHCKB850 + BHCKB854 + BHCKB858 + BHCKC026 + BHCKG336 + BHCKG340 + BHCKG344) + (BHCKB841 + BHCKB845 + BHCKB849 + BHCKB853 + BHCKB857 + BHCKB861 + BHCKC027 + BHCKG339 + BHCKG343 + BHCKG347)
OTHOPAQ	Mortgage-backed or asset-backed securities classified as available-for-sale (AFS) or held-to-maturity (HTM) that	Assets - Loan - TRADE – TRANSP

	are not explicitly or implicitly guaranteed by a federal government-related entity as well as other opaque assets that include fixed assets, intangible assets, other assets, investment in an unconsolidated subsidiary, and other real estate owned	
TOTALDERIV	The gross notional amount of derivatives (Interest rate contracts, Foreign Exchange Contracts, Equity Derivative Contracts, and Commodity and Other Contracts) used for either trading or hedging purposes	BHCKA126 + BHCKA127+BHCK8723 + BHCK8724 + BHCK8725 + BHCK8726 + BHCK8727 + BHCK8728

Figures

Figure 1: Causes and Indicators of Bank Opacity

This figure provides a snapshot of the major causes and indicators of Bank Opacity. Bank Opacity is caused by the operating and reporting environment of the bank, as shown in the center of the figure. On the left side of the figure, the major causes of opacity are listed, while, on the right side, major indicators used in literature to measure opacity are provided.

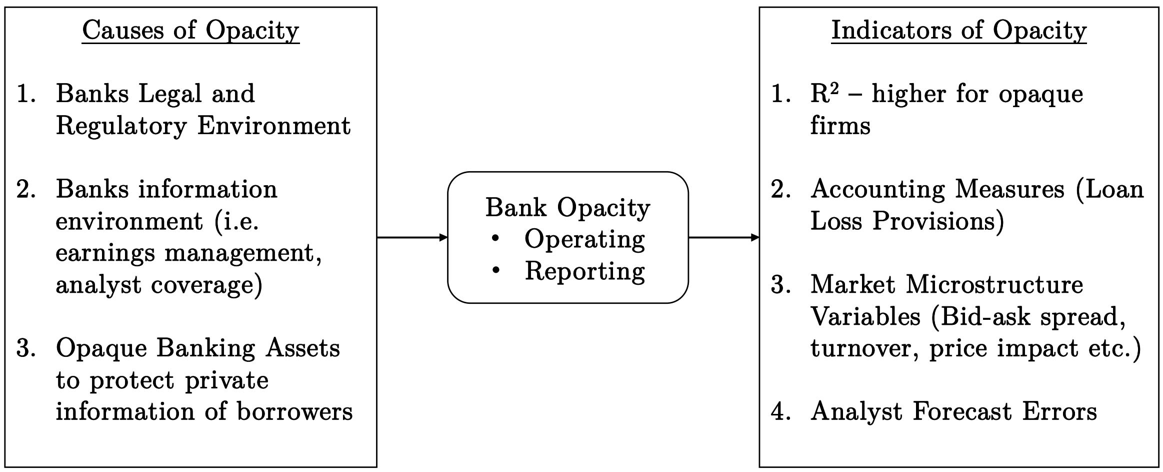


Figure 2: Proposed Model for Opacity of Banking Assets

This figure provides the representation of the proposed MIMIC model to compute the latent opacity. This figure captures the MIMIC model represented in the equations 6-9. At the bottom of the figure, the causes of opacity entering the structural model have been shown. The latent variable Bank Opacity (shown in oval) influences three indicator variables selected in the proposed model (Effective Spread, Price Impact, and Standard Deviation of Returns). The indicator variables are also influenced by the other bank characteristics – Market Capitalization, Trading Price, Turnover, and Leverage. As shown exchange dummy is also included in the measurement model.

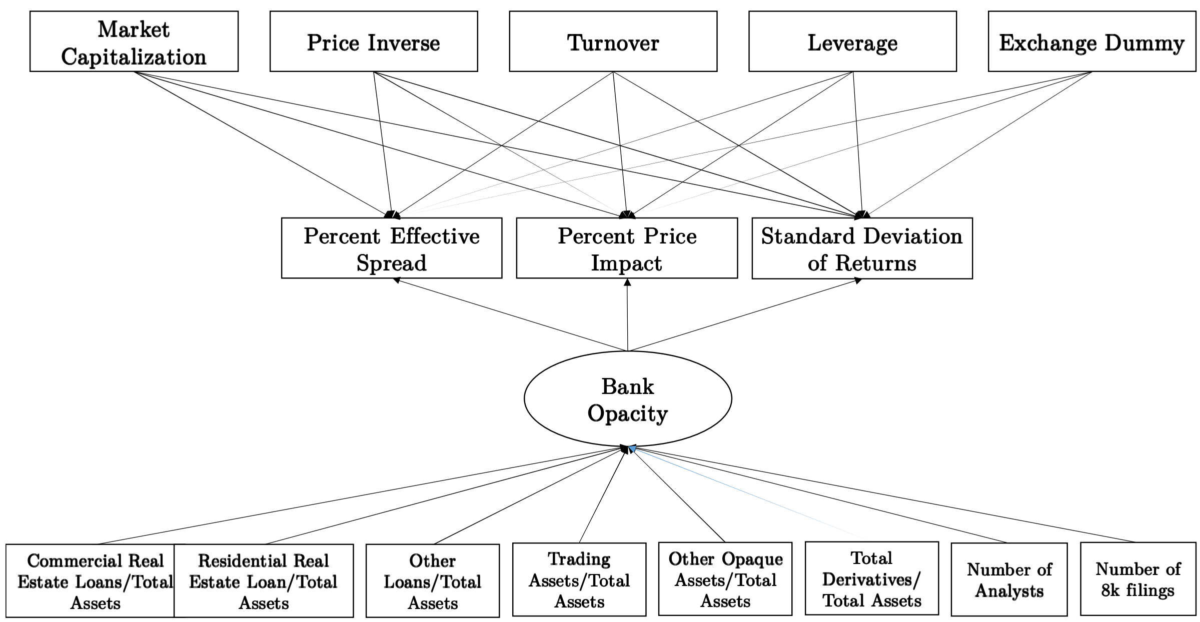


Figure 3: Predicted Opacity and Indicator variables over the period of time in the sample period

This figure shows the pattern of predicted opacity and three indicator variables (Effective Spread, Price Impact, and Standard Deviation of Returns) over the sample period (2002-2016). The predicted opacity and standard deviation of returns are plotted on the primary y-axis (left side), while Effective Spread and Price Impact are plotted on the secondary y-axis (right side). We see that even though predicted opacity is correlated with the other indicator variables, it has additional information content. As already shown in the literature, the predicted opacity and other microstructure variables increased during the financial crisis.

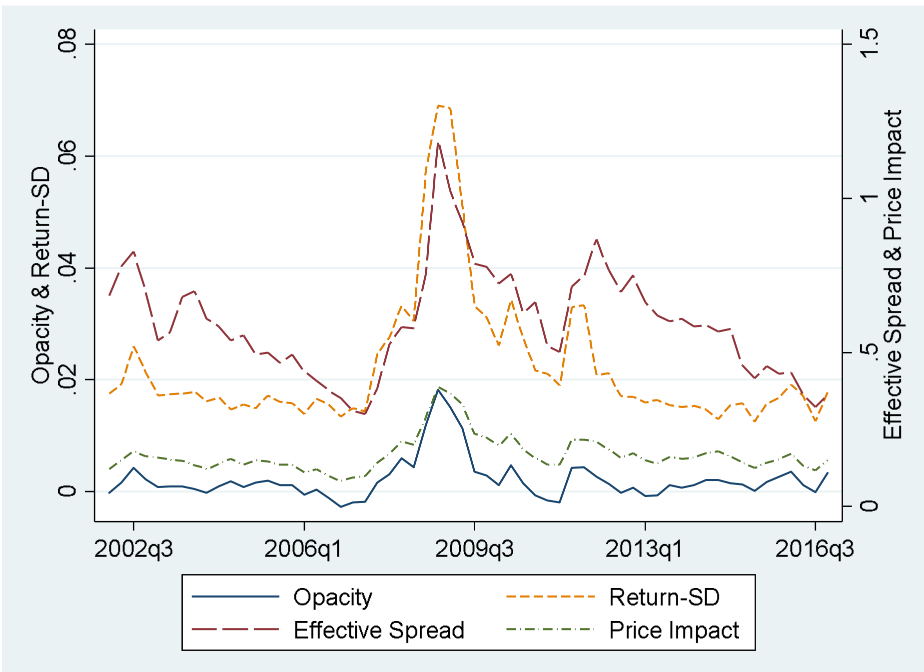
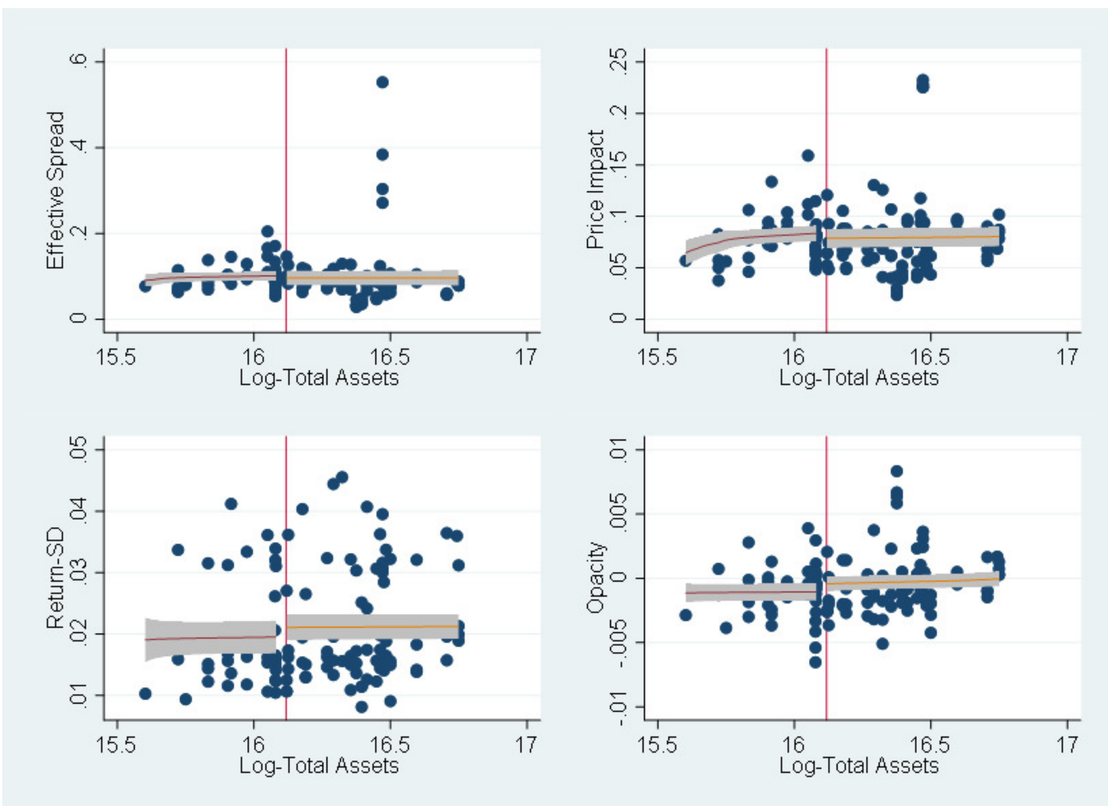


Figure 4: Predicted Opacity and indicator variables of banks on the boundary of $10Bn total assets for the pre-stress test period (Oct2011-Sep2012)

Panel A: Graphical representation of the discontinuity using local linear polynomials

This figure shows a graphical representation of the discontinuity for Effective Spread, Price Impact, Standard Deviation of Returns and predicted opacity of banks with less than $10Bn in total assets and banks with more than $10Bn in total assets for the pre-stress test period (Oct2011-Sep2012) using local linear polynomials. Effective Spread, Price Impact, Standard Deviation of returns, and predicted opacity are plotted on the y-axis while Log(Total Assets) represents the x-axis. All four plots show two local polynomial lines (solid red lines) for two sets of banks (one with total assets less than $10Bn and the other with total assets greater than $10Bn) using local linear regression. The shaded area represents the 95% confidence interval for the local linear regression. Individual data points are shown with solid blue dots, while the discontinuity is illustrated by a red vertical line at a total asset of $10Bn.



Panel B: Graphical representation of the discontinuity using predicted variables from non-parametric kernel regressions

This figure shows a graphical representation of the discontinuity for Effective Spread, Price Impact, Standard Deviation of Returns and predicted opacity of banks less than $10Bn in total assets and more than $10Bn in total assets for the pre-stress test period (Oct2011-Sep2012) using predicted values from non-parametric kernel regressions. Predicted values of the Effective Spread, Price Impact, Standard Deviation of Returns, and the predicted opacity are plotted on the y-axis while Log(Total Assets) represents the x-axis. Predicted values from the non-parametric kernel regressions are shown with blue dots. The discontinuity is shown by a red vertical line at a total asset of $10Bn.

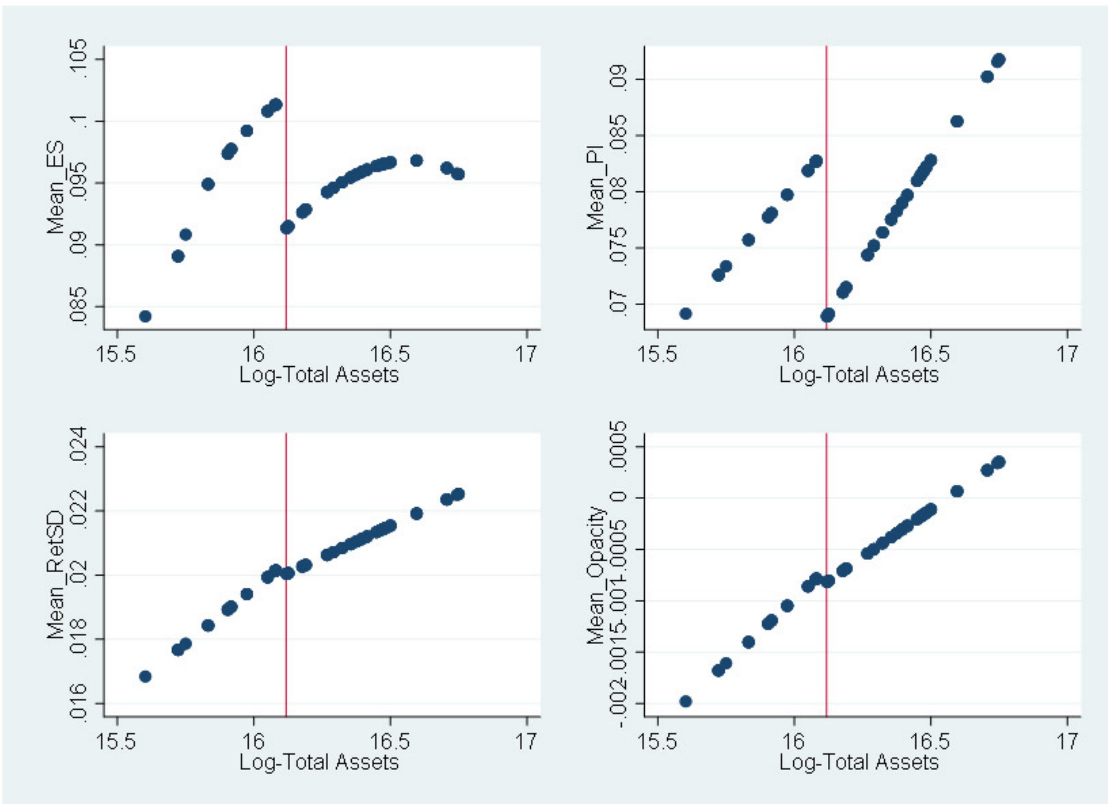
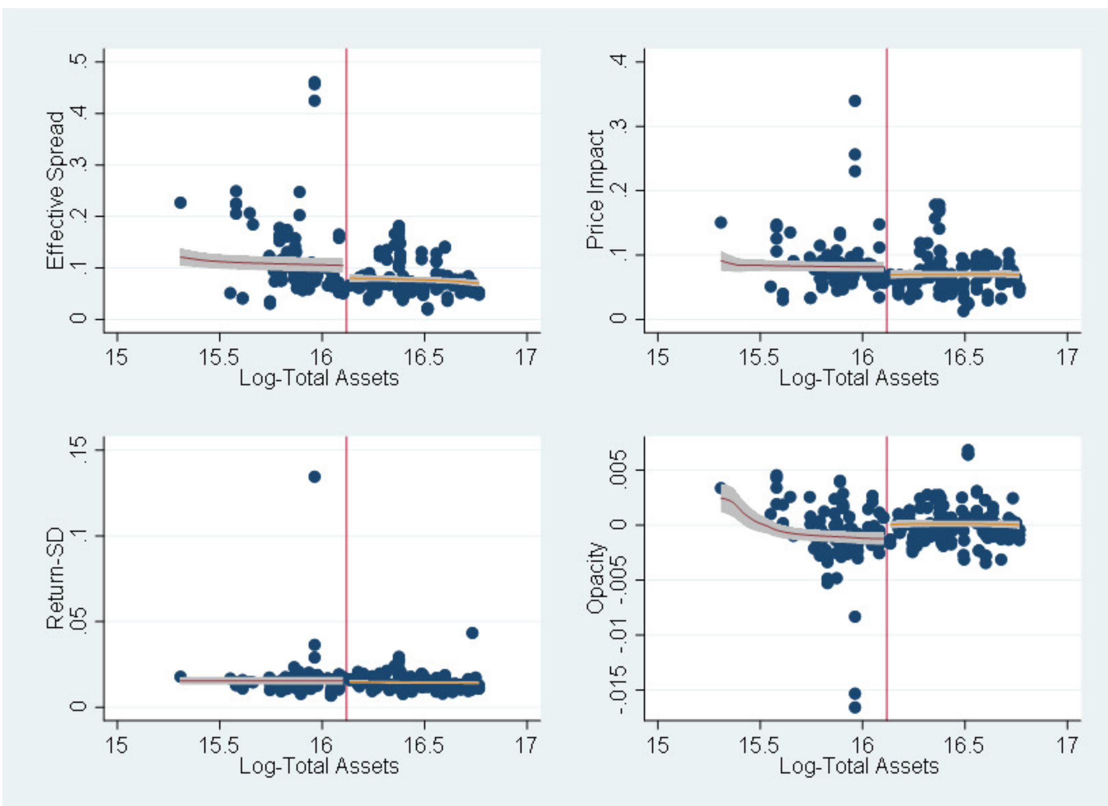


Figure 5: Predicted Opacity and indicator variables of banks on the boundary of $10Bn total assets for the period when the results of the stress tests were reported only to the regulator and not to the public (Sep2013-Mar2015)

Panel A: Graphical representation of the discontinuity using local linear polynomials

This figure shows a graphical representation of the discontinuity for Effective Spread, Price Impact, Standard Deviation of Returns and predicted opacity of banks with less than $10Bn in total assets and banks with more than $10Bn in total assets for the period when the results of the stress tests were reported only to the regulator and not to the public (Sep2013-Mar2015) using local linear polynomials. Effective Spread, Price Impact, Standard Deviation of returns, and predicted opacity are plotted on the y-axis while Log(Total Assets) represents the x-axis. All four plots show two local polynomial lines (solid red lines) for two sets of banks (one with total assets less than $10Bn and the other with total assets greater than $10Bn) using local linear regression. The shaded area represents the 95% confidence interval for the local linear regression. Individual data points are shown with solid blue dots, while the discontinuity is illustrated by a red vertical line at a total asset of $10Bn.



Panel B: Graphical representation of the discontinuity using predicted variables from non-parametric kernel regressions

This figure shows a graphical representation of the discontinuity for Effective Spread, Price Impact, Standard Deviation of Returns and predicted opacity of banks less than \$10Bn in total assets and more than \$10Bn in total assets for the period when the results of the stress tests were reported only to the regulator and not to the public (Sep2013-Mar2015) using predicted values from non-parametric kernel regressions. Predicted values of the Effective Spread, Price Impact, Standard Deviation of Returns, and the predicted opacity are plotted on the y-axis while Log(Total Assets) represents the x-axis. Predicted values from the non-parametric kernel regressions are shown with blue dots. The discontinuity is shown by a red vertical line at a total asset of \$10Bn.

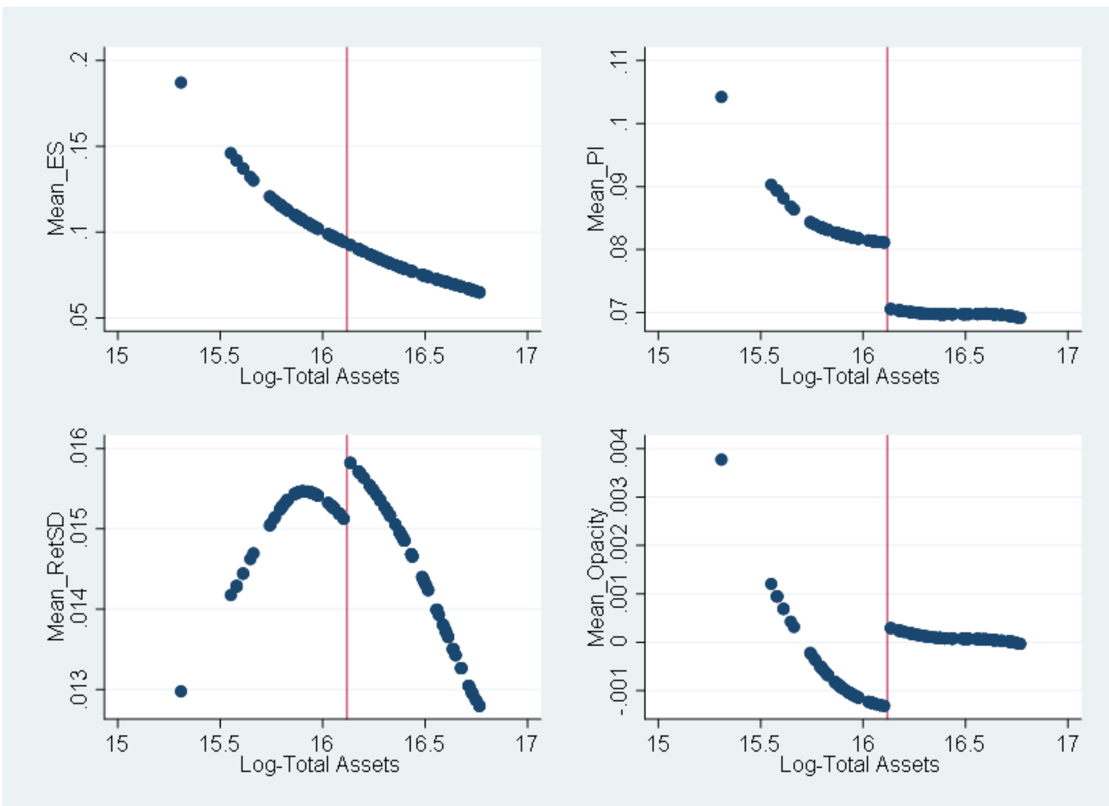
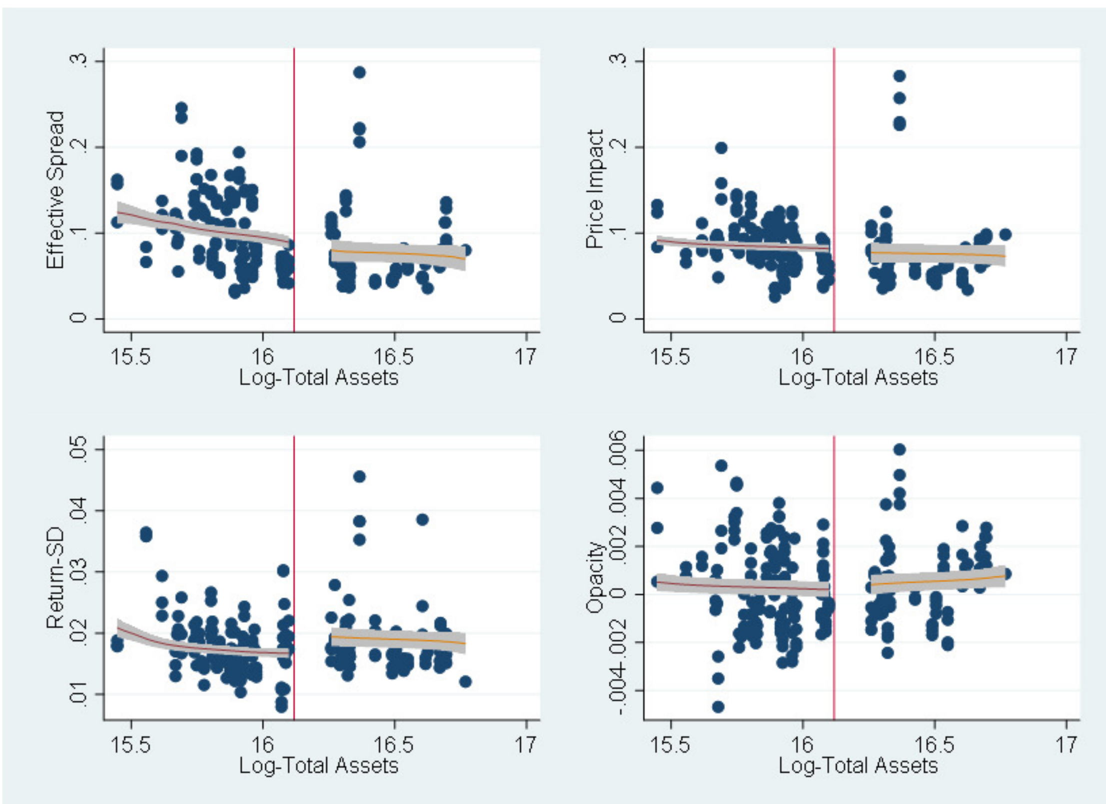


Figure 6: Predicted Opacity and indicator variables of banks on the boundary of \$10Bn total assets for the period when the results of the stress test were reported both to the regulator and the public (Jul2015-Jun2016)

Panel A: Graphical representation of the discontinuity using local linear polynomials

This figure shows a graphical representation of the discontinuity for Effective Spread, Price Impact, Standard Deviation of Returns and predicted opacity of banks with less than \$10Bn in total assets and banks with more than \$10Bn in total assets for the period when the results of the stress test were reported both to the regulator and the public (Jul2015-Jun2016) using local linear polynomials. Effective Spread, Price Impact, Standard Deviation of returns, and predicted opacity are plotted on the y-axis while Log(Total Assets) represents the x-axis. All four plots show two local polynomial lines (solid red lines) for two sets of banks (one with total assets less than \$10Bn and the other with total assets greater than \$10Bn) using local linear regression. The shaded area represents the 95% confidence interval for the local linear regression. Individual data points are shown with solid blue dots, while the discontinuity is illustrated by a red vertical line at a total asset of \$10Bn.



Panel B: Graphical representation of the discontinuity using predicted variables from non-parametric kernel regressions

This figure shows a graphical representation of the discontinuity for Effective Spread, Price Impact, Standard Deviation of Returns and predicted opacity of banks less than $10Bn in total assets and more than $10Bn in total assets for the period when the results of the stress test were reported both to the regulator and the public (Jul2015-Jun2016) using predicted values from non-parametric kernel regressions. Predicted values of the Effective Spread, Price Impact, Standard Deviation of Returns, and the predicted opacity are plotted on the y-axis while Log(Total Assets) represents the x-axis. Predicted values from the non-parametric kernel regressions are shown with blue dots. The discontinuity is shown by a red vertical line at a total asset of $10Bn.

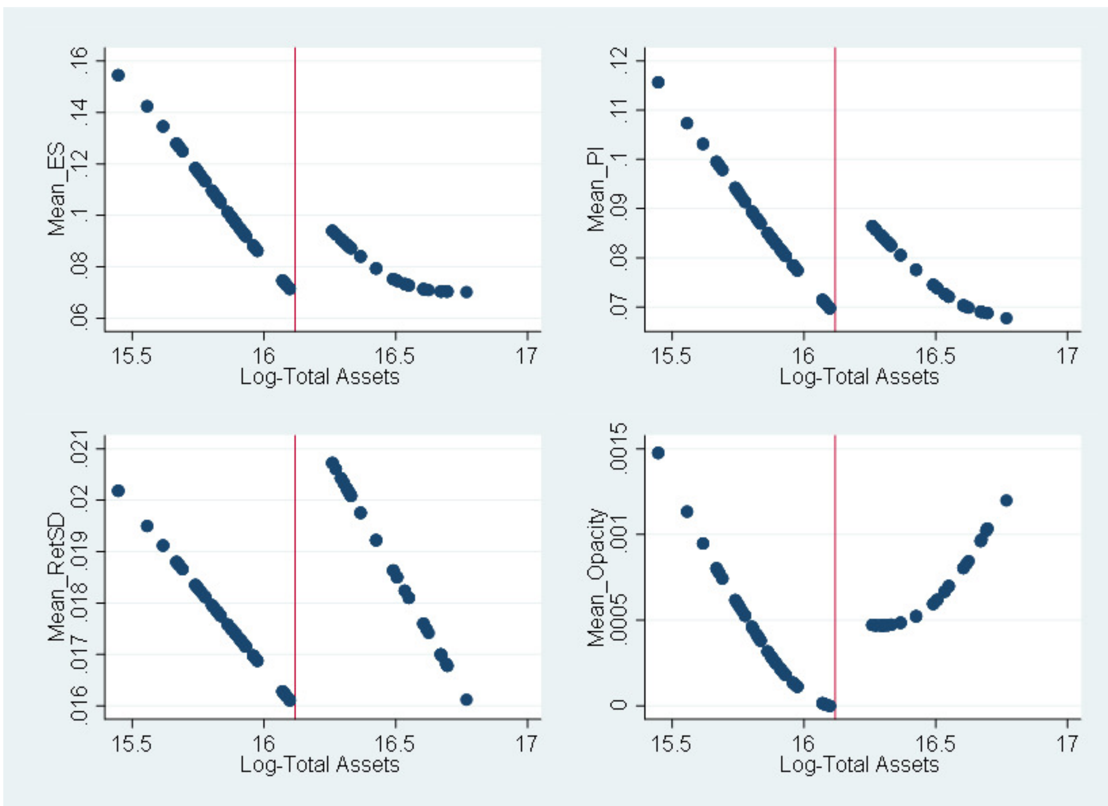
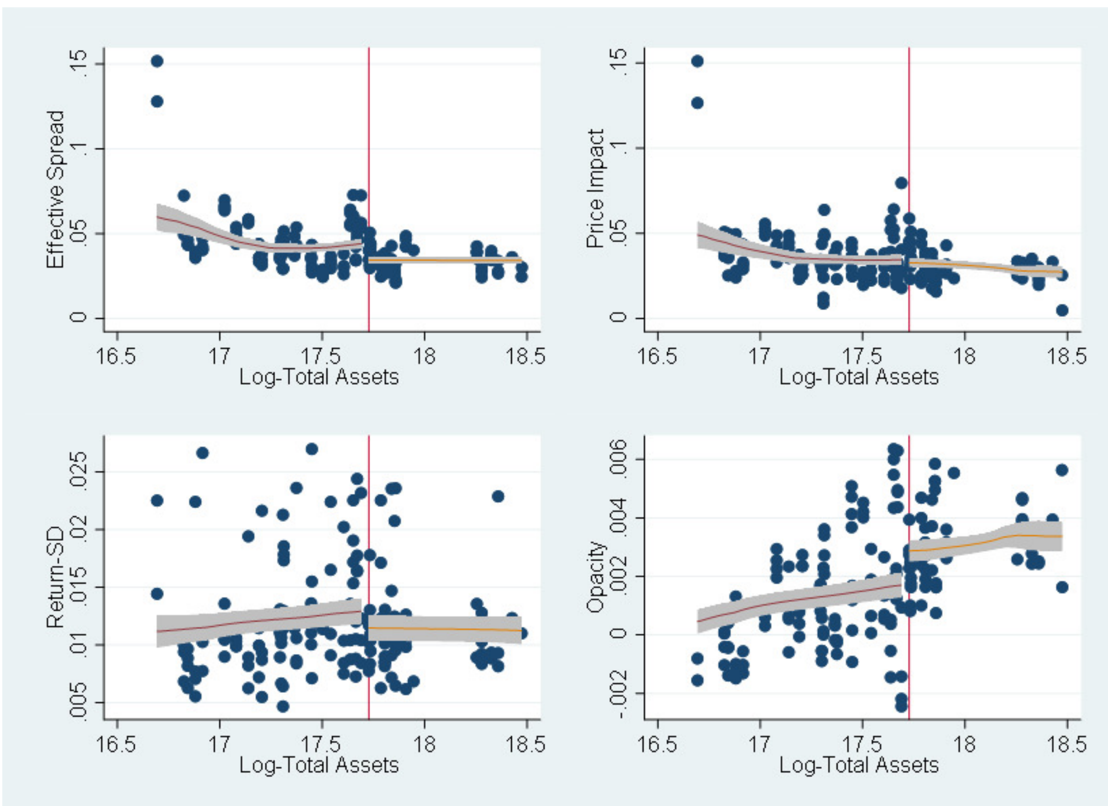


Figure 7: Predicted Opacity and indicator variables of banks on the boundary of $50Bn total assets for the period before the start of the financial crisis (Oct2005-Sep2007)

Panel A: Graphical representation of the discontinuity using local linear polynomials
This figure shows a graphical representation of the discontinuity for Effective Spread, Price Impact, Standard Deviation of Returns and predicted opacity of banks with less than $50Bn in total assets and banks with more than $50Bn in total assets for the period before the start of the financial crisis (Oct2005-Sep2007) using local linear polynomials. Effective Spread, Price Impact, Standard Deviation of returns, and predicted opacity are plotted on the y-axis while Log(Total Assets) represents the x-axis. All four plots show two local polynomial lines (solid red lines) for two sets of banks (one with total assets less than $50Bn and the other with total assets greater than $50Bn) using local linear regression. The shaded area represents the 95% confidence interval for the local linear regression. Individual data points are shown with solid blue dots, while the discontinuity is illustrated by a red vertical line at a total asset of $50Bn.



Panel B: Graphical representation of the discontinuity using predicted variables from non-parametric kernel regressions

This figure shows a graphical representation of the discontinuity for Effective Spread, Price Impact, Standard Deviation of Returns and predicted opacity of banks less than $50Bn in total assets and more than $50Bn in total assets for the period before the start of the financial crisis (Oct2005-Sep2007) using predicted values from non-parametric kernel regressions. Predicted values of the Effective Spread, Price Impact, Standard Deviation of Returns, and the predicted opacity are plotted on the y-axis while Log(Total Assets) represents the x-axis. Predicted values from the non-parametric kernel regressions are shown with blue dots. The discontinuity is shown by a red vertical line at a total asset of $50Bn.

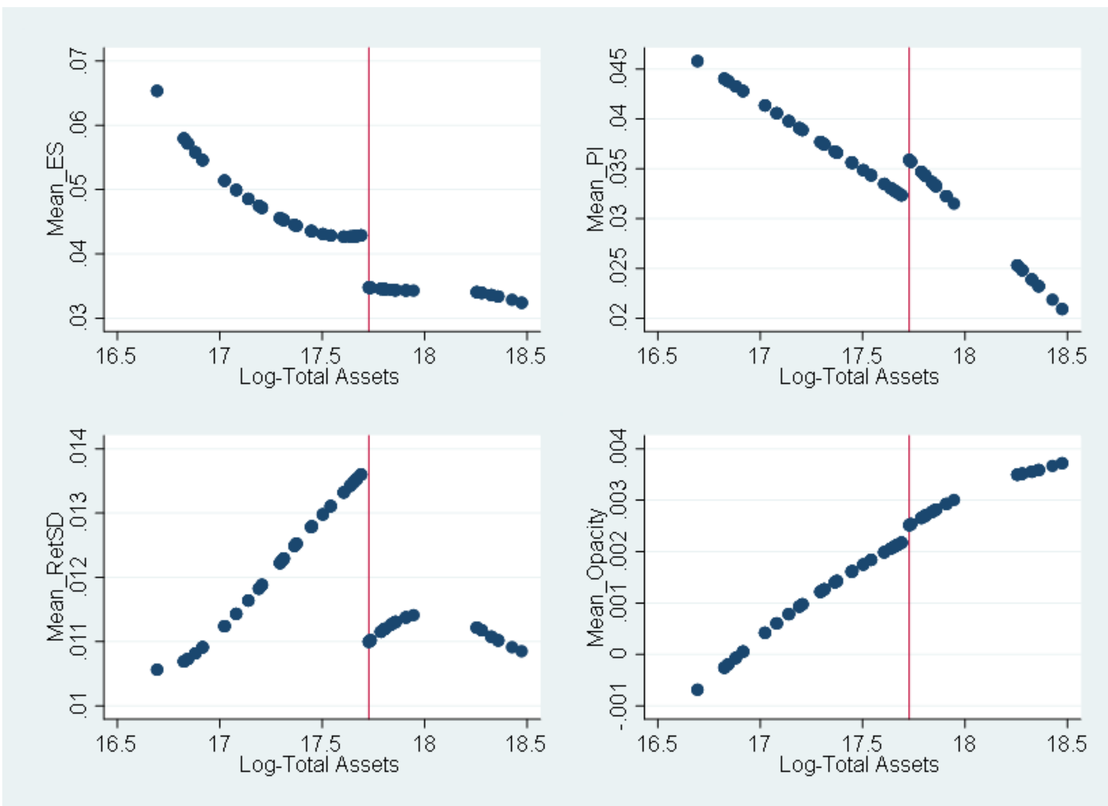
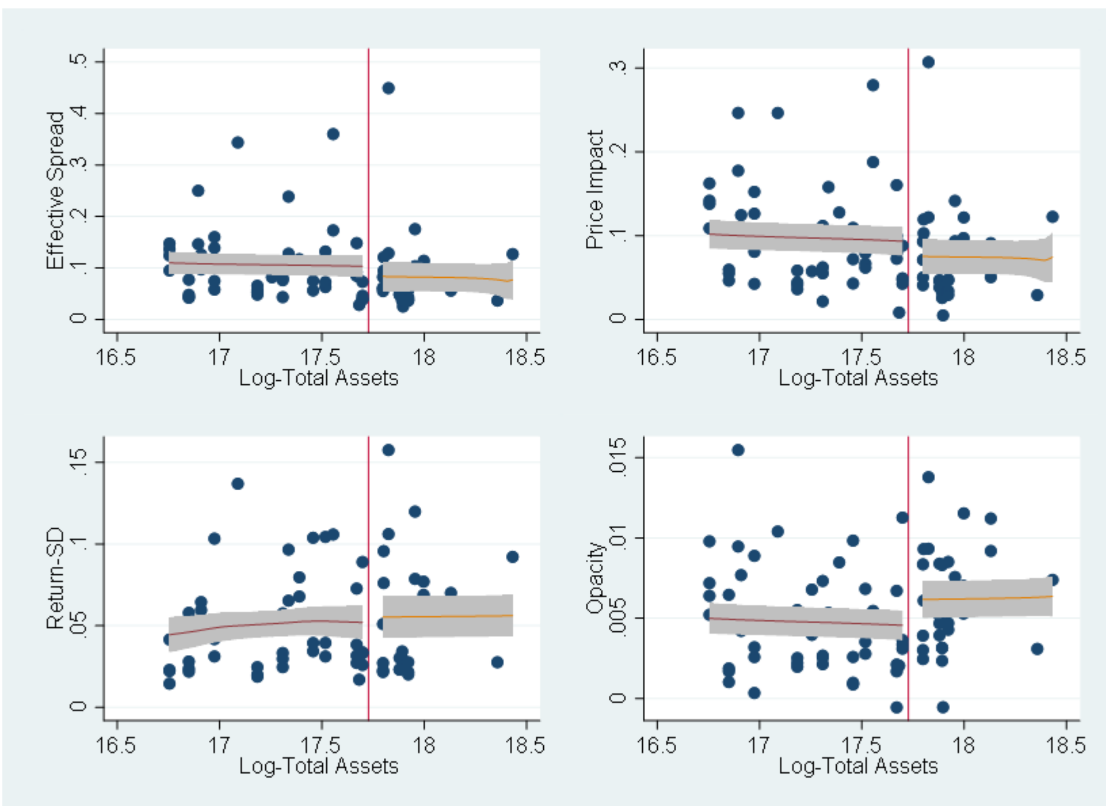


Figure 8: Predicted Opacity and indicator variables of banks on the boundary of $50Bn total assets for the period during the financial crisis but before results of 1st stress tests (SCAP-2009) were disclosed (Oct2007-Mar2009)

Panel A: Graphical representation of the discontinuity using local linear polynomials

This figure shows a graphical representation of the discontinuity for Effective Spread, Price Impact, Standard Deviation of Returns and predicted opacity of banks with less than $50Bn in total assets and banks with more than $50Bn in total assets for the period during the financial crisis but before results of 1st stress tests (SCAP-2009) were disclosed (Oct2007-Mar2009) using local linear polynomials. Effective Spread, Price Impact, Standard Deviation of returns, and predicted opacity are plotted on the y-axis while Log(Total Assets) represents the x-axis. All four plots show two local polynomial lines (solid red lines) for two sets of banks (one with total assets less than $50Bn and the other with total assets greater than $50Bn) using local linear regression. The shaded area represents the 95% confidence interval for the local linear regression. Individual data points are shown with solid blue dots, while the discontinuity is illustrated by a red vertical line at a total asset of $50Bn.



Panel B: Graphical representation of the discontinuity using predicted variables from non-parametric kernel regressions

This figure shows a graphical representation of the discontinuity for Effective Spread, Price Impact, Standard Deviation of Returns and predicted opacity of banks less than $50Bn in total assets and more than $50Bn in total assets for the period during the financial crisis but before results of 1st stress tests (SCAP-2009) were disclosed (Oct2007-Mar2009) using predicted values from non-parametric kernel regressions. Predicted values of the Effective Spread, Price Impact, Standard Deviation of Returns, and the predicted opacity are plotted on the y-axis while Log(Total Assets) represents the x-axis. Predicted values from the non-parametric kernel regressions are shown with blue dots. The discontinuity is shown by a red vertical line at a total asset of $50Bn.

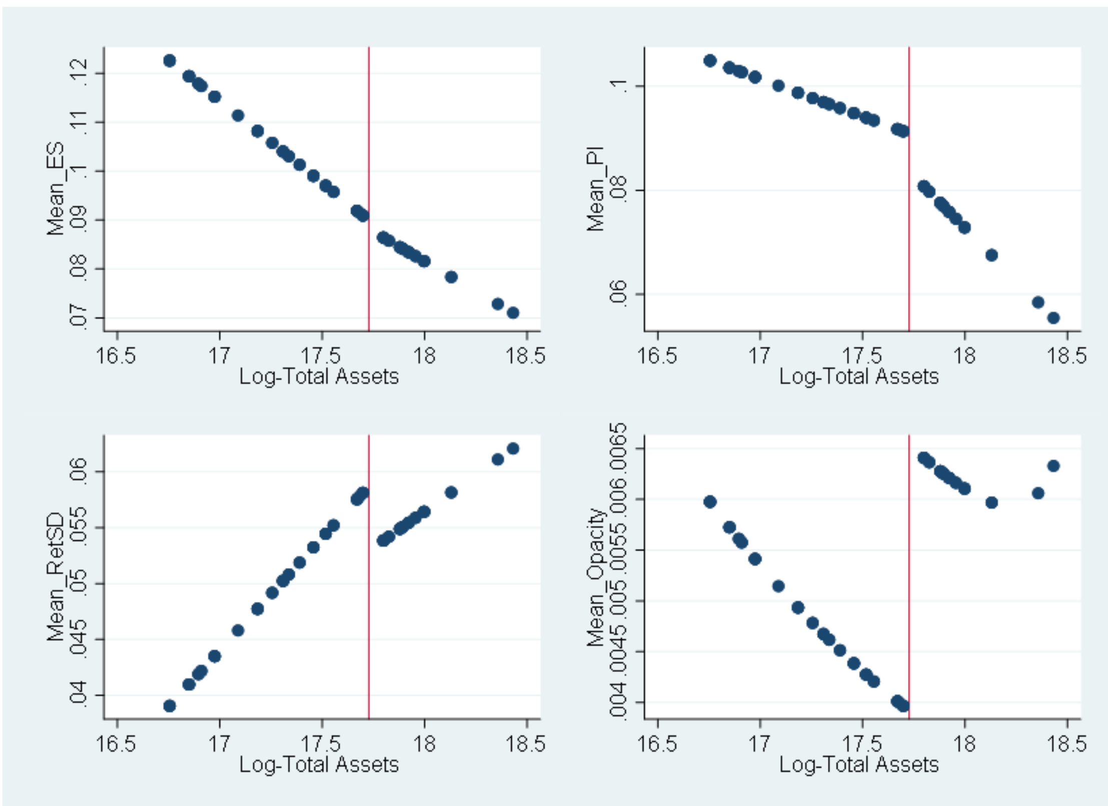
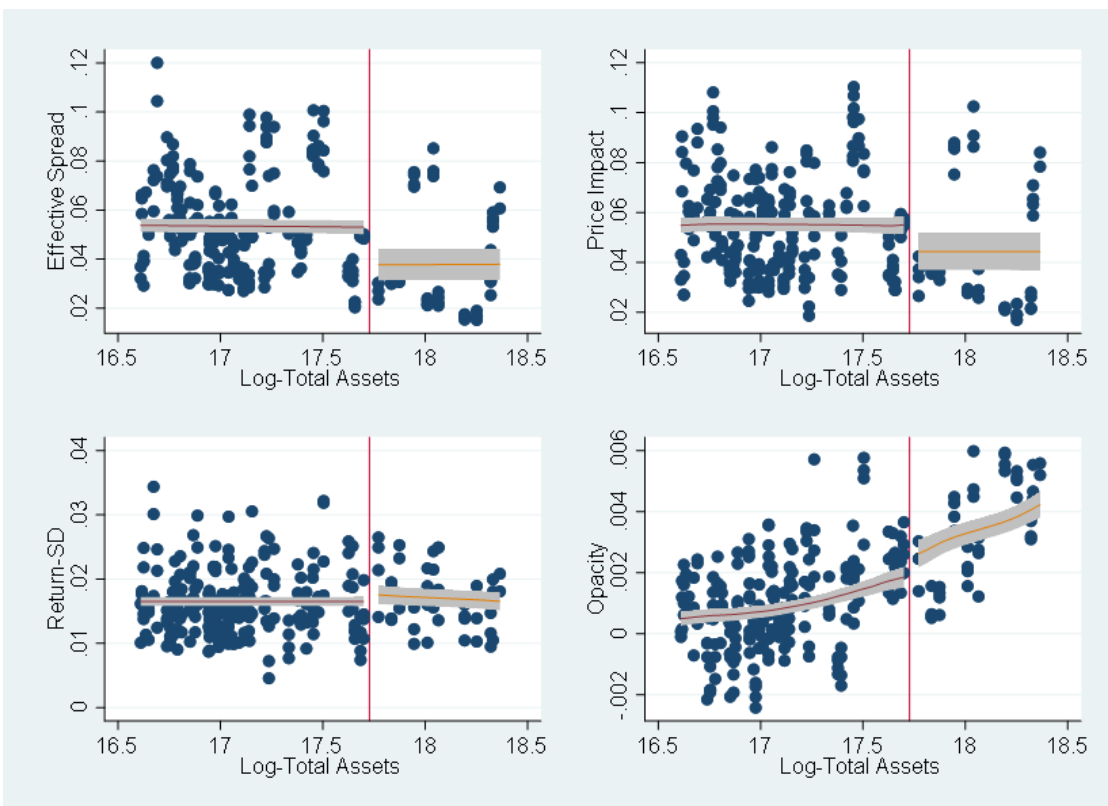


Figure 9: Predicted Opacity and indicator variables of banks on the boundary of $50Bn total assets for the period after few rounds of stress test results were disclosed (Oct2014-Sep2016)

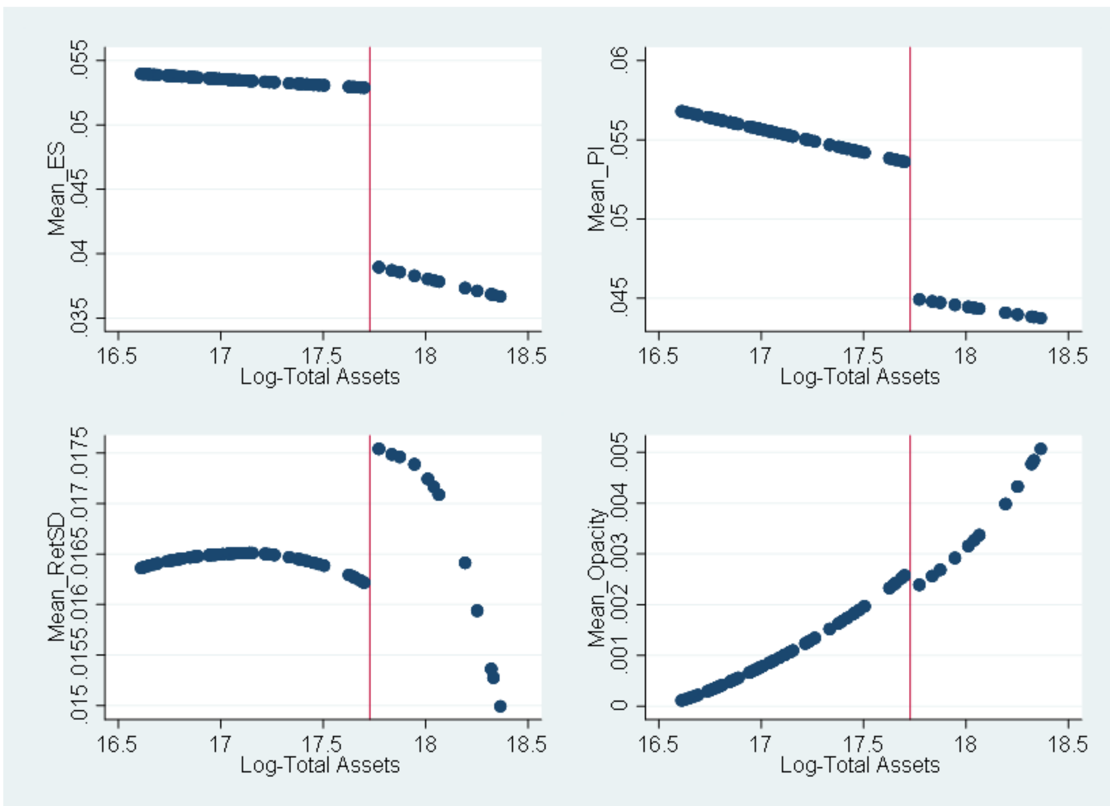
Panel A: Graphical representation of the discontinuity using local linear polynomials

This figure shows a graphical representation of the discontinuity for Effective Spread, Price Impact, Standard Deviation of Returns and predicted opacity of banks with less than $50Bn in total assets and banks with more than $50Bn in total assets for the period after few rounds of stress test results were disclosed (Oct2014-Sep2016) using local linear polynomials. Effective Spread, Price Impact, Standard Deviation of returns, and predicted opacity are plotted on the y-axis while Log(Total Assets) represents the x-axis. All four plots show two local polynomial lines (solid red lines) for two sets of banks (one with total assets less than $50Bn and the other with total assets greater than $50Bn) using local linear regression. The shaded area represents the 95% confidence interval for the local linear regression. Individual data points are shown with solid blue dots, while the discontinuity is illustrated by a red vertical line at a total asset of $50Bn.



Panel B: Graphical representation of the discontinuity using predicted variables from non-parametric kernel regressions

This figure shows a graphical representation of the discontinuity for Effective Spread, Price Impact, Standard Deviation of Returns and predicted opacity of banks less than $50Bn in total assets and more than $50Bn in total assets for the period after few rounds of stress test results were disclosed (Oct2014-Sep2016) using predicted values from non-parametric kernel regressions. Predicted values of the Effective Spread, Price Impact, Standard Deviation of Returns, and the predicted opacity are plotted on the y-axis while Log(Total Assets) represents the x-axis. Predicted values from the non-parametric kernel regressions are shown with blue dots. The discontinuity is shown by a red vertical line at a total asset of $50Bn.



Tables

Table 1: Summary Statistics

This table shows the summary statistics for the variables used in the MIMIC model for the sample period (2002-2016). The sample consists of 742 unique BHCs and 32 unique Commercial Banks during the sample period. Out of which, 113 banks are listed on NYSE and 670 banks listed on NASDAQ during the sample period. 21 banks shifted listing from one exchange to the other exchange during the sample period.

Panel A: Banks quarterly variables used in the measurement model

This table shows summary statistics for the market variables used in the measurement model at the firm-quarter level for the sample period (2002-2016). Effective Spread and Price Impact have been calculated daily from TAQ, and then the volume-weighted average has been calculated for each quarter. TOVER has been calculated as the number of shares traded, divided by the average number of shares outstanding during the quarter. The standard deviation of returns has been calculated as the standard deviation of daily stock returns from CRSP over the quarter. Market capitalization has been computed as the quarterly average of the daily market value of common equity. Market Leverage is calculated as the total book value liabilities plus the market value of common equity divided by the market value of common equity. The number of analysts covering the stock and the number of 8-K filing with the SEC has been calculated from IBES and WRDS SEC Analytics Suite. Separate summary statistics have been provided for the banks listed on NYSE and NASDAQ.

	N	Mean	SD	Min	Max	Median
Banks (NYSE listed)						
Effective Spread (%)	3262	0.094	0.103	0.012	1.585	0.062
Price Impact (%)	3262	0.072	0.061	-0.018	0.628	0.055
TOVER	3262	0.409	0.366	0.001	5.167	0.319
Price ($)	3262	33.95	24.58	2.09	203.59	28.71
Market Cap ($ Mn)	3262	20,086	41,791	33	287,673	3,703
Return SD (daily)	3251	0.02	0.015	0.0	0.174	0.015
Market Leverage	3262	9.32	14.91	1.07	433.16	7.16
Number of analysts	3262	10.14	7.94	0	35	8
Number of 8-K filings	3023	4.73	4.51	1	69	4
Banks (NASDAQ listed)						
Effective Spread (%)	15254	0.696	0.668	0.02	4.888	0.472
Price Impact (%)	15254	0.185	0.127	0.001	1.512	0.155
TOVER	15254	0.192	0.256	0.003	10.107	0.123
Price ($)	15254	21.46	14.10	2.00	345.60	19.09
Market Cap ($ Mn)	15254	703	1,754	2.56	34,967	243
Return SD (daily)	15252	0.022	0.015	0.001	0.208	0.017
Market Leverage	15254	9.68	8.53	1.02	258.35	7.57
Number of analysts	15254	2.57	3.47	0	33	1
Number of 8-K filings	13623	3.09	1.86	1	18	3

Panel B: Banks quarterly asset variables used in the structural model

This table shows summary statistics for the asset variables used in the structural model at the firm-quarter level for the sample period (2002-2016). The bank universe is based on the PERMCO-RSSD links for the BHCs and Commercial Banks from June 20, 1986, to December 31, 2016, provided on the New York Federal Reserve website. Quarterly financial assets information is from the filings of the Federal Reserve's Quarterly consolidated financial statements (FR Y-9C) for BHCs and 'Call Reports' (FFIEC 031, if the bank has both foreign and domestic offices, or FFIEC 041, if it has only domestic offices). The variables have been calculated based on the definition provided in Appendix-A. Separate summary statistics have been provided for the banks listed on NYSE and NASDAQ.

$ Mn	N	Mean	SD	Min	Max	Median
Banks (NYSE listed)						
Commercial Real Estate Loans	3262	10328	18765	0	146033	2960
Residential Real Estate Loans	3262	21632	57566	0	437093	2930
Other Loans	3262	37916	91203	0	611363	4281
Trading Assets	3262	20508	76442	0	581220	46
Other Opaque Assets	3262	19084	44156	0	327893	1837
Transparent Assets	3262	57655	150249	75	1212972	5684
Total Derivatives	3258	2808798	11278761	0	88595893	2604
Total Assets	3262	166708	395212	284	2577148	22535
Total Liabilities	3262	150480	358907	90	2340890	20053
Banks (NASDAQ listed)						
Commercial Real Estate Loans	15254	1215	1987	0	23486	575
Residential Real Estate Loans	15254	814	2023	0	28750	297
Other Loans	15254	1032	3443	0	62204	250
Trading Assets	15254	18	130	0	3285	0
Other Opaque Assets	15254	331	809	0	11862	103
Transparent Assets	15254	1363	4267	5	87104	435
Total Derivatives	15225	1284	12207	0	279007	9
Total Assets	15254	4765	10908	48	143625	1819
Total Liabilities	15254	4263	9804	32	126871	1639

Table 2: MIMIC Model Estimation

This table shows the estimates of the MIMIC model. The MIMIC model equations are as follows:

$$\begin{aligned} STD_{it} = \alpha_1 + \gamma_1 Opacity_{it} + \delta_{11}(PINV_{it}) + \delta_{12}(LNMVEQ_{it}) + \delta_{13}(TOVER_{it}) + \delta_{14}(MVLEV_{it}) \\ + \delta_{15}(Exchange\ Dummy) + \varepsilon_{1it} \end{aligned} \tag{i}$$

$$\begin{aligned} ES_{it} = \alpha_2 + \gamma_2 Opacity_{it} + \delta_{21}(PINV_{it}) + \delta_{22}(LNMVEQ_{it}) + \delta_{23}(TOVER_{it}) + \delta_{24}(MVLEV_{it}) \\ + \delta_{25}(Exchange\ Dummy) + \varepsilon_{2it} \end{aligned} \tag{ii}$$

$$\begin{aligned} PI_{it} = \alpha_3 + \gamma_3 Opacity_{it} + \delta_{31}(PINV_{it}) + \delta_{32}(LNMVEQ_{it}) + \delta_{33}(TOVER_{it}) + \delta_{34}(MVLEV_{it}) \\ + \delta_{35}(Exchange\ Dummy) + \varepsilon_{3it} \end{aligned} \tag{iii}$$

$$\begin{aligned} Opacity_{it} = \alpha_4 + \beta_1(\text{COMREAL\_A}_{i,t-1}) + \beta_2(\text{RESREAL\_A}_{i,t-1}) + \beta_3(\text{OTHLOAN\_A}_{i,t-1}) \\ + \beta_4(\text{TRADE\_A}_{i,t-1}) + \beta_5(\text{OTHOPAQ\_A}_{i,t-1}) + \beta_6(\text{TOTALDERIV\_A}_{i,t-1}) \\ + \beta_7(Ln(1 + Num_{Analyst})) + \beta_8(NUM\_8K) + \varepsilon_{4it} \end{aligned} \tag{iv}$$

for bank i and quarter t. The first three equations are the measurement model, while the fourth equation is the structural model. The estimates for the unstandardized and standardized coefficients for the model have been shown in columns 1 and 2, respectively. Unstandardized coefficients are model parameter estimates based on the raw data, while standardized coefficients are model parameter estimates based on the standardized data where all variables have unit variance. z-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Unstandardized	Standardized
Return_SD:	(1)	(2)
Opacity	1	.499***
	(constrained)	(9.6)
LNMVEQ	-.00181***	-.213***
	(-7.3)	(-9.6)
PINV	.0385***	.160***
	(5.7)	(7.8)
TOVER	.0215***	.408***
	(7.4)	(12.8)
MVLEV	.00047***	.245***
	(5)	(7.2)
Exchange Dummy	.00055*	.0149*
	(1.7)	(1.9)
CONS	.0177***	1.22***
	(9.2)	(4.7)
ESPREAD:		
Opacity	20.2***	.249***
	(5.7)	(10.6)
LNMVEQ	-.188***	-.548***
	(-26)	(-29.9)
PINV	.803***	.0826***

	(4.8)	(5.0)
TOVER	-.493***	-.232***
	(-12)	(-12.1)
MVLEV	.0165***	.216***
	(7.5)	(7.8)
Exchange Dummy	-.106***	-.0707***
	(-12)	(-13.0)
CONS	1.65***	2.81***
	(31)	(34.7)
Price Impact:		
Opacity	11.6***	.693***
	(5.8)	(25.7)
LNMVEQ	-.0357***	-.503***
	(-15)	(-19.2)
PINV	.228***	.113***
	(5.4)	(5.4)
TOVER	-.0416***	-.0945***
	(-6.5)	(-5.7)
MVLEV	.0027***	.170***
	(5.3)	(6.0)
Exchange Dummy	.00631***	.0203***
	(2.7)	(2.9)
CONS	.325***	2.68***
	(17)	(10.9)
Opacity:		
COMREAL_TA	.00164	.0356
	(.78)	(.91)
RESREAL_TA	-.0012	-.0188
	(-1.3)	(-1.0)
OTHLOAN_TA	.00687**	.109***
	(2.6)	(5.2)
TRADE_TA	.0201**	.0854***
	(2.1)	(3.1)
OTHOPAQ_TA	.00726*	.0554***
	(1.7)	(2.61)
TOTALDERIV_TA	7.9e-06	.00450
	(.18)	(0.18)
LN_NUM_ANALYST	-.00041	-0.0522
	(-1.6)	(-1.6)
NUM_8K	9.4e-05*	.0345**
	(1.8)	(2.31)
Goodness of Fit		
N	15650	15650
SRMR	0.012	0.012
CD	0.938	0.938

Table 3: Properties of predicted opacity

Panel A: Correlation between predicted opacity and other microstructure variables

This table shows the correlation matrix for the predicted opacity using the estimated MIMIC model with the three indicator variables (Effective Spread, Price Impact, and Standard Deviation of Returns) included in the measurement model for the sample period (2002-2016).

	Opacity	Effective Spread	Price Impact	Return-SD
Opacity	1			
Effective Spread	0.2289	1		
Price Impact	0.7110	0.6566	1	
Return-SD	0.4901	0.2994	0.5326	1

Panel B: Correlation between predicted opacity and bank's asset and environment variables

This table shows the correlation matrix for the predicted opacity using the estimated MIMIC model with the nine causal variables (six asset ratio variables, the number of analysts covering the bank stock, and the number of 8-K filings with the SEC) included in the structural model for the sample period (2002-2016).

	Opacity	COMREAL_TA	RESREAL_TA	OTHLOAN_TA	TRADE_TA	OTHOPAQ_TA	TOTALDERIV_TA	NUM_ANALYST	NUM_8K
Opacity	1.00								
COMREAL_TA	-0.03	1.00							
RESREAL_TA	-0.08	-0.23	1.00						
OTHLOAN_TA	0.09	-0.35	-0.32	1.00					
TRADE_TA	0.10	-0.29	-0.12	0.00	1.00				
OTHOPAQ_TA	0.05	-0.26	-0.11	-0.07	0.19	1.00			
TOTALDERIV_TA	0.09	-0.23	-0.11	-0.01	0.90	0.07	1.00		
NUM_ANALYST	0.07	-0.36	-0.13	0.31	0.31	0.28	0.26	1.00	
NUM_8K	0.06	-0.14	-0.01	0.07	0.33	0.13	0.35	0.35	1.00

Table 4: Estimates for the parametric and non-parametric regressions for the banks on the boundary of \$10Bn total assets for the pre-stress test period (Oct2011-Sep2012)

The tables in Panels A-D study the discontinuity in the predicted opacity and three indicator variables for the banks with less than \$10Bn in total assets and banks with more than \$10Bn in total assets for the pre-stress test period (Oct2011-Sep2012) using the following four model specifications:

$$M_{it} = \alpha + \beta_1(\textit{Stress Test}) + \beta_2(log(\Delta \textit{Total\_Asset})) + \mu_{it} \tag{i}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\textit{Stress Test}) + \beta_2(log(\Delta \textit{Total\_Asset})) + \beta_3(\text{COMREAL\_A}_{it}) \\ &+ \beta_4(\text{RESREAL\_A}_{it}) + \beta_5(\text{OTHLOAN\_A}_{it}) + \beta_6(\text{TRADE\_A}_{it}) \\ &+ \beta_7(\text{OTHOPAQ\_A}_{it}) + \beta_8(\text{TOTALDERIV\_A}_{it}) \\ &+ \beta_9(Ln(1 + Num_{Analyst})) + \beta_{10}(\textit{NUM\_8K}) + \mu_{it} \end{aligned} \tag{ii}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\textit{Stress Test}) + \beta_2(log(\Delta \textit{Total\_Asset})) \\ &+ \beta_3(log(\Delta \textit{Total\_Asset}) * \textit{Stress Test}) + \mu_{it} \end{aligned} \tag{iii}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\textit{Stress Test}) + \beta_2(log(\Delta \textit{Total\_Asset})) \\ &+ \beta_3(log(\Delta \textit{Total\_Asset}) * \textit{Stress Test}) + \beta_4(\text{COMREAL\_A}_{it}) \\ &+ \beta_5(\text{RESREAL\_A}_{it}) + \beta_6(\text{OTHLOAN\_A}_{it}) + \beta_7(\text{TRADE\_A}_{it}) \\ &+ \beta_8(\text{OTHOPAQ\_A}_{it}) + \beta_9(\text{TOTALDERIV\_A}_{it}) \\ &+ \beta_{10}(Ln(1 + Num_{Analyst})) + \beta_{11}(\textit{NUM\_8K}) + \mu_{it} \end{aligned} \tag{iv}$$

for bank i and quarter t. Dependent variable (M_{it}) is the predicted opacity, effective spread, price impact, and standard deviation of returns. Δ*Total_Asset* is Total Asset – Total Asset Cutoff (\$10Bn), and *Stress Test* is a dummy that equals 1 if a bank has total assets more than Total Asset Cutoff else 0. Estimates of the models shown in equations (i), (ii), (iii), and (iv) are provided in columns 1, 2, 3, and 4, respectively. Standard errors are clustered at the bank level. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Predicted Opacity as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	-.0002	-.00103	-.00011	-.00086
	(-.21)	(-1.2)	(-.11)	(-.87)
Log(ΔTotal_Assets)	.00225**	.0038***	.00103	.00114
	(2.1)	(2.8)	(.32)	(.3)
COMREAL_TA		.00198		.00222
		(1.1)		(1.1)
RESREAL_TA		.00194		.00135
		(1)		(.76)
OTHLOAN_TA		-.00139		-.00235
		(-.48)		(-.74)
TRADE_TA		.0579***		.0555***
		(5)		(4.7)
OTHOPAQ_TA		-.00103		.0001
		(-.2)		(.019)
TOTALDERIV_TA		-.00483***		-.00468***
		(-3.4)		(-3.5)
LN_NUM_ANALYST		-.00014		-.0002
		(-.37)		(-.56)
NUM_8K		-7.8e-06		-3.8e-06
		(-.11)		(-.053)
Stress Test#Log(ΔTotal_Assets)			.00159	.00362
			(.47)	(.9)
CONS	-.00073	-.00047	-.00092	-.00067
	(-1.2)	(-.33)	(-.99)	(-.44)
N	123	122	123	122
Adjusted R^2	.0357	.403	.0298	.406
RMSE	.00227	.00179	.00227	.00179

Panel B: Effective Spread as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	-.00833	-.0178	-.0108	-.0217
	(-.58)	(-1.4)	(-.66)	(-1.6)
Log(ΔTotal_Assets)	.0122	.0501	.0455	.108
	(.37)	(1.1)	(1)	(1.4)
COMREAL_TA		.173**		.168**
		(2.5)		(2.4)
RESREAL_TA		.0317		.0446
		(.6)		(.91)
OTHLOAN_TA		.174		.195
		(1.2)		(1.4)
TRADE_TA		1.09		1.14
		(1.3)		(1.3)
OTHOPAQ_TA		-.48		-.505
		(-1.3)		(-1.4)
TOTALDERIV_TA		-.124		-.128
		(-1.3)		(-1.3)
LN_NUM_ANALYST		-.0346*		-.0332*
		(-1.9)		(-1.9)
NUM_8K		.00475		.00467
		(1.2)		(1.2)
Stress Test#Log(ΔTotal_Assets)			-.0435	-.0788
			(-.73)	(-1.1)
CONS	.101***	.119***	.106***	.124***
	(10)	(3.3)	(7.5)	(3.4)
N	123	122	123	122
Adjusted R^2	-.0151	.294	-.0214	.293
RMSE	.0628	.0525	.0629	.0525

Panel C: Price Impact as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	-.0138	-.0221***	-.0149	-.0229***
	(-1.5)	(-3.4)	(-1.4)	(-3)
Log(ΔTotal_Assets)	.031	.0635**	.046	.0745
	(1.7)	(2.3)	(1.5)	(1.5)
COMREAL_TA		.142***		.141***
		(3.4)		(3.4)
RESREAL_TA		.0289		.0313
		(1.1)		(1.2)
OTHLOAN_TA		.0762		.0802
		(1)		(1.1)
TRADE_TA		.428		.437
		(1)		(1)
OTHOPAQ_TA		-.186		-.191
		(-1)		(-1)
TOTALDERIV_TA		-.0661		-.0667
		(-1.4)		(-1.4)
LN_NUM_ANALYST		-.0182*		-.018*
		(-2)		(-2)
NUM_8K		.00148		.00146
		(1.1)		(1.1)
Stress Test#Log(ΔTotal_Assets)			-.0196	-.015
			(-.51)	(-.34)
CONS	.0842***	.0817***	.0866***	.0825***
	(14)	(4.3)	(9.8)	(4.1)
N	123	122	123	122
Adjusted R^2	.00289	.314	-.00408	.309
RMSE	.036	.0299	.0361	.03

Panel D: Standard Deviation of Returns as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	-.0009	-.00235*	-.00073	-.00203
	(-.54)	(-1.7)	(-.46)	(-1.5)
Log(ΔTotal_Assets)	.00621*	.0096**	.00395	.0047
	(1.8)	(2.7)	(.64)	(.75)
COMREAL_TA		.0147*		.0152**
		(2)		(2.1)
RESREAL_TA		-.00665		-.00774
		(-1.1)		(-1.3)
OTHLOAN_TA		.0146*		.0128
		(1.8)		(1.5)
TRADE_TA		.0657*		.0614
		(1.8)		(1.6)
OTHOPAQ_TA		-.0162		-.0141
		(-.84)		(-.73)
TOTALDERIV_TA		-.00182		-.00155
		(-.3)		(-.27)
LN_NUM_ANALYST		-.00213		-.00224
		(-1.5)		(-1.5)
NUM_8K		.00016		.00016
		(.43)		(.45)
Stress Test#Log(ΔTotal_Assets)			.00296	.00667
			(.4)	(.91)
CONS	.0203***	.0204***	.0199***	.02***
	(29)	(5.1)	(28)	(5.2)
N	123	122	123	122
Adjusted R^2	.00614	.00666	-.00168	-.00028
RMSE	.00887	.0089	.00891	.00893

Panel E: Non-parametric kernel regression of predicted opacity and other indicator variables

This table shows the estimates of the non-parametric kernel regression of predicted opacity, Effective Spread, Price Impact, and Standard Deviation of Return for the banks with less than \$10Bn in total assets and banks with more than \$10Bn in total assets for the pre-stress test period (Oct2011-Sep2012). The estimates are provided for the following model:

$$M_{it} = \alpha + \beta_1(Stress\ Test) + \beta_2(log(\Delta Total\_Asset)) + \mu_{it}$$

$\Delta Total\_Asset$ is Total Asset – Total Asset Cutoff (\$10Bn), and *Stress Test* is a dummy that equals 1 if a bank has total assets more than Total Asset Cutoff else 0. Estimates for predicted opacity, effective spread, price impact, and standard deviation of returns are provided in columns 1, 2, 3, and 4, respectively. Epanechnikov kernel is used for $\Delta Total\_Asset$ and Li–Racine kernel is used for *Stress Test*. 500 replications are used to compute bootstrap standard errors and percentile confidence intervals. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) Opacity	(2) E-Spread	(3) Price Impact	(4) Return-SD
Opacity	-.00057***			
	(-2.7)			
E-Spread		.0961***		
		(17)		
Price Impact			.0792***	
			(25)	
Return-SD				.0205***
				(19)
Effect:				
Log(ΔTotal_Assets)	.00209**	.0126	.0331**	.00496
	(2)	(.61)	(2.4)	(.77)
Stress Test	-.00021	-.00987	-.0138**	-.00076
	(-.3)	(-1.1)	(-2)	(-.32)
N	123	123	123	123

Table 5: Estimates for the parametric and non-parametric regressions for the banks on the boundary of \$10Bn total assets for the period when the results of the stress tests were reported only to the regulator and not to the public (Sep2013-Mar2015)

The tables in Panels A-D study the discontinuity in the predicted opacity and three indicator variables for the banks with less than \$10Bn in total assets and banks with more than \$10Bn in total assets for the period when the results of the stress tests were reported only to the regulator and not to the public (Sep2013-Mar2015) using following four model specifications:

$$M_{it} = \alpha + \beta_1(\mathit{Stress\ Test}) + \beta_2(\mathit{log}(\Delta \mathit{Total\_Asset})) + \mu_{it} \tag{i}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\mathit{Stress\ Test}) + \beta_2(\mathit{log}(\Delta \mathit{Total\_Asset})) + \beta_3(\text{COMREAL\_A}_{it}) \\ &+ \beta_4(\text{RESREAL\_A}_{it}) + \beta_5(\text{OTHLOAN\_A}_{it}) + \beta_6(\text{TRADE\_A}_{it}) \\ &+ \beta_7(\text{OTHOPAQ\_A}_{it}) + \beta_8(\text{TOTALDERIV\_A}_{it}) \\ &+ \beta_9(\mathit{Ln}(1 + \mathit{Num}_{\mathit{Analyst}})) + \beta_{10}(\mathit{NUM\_8K}) + \mu_{it} \end{aligned} \tag{ii}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\mathit{Stress\ Test}) + \beta_2(\mathit{log}(\Delta \mathit{Total\_Asset})) \\ &+ \beta_3(\mathit{log}(\Delta \mathit{Total\_Asset}) * \mathit{Stress\ Test}) + \mu_{it} \end{aligned} \tag{iii}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\mathit{Stress\ Test}) + \beta_2(\mathit{log}(\Delta \mathit{Total\_Asset})) \\ &+ \beta_3(\mathit{log}(\Delta \mathit{Total\_Asset}) * \mathit{Stress\ Test}) + \beta_4(\text{COMREAL\_A}_{it}) \\ &+ \beta_5(\text{RESREAL\_A}_{it}) + \beta_6(\text{OTHLOAN\_A}_{it}) + \beta_7(\text{TRADE\_A}_{it}) \\ &+ \beta_8(\text{OTHOPAQ\_A}_{it}) + \beta_9(\text{TOTALDERIV\_A}_{it}) \\ &+ \beta_{10}(\mathit{Ln}(1 + \mathit{Num}_{\mathit{Analyst}})) + \beta_{11}(\mathit{NUM\_8K}) + \mu_{it} \end{aligned} \tag{iv}$$

for bank i and quarter t. Dependent variable (M_{it}) is the predicted opacity, effective spread, price impact, and standard deviation of returns. $\Delta \mathit{Total\_Asset}$ is Total Asset − Total Asset Cutoff (\$10Bn), and *Stress Test* is a dummy that equals 1 if a bank has total assets more than Total Asset Cutoff else 0. Estimates of the models shown in equations (i), (ii), (iii), and (iv) are provided in columns 1, 2, 3, and 4, respectively. Standard errors are clustered at the bank level. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Predicted Opacity as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	.00203**	.00169**	.00223**	.0019***
	(2.2)	(2.4)	(2.4)	(2.8)
Log(ΔTotal_Assets)	-.00191	-.00162	-.00552**	-.00486**
	(-1.5)	(-1.3)	(-2.3)	(-2.1)
COMREAL_TA		.00045		-2.2e-05
		(.21)		(-.011)
RESREAL_TA		-.00172		-.00199
		(-.67)		(-.84)
OTHLOAN_TA		-.00039		-.00027
		(-.22)		(-.16)
TRADE_TA		.0296***		.0318***
		(3.8)		(4.2)
OTHOPAQ_TA		.00423		.00271
		(1)		(.66)
TOTALDERIV_TA		-.0003		6.2e-05
		(-.43)		(.084)
LN_NUM_ANALYST		1.9e-05		-9.9e-05
		(.1)		(-.51)
NUM_8K		.00013*		.00011*
		(2)		(2)
Stress Test#Log(ΔTotal_Assets)			.00543**	.00477*
			(2.1)	(1.9)
CONS	-.00131**	-.00169	-.00213**	-.00195
	(-2.3)	(-1)	(-2.6)	(-1.3)
N	255	251	255	251
Adjusted R^2	.0509	.269	.0784	.299
RMSE	.00226	.0016	.00223	.00156

Panel B: Effective Spread as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	.00353	.0189	.00728	.0267*
	(.15)	(1)	(.3)	(1.7)
Log(ΔTotal_Assets)	-.0629*	-.0766**	-.132*	-.194***
	(-1.9)	(-2.2)	(-1.8)	(-3.3)
COMREAL_TA		-.0264		-.0434
		(-.48)		(-.94)
RESREAL_TA		.0515		.0416
		(.7)		(.63)
OTHLOAN_TA		.0474		.0515
		(.75)		(.87)
TRADE_TA		-.117		-.0358
		(-.57)		(-.18)
OTHOPAQ_TA		-.0292		-.0841
		(-.22)		(-.68)
TOTALDERIV_TA		.00343		.0166
		(.15)		(.73)
LN_NUM_ANALYST		-.0116*		-.0159**
		(-1.8)		(-2.4)
NUM_8K		.00128		.00072
		(.75)		(.47)
Stress Test#Log(ΔTotal_Assets)			.104	.173***
			(1.4)	(2.9)
CONS	.094***	.087*	.0784***	.0776**
	(6.5)	(2)	(3.8)	(2)
N	255	251	255	251
Adjusted R^2	.104	.177	.12	.242
RMSE	.0534	.0425	.053	.0407

Panel C: Price Impact as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	-.00768	.00343	-.00642	.00653
	(-.47)	(.26)	(-.39)	(.52)
Log(ΔTotal_Assets)	-.00939	-.0212	-.0326	-.0679**
	(-.45)	(-1)	(-.81)	(-2.3)
COMREAL_TA		.00042		-.00637
		(.014)		(-.23)
RESREAL_TA		.0507		.0467
		(1.4)		(1.4)
OTHLOAN_TA		.0211		.0227
		(.55)		(.6)
TRADE_TA		-.0641		-.0316
		(-.48)		(-.24)
OTHOPAQ_TA		-.0187		-.0407
		(-.22)		(-.5)
TOTALDERIV_TA		.00378		.00906
		(.23)		(.53)
LN_NUM_ANALYST		-.00849*		-.0102**
		(-1.7)		(-2)
NUM_8K		.00215*		.00192*
		(2)		(1.8)
Stress Test#Log(ΔTotal_Assets)			.0348	.069**
			(.78)	(2.1)
CONS	.0805***	.0666***	.0753***	.0628***
	(9.6)	(3)	(6.2)	(3)
N	255	251	255	251
Adjusted R^2	.0278	.147	.0295	.17
RMSE	.0347	.0274	.0347	.027

Panel D: Standard Deviation of Returns as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	.00067	.00207	.00036	.00205
	(.23)	(1.3)	(.11)	(1.4)
Log(ΔTotal_Assets)	-.00277	-.00378	.00301	-.00356
	(-.98)	(-1.7)	(.47)	(-1.5)
COMREAL_TA		.00118		.00121
		(.36)		(.37)
RESREAL_TA		-.00394		-.00392
		(-1.1)		(-1.1)
OTHLOAN_TA		.00547		.00546
		(1.4)		(1.4)
TRADE_TA		.0154		.0152
		(1.1)		(1.1)
OTHOPAQ_TA		-.00482		-.00472
		(-.55)		(-.55)
TOTALDERIV_TA		.0055***		.00548***
		(3.2)		(3.1)
LN_NUM_ANALYST		-.0005		-.00049
		(-.76)		(-.75)
NUM_8K		7.5e-05		7.6e-05
		(.69)		(.67)
Stress Test#Log(ΔTotal_Assets)			-.00867	-.00032
			(-1.2)	(-.094)
CONS	.0148***	.0133***	.0161***	.0133***
	(7.4)	(6.6)	(5.6)	(6.5)
N	255	251	255	251
Adjusted R^2	-.00264	.114	-.00094	.11
RMSE	.00869	.00403	.00868	.00403

Panel E: Non-parametric kernel regression of predicted opacity and other indicator variables

This table shows the estimates of the non-parametric kernel regression of predicted opacity, Effective Spread, Price Impact, and Standard Deviation of Return for the banks with less than $10Bn in total assets and banks with more than $10Bn in total assets for the period when the results of the stress tests were reported only to the regulator and not to the public (Sep2013-Mar2015). The estimates are provided for the following model:

$$M_{it} = \alpha + \beta_1(Stress\ Test) + \beta_2(log(\Delta Total\_Asset)) + \mu_{it}$$

$\Delta Total\_Asset$ is Total Asset – Total Asset Cutoff ($10Bn), and *Stress Test* is a dummy that equals 1 if a bank has total assets more than Total Asset Cutoff else 0. Estimates for predicted opacity, effective spread, price impact, and standard deviation of returns are provided in columns 1, 2, 3, and 4, respectively. Epanechnikov kernel is used for $\Delta Total\_Asset$ and Li–Racine kernel is used for *Stress Test*. 500 replications are used to compute bootstrap standard errors and percentile confidence intervals. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) Opacity	(2) E-Spread	(3) Price Impact	(4) Return-SD
Opacity	-.00028**			
	(-2)			
E-Spread		.091***		
		(26)		
Price Impact			.0755***	
			35)	
Return-SD				.0148***
				(30)
Effect:				
Log(ΔTotal_Assets)	-.00186***	-.056***	-.00641	-.00293
	(-2.6)	(-3.2)	(-.55)	(-1.4)
Stress Test	.00162***	-.00057	-.0105	.00084
	(3.2)	(-.044)	(-1.3)	(.4)
N	255	255	255	255

Table 6: Estimates for the parametric and non-parametric regressions for the banks on the boundary of $10Bn total assets for the period when the results of the stress test were reported both to the regulator and the public (Jul2015-Jun2016)

The tables in Panels A-D study the discontinuity in the predicted opacity and three indicator variables for the banks with less than $10Bn in total assets and banks with more than $10Bn in total assets for the period when the results of the stress test were reported both to the regulator and the public (Jul2015-Jun2016) using following four model specifications:

$$M_{it} = \alpha + \beta_1(\mathit{Stress\ Test}) + \beta_2(log(\Delta \mathit{Total\_Asset})) + \mu_{it} \quad \text{(i)}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\mathit{Stress\ Test}) + \beta_2(log(\Delta \mathit{Total\_Asset})) + \beta_3(\text{COMREAL\_A}_{it}) \\ &+ \beta_4(\text{RESREAL\_A}_{it}) + \beta_5(\text{OTHLOAN\_A}_{it}) + \beta_6(\text{TRADE\_A}_{it}) \\ &+ \beta_7(\text{OTHOPAQ\_A}_{it}) + \beta_8(\text{TOTALDERIV\_A}_{it}) \\ &+ \beta_9(Ln(1 + Num_{Analyst})) + \beta_{10}(\mathit{NUM\_8K}) + \mu_{it} \end{aligned} \quad \text{(ii)}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\mathit{Stress\ Test}) + \beta_2(log(\Delta \mathit{Total\_Asset})) \\ &+ \beta_3(log(\Delta \mathit{Total\_Asset}) * \mathit{Stress\ Test}) + \mu_{it} \end{aligned} \quad \text{(iii)}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\mathit{Stress\ Test}) + \beta_2(log(\Delta \mathit{Total\_Asset})) \\ &+ \beta_3(log(\Delta \mathit{Total\_Asset}) * \mathit{Stress\ Test}) + \beta_4(\text{COMREAL\_A}_{it}) \\ &+ \beta_5(\text{RESREAL\_A}_{it}) + \beta_6(\text{OTHLOAN\_A}_{it}) + \beta_7(\text{TRADE\_A}_{it}) \\ &+ \beta_8(\text{OTHOPAQ\_A}_{it}) + \beta_9(\text{TOTALDERIV\_A}_{it}) \\ &+ \beta_{10}(Ln(1 + Num_{Analyst})) + \beta_{11}(\mathit{NUM\_8K}) + \mu_{it} \end{aligned} \quad \text{(iv)}$$

for bank i and quarter t. Dependent variable M_{it} is the predicted opacity, effective spread, price impact, and standard deviation of returns. $\Delta \mathit{Total\_Asset}$ is Total Asset − Total Asset Cutoff ($10Bn), and *Stress Test* is a dummy that equals 1 if a bank has total assets more than Total Asset Cutoff else 0. Estimates of the models shown in equations (i), (ii), (iii), and (iv) are provided in columns 1, 2, 3, and 4, respectively. Standard errors are clustered at the bank level. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Predicted Opacity as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	.00073	.00149	.00022	.00074
	(.81)	(1.5)	(.25)	(.73)
Log(ΔTotal_Assets)	-.00082	-.00204	-.00257	-.00434***
	(-.61)	(-1.4)	(-1.5)	(-2.9)
COMREAL_TA		-.00071		-.00063
		(-.36)		(-.33)
RESREAL_TA		-.00182		-.00185
		(-.97)		(-1)
OTHLOAN_TA		.00433**		.00404*
		(2)		(1.9)
TRADE_TA		.00629		.00812
		(.69)		(.98)
OTHOPAQ_TA		.00466		.007*
		(1.2)		(1.8)
TOTALDERIV_TA		-.00214**		-.00172*
		(-2.3)		(-1.7)
LN_NUM_ANALYST		-.00021		-.00038
		(-.95)		(-1.6)
NUM_8K		-3.9e-05		-8.3e-05
		(-.46)		(-.97)
Stress Test#Log(ΔTotal_Assets)			.00456*	.00612**
			(2)	(2.5)
CONS	.0001	-.00017	-.00033	-.00053
	(.27)	(-.13)	(-.76)	(-.42)
N	210	204	210	204
Adjusted R^2	-.00024	.131	.0302	.176
RMSE	.00177	.00167	.00174	.00163

Panel B: Effective Spread as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	.035	.0393	.022	.0225
	(1.5)	(1.4)	(.83)	(.7)
Log(ΔTotal_Assets)	-.098***	-.113***	-.142***	-.165***
	(-3.2)	(-3.1)	(-4.3)	(-4.3)
COMREAL_TA		-.0437		-.0419
		(-.95)		(-.98)
RESREAL_TA		.0451		.0444
		(.74)		(.74)
OTHLOAN_TA		.165**		.158**
		(2.4)		(2.2)
TRADE_TA		-.596*		-.555
		(-1.9)		(-1.7)
OTHOPAQ_TA		.0242		.0769
		(.22)		(.68)
TOTALDERIV_TA		-.0217		-.0121
		(-.84)		(-.41)
LN_NUM_ANALYST		-.0129*		-.0166**
		(-2)		(-2.6)
NUM_8K		.00063		-.00037
		(.44)		(-.31)
Stress Test#Log(ΔTotal_Assets)			.116*	.138*
			(1.9)	(1.8)
CONS	.0756***	.065*	.0646***	.0568*
	(8.2)	(1.7)	(7.3)	(1.7)
N	210	204	210	204
Adjusted R^2	.143	.235	.172	.268
RMSE	.043	.0409	.0423	.04

Panel C: Price Impact as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	.0249	.0296	.0192	.0235
	(1.2)	(1.2)	(.8)	(.77)
Log(ΔTotal_Assets)	-.0567**	-.0693**	-.076***	-.0882***
	(-2.6)	(-2.3)	(-3.5)	(-3.6)
COMREAL_TA		-.0327		-.0321
		(-1.1)		(-1.1)
RESREAL_TA		.0525		.0522
		(1.7)		(1.7)
OTHLOAN_TA		.125**		.123**
		(2.2)		(2.1)
TRADE_TA		-.319*		-.304*
		(-1.9)		(-1.7)
OTHOPAQ_TA		-.021		-.0019
		(-.34)		(-.028)
TOTALDERIV_TA		-.024		-.0205
		(-1)		(-.76)
LN_NUM_ANALYST		-.0125**		-.0138***
		(-2.4)		(-3)
NUM_8K		.00032		-4.4e-05
		(.35)		(-.054)
Stress Test#Log(ΔTotal_Assets)			.0507	.05
			(1)	(.77)
CONS	.0704***	.0671***	.0656***	.0641***
	(11)	(3.5)	(11)	(3.5)
N	210	204	210	204
Adjusted R^2	.0598	.19	.066	.194
RMSE	.0344	.0323	.0343	.0322

Panel D: Standard Deviation of Returns as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	.00609**	.00754**	.00578*	.00812**
	(2)	(2.2)	(1.9)	(2)
Log(ΔTotal_Assets)	-.00798*	-.0106**	-.00904	-.00888*
	(-2)	(-2.4)	(-1.6)	(-1.8)
COMREAL_TA		.00063		.00057
		(.14)		(.13)
RESREAL_TA		-.00274		-.00271
		(-.54)		(-.52)
OTHLOAN_TA		.0123*		.0125*
		(1.8)		(1.8)
TRADE_TA		.109***		.108***
		(3.8)		(3.5)
OTHOPAQ_TA		-.0182*		-.02*
		(-1.8)		(-2)
TOTALDERIV_TA		-.00068		-.00101
		(-.23)		(-.3)
LN_NUM_ANALYST		.00014		.00027
		(.2)		(.47)
NUM_8K		.00027*		.00031**
		(1.9)		(2.1)
Stress Test#Log(ΔTotal_Assets)			.00278	-.00469
			(.35)	(-.52)
CONS	.0156***	.013***	.0153***	.0133***
	(13)	(5)	(10)	(5.1)
N	210	204	210	204
Adjusted R^2	.0605	.203	.0575	.203
RMSE	.00505	.0047	.00506	.0047

Panel E: Non-parametric kernel regression of predicted opacity and other indicator variables

This table shows the estimates of the non-parametric kernel regression of predicted opacity, Effective Spread, Price Impact, and Standard Deviation of Return for the banks with less than $10Bn in total assets and banks with more than $10Bn in total assets for the period when the results of the stress test were reported both to the regulator and the public (Jul2015-Jun2016). The estimates are provided for the following model:

$$M_{it} = \alpha + \beta_1(Stress\ Test) + \beta_2(log(\Delta Total\_Asset)) + \mu_{it}$$

$\Delta Total\_Asset$ is Total Asset – Total Asset Cutoff ($10Bn), and *Stress Test* is a dummy that equals 1 if a bank has total assets more than Total Asset Cutoff else 0. Estimates for predicted opacity, effective spread, price impact, and standard deviation of returns are provided in columns 1, 2, 3, and 4, respectively. Epanechnikov kernel is used for $\Delta Total\_Asset$ and Li–Racine kernel is used for *Stress Test*. 500 replications are used to compute bootstrap standard errors and percentile confidence intervals. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) Opacity	(2) E-Spread	(3) Price Impact	(4) Return-SD
Opacity	.00046***			
	(3.5)			
E-Spread		.0934***		
		(31)		
Price Impact			.0822***	
			(37)	
Return-SD				.0181***
				(51)
Effect:				
Log(ΔTotal_Assets)	-.00092	-.106***	-.0603***	-.00727***
	(-1.1)	(-6.2)	(-4.9)	(-2.8)
Stress Test	.00067	.0406***	.0266***	.00612***
	(1.4)	(3.6)	(2.6)	(3.4)
N	210	210	210	210

Table 7: Estimates for the parametric and non-parametric regressions for the banks on the boundary of \$50Bn total assets for the period before the start of the financial crisis (Oct2005-Sep2007)

The tables in Panels A-D study the discontinuity in the predicted opacity and three indicator variables for the banks with less than \$50Bn in total assets and banks with more than \$50Bn in total assets for the period before the start of the financial crisis (Oct2005-Sep2007) using following four model specifications:

$$M_{it} = \alpha + \beta_1(\textit{Stress Test}) + \beta_2(log(\Delta \textit{Total\_Asset})) + \mu_{it} \tag{i}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\textit{Stress Test}) + \beta_2(log(\Delta \textit{Total\_Asset})) + \beta_3(\text{COMREAL\_A}_{it}) \\ &+ \beta_4(\text{RESREAL\_A}_{it}) + \beta_5(\text{OTHLOAN\_A}_{it}) + \beta_6(\text{TRADE\_A}_{it}) \\ &+ \beta_7(\text{OTHOPAQ\_A}_{it}) + \beta_8(\text{TOTALDERIV\_A}_{it}) \\ &+ \beta_9(Ln(1 + Num_{Analyst})) + \beta_{10}(\textit{NUM\_8K}) + \mu_{it} \end{aligned} \tag{ii}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\textit{Stress Test}) + \beta_2(log(\Delta \textit{Total\_Asset})) \\ &+ \beta_3(log(\Delta \textit{Total\_Asset}) * \textit{Stress Test}) + \mu_{it} \end{aligned} \tag{iii}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\textit{Stress Test}) + \beta_2(log(\Delta \textit{Total\_Asset})) \\ &+ \beta_3(log(\Delta \textit{Total\_Asset}) * \textit{Stress Test}) + \beta_4(\text{COMREAL\_A}_{it}) \\ &+ \beta_5(\text{RESREAL\_A}_{it}) + \beta_6(\text{OTHLOAN\_A}_{it}) + \beta_7(\text{TRADE\_A}_{it}) \\ &+ \beta_8(\text{OTHOPAQ\_A}_{it}) + \beta_9(\text{TOTALDERIV\_A}_{it}) \\ &+ \beta_{10}(Ln(1 + Num_{Analyst})) + \beta_{11}(\textit{NUM\_8K}) + \mu_{it} \end{aligned} \tag{iv}$$

for bank i and quarter t. Dependent variable M_{it} is the predicted opacity, effective spread, price impact, and standard deviation of returns. $\Delta \textit{Total\_Asset}$ is Total Asset − Total Asset Cutoff (\$50Bn), and *Stress Test* is a dummy that equals 1 if a bank has total assets more than Total Asset Cutoff else 0. Estimates of the models shown in equations (i), (ii), (iii), and (iv) are provided in columns 1, 2, 3, and 4, respectively. Standard errors are clustered at the bank level. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Predicted Opacity as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	.00019	.00108	.00025	.00107
	(.16)	(1.5)	(.21)	(1.4)
Log(ΔTotal_Assets)	.00242*	.00112	.003*	.00123
	(2)	(1.4)	(1.8)	(1.3)
COMREAL_TA		-.00444*		-.00429
		(-1.8)		(-1.6)
RESREAL_TA		-.00778**		-.00765**
		(-2.8)		(-2.6)
OTHLOAN_TA		-.00119		-.00113
		(-.65)		(-.59)
TRADE_TA		-.00464		-.005
		(-.54)		(-.58)
OTHOPAQ_TA		.0046*		.00471*
		(1.8)		(1.8)
TOTALDERIV_TA		-.00018		-.00015
		(-.58)		(-.48)
LN_NUM_ANALYST		.00061**		.00061**
		(2.6)		(2.5)
NUM_8K		-1.7e-05		-1.6e-05
		(-.28)		(-.26)
Stress Test#Log(ΔTotal_Assets)			-.0018	-.00031
			(-.94)	(-.26)
CONS	.00226**	.00254	.00251**	.00249
	(2.5)	(1.4)	(2.2)	(1.4)
N	161	148	161	148
Adjusted R^2	.308	.577	.318	.574
RMSE	.00163	.00127	.00162	.00128

Panel B: Effective Spread as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	-.00239	-.00736	-.00283	-.00724
	(-.29)	(-1.2)	(-.35)	(-1.2)
Log(ΔTotal_Assets)	-.0142	.00381	-.0186	.00157
	(-1.2)	(.57)	(-1.1)	(.17)
COMREAL_TA		-.011		-.014
		(-.63)		(-.74)
RESREAL_TA		-.00783		-.0106
		(-.31)		(-.39)
OTHLOAN_TA		-.0414**		-.0426**
		(-2.1)		(-2.1)
TRADE_TA		-.064		-.0568
		(-.65)		(-.57)
OTHOPAQ_TA		-.0303		-.0325
		(-1.5)		(-1.6)
TOTALDERIV_TA		-.00343		-.00386
		(-1.2)		(-1.2)
LN_NUM_ANALYST		-.00319		-.00318
		(-1.1)		(-1.1)
NUM_8K		.00068*		.00065
		(1.8)		(1.7)
Stress Test#Log(ΔTotal_Assets)			.0136	.00642
			(.76)	(.66)
CONS	.0401***	.0682***	.0383***	.0692***
	(7.3)	(4.3)	(4.9)	(4.4)
N	161	148	161	148
Adjusted R^2	.184	.332	.191	.33
RMSE	.0143	.00931	.0142	.00932

Panel C: Price Impact as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	.00543	.00497	.00522	.00483
	(.82)	(1.1)	(.81)	(1.1)
Log(ΔTotal_Assets)	-.018	-.00731	-.02	-.00465
	(-1.6)	(-1.4)	(-1.2)	(-.72)
COMREAL_TA		-.0197*		-.0161
		(-2)		(-1.7)
RESREAL_TA		-.0172		-.0139
		(-1.1)		(-.83)
OTHLOAN_TA		-.0435***		-.0421***
		(-3)		(-2.9)
TRADE_TA		.0417		.0331
		(.52)		(.4)
OTHOPAQ_TA		-.0124		-.0098
		(-.75)		(-.62)
TOTALDERIV_TA		-.00279		-.00228
		(-1.6)		(-1.2)
LN_NUM_ANALYST		.00028		.00027
		(.1)		(.095)
NUM_8K		.00015		.00019
		(.43)		(.51)
Stress Test#Log(ΔTotal_Assets)			.00653	-.00764
			(.38)	(-.8)
CONS	.0299***	.0496***	.0291***	.0483***
	(7.7)	(4.1)	(5)	(4.3)
N	161	148	161	148
Adjusted R^2	.122	.105	.119	.103
RMSE	.015	.0105	.015	.0105

Panel D: Standard Deviation of Returns as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	-.00241	-.00151	-.00223	-.00151
	(-1.3)	(-1.1)	(-1.4)	(-1.1)
Log(ΔTotal_Assets)	.00227	.00168	.00377	.00262
	(1.2)	(.99)	(1.5)	(1.5)
COMREAL_TA		-.00862**		-.0073*
		(-2.4)		(-1.9)
RESREAL_TA		-.00986**		-.0087*
		(-2.2)		(-1.9)
OTHLOAN_TA		-.00402*		-.00351
		(-1.7)		(-1.4)
TRADE_TA		.0352		.0328
		(1.7)		(1.6)
OTHOPAQ_TA		.00016		.00115
		(.045)		(.3)
TOTALDERIV_TA		-.00144**		-.00123*
		(-2.3)		(-1.8)
LN_NUM_ANALYST		.00136**		.00133**
		(2.2)		(2.2)
NUM_8K		6.9e-08		1.2e-05
		(.00056)		(.092)
Stress Test#Log(ΔTotal_Assets)			-.00496*	-.00307
			(-2)	(-1.2)
CONS	.0133***	.0146***	.0139***	.0142***
	(11)	(4.9)	(9.6)	(4.6)
N	160	147	160	147
Adjusted R^2	.0125	.0664	.0231	.0632
RMSE	.00473	.00459	.00471	.0046

Panel E: Non-parametric kernel regression of predicted opacity and other indicator variables

This table shows the estimates of the non-parametric kernel regression of predicted opacity, Effective Spread, Price Impact, and Standard Deviation of Return for the banks with less than $50Bn in total assets and banks with more than $50Bn in total assets for the period before the start of the financial crisis (Oct2005-Sep2007). The estimates are provided for the following model:

$$M_{it} = \alpha + \beta_1(Stress\ Test) + \beta_2(log(\Delta Total\_Asset)) + \mu_{it}$$

$\Delta Total\_Asset$ is Total Asset – Total Asset Cutoff ($50Bn), and *Stress Test* is a dummy that equals 1 if a bank has total assets more than Total Asset Cutoff else 0. Estimates for predicted opacity, effective spread, price impact, and standard deviation of returns are provided in columns 1, 2, 3, and 4, respectively. Epanechnikov kernel is used for $\Delta Total\_Asset$ and Li–Racine kernel is used for *Stress Test*. 500 replications are used to compute bootstrap standard errors and percentile confidence intervals. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) Opacity	(2) E-Spread	(3) Price Impact	(4) Return-SD
Opacity	.00185***			
	(13)			
E-Spread		.0424***		
		(30)		
Price Impact			.0351***	
			(28)	
Return-SD				.0119***
				(30)
Effect:				
Log(ΔTotal_Assets)	.00243***	-.0127**	-.016***	.00251
	(4.5)	(-2)	(-3.3)	(1.6)
Stress Test	.00023	-.00515	.00519	-.00252**
	(.45)	(-1.5)	(1.2)	(-2.1)
N	161	161	161	160

Table 8: Estimates for the parametric and non-parametric regressions for the banks on the boundary of \$50Bn total assets for the period during the financial crisis but before results of 1st stress tests (SCAP-2009) were disclosed (Oct2007-Mar2009)

The tables in Panels A-D study the discontinuity in the predicted opacity and three indicator variables for the banks with less than \$50Bn in total assets and banks with more than \$50Bn in total assets for the period during the financial crisis but before results of 1st stress tests (SCAP-2009) were disclosed (Oct2007-Mar2009) using following four model specifications:

$$M_{it} = \alpha + \beta_1(\mathit{Stress\ Test}) + \beta_2(log(\Delta \mathit{Total\_Asset})) + \mu_{it} \tag{i}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\mathit{Stress\ Test}) + \beta_2(log(\Delta \mathit{Total\_Asset})) + \beta_3(\text{COMREAL\_A}_{it}) \\ &+ \beta_4(\text{RESREAL\_A}_{it}) + \beta_5(\text{OTHLOAN\_A}_{it}) + \beta_6(\text{TRADE\_A}_{it}) \\ &+ \beta_7(\text{OTHOPAQ\_A}_{it}) + \beta_8(\text{TOTALDERIV\_A}_{it}) \\ &+ \beta_9(Ln(1 + Num_{Analyst})) + \beta_{10}(\mathit{NUM\_8K}) + \mu_{it} \end{aligned} \tag{ii}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\mathit{Stress\ Test}) + \beta_2(log(\Delta \mathit{Total\_Asset})) \\ &+ \beta_3(log(\Delta \mathit{Total\_Asset}) * \mathit{Stress\ Test}) + \mu_{it} \end{aligned} \tag{iii}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\mathit{Stress\ Test}) + \beta_2(log(\Delta \mathit{Total\_Asset})) \\ &+ \beta_3(log(\Delta \mathit{Total\_Asset}) * \mathit{Stress\ Test}) + \beta_4(\text{COMREAL\_A}_{it}) \\ &+ \beta_5(\text{RESREAL\_A}_{it}) + \beta_6(\text{OTHLOAN\_A}_{it}) + \beta_7(\text{TRADE\_A}_{it}) \\ &+ \beta_8(\text{OTHOPAQ\_A}_{it}) + \beta_9(\text{TOTALDERIV\_A}_{it}) \\ &+ \beta_{10}(Ln(1 + Num_{Analyst})) + \beta_{11}(\mathit{NUM\_8K}) + \mu_{it} \end{aligned} \tag{iv}$$

for bank i and quarter t. Dependent variable M_{it} is the predicted opacity, effective spread, price impact, and standard deviation of returns. $\Delta \mathit{Total\_Asset}$ is Total Asset − Total Asset Cutoff (\$50Bn), and *Stress Test* is a dummy that equals 1 if a bank has total assets more than Total Asset Cutoff else 0. Estimates of the models shown in equations (i), (ii), (iii), and (iv) are provided in columns 1, 2, 3, and 4, respectively. Standard errors are clustered at the bank level. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Predicted Opacity as the dependent variable

	(1)	(2)	(3)	(4)
	model 1	model 2	model 3	model 4
Stress Test	.0027**	.00265**	.00214	.00259**
	(2.2)	(2.9)	(1.6)	(2.7)
Log(ΔTotal_Assets)	-.0019	-.00195	-.00244	-.00217
	(-1)	(-1.6)	(-1.2)	(-1.4)
COMREAL_TA		.00555		.00541
		(.88)		(.81)
RESREAL_TA		.0017		.00188
		(.28)		(.32)
OTHLOAN_TA		.00856		.00821
		(1.7)		(1.3)
TRADE_TA		-.00432		-.00317
		(-.24)		(-.16)
OTHOPAQ_TA		.0162*		.0153
		(1.9)		(1.5)
TOTALDERIV_TA		.00217		.00203
		(1.6)		(1.2)
LN_NUM_ANALYST		-.00137		-.00138
		(-1.6)		(-1.6)
NUM_8K		.0006***		.00061***
		(5.6)		(5.4)
Stress Test#Log(ΔTotal_Assets)			.00437	.00119
			(.89)	(.2)
CONS	.00389***	-.00171	.00364***	-.00163
	(6.6)	(-.44)	(5.5)	(-.4)
N	81	80	81	80
Adjusted R^2	.0439	.216	.0451	.205
RMSE	.00321	.00286	.00321	.00288

Panel B: Effective Spread as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	-.00534	-.0046	-.00416	-.00552
	(-.14)	(-.11)	(-.097)	(-.13)
Log(ΔTotal_Assets)	-.0254	-.0109	-.0243	-.0145
	(-.65)	(-.31)	(-.57)	(-.34)
COMREAL_TA		.122		.12
		(.73)		(.69)
RESREAL_TA		.197		.2
		(1.4)		(1.4)
OTHLOAN_TA		.17		.164
		(1.6)		(1.3)
TRADE_TA		-.392		-.373
		(-.59)		(-.56)
OTHOPAQ_TA		.263		.249
		(.78)		(.66)
TOTALDERIV_TA		.019		.0168
		(.85)		(.57)
LN_NUM_ANALYST		-.0446**		-.0448**
		(-2.2)		(-2.2)
NUM_8K		.00857		.00874
		(1.2)		(1.3)
Stress Test#Log(ΔTotal_Assets)			-.00926	.0199
			(-.1)	(.21)
CONS	.0937***	.0353	.0943***	.0367
	(4.1)	(.31)	(3.9)	(.31)
N	81	80	81	80
Adjusted R^2	.00677	.0371	-.006	.0234
RMSE	.0722	.0711	.0727	.0716

Panel C: Price Impact as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	.0025	-.00565	-.00077	-.00709
	(.073)	(-.17)	(-.022)	(-.21)
Log(ΔTotal_Assets)	-.0369	-.0272	-.04	-.0328
	(-.96)	(-.93)	(-.95)	(-.94)
COMREAL_TA		.0711		.0673
		(.56)		(.51)
RESREAL_TA		.118		.123
		(1.2)		(1.2)
OTHLOAN_TA		.206**		.197*
		(2.4)		(1.9)
TRADE_TA		-.356		-.326
		(-.72)		(-.67)
OTHOPAQ_TA		.209		.186
		(.95)		(.77)
TOTALDERIV_TA		.0165		.0129
		(.83)		(.51)
LN_NUM_ANALYST		-.0405**		-.0406**
		(-2.6)		(-2.5)
NUM_8K		.00812*		.0084*
		(1.9)		(2)
Stress Test#Log(ΔTotal_Assets)			.0256	.0313
			(.38)	(.39)
CONS	.0805***	.0406	.079***	.0427
	(3.7)	(.49)	(3.4)	(.48)
N	81	80	81	80
Adjusted R^2	.0394	.15	.0284	.139
RMSE	.0569	.0532	.0573	.0535

Panel D: Standard Deviation of Returns as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	-.00302	.00638	-.00396	.0033
	(-.23)	(.37)	(-.23)	(.18)
Log(ΔTotal_Assets)	.0139	.00948	.013	-.00248
	(1.3)	(.86)	(1.2)	(-.2)
COMREAL_TA		.0756		.0677
		(1.2)		(1)
RESREAL_TA		.124		.134*
		(1.6)		(1.8)
OTHLOAN_TA		.0518		.0322
		(1.1)		(.61)
TRADE_TA		-.0551		.0095
		(-.18)		(.033)
OTHOPAQ_TA		.0767		.0272
		(.48)		(.16)
TOTALDERIV_TA		.00318		-.00437
		(.35)		(-.39)
LN_NUM_ANALYST		-.00836		-.00876
		(-.95)		(-.97)
NUM_8K		.00457**		.00515***
		(2.7)		(3.2)
Stress Test#Log(ΔTotal_Assets)			.00721	.0667
			(.18)	(1.5)
CONS	.0558***	-.0103	.0554***	-.00582
	(11)	(-.28)	(11)	(-.15)
N	80	80	80	80
Adjusted R^2	-.0005	.0635	-.0132	.0776
RMSE	.0305	.0295	.0307	.0293

Panel E: Non-parametric kernel regression of predicted opacity and other indicator variables

This table shows the estimates of the non-parametric kernel regression of predicted opacity, Effective Spread, Price Impact, and Standard Deviation of Return for the banks with less than \$50Bn in total assets and banks with more than \$50Bn in total assets for the period during the financial crisis but before results of 1st stress tests (SCAP-2009) were disclosed (Oct2007-Mar2009). The estimates are provided for the following model:

$$M_{it} = \alpha + \beta_1(Stress\ Test) + \beta_2(log(\Delta Total\_Asset)) + \mu_{it}$$

$\Delta Total\_Asset$ is Total Asset – Total Asset Cutoff (\$50Bn), and *Stress Test* is a dummy that equals 1 if a bank has total assets more than Total Asset Cutoff else 0. Estimates for predicted opacity, effective spread, price impact, and standard deviation of returns are provided in columns 1, 2, 3, and 4, respectively. Epanechnikov kernel is used for $\Delta Total\_Asset$ and Li–Racine kernel is used for *Stress Test*. 500 replications are used to compute bootstrap standard errors and percentile confidence intervals. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) Opacity	(2) E-Spread	(3) Price Impact	(4) Return-SD
Opacity	.00537***			
	(15)			
E-Spread		.0969***		
		(13)		
Price Impact			.0891***	
			(15)	
Return-SD				.0517***
				(15)
Effect:				
Log(ΔTotal_Assets)	-.00181	-.03	-.0242	.0175
	(-1.2)	(-.45)	(-.46)	(.65)
Stress Test	.00263**	-.00371	-.00201	-.00426
	(2.2)	(-.098)	(-.074)	(-.28)
N	81	81	81	80

Table 9: Estimates for the parametric and non-parametric regressions for the banks on the boundary of \$50Bn total assets for the period after few rounds of stress test results were disclosed (Oct2014-Sep2016)

The tables in Panels A-D study the discontinuity in the predicted opacity and three indicator variables for the banks with less than \$50Bn in total assets and banks with more than \$50Bn in total assets for the period after few rounds of stress test results were disclosed (Oct2014-Sep2016) using following four model specifications:

$$M_{it} = \alpha + \beta_1(\mathit{Stress\ Test}) + \beta_2(log(\Delta \mathit{Total\_Asset})) + \mu_{it} \tag{i}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\mathit{Stress\ Test}) + \beta_2(log(\Delta \mathit{Total\_Asset})) + \beta_3(\mathrm{COMREAL\_A}_{it}) \\ &+ \beta_4(\mathrm{RESREAL\_A}_{it}) + \beta_5(\mathrm{OTHLOAN\_A}_{it}) + \beta_6(\mathrm{TRADE\_A}_{it}) \\ &+ \beta_7(\mathrm{OTHOPAQ\_A}_{it}) + \beta_8(\mathrm{TOTALDERIV\_A}_{it}) \\ &+ \beta_9(Ln(1 + Num_{Analyst})) + \beta_{10}(\mathit{NUM\_8K}) + \mu_{it} \end{aligned} \tag{ii}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\mathit{Stress\ Test}) + \beta_2(log(\Delta \mathit{Total\_Asset})) \\ &+ \beta_3(log(\Delta \mathit{Total\_Asset}) * \mathit{Stress\ Test}) + \mu_{it} \end{aligned} \tag{iii}$$

$$\begin{aligned} M_{it} = \alpha &+ \beta_1(\mathit{Stress\ Test}) + \beta_2(log(\Delta \mathit{Total\_Asset})) \\ &+ \beta_3(log(\Delta \mathit{Total\_Asset}) * \mathit{Stress\ Test}) + \beta_4(\mathrm{COMREAL\_A}_{it}) \\ &+ \beta_5(\mathrm{RESREAL\_A}_{it}) + \beta_6(\mathrm{OTHLOAN\_A}_{it}) + \beta_7(\mathrm{TRADE\_A}_{it}) \\ &+ \beta_8(\mathrm{OTHOPAQ\_A}_{it}) + \beta_9(\mathrm{TOTALDERIV\_A}_{it}) \\ &+ \beta_{10}(Ln(1 + Num_{Analyst})) + \beta_{11}(\mathit{NUM\_8K}) + \mu_{it} \end{aligned} \tag{iv}$$

for bank i and quarter t. Dependent variable M_{it} is the predicted opacity, effective spread, price impact, and standard deviation of returns. $\Delta \mathit{Total\_Asset}$ is Total Asset − Total Asset Cutoff (\$50Bn), and *Stress Test* is a dummy that equals 1 if a bank has total assets more than Total Asset Cutoff else 0. Estimates of the models shown in equations (i), (ii), (iii), and (iv) are provided in columns 1, 2, 3, and 4, respectively. Standard errors are clustered at the bank level. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Predicted Opacity as the dependent variable

	(1)	(2)	(3)	(4)
	model 1	model 2	model 3	model 4
Stress Test	7.2e-05	.00018	-.00096	-.00084
	(.08)	(.17)	(-1)	(-.77)
Log(ΔTotal_Assets)	.00239***	.00177***	.00206***	.0013**
	(3.8)	(2.9)	(3.2)	(2.2)
COMREAL_TA		-.00162		-.00203
		(-1.2)		(-1.6)
RESREAL_TA		-.00571***		-.00616***
		(-3.4)		(-3.8)
OTHLOAN_TA		-.0013		-.00264*
		(-.77)		(-1.9)
TRADE_TA		.0115		.0133
		(.96)		(1.2)
OTHOPAQ_TA		-.00093		-.0002
		(-.37)		(-.082)
TOTALDERIV_TA		.0006		.0005
		(1)		(.88)
LN_NUM_ANALYST		7.7e-05		6.4e-05
		(.39)		(.33)
NUM_8K		.00014***		.00015***
		(3.4)		(3.9)
Stress Test#Log(ΔTotal_Assets)			.00393**	.00516**
			(2.1)	(2.2)
CONS	.0025***	.003**	.00229***	.00313***
	(5.1)	(2.7)	(4.5)	(2.9)
N	256	248	256	248
Adjusted R^2	.404	.499	.431	.531
RMSE	.00139	.00125	.00136	.00121

Panel B: Effective Spread as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	-.0124	-.00886	-.0148	-.00543
	(-.93)	(-.7)	(-1)	(-.42)
Log(ΔTotal_Assets)	-.00329	-.00656	-.00403	-.00497
	(-.33)	(-.77)	(-.38)	(-.51)
COMREAL_TA		-.00991		-.00852
		(-.41)		(-.36)
RESREAL_TA		.0124		.0139
		(.59)		(.66)
OTHLOAN_TA		-.0254		-.0209
		(-1.2)		(-.91)
TRADE_TA		-.173		-.179
		(-1.3)		(-1.4)
OTHOPAQ_TA		-.0735**		-.076**
		(-2.2)		(-2.2)
TOTALDERIV_TA		.0351***		.0354***
		(4.6)		(4.7)
LN_NUM_ANALYST		-.00109		-.00104
		(-.39)		(-.37)
NUM_8K		3.2e-05		-5.3e-06
		(.046)		(-.0075)
Stress Test#Log(ΔTotal_Assets)			.00896	-.0174
			(.28)	(-.75)
CONS	.0514***	.0583***	.0509***	.0579***
	(6.4)	(3.3)	(6)	(3.3)
N	256	248	256	248
Adjusted R^2	.0802	.285	.0778	.285
RMSE	.0196	.0173	.0197	.0173

Panel C: Price Impact as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	-.00905	-.00518	-.00881	8.1e-05
	(-.65)	(-.37)	(-.54)	(.0051)
Log(ΔTotal_Assets)	-.00206	-.00253	-.00199	-8.7e-05
	(-.21)	(-.28)	(-.19)	(-.0086)
COMREAL_TA		.00962		.0117
		(.51)		(.64)
RESREAL_TA		.0411*		.0434**
		(2)		(2.1)
OTHLOAN_TA		-.0211		-.0142
		(-1.1)		(-.72)
TRADE_TA		.107		.0981
		(.69)		(.62)
OTHOPAQ_TA		-.0683*		-.072*
		(-1.8)		(-1.9)
TOTALDERIV_TA		.0221**		.0227**
		(2.7)		(2.7)
LN_NUM_ANALYST		-.00259		-.00252
		(-.81)		(-.79)
NUM_8K		.0011		.00104
		(1.3)		(1.3)
Stress Test#Log(ΔTotal_Assets)			-.00094	-.0267
			(-.023)	(-.76)
CONS	.0541***	.0529***	.0541***	.0522***
	(6.9)	(3.1)	(6.6)	(3.2)
N	256	248	256	248
Adjusted R^2	.0337	.242	.0299	.245
RMSE	.0207	.0182	.0207	.0182

Panel D: Standard Deviation of Returns as the dependent variable

	(1) model 1	(2) model 2	(3) model 3	(4) model 4
Stress Test	.00116	-.00091	.00317	.00154
	(.46)	(-.46)	(1.4)	(.99)
Log(ΔTotal_Assets)	-.0006	-.00153	3.2e-05	-.00039
	(-.29)	(-1)	(.015)	(-.27)
COMREAL_TA		-.00797**		-.00698**
		(-2.4)		(-2.1)
RESREAL_TA		-.00619*		-.0051
		(-1.9)		(-1.5)
OTHLOAN_TA		-.00297		.00025
		(-.54)		(.049)
TRADE_TA		-.0615***		-.0657***
		(-3.3)		(-3.7)
OTHOPAQ_TA		-.00979		-.0116*
		(-1.6)		(-1.7)
TOTALDERIV_TA		-5.1e-08		.00025
		(-5.1e-05)		(.27)
LN_NUM_ANALYST		.00215***		.00219***
		(3.3)		(3.4)
NUM_8K		.00013		.0001
		(.85)		(.68)
Stress Test#Log(ΔTotal_Assets)			-.00763*	-.0125***
			(-2)	(-2.8)
CONS	.0161***	.0152***	.0165***	.0149***
	(10)	(4.6)	(10)	(4.6)
N	256	248	256	248
Adjusted R^2	-.00493	.102	.005	.123
RMSE	.00509	.00482	.00507	.00477

Panel E: Non-parametric kernel regression of predicted opacity and other indicator variables

This table shows the estimates of the non-parametric kernel regression of predicted opacity, Effective Spread, Price Impact, and Standard Deviation of Return for the banks with less than $50Bn in total assets and banks with more than $50Bn in total assets for the period after few rounds of stress test results were disclosed (Oct2014-Sep2016). The estimates are provided for the following model:

$$M_{it} = \alpha + \beta_1(Stress\ Test) + \beta_2(log(\Delta Total\_Asset)) + \mu_{it}$$

$\Delta Total\_Asset$ is Total Asset – Total Asset Cutoff ($50Bn), and *Stress Test* is a dummy that equals 1 if a bank has total assets more than Total Asset Cutoff else 0. Estimates for predicted opacity, effective spread, price impact, and standard deviation of returns are provided in columns 1, 2, 3, and 4, respectively. Epanechnikov kernel is used for $\Delta Total\_Asset$ and Li–Racine kernel is used for *Stress Test*. 500 replications are used to compute bootstrap standard errors and percentile confidence intervals. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) Opacity	(2) E-Spread	(3) Price Impact	(4) Return-SD
Opacity	.00146***			
	(13)			
E-Spread		.0507***		
		(39)		
Price Impact			.0535***	
			(40)	
Return-SD				.0165***
				(50)
Effect:				
Log(ΔTotal_Assets)	.00234***	-.0017	-.00276	-.00043
	(7.7)	(-.37)	(-.21)	(-.37)
Stress Test	-.00042	-.0124**	-.00897	.00223
	(-1.2)	(-2.1)	(-1.5)	(1.6)
N	256	256	256	256