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Bank opacity and the efficiency of stock prices

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ABSTRACT

Prior research argues that the process of intermediation is opaque and produces uncertainty about the riskiness of banks, which may adversely affect the efficiency of bank stock prices. Using the Hou and Moskowitz (2005) measure of price delay, which captures the inefficiency of stock prices, we test for, and find evidence supporting the idea that opacity is positively associated with price delay. Bank stocks have markedly higher delay than similar non-bank stocks. This higher level of delay is driven, in part, by market-based measures of informational opacity as well as the asset composition of the bank's balance sheet. Combined, our findings suggest that bank opacity reduces the efficiency of financial markets.

1. Introduction

The theory of efficient markets posits that asset prices reflect all available information. However, what if information about the risks associated with the asset are relatively opaque? In this study, we test the hypothesis that this type of opacity within firms will result in less efficient stock prices. We focus our analysis on banks, which are arguably more opaque than other types of firms, and explore how well bank stocks incorporate market-wide information. Prior research motivates this analysis by suggesting that firm opacity can decrease the stability of stock prices and lead to lower levels of market efficiency (Fishman and Hagerty, 1989; Jin and Myers, 2006; Haggard et al., 2008). For example, Veldkamp (2006) develops a model in which investors have incomplete, firm-specific information and must rely upon common signals to predict the cash flows of firms. The lack of information leads to greater comovement across securities and, consequently, less informed stock prices. Similarly, our hypothesis suggests that the opacity of banks might adversely influence the ability of outsiders to accurately value banks, which may lead to less informational efficiency in the stock prices of banks.

To test this hypothesis, we follow Hou and Moskowitz (2005) and estimate price delay for a broad sample of both banks and non-banks. Price delay, which is a parsimonious measure of informational inefficiency, identifies stocks that have difficulty incorporating market-wide information into their share prices. If opacity creates informational uncertainty, then bank stocks are likely to have greater difficulty incorporating (or interpreting) market-wide information. Using this measure of price delay, we conduct two sets of tests. First, we test whether the price delay of bank stocks is greater than the price delay of matched non-bank stocks. Second, focusing strictly on our sample of banks, we investigate whether opaque banks have less efficient stock prices than non-opaque banks.

The motivation for our tests is based on existing theory that suggests that opacity in the intermediation process provides uncertainty to outsiders about the inherent risks of banks (Berlin and Loeys, 1988; Diamond, 1989, 1991).[1] Campbell and Kracaw (1980) present a model that suggests that while the market can produce information, which reflects the true value of the firm's assets, the opacity associated with the risks in the intermediation process make this information production inefficient and/or costly. Empirically, Morgan (2002) finds greater heterogeneity in bond ratings for banks than for non-banks. This result seems to indicate that, because of opacity, rating agencies have difficulty understanding the risks associated with the intermediation process. Following this line of research, we argue that investors might have difficulty

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[1] Some of the literature suggests that the riskiness of banks can be explained by other characteristics, such as abnormal loan growth (Laeven and Majnoni, 2003; Berger and Udell, 2004; Foos, Norden, and Weber, 2010), regulation and diversification (Wall, 1987; Boyd, Graham, and Hewitt, 1993; Demsetz and Strahan, 1997), credit and liquidity risk (Nijskens and Wagner, 2011), and systemic risk (Diamond and Dybvig, 1983; Rochet and Tirole, 1996; Freixas, Parigi, and Rochet, 2000).

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assessing the true value of banks and, therefore, bank stock prices will be less efficient than non-bank stock prices.

Our tests are also motivated by a more recent line of research. Flannery et al., (2004 and 2013) argue that if outside investors have difficulty valuing banks, then market microstructure theory suggests that bank shares should have distinct trading characteristics, such as higher bid-ask spreads and less trading volume.[2] Flannery et al., (2004 and 2013) provide some evidence that bank stocks have less market liquidity than comparable non-banks, particularly during the recent financial crisis. Furthermore, their results are driven by banks that are most likely to be opaque. In another related study, Jones et al., (2012) 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 – particularly for those with a greater degree of opacity. These findings again suggest that some investors have difficulty assessing the value of banks and therefore rely on merger valuations. The results in Flannery et al., (2004 and 2013) and Jones et al., (2012), which show that outsiders have difficulty assessing the true value of opaque banks, make tests of our hypothesis more compelling.

Consistent with our hypothesis, our first set of results show that, for a broad sample of securities, price delay is markedly higher for banks than for non-banks. In particular, we follow Flannery et al., (2004) and create matched pairs of banks and non-banks based on market capitalization and share prices. Our multivariate tests show that, after controlling for other factors that influence the level of price delay, banks experience price delay that is between 5.6% and 8.2% higher than matched non-banks, suggesting that the differences are not only statistically significant but they are also economically meaningful. Our results are stronger during the recent financial crisis period but persist during other periods.

In our second set of tests, we determine whether the less efficient stock prices observed in banks are truly driven by opacity. These tests are conducted in two ways. First, we follow Flannery et al., (2004 and 2013) and test whether microstructure measures of liquidity influence price delay for our sample of banks. Consistent with the notion that opacity (as measured by illiquidity) directly contributes to higher levels of price delay, we find that banks with higher bid-ask spreads, banks with less trading activity, and banks with larger measures of Amihud's (2002) illiquidity have higher levels of price delay. These results are both statistically and economically significant. For example, a one standard deviation increase in bid-ask spreads is associated with an increase in price delay that represents about 22% of price delay for the average bank stock.

Second, we use opaque asset structures to test whether bank opacity drives the higher levels of price delay. Consistent with much of the theoretical research that argues that bank loans are informationally opaque (Campbell and Kracaw, 1980; Berlin and Loeys, 1988; Diamond, 1989, 1991; Kwan and Carleton, 2004), we find that the ratio of real estate loans to total assets is directly related to the price delay of banks. This relation is both statistically and economically significant. For instance, our multivariate tests show that a one standard deviation increase in the ratio of real estate loans to total assets is associated with a 0.6% to a 1.2% increase in price delay. Our tests also show that the ratio of non-real estate loans to total assets is positively associated with the level of price delay for banks. In economic terms, a one standard deviation increase in the ratio of non-real-estate loans to total assets is associated with a 0.64% to a 1.30% increase in price delay. The results from these tests provide support for the idea that 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.

For robustness, we use multivariate time-series analysis to examine how bank returns and non-bank returns respond to exogenous shocks in market-wide returns. Using a vector auto regressive (VAR) process, we estimate impulse responses functions (IRFs) of both bank stock returns and non-bank stock returns in response to exogenous shocks in market returns. These time-series tests complement our analysis of price delay given that delay captures the difficulty of individual stock prices in incorporating market-wide information. The impulse response functions measure how bank stock returns respond to exogenous shocks to market-wide returns. Our results seem to indicate that, relative to non-bank stock returns, it takes longer for bank returns to revert back to normal levels following these innovations in market-wide returns. These findings provide confirmation for our earlier results that banks are less efficient than non-banks. Additionally, we estimate the VAR processes for our sample of banks to determine whether IRFs differ between a sample of opaque banks and non-opaque banks. Opaque banks are first defined as those that have the highest bid-ask spreads (the most opaque banks) while non-opaque banks are those banks with the lowest bid-ask spreads (the least opaque banks). The results from these tests provide supportive evidence that innovations in market returns destabilize the returns of opaque banks more than the returns of non-opaque banks. As an additional measure of robustness, we also examine the IRFs of banks with the highest loan-to-asset ratios and banks with the lowest loan-to-asset ratios. These results show some evidence, albeit weaker, that opaque banks respond differently to shocks in market-wide returns than non-opaque banks.

The results in this study provide an important contribution to the literature by documenting that not only are the stock prices of banks less efficient than those of similar non-banks, but the inefficiency of bank stocks is driven, to some degree, by the level of opacity. These results provide a greater understanding about the role of opacity as it relates to the flow of information into stock prices. As Morgan (2002) argues, much of the regulatory structure for banks is based on the idea that outsiders face inherent uncertainty about the riskiness of banks. Our results suggest that this uncertainty reduces the ability of outsiders to properly access value-related information (Campbell and Kracaw (1980)). Morgan (2002) and Jones et al., (2012) argue that the opacity of banks inhibits effective market discipline, which exposes the entire financial system to bank runs, contagion, and other strains of systemic risk. Consistent with this argument, our findings suggest that the lack of market discipline created by bank opacity can also influence the informational efficiency of stock prices.

2. Data description

To carry out our analysis, we obtain every listed security on the Center for Research in Security Prices (CRSP) for the period January of 1996 to December of 2008.[3] From CRSP, we obtain daily returns, volume, market capitalization, and shares outstanding. From Compustat, we gather balance sheet data for each firm used in the sample. We follow Flannery et al., (2004) and create a sample of banks and matched non-banks. First, we extract all

[2] Kyle (1985), Glosten and Milgrom (1985), and Copeland and Galai (1983) provide the theoretical foundation showing that, in the presence of information asymmetries, bid-ask spreads will widen and trading activity will decrease.

[3] Our choice of time period is based on the likelihood that the financial crisis brought about regulation targeting banks, which likely affected the efficiency of bank stock prices. For fear that our results could be driven by this time period, we chose to conclude our sample in the end of 2008 before many of these regulation policies went into effect. We realize that the cutoff is ambiguous so we have replicated much of our analysis without including 2008 and find the results to be qualitatively similar to those reported in this study.

financial firms (SIC code 6000–6999). We then obtain regulatory identification numbers (RSSD ID) from the National Information Center (NIC) and merge the banks to their permanent company numbers (PERMCO) from CRSP for our sample period. This list includes Bank Holding Companies, Thrift Holding Companies, and Commercial Banks. More than 88% of the firms in our sample are considered Bank Holding Companies while only 2.7% and 8.5% are Thrift Holding Companies and Commercial Banks, respectively. After obtaining the sample of financial firms, we then find the intersection between banks with CRSP data and banks with data available on Bank Compustat.[4] We are left with 361 financial institutions.

We then compare bank's market capitalization to non-financial firms and match firms whose market value is closest to each particular financial firm and whose share price is within 25% of the bank's share price.[5] We also require the matched non-bank to be listed on the same exchange as the bank. We conduct this matching procedure each year. Throughout the analysis, we use pooled stock-year observations. Our entire sample consists of 18,082 firm-year observations.

To calculate the measure of stock price inefficiency, we closely follow Hou and Moskowitz (2005) and create weekly, Wednesday-to-Wednesday returns using daily CRSP returns.[6] We then estimate the following equation with the weekly returns.

$$R_{i,t} = \alpha_i + \beta_i Rm_t + \sum_{n=1}^{4} \gamma_{i,t-n} Rm_{t-n} + \varepsilon_{i,t} \tag{1}$$

The dependent variable $R_{i,t}$ is the weekly return for each firm i during week t. We include as independent variables the contemporaneous (value-weighted) market return $Rm_{i,t}$ and the lagged market return during week $t-n$ ($Rm_{i,t-n}$), where $n = \{1, 2, 3, \text{or } 4\}$. From this first regression of the full model, we extract the R^2, which we denote as the unrestricted R^2. Next, we estimate Eq. (1) again but restrict $\gamma_{i,t-n} = 0$ and only include the contemporaneous market return as the sole independent variable. In this restricted regression, we obtain the R^2s for each stock in each year and denote this as the restricted R^2. Accordingly, delay as defined in Hou and Moskowitz (2005), is equal to the following.

$$\frac{Unrestricted\,R^2 - Restricted\,R^2}{Unrestricted\,R^2} \tag{2}$$

Eq. (2) measures the increase in explanatory power by including lagged market returns in Eq. (1). The greater the ratio in Eq. (2), the greater the delay with which a particular stock incorporates market-wide information.

Hou and Moskowitz (2005) denote the results from estimating Eq. (2) as first-stage delay but recognize the possibility that this estimate is noisy. Therefore, Hou and Moskowitz use a portfolio approach to reduce the possibility of noise in the estimate in Eq. (2), and denote the portfolio approach as second-stage delay. We closely follow their portfolio approach by sorting stocks into market cap deciles and then, within each market cap decile, we sort stocks into first-stage delay deciles. We then estimate delay for the 100 portfolios and assign stocks in each portfolio this newly estimated measure of portfolio delay. In the results that follow, we use second-stage delay. We replicate much of our analysis using first-stage delay and find results that are qualitatively similar to those reported in this study.

3. Empirical results

In this section, we present summary statistics and begin by providing comparisons between delay for banks and delay for comparable non-banks. We then attempt to identify factors that influence the level of delay for banks. In particular, we look at several firm-specific factors that might influence the level of delay, such as asset structure, measures of market liquidity, firm size, systematic and idiosyncratic risk, and liquidity.

3.1. Summary statistics

We begin by presenting statistics that describe our sample of banks and the sample of matched non-banks. Table 1 reports summary statistics for the variables used throughout the analysis. *Delay* is the Hou and Moskowitz (2005) measure of second-stage price delay. *Turn* is the average daily share turnover, which is the ratio of daily volume to shares outstanding (in percent). *Spread* is average daily percentage bid-ask spread and is calculated as the difference between the ask price and bid price scaled by the spread midpoint. We note that *Spread* is calculated using closing bid and ask prices from CRSP, as recommended by Chung and Zhang (2014) and Roll and Subrahmanyam (2010), who show that the CRSP-based spread is highly correlated with the intraday TAQ-based spread. *Illiq* is Amihud's (2002) measure of illiquidity and is obtained by dividing the absolute value of daily returns by daily price volume (in 100,000 s). We note that Flannery et al., (2013) also use Amihud's measure of illiquidity, which measures the price impact of daily trading volume.[7] We also include the following as additional control variables. *Price* is the average closing price obtained from CRSP. *Size*, which is the firms' market capitalization in $billions. *B/M* is the book-to-market ratio. *Beta* is the estimated systematic risk factor obtained from evaluating a daily CAPM model. *IdioVolt* is an estimate for idiosyncratic risk, which is calculated as the standard deviation of daily CAPM residual returns.

Panel A reports the results for our sample of non-banks, while Panel B shows the results for our sample of banks. In Panel A, we find that for non-banks, the mean delay is 0.1044 and the median delay is 0.0317. In Panel B, we find that banks have a mean delay of 0.1120 and a median of 0.0623. It is important to note that the median delay in both panels is similar to the median (second-stage) delay reported in Hou and Moskowitz (2005).

The average non-bank (Panel A) has a share turnover of 0.7939, a bid-ask spread of 1.81%, an illiquidity measure of 0.7037, a price of $25.65, a market cap of $4.6847 billion, a book-to-market ratio of 0.1312, a CAPM beta of 1.1477, and idiosyncratic volatility of 3.28%. The average bank in our sample (Panel B) has a share turnover of 0.2282, a bid-ask spread of 1.76%, an illiquidity measure of 1.9120, a share price of $27.10, a market cap of $4.77 billion, a book-to-market ratio of 0.1178, a CAPM beta of 0.5590, and idiosyncratic volatility of 1.99%. We note that the difference in market cap between panels is 0.0831 and is not significantly different from zero (t-statistic = 0.19). This is expected given the construction of our matched sample.

[4] Bank Compustat reports data for the operations of a parent company and one or more subsidiaries that are consolidated into the company's financial statement.

[5] In our sample of non-financials, we disregard regulated utilities (SIC code 4800–4900).

[6] Hou and Moskowitz (2005) use Wednesday-to-Wednesday returns to control for autocorrelations that are apparent in Friday-to-Friday returns and Monday-to-Monday returns (Chordia and Swaminathan, 2000).

[7] We further note that our objective in this paper is to identify determinants of price delay for banks. While Flannery, Kwan, and Nimalendran use the adverse selection component of the bid-ask spread, effective spreads, Amihud's illiquidity, and share turnover as microstructure measures that might capture differences in the opacity of banks, we elect to use share turnover and Amihud's illiquidity. Instead of calculating effective spreads, we are interested in simply controlling for the size of bid-ask spreads using closing bid and ask prices on CRSP. Prior results shows that these closing bid and ask prices are very correlated to the microstructure variables used in Flannery, Kwan, and Nimalendran (2013). See, for example, Roll and Subrahmanyam (2010).

Table 1
Summary statistics.

	Mean	Std. Deviation	Minimum	Median	Maximum
Panel A. Stock characteristics of non-banks					
	[1]	[2]	[3]	[4]	[5]
Delay	0.1044	0.1502	0.0002	0.0317	0.9302
Turn	0.7939	1.8309	0.0004	0.4951	152.4446
Spread	0.0181	0.0266	−0.0039	0.0096	0.9696
Illiq	0.7037	2.3566	0.0000	0.0248	72.2419
Price	25.65	27.12	0.06	20.16	909.90
Size ($B)	4.6847	17.2925	0.0001	0.4147	469.5195
B/M	0.1312	0.3412	−0.0043	0.0484	2.6223
Beta	1.1477	1.3954	−2.2087	0.9508	6.3171
IdioVolt	0.0328	0.0216	0.0031	0.0275	0.7324
Panel B. Stock characteristics of banks					
Delay	0.1120	0.1284	0.0002	0.0623	0.8825
Turn	0.2282	0.3122	0.0015	0.1566	9.4803
Spread	0.0176	0.0199	−0.0000	0.0126	0.3753
Illiq	1.9120	4.0944	0.0000	0.2416	52.2227
Price	27.10	27.06	0.47	22.31	496.13
Size ($B)	4.7678	17.1867	0.0030	0.1863	225.1577
B/M	0.1178	0.3732	0.0189	0.0590	3.2940
Beta	0.5590	0.7494	−1.3900	0.4920	3.1543
IdioVolt	0.0199	0.0107	0.0056	0.0180	0.1944
Panel C. Balance sheet characteristics of banks					
Assets ($M)	371.24	1593.80	0.66	12.85	29,503.16
Equity ($M)	25.25	101.40	0.05	1.13	1468.03
L-T Debt ($M)	31.51	143.32	0.00	0.72	1691.82
Deposits ($M)	193.79	726.41	0.53	9.04	8051.77
Inv. Sec. ($M)	47.65	194.92	0.00	2.40	3288.73
D/E	10.68	3.34	1.09	10.43	51.52
REloans ($M)	58.14	238.86	0.00	0.00	3588.29
OtherLoans($M)	86.15	350.38	0.00	0.00	5175.15
OtherOpaq ($M)	203.26	1094.17	0.66	12.07	26,221.29

The table reports statistics that summarize the data used in the analysis. Panel A reports stock characteristics for the control sample of non-banks, while Panel B shows the same summary statistics for sample of banks. Panel C presents the balance sheet characteristics for our sample of banks. The number of banks in the sample is 361 while the number of non-banks is approximately 1800. *Delay* is the Hou and Moskowitz (2005) second stage measure of price delay. *Turn* is the share turnover or the ratio of daily volume to shares outstanding (in percent). *Spread* is the percentage bid-ask spread or the difference between the closing CRSP ask price and the closing CRSP bid price divided by the closing spread midpoint. *Illiq* is Amihud's (2002) measure of illiquidity and is calculated as the ratio of the absolute value of the daily return scaled by the daily volume (in 100,000 s). *Turn, Spread*, and *Illiq* are calculated at the daily level and averaged across each year for each stock. *Price* is the price obtained from CRSP. *Size* is the market capitalization in $billions. *B/M* is the book-to-market ratio. *Beta* is the CAPM beta estimate for each firm during the year. *IdioVolt* is the idiosyncratic volatility which is calculated by estimating the standard deviations of residuals from estimating a daily CAPM model. In Panel C, *Assets* is the total assets. *LTDebt* is the long-term debt. *Equity* is shareholder equity. *Deposits* is the amount of deposits. *InvSec* is the amount of investment securities. D/E is the debt-to-equity ratio. *REloans* is the amount of real estate loans. *OtherLoans* is the total dollar value of all outstanding domestic loans not classified into other loan components. *OtherOpaq* is defined as other opaque assets (according to Jones et al., 2012) in $millions.

In Panel C, we report several balance sheet characteristics for our sample of banks obtained from Compustat. *Assets* is the total assets. *Equity* is shareholder equity. *LTDebt* is the long-term debt. *Deposits* is the amount of deposits. *InvSec* is the amount of investment securities. *D/E* is the debt-to-equity ratio. *RELoans* is the amount of real estate loans. *OtherLoans* is the total dollar value of all outstanding domestic loans not classified as real estate loans components. *OtherOpaque* is defined as other opaque assets in accordance with Jones et al., (2012). Specifically, *OtherOpaque* is defined as assets less the sum of real estate loans, other loans and transparent assets, where transparent assets are measured as the sum of cash, federal funds sold, securities purchased under agreements to resell, guaranteed AFS and HTM securities. We note that all of these balance sheet variables are denoted in $millions. The average bank in our sample has assets of $371.24, shareholder equity of $25.25, long-term debt of $31.51, deposits of $193.79, investment securities held of $47.65, a debt-to-equity ratio of 10.68, real estate loans of $58.14, non-real estate loans of $86.15, and other opaque assets of $203.26.

3.2. Comparing price delay in banks to non-banks: univariate tests

We begin by examining the differences in delay across various time periods of our study. In Table 2, we report the mean delay for banks in Column [1] and mean delay for our sample of similar non-banks in Column [2]. Column [3] reports the difference between Columns [1] and [2] with a corresponding *t*-statistic in parentheses. We report the comparisons for all years of our sample time period and the for the Pre-Technology Bubble period (1996–1997), the Technology Bubble Period (1998–1999), the Technology Crash (2000–2002), the real estate bubble period (2003–2006), and the financial crisis (2007–2008). We closely follow prior research and define the period of the technology bubble and the subsequent correction period (Ofek and Richardson (2003) and

Table 2
Differences in delay across the sample time period.

	Sample of banks	*Sample of non-banks*	*Difference in means*
	[1]	[2]	[3]
All Years	0.1120	0.1044	−0.0076** (−2.03)
1996–1997 (Pre-Tech Bubble)	0.0935	0.0791	−0.0144** (−2.54)
1998–1999 (Tech Bubble)	0.1570	0.1977	0.0407** (2.07)
2000–2002 (Tech Crash)	0.1366	0.1242	−0.0125* (−1.87)
2003–2006 (RE Bubble)	0.0933	0.0714	−0.0219*** (−4.93)
2007–2008 (Financial Crisis)	0.1221	0.0507	−0.0714*** (−10.69)

The table reports Delay, which is the Hou and Moskowitz (2005) second stage measure of price delay in each year of our sample time period. Column [1] reports the results for our sample of Bank Holding Companies (Banks) while column [2] presents the findings for our sample of matched non-banks. In column [3], we report the difference in means along with a corresponding t-statistic testing whether the difference is different from zero.
*** statistical significance at the 0.01.
** statistical significance at the 0.05.
* statistical significance at the 0.10 levels.

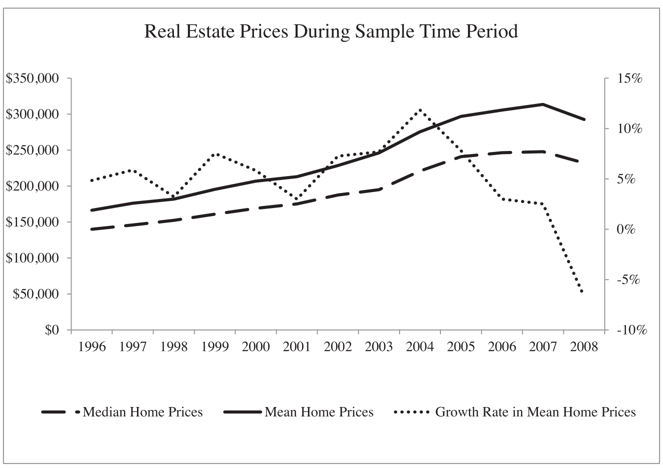

Fig. 1. The figure shows real estate prices (both median and mean prices) during the sample time period. The figure also shows the percentage change in mean real estate prices.

Battalio and Schultz (2006)). Fig. 1 shows median and mean home prices in the U.S. along with the growth rate of mean home prices. Beginning in 2003, we observe a sharp increase in the growth rate of prices. Both median and mean home prices continue to increase until 2007. Therefore, we define the real estate bubble as the period of 2003 to 2006.[8] As mentioned above, 2007 saw a dramatic correction in the price of financial stocks as the average financial stock reported a 30% decrease in price. Therefore, we denote the period 2007–2008 as the financial crisis.

Table 2 shows that for all years in our sample time period, the delay for banks is markedly higher than delay for the sample of non-banks (difference = −0.0076, *t*-statistic = −2.03). In economic terms, this difference reflects 7.3% of non-bank mean delay. A closer look at the table, however, indicates that the higher levels of delay in banks depends on the different sub-time periods. For instance, we find that during the technology bubble (when prices of banks were likely to be less affected than non-banks), bank delay was lower than the delay of non-banks. This results is interesting given the finding in the literature that discusses that stock prices become less efficient during bubble periods (see Goodhart (1995), Senhadji and Collyns (2002), Gerlach and Peng (2005), Greenwood and Nagel (2009) and Blau (2012)). We note that during the technology bubble, bank stocks prices were less affected than non-banks. For instance, over this two-year period, non-banks had an average annual stock return of 18.41% while banks had an average return that was effectively zero. This difference is both statistically and economically significant (*t*-statistic = 8.08). Given that banks were less affected by the technology bubble than non-banks, observing higher delay in non-banks than in banks during this period is not entirely unexpected. During the real estate bubble period (when prices of banks were likely to be more affected than non-banks), the bank delay is approximately 31% higher than non-bank delay. The difference between bank delay and non-bank delay is even more pronounced during the financial crisis, representing about 141% of non-bank delay. Our findings seem to indicate that bubbles and crises that directly impact the financial sector drive the higher levels of price delay for our sample of banks.

The purpose of showing that the difference in delay between banks and non-banks depends on various time periods is important for at least two reasons. First, our results illustrate time is an important determinant in the Hou and Moskowitz (2005) measure of price delay, highlighting the need to control for year fixed effects in a multivariate setting. Second, and perhaps more importantly, our findings indicate that bubbles and crises seem to drive the higher levels of price delay for banks. Therefore, the results in Table 2 indicate that the effects from bank opacity, such as asset mispricing, are exacerbated during times of market distress.

3.3. Comparing price delay in banks to non-banks: multivariate tests

While the results from Table 2 indicate that banks generally have higher delay than similar non-banks, we must interpret these results with caution for two reasons: One, several other firm-specific factors likely influence delay. Two, delay seems to be time variant. We, therefore, recognize the need to control for these variables in a multivariate framework. We estimate the following equation using pooled stock-year data.

$$\begin{aligned} Delay_{i,t} = {} & \alpha + \beta_1 BANKS_i + \beta_2 Turn_{i,t} + \beta_3 Spread_{i,t} + \beta_4 Illiq_{i,t} \\ & + \beta_5 Size_{i,t} + \beta_6 B/M_{i,t} + \beta_7 D/E_{i,t} + \beta_8 ln(Assets_{i,t}) \\ & + \beta_9 Beta_{i,t} + \beta_{10} IdioVolt_{i,t} + \beta_{11} Price_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (3)$$

The dependent variable is the Hou and Moskowitz (2005) second-stage measure of price delay for stock *i* during year *t* ($Delay_{i,t}$). The independent variable of interest is an indicator variable *BANKS*, which equals unity if the cross-sectional observation is in the sample of banks – zero otherwise. We include the following variables as controls: *Turn, Spread, Illiq, Size, B/M, D/E,* Ln*(Assets), Beta, IdioVolt,* and *Price*. The control variables have been defined previously. Because the data is pooled, we estimate

[8] Our results are robust to other definitions of the bubble period. For instance, we use the period 2002 to 2007, 2003 to 2007, and find that our result are robust to these different definitions.

Table 3
Panel regressions – Price delay.

	[1]	[2]	[3]	[4]	[5]	[6]
Intercept	0.2470***	0.2181***	0.2132***	0.2338***	0.1725***	0.1709***
	(23.27)	(18.49)	(19.81)	(24.97)	(12.74)	(14.04)
$BANKS_i$	0.0767***	0.0613***	0.0568***	0.0818***	0.0642***	0.0598***
	(21.35)	(20.05)	(18.28)	(25.69)	(20.79)	(22.23)
$Turn_{i,t}$	−0.0091*	−0.0034	−0.0035	−0.0080*	−0.0023	−0.0024
	(−1.83)	(−1.29)	(−1.32)	(−1.79)	(−1.09)	(−1.14)
$Spread_{i,t}$		1.6412***	1.4665***		1.8519***	1.6301***
		(10.19)	(8.52)		(8.44)	(6.64)
$Illiq_{i,t}$			0.0033***			0.0036***
			(3.85)			(3.32)
$Size_{i,t}$	0.0006***	0.0005***	0.0005***	0.0006***	0.0005***	0.0005***
	(13.34)	(12.85)	(12.90)	(11.13)	(9.85)	(9.89)
$B/M_{i,t}$	0.0027***	0.0005	0.0005	0.0027***	0.0005	0.0004
	(2.66)	(0.59)	(0.56)	(3.08)	(0.60)	(0.59)
$D/E_{i,t}$	0.0000	0.0000	0.0000	−0.0000	0.0000	−0.0000
	(0.01)	(0.51)	(0.26)	(−0.35)	(0.18)	(−0.12)
$Ln(Assets_{i,t})$	−0.0299***	−0.0257***	−0.0250	−0.0311***	−0.0273***	−0.0265***
	(−31.31)	(−24.62)	(−26.76)	(−35.46)	(−26.48)	(−30.62)
$Beta_{i,t}$	−0.0006	−0.0003	−0.0003	−0.0004	−0.0001	−0.0001
	(−1.47)	(−1.22)	(−1.23)	(−1.24)	(−0.64)	(−0.64)
$IdioVolt_{i,t}$	1.9419***	0.9528***	1.0095***	1.5021***	0.4649**	0.5270***
	(10.08)	(4.65)	(5.21)	(8.52)	(2.25)	(2.72)
$Price_{i,t}$	−0.0007***	−0.0006***	−0.0006***	−0.0007***	−0.0006***	−0.0006***
	(−6.15)	(−6.17)	(−6.19)	(−6.11)	(−6.03)	(−6.02)
Adj. R^2	0.3715	0.4205	0.4229	0.5373	0.5917	0.5943
Year FE	No	No	No	Yes	Yes	Yes

The table reports the results from estimating the following equation using pooled data.

$$Delay_{i,t} = \alpha + \beta_1 BANKS_i + \beta_2 Turn_{i,t} + \beta_3 Spread_{i,t} + \beta_4 Illiq_{i,t} + \beta_5 Size_{i,t} + \beta_6 B/M_{i,t} + \beta_7 D/E_{i,t} + \beta_8 ln(Assets_{i,t}) + \beta_9 Beta_{i,t} + \beta_{10} IdioVolt_{i,t} + \beta_{11} Price_{i,t} + \varepsilon_{i,t}$$

The dependent variable is the Hou and Moskowitz (2005) second stage measure of price delay ($Delay_{i,t}$). We include the following variables as independent variables. *BANKS* is an indicator variable capturing the firms that are financial institutions (according to Bank Compustat) – zero otherwise. *Turn* is the average daily share turnover or the ratio of volume to shares outstanding. *Spread* is the average daily percentage bid-ask spread. *Illiq* is the average daily illiquidity measure according to Amihud (2002). *Size* is the market capitalization in $billions. *B/M* is the book-to-market ratio. *D/E* is the debt-to-equity ratio. *Assets* is the total assets in $millions. *Beta* is the CAPM beta estimate for each firm during the year. *IdioVolt* is the idiosyncratic volatility which is calculated by estimating the standard deviations of residuals from estimating a daily CAPM model. *Price* is the price obtained from CRSP. Columns [1] through [3] report the results without year fixed effects while columns [4] through [6] present the results while including year fixed effects. We do not tabulate the fixed effects estimates for brevity. We report *t*-statistics in parentheses that are obtained after controlling for two-dimensional clustering. Similar results are found when we control for conditional heteroskedasticity.

*** statistical significance at the 0.01.
** statistical significance at the 0.05.
* statistical significance at the 0.10 levels.

a Hausman statistic to determine whether Random Effects exist in the estimation of Eq. (3). The Hausman test rejects the presence of Random Effects. However, an *F*-test indicates that there are observed differences across years. Therefore, we estimate Eq. (3) with and without controls for year fixed effects.[9,10]

Table 3 reports the results from estimating Eq. (3). Columns [1] through [3] report the results excluding year fixed effects, while Columns [4] through [6] present the results while including year fixed effects. We do not tabulate the fixed effects estimates for brevity. We also report *t*-statistics in parentheses that are obtained after controlling for two-dimensional clustering across both firm and time.[11] Given the possibility that our liquidity measures are highly collinear, we estimate Eq. (3) using various combinations of liquidity variables to show that our results are robust.

In Column [3], we find that delay is negatively related to the natural log of assets and share prices. Further, delay is positively related to idiosyncratic volatility and market cap.[12] Similar results to these are found in Hou and Moskowitz (2005). We also find both *Spread* and *Illiq* positively affect delay, suggesting that the illiquid stocks tend to have more difficulty incorporating market-wide information. Book-to-market ratios, debt-to-equity ratios, and *Betas* appear to be unrelated to delay in our sample. The variable of interest, *BANKS*, consistently produces positive estimates in Columns [1] through [3]. As seen in Table 3, the coefficients for *BANKS*, while positive and statistically significant, vary in magnitude across columns. Specifically, the difference in delay between banks and similar non-banks ranges from 0.0568 to 0.0767.

In Columns [4] through [6], we find that, after controlling for year fixed effects, the results are qualitatively similar to those in Columns [1] through [3]; however, there are important quantita-

[9] Because we include the dummy variable *BANKS*, we do not include Firm Fixed Effects in order to avoid violating the full rank assumption required for consistent estimates.

[10] When controlling for Year Fixed Effects, we exclude the dummy variable for 1996 and include dummy variables for each year from 1997 to 2008.

[11] In unreported results, we control for conditional heteroskedasticity and find the results are qualitatively similar to those reported in Table 3. As another means of robustness, we estimate variance inflation factors for the full model in columns [3] and [6] and find that all factors are under 2.55, indicating that standard errors do not appear to be affected by multicollinearity. We note that the variance inflation factor for the variable BANKS is only 1.1636.

[12] The positive relation between delay and market capitalization is surprising. Additional analysis shows that when we do not include assets and book-to-market ratios in the regressions, the coefficient on size becomes negative and significant suggesting that the negative effect of assets on delay is stronger than the negative effect of market cap on delay.

tive differences. If anything, we find that the magnitude of the estimate for *BANKS* increases, after controlling for year fixed effects. In particular, the coefficients on *BANKS* suggest that our sample of banks have delay that is from 0.06 to 0.08 higher than the sample of matched non-banks. The results in the latter columns indicate that including year fixed effects increases the economic and statistical significance of our findings, as *BANKS* produce larger and more statistically significant estimates in columns [4] through [6]. The results from Table 3 provide support for the hypothesis that, perhaps because of opacity, banks have less efficient stock prices than non-banks. The findings in this table also suggest that firm type is an additional determinant in the Hou and Moskowitz (2005) measure of price delay.[13]

3.4. Comparing price delay in banks to non-banks: conditioning on the financial crisis

We continue our examination of the time-varying properties of our comparison of bank price delay to non-bank price delay using multivariate tests. Table 4 reports the results from estimating the following equation using our sample of pooled stock-year data for both banks and similar non-banks.

$$\begin{aligned} Delay_{i,t} = \alpha &+ \beta_1 BANKS_i + \beta_2 Crisis_t + \beta_3 BANKS_i \times Crisis_t \\ &+ \beta_4 Turn_{i,t} + \beta_5 Spread_{i,t} + \beta_6 Illiq_{i,t} + \beta_7 Size_{i,t} \\ &+ \beta_8 B/M_{i,t} + \beta_9 D/E_{i,t} + \beta_{10} Ln(Assets_{i,t}) + \beta_{11} Beta_{i,t} \\ &+ \beta_{12} IdioVolt_{i,t} + \beta_{13} Price_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

As in the previous equation, the dependent variable is the Hou and Moskowitz (2005) second stage measure of price delay ($Delay_{i,t}$). The independent variables have been defined previously, with the exception of *Crisis*, which is an indicator variable equal to one for years 2007 and 2008, zero otherwise. We also include an interaction term between the two indicator variables *Crisis* and *BANKS*. Given the findings in Flannery et al., (2013) that show that during the financial crisis, banks exhibited more informational uncertainty than non-banks, it is possible that the higher delay observed in bank stocks is simply an artifact of the financial crisis period. A positive interaction coefficient in Eq. (4) would indicate that the difference between delay for banks and delay for similar non-banks is driven, in part, by higher bank delay during the recent financial crisis. However, after controlling explicitly for the crisis period, a positive coefficient on *BANKS* would suggest that during the non-crisis period, banks still have higher delay than similar non-banks.

In unreported tests, we estimate various specifications of Eq. (4) to show that our results are robust to the inclusion of different combinations of independent variables. In other unreported tests, we estimate variance inflation factors and find that all factors are below 2.2. Further, estimated variance inflation factors for *BANKS, Crisis*, and *BANKS*×*Crisis* are each below 1.30. As before, we report *t*-statistics that are obtained from standard errors that control for two-dimensional clustering. We do not control for year fixed effects because we have included the dummy variable *Crisis*. Including year fixed effects and *Crisis* would violate the full rank condition required for consistent estimates. Column [1] reports the results before including the interaction variable. We find that while *BANKS* produces a positive and significant estimate, *Crisis* produces a negative and significant coefficient suggesting that, first, delay is higher for banks than for non-banks and second, after controlling for other factors that influence delay, delay is generally lower for the entire sample during the financial crisis than during the non-crisis period.

Column [2] reports the results when including the interaction between *Crisis* and *BANKS*. Interestingly, we find a positive and significant interaction estimate (estimate = 0.0162, *t*-statistic = 2.61). This positive interaction estimate suggests that the differences in delay between banks and non-banks are driven, in part, by the crisis period. In economic terms, the marginal increase in the delay difference is about 160 basis points. When relating this finding to our first research question, we are able to infer that while our earlier tests show that banks have higher delay than non-banks, these differences in delay are most observable during the financial crisis. This finding is consistent with our expectations given the results in Flannery et al., (2013).[14] We are careful to note, however, that the estimate for *BANKS* in column [2] is still positive and highly significant suggesting that the price delay of banks was generally higher than non-banks during the non-crisis period.

Columns [3] through [6] show the results when including difference combinations of our liquidity measures. We find that when controlling for bid-ask spreads in Columns [3] and [5], the coefficient on *Crisis* is no longer reliably different from zero. Regardless of whether we control explicitly for spreads or Amihud's (2002) illiquidity, we still observe positive and significant coefficients on both the indicator variable *BANKS* and the interaction variable.

3.5. Is the higher delay in banks driven by opacity?

Thus far, we have documented a stark difference in price delay between banks and non-banks, which is consistent with the idea that opacity adversely affects the informational efficiency of bank stock prices vis-à-vis non-bank stock prices. In this section, we attempt to directly link the unusually higher levels of delay in banks to opacity. As mentioned previously, we posit that Morgan's (2002) argument that the opacity of banks will cause the prices of bank stocks to have difficulty incorporating relevant information. We test this conjecture below.

We begin by following prior literature and identifying several opacity measures that are directly associated with information asymmetry in financial markets. Flannery et al., (2004 and 2013) argue that the informational opacity of banks' assets affects several key microstructure variables such as the bid-ask spread, price impact, and trading volume. The use of these market microstructure measures to proxy for bank opacity is based on the notion that, when facing uncertainty about the value of stocks, liquidity providers will increase the size of the bid-ask spread and reduce the liquidity of the stock (Copeland and Galai (1983); Glosten and Milgrom (1985) and Kyle (1985)).

We focus on three liquidity measures that relate to information asymmetry: the bid-ask spread (*Spread*), Amihud's (2002) measure of price impact (*Illiq*), and share turnover (*Turn*). Theory in Glosten and Milgrom (1985) shows that information asymmetry, or the presence of traders with superior information about the true value of firms, leads to a positive bid-ask spread. In addition, the model in Kyle (1985) predicts that more opaque assets will be less liquid and trade with a larger bid-ask spread. To the extent that the opac-

[13] We note that the higher delay for Banks relative to non-banks holds before we conduct our matching procedure. That is, after gathering the universe of the firms with a CRSP share code of 10 or 11, Banks, on average, have higher delay than non-banks.

[14] We conduct a series of tests that attempt to replicate the findings in Flannery, Kwan, and Nimalendran (2013). In essence, we replicate Table 4 but instead of Delay as the dependent variable, we include both bid-ask spreads or Amihud's (2002) illiquidity as the dependent variables. These are similar to the variables used in Flannery, Kwan, and Nimalendran (2013). Result show that that 1) banks have both larger spreads and greater illiquidity than non-banks and 2) this result is driven by periods of the financial crisis. These findings support the results in Flannery, Kwan, and Nimalendran (2013) and also emphasize our findings that show that, after controlling for liquidity, delay is greater for banks and for non-banks – particularly during the financial crisis.

Table 4
Panel regressions – Price delay.

	[1]	[2]	[3]	[4]	[5]	[6]
Intercept	0.2471***	0.2472***	0.2180***	0.2180***	0.2132***	0.2133***
	(23.35)	(23.36)	(18.36)	(18.37)	(19.74)	(19.75)
$BANKS_i$	0.0765***	0.0745***	0.0613***	0.0595***	0.0568***	0.0557***
	(21.53)	(20.51)	(20.05)	(18.19)	(18.26)	(16.90)
$CRISIS_t$	−0.0100***	−0.0118***	0.0024	0.0007	−0.0003	−0.0013
	(−3.76)	(−4.09)	(1.04)	(0.31)	(−0.11)	(−0.50)
$CRISIS_t \times BANKS_i$		0.0162***		0.0151***		0.0097*
		(2.61)		(2.74)		(1.77)
$Turn_{i,t}$		−0.0089*	−0.0034	−0.0034	−0.0035	−0.0035
		(−1.82)	(−1.26)	(−1.29)	(−1.32)	(−1.32)
$Spread_{i,t}$			1.6454***	1.6452***	1.4657***	1.4673***
			(10.08)	(10.08)	(8.34)	(8.34)
$Illiq_{i,t}$					0.0033***	0.0033***
					(3.76)	(3.71)
$Size_{i,t}$	0.0006***	0.0006***	0.0005***	0.0005***	0.0005***	0.0005***
	(13.39)	(13.40)	(12.81)	(12.81)	(12.89)	(12.89)
$B/M_{i,t}$	0.0027***	0.0027***	0.0005	0.0005	0.0005	0.0005
	(2.65)	(2.65)	(0.59)	(0.59)	(0.56)	(0.56)
$D/E_{i,t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.08)	(0.10)	(0.50)	(0.51)	(0.26)	(0.27)
$Ln(Assets_{i,t})$	−0.0297***	−0.0297***	−0.0258***	−0.0257***	−0.0250***	−0.0250***
	(−31.65)	(−31.69)	(−24.92)	(−24.93)	(−27.23)	(−27.21)
$Beta_{i,t}$	−0.0006	−0.0006	−0.0003	−0.0003	−0.0003	−0.0003
	(−1.47)	(−1.47)	(−1.22)	(−1.22)	(−1.23)	(−1.23)
$IdioVolt_{i,t}$	1.9327***	1.9314***	0.9524***	0.9513***	1.0096***	1.0083***
	(10.03)	(10.03)	(4.65)	(4.64)	(5.22)	(5.21)
$Price_{i,t}$	−0.0007***	−0.0007***	−0.0006***	−0.0006***	−0.0006***	−0.0006***
	(−6.15)	(−6.15)	(−6.17)	(−6.17)	(−6.19)	(−6.18)
Adj. R^2	0.3719	0.3720	0.4205	0.4206	0.4229	0.4229
Year FE	No	No	No	No	No	No

The table reports the results from estimating the following equation using pooled data.

$$Delay_{i,t} = \alpha + \beta_1 BANKS_i + \beta_2 Crisis_t + \beta_3 BANKS_i \times Crisis_t + \beta_4 Turn_{i,t} + \beta_5 Spread_{i,t} + \beta_6 Illiq_{i,t} + \beta_7 Size_{i,t} + \beta_8 B/M_{i,t} + \beta_9 D/E_{i,t} + \beta_{10} ln(Assets_{i,t}) + \beta_{11} Beta_{i,t} + \beta_{12} IdioVolt_{i,t} + \beta_{13} Price_{i,t} + \varepsilon_{i,t}$$

The dependent variable is the Hou and Moskowitz (2005) second stage measure of price delay ($Delay_{i,t}$). We include the following variables as independent variables. *BANKS* is an indicator variable capturing the firms that are financial institutions (according to Bank Compustat) – zero otherwise. *Crisis* is an indicator variable equal to one during the financial crisis period (2007–2008)– zero otherwise. We also include the interaction between these two indicator variables ($BANKS_i \times Crisis_t$).*Turn* is the average daily share turnover or the ratio of volume to shares outstanding. *Spread* is the average daily percentage bid-ask spread. *Illiq* is the average daily illiquidity measure according to Amihud (2002). *Size* is the market capitalization in $billions. *B/M* is the book-to-market ratio. *D/E* is the debt-to-equity ratio. *Assets* is the total assets in $millions. *Beta* is the CAPM beta estimate for each firm during the year. *IdioVolt* is the idiosyncratic volatility which is calculated by estimating the standard deviations of residuals from estimating a daily CAPM model. *Price* is the price obtained from CRSP. In order to avoid violating the full rank condition, we do not include year fixed effects when including the indicator variable *Crisis*. We do, however, report *t*-statistics in parentheses that are obtained after controlling for two-dimensional clustering. Similar results are found when we control for conditional heteroskedasticity.

** statistical significance at the 0.05.

*** statistical significance at the 0.01.

* statistical significance at the 0.10 levels.

ity of bank stocks leads to less informational efficiency in stock prices, we expect price delay to be negatively related to stock liquidity for our sample of bank stocks.

We test this hypothesis by estimating the following equation using pooled stock-year data for our sample of 361 banks.

$$\begin{aligned} Delay_{i,t} = {} & \alpha + \beta_1 Turn_{i,t} + \beta_2 Spread_{i,t} + \beta_3 Illiq_{i,t} + \beta_4 ln(Assets_{i,t}) \\ & + \beta_5 ln(LTDebt_{i,t}) + \beta_6 ln(Equity_{i,t}) + \beta_7 ln(Deposits_{i,t}) \\ & + \beta_8 ln(InvSec_{i,t}) + \beta_9 D/E_{i,t} + \beta_{10} Size_{i,t} + \beta_{11} B/M_{i,t} \\ & + \beta_{12} Beta_{i,t} + \beta_{13} IdioVolt_{i,t} + \beta_{14} Price_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{5}$$

The dependent variable is the Hou and Moskowitz (2005) second-stage price delay. We include year fixed effects and all remaining independent variables have been defined previously. We report *t*-statistics in parentheses that are obtained after controlling for two-dimensional clustering. The results of estimating Eq. (5) are reported in Table 5. With respect to the control variables, we find that, in general, D/E ratios, size, B/M ratios, and idiosyncratic volatility all positively affect the level of bank price delay. Further, delay is negatively related to the amount of assets and the amount of investment securities.

We now turn our attention to the liquidity proxies, our independent variables of interest. Consistent with our expectations, we find that the delay of banks' stock prices is negatively associated with turnover and positively associated with spreads and illiquidity. For instance, in Column [1], we report a significant negative coefficient on turnover (estimate = −0.0148, *t*-statistic = −3.15), indicating that stocks with less share turnover typically have higher bank delay (less informational efficiency). Similarly, we find positive and significant coefficients on *Spread* (estimate = 1.2443, *t*-statistic = 2.06) and on *Illiq* (estimate = 0.0035, *t*-statistic = 6.52).

Column [4] shows the results when we include all three liquidity measures in the model. We find that the positive relation between delay and illiquidity remains intact. The coefficient on spread remains positive, although the estimate is only marginally significant (*t*-statistic = 1.76). Overall, the results in Table 5 show that bank stocks with lower share turnover, higher bid-ask spreads, and higher price impact have higher delay. These findings are consistent with the notion that the most opaque banks, with respect to these microstructure proxies, have the highest price delay. Stated differently, the stock prices of the most opaque banks

Table 5
Panel regressions – Price delay.

	[1]	[2]	[3]	[4]
Intercept	0.4413***	0.3872***	0.4285***	0.3856***
	(11.94)	(8.05)	(11.62)	(8.58)
$Turn_{i,t}$	−0.0148***			0.0023
	(−3.15)			(0.28)
$Spread_{i,t}$		1.2443**		1.0459*
		(2.06)		(1.76)
$Illiq_{i,t}$			0.0035***	0.0023***
			(6.52)	(2.94)
$Ln(Assets_{i,t})$	−0.0530*	−0.0433	−0.0555*	−0.0457
	(−1.78)	(−1.48)	(−1.89)	(−1.57)
$Ln(LTDebt_{i,t})$	0.0029	0.0024	0.0024	0.0022
	(1.55)	(1.31)	(1.32)	(1.22)
$Ln(Equity_{i,t})$	0.0187	0.0185	0.0240	0.0218
	(0.95)	(0.96)	(1.22)	(1.13)
$Ln(Deposits_{i,t})$	−0.0114	−0.0164	−0.0108	−0.0155
	(−0.80)	(−1.17)	(−0.77)	(−1.11)
$Ln(InvSec_{i,t})$	−0.0064**	−0.0065**	−0.0070**	−0.0068**
	(−2.06)	(−2.14)	(−2.29)	(−2.25)
$D/E_{\ i,t}$	0.0046***	0.0042***	0.0049***	0.0044***
	(2.70)	(2.55)	(2.92)	(2.66)
$Size_{\ i,t}$	0.0018***	0.0016***	0.0017***	0.0015***
	(10.12)	(8.02)	(10.09)	(8.65)
$B/M_{\ i,t}$	0.0123***	0.0110***	0.0121***	0.0110***
	(4.52)	(4.36)	(4.50)	(4.39)
$Beta_{\ i,t}$	−0.0007	0.0004	0.0001	0.0005
	(−0.50)	(0.36)	(0.03)	(0.49)
$IdioVolt_{\ i,t}$	1.0728***	0.1357	0.7543**	0.1388
	(3.47)	(0.30)	(2.36)	(0.28)
$Price_{i,t}$	−0.0001	−0.0001	−0.0001	−0.0001
	(−1.08)	(−1.01)	(−1.59)	(−1.34)
Adj. R^2	0.6199	0.6354	0.6290	0.6393
Year FE	Yes	Yes	Yes	Yes

The table reports the results from estimating the following equation using pooled data.

$$Delay_{i,t} = \alpha + \beta_1 Turn_{i,t} + \beta_2 Spread_{i,t} + \beta_3 Illiq_{i,t} + \beta_4 ln(Assets_{i,t}) + \beta_5 ln(LTDebt_{i,t}) + \beta_6 ln(Equity_{i,t}) + \beta_7 ln(Deposits_{i,t}) + \beta_8 ln(InvSec_{i,t}) + \beta_9 D/E_{i,t} + \beta_{10} Size_{i,t} + \beta_{11} B/M_{i,t} + \beta_{12} Beta_{i,t} + \beta_{13} IdioVolt_{i,t} + \beta_{14} Price_{i,t} + \varepsilon_{i,t}$$

The dependent variable is the Hou and Moskowitz (2005) second stage measure of price delay ($Delay_{i,t}$). We include the following variables as independent variables. *Turn* is the average daily share turnover or the ratio of volume to shares outstanding. *Spread* is the average daily percentage bid-ask spread. *Illiq* is the average daily illiquidity measure according to Amihud (2002). *Size* is the market capitalization in $billions. Ln*(Assets)* is the natural log of total assets. Ln*(LTDebt)* is the natural log of long-term debt. Ln*(Equity)* is the natural log of shareholder equity. Ln*(Deposits)* is the natural log of deposits. Ln*(InvSec)* is the natural log of investment securities. D/E is the debt-to-equity ratio. All of the balance sheet information is initially denominated in $millions. *B/M* is the book-to-market ratio. *D/E* is the debt-to-equity ratio. *Beta* is the CAPM beta estimate for each firm during the year. *IdioVolt* is the idiosyncratic volatility which is calculated by estimating the standard deviations of residuals from estimating a daily CAPM model. *Price* is the price obtained from CRSP. We report *t*-statistics in parentheses that are obtained after controlling for two-dimensional clustering. Similar results are found when we control for conditional heteroskedasticity.

*** statistical significance at the 0.01.
** statistical significance at the 0.05.
* statistical significance at the 0.10 levels.

have the greatest difficulty incorporating new market-wide information. We note, however, that including all three of these microstructure measures may result in multicollinearity issues. For instance, *Spread* and *Illiq* are heavily correlated (correlation coefficient = 0.38) while *Spread* and *Turn* are negatively correlated (correlation coefficient = −0.18).

Next, we extend our analysis by identifying an alternative proxy for bank opacity. Research in Campbell and Kracaw (1980), Berlin and Loeys (1988), and Diamond (1989, 1991) suggest that lending process is the likely cause of the opacity in banks. Therefore, we follow Jones et al., (2012) and Flannery et al., (2013) and approximate opacity using the amount of loans on the asset side of the bank's balance sheet. We categorize opaque assets in three different ways. First, we examine the amount of real estate loans relative to total assets (*RELoans*). Second, we examine the ratio of all other loans to total assets (*OtherLoans*). Finally, we follow Jones et al., (2012) and classify cash, federal funds sold, securities purchased under agreement to resell, and guaranteed AFS and HTM securities as transparent assets and then identify other opaque assets by taking the amount of total assets of each firm (less all loans) minus the transparent assets (*OtherOpaque*). We also scale this third measure of other opaque assets by total assets. The first two measures of opacity are related to the uncertainty about the inherent risks associated with the bank's loans. Outside investors are most likely unaware of the credit risk of loans as well as the uncertainty regarding the length of the loan. The third measure captures other assets (other than loans and transparent assets) that are opaque to outside investors.

To test whether the opacity of bank assets affects the price delay of banks, we estimate the following equation using pooled stock-year data for our sample of 361 banks only.

$$\begin{aligned} Delay_{i,t} = \alpha &+ \beta_1 RELoans_{i,t} + \beta_2 OtherLoans_{i,t} + \beta_3 OtherOpaque_{i,t} \\ &+ \beta_4 Turn_{i,t} + \beta_5 Spread_{i,t} + \beta_6 Illiq_{i,t} + \beta_7 ln(Assets_{i,t}) \\ &+ \beta_8 ln(LTDebt_{i,t}) + \beta_9 ln(Equity_{i,t}) + \beta_{10} ln(Deposits_{i,t}) \\ &+ \beta_{11} ln(InvSec_{i,t}) + \beta_{12} D/E_{i,t} + \beta_{13} Size_{i,t} + \beta_{14} B/M_{i,t} \\ &+ \beta_{15} Beta_{i,t} + \beta_{16} IdioVolt_{i,t} + \beta_{17} Price_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{6}$$

As before, the dependent variable is the Hou and Moskowitz (2005) second-stage measure of price delay ($Delay_{i,t}$). We control for additional balance sheet variables as well as other firm-specific variables, all of which have been defined previously. As before, we report *t*-statistics in parentheses that are obtained after controlling for two-dimensional clustering, and we include year fixed effects because of the time varying nature of delay.[15] The results from estimating Eq. (6) are reported in Table 6.

Column [1] reports the results when including *RELoans* as the opaque assets variable. Consistent with our expectation, we find that banks with a higher ratio of real estate loans to assets have higher delay (estimate = 0.0430, *t*-statistic = 2.03). In economic terms, a one percent increase in the ratio of real estate loans to total assets would increase delay nearly 0.043 after holding other factors constant. To the extent that banks with more real estate loans are more opaque, our findings in Column [5] support the idea that asset opacity leads to less efficient stock prices for banks. Column [2] shows the results when we include *OtherLoans* as the opaque assets variable. Again, we find a positive and significant estimate (estimate = 0.0411, *t*-statistic = 2.12). The statistical significance and the economic magnitude of the estimate for *OtherLoans* are similar to the estimate of *RELoans* in column [2].

Column [3] shows the results when we include *OtherOpaque* as the opaque assets variable. Contrary to our expectations, we find that a negative and significant estimate for *OtherOpaque*. This finding, while contrary to our hypothesis that opacity increases the frictions in the flow of information into stock prices, suggests that opaque assets other than loans do not increase the inefficiency of bank stock prices. We conduct several robustness tests to examine this peculiar result. First, we create three dummy variables for banks with the most real estate loans, the most other loans, and the most other opaque assets. We then re-estimate Eq. (6) while substituting various combinations of these three dummy variables in for the three ratio variables. We are able to find positive and significant estimates for each of the three indicator variables suggesting that, while in ratio form, *OtherOpaque* produces a negative estimate, in categorical form the sign is positive.[16] Therefore, we are careful to note that the association between *OtherOpaque* and price

[15] Similar results are found when we control for conditional heteroskedasticity.

[16] In unreported tests, we examine the relation between delay and analyst dispersion for Banks, where analyst dispersion is the ratio of the standard deviation

Table 6
Panel regressions – Price delay.

	[1]	[2]	[3]	[4]
Intercept	0.3961***	0.4002***	0.4255***	0.4296***
	(8.60)	(8.63)	(8.46)	(7.44)
$RELoans_{i,t}$	0.0430**			−0.0032
	(2.03)			(−0.07)
$OtherLoans_{i,t}$		0.0411**		−0.0089
		(2.12)		(−0.19)
$OtherOpaque_{i,t}$			−0.0287**	−0.0344
			(−2.41)	(−0.80)
$Turn_{i,t}$	0.0026	0.0028	0.0027	0.0026
	(0.31)	(0.32)	(0.31)	(0.30)
$Spread_{i,t}$	1.0209*	1.0220*	1.0094*	1.0091*
	(1.73)	(1.73)	(1.72)	(1.72)
$Illiq_{i,t}$	0.0023***	0.0022***	0.0022***	0.0022***
	(2.95)	(2.87)	(2.89)	(2.89)
$Ln(Assets_{i,t})$	−0.0453	−0.0475	−0.0430	−0.0421
	(−1.54)	(−1.60)	(−1.45)	(−1.39)
$Ln(LTDebt_{i,t})$	0.0020	0.0022	0.0023	0.0023
	(1.11)	(1.19)	(1.23)	(1.23)
$Ln(Equity_{i,t})$	0.0252	0.0256	0.0225	0.0216
	(1.27)	(1.28)	(1.13)	(1.01)
$Ln(Deposits_{i,t})$	−0.0209	−0.0203	−0.0223	−0.0223
	(−1.49)	(−1.43)	(−1.58)	(−1.57)
$Ln(InvSec_{i,t})$	−0.0070**	−0.0065**	−0.0065**	−0.0064**
	(−2.31)	(−2.16)	(−2.15)	(−2.11)
$D/E_{\ i,t}$	0.0049***	0.0050***	0.0048***	0.0047***
	(2.83)	(2.89)	(2.79)	(2.56)
$Size_{\ i,t}$	0.0016***	0.0016***	0.0016***	0.0016***
	(8.55)	(8.72)	(8.64)	(8.52)
$B/M_{\ i,t}$	0.0112***	0.0111***	0.0112***	0.0112***
	(4.34)	(4.30)	(4.29)	(4.29)
$Beta_{\ i,t}$	0.0006	0.0006	0.0006	0.0006
	(0.56)	(0.52)	(0.52)	(0.52)
$IdioVolt_{\ i,t}$	0.2357	0.2167	0.2566	0.2561
	(0.49)	(0.44)	(0.53)	(0.53)
$Price_{i,t}$	−0.0001	−0.0001	−0.0001	−0.0001
	(−1.53)	(−1.38)	(−1.50)	(−1.50)
Adj. R^2	0.6407	0.6405	0.6411	0.6411
Year FE	Yes	Yes	Yes	Yes

The table reports the results from estimating the following equation using pooled data.

$$\begin{aligned} Delay_{i,t} &= \alpha + \beta_1 RELoans_{i,t} + \beta_2 OtherLoans_{i,t} + \beta_3 OtherOpaque_{i,t} + \beta_4 Turn_{i,t} \\ &+ \beta_5 Spread_{i,t} + \beta_6 Illiq_{i,t} + \beta_7 ln(Assets_{i,t}) + \beta_8 ln(LTDebt_{i,t}) \\ &+ \beta_9 ln(Equity_{i,t}) + \beta_{10} ln(Deposits_{i,t}) + \beta_{11} ln(InvSec_{i,t}) + \beta_{12} D/E_{i,t} \\ &+ \beta_{13} Size_{i,t} + \beta_{14} B/M_{i,t} + \beta_{15} Beta_{i,t} + \beta_{16} IdioVolt_{i,t} + \beta_{17} Price_{i,t} + \varepsilon_{i,t} \end{aligned}$$

The dependent variable is the Hou and Moskowitz (2005) second stage measure of price delay ($Delay_{i,t}$). We include the following variables as independent variables. *RELoans* is the ratio of real estate loans to total assets. *OtherLoans* is the ratio of all other loans to total assets. *OtherOpaq* is the ratio of other opaque assets (according to Jones et al., 2012) to total assets. *Turn* is the average daily share turnover or the ratio of volume to shares outstanding. *Spread* is the average daily percentage bid-ask spread. *Illiq* is the average daily illiquidity measure according to Amihud (2002). *Size* is the market capitalization in $billions. Ln*(Assets)* is the natural log of total assets. Ln*(LTDebt)* is the natural log of long-term debt. Ln*(Equity)* is the natural log of shareholder equity. Ln*(Deposits)* is the natural log of deposits. Ln*(InvSec)* is the natural log of investment securities. D/E is the debt-to-equity ratio. All of the balance sheet information is initially denominated in $millions. *B/M* is the book-to-market ratio. *D/E* is the debt-to-equity ratio. *Beta* is the CAPM beta estimate for each firm during the year. *IdioVolt* is the idiosyncratic volatility which is calculated by estimating the standard deviations of residuals from estimating a daily CAPM model. *Price* is the price obtained from CRSP. We report *t*-statistics in parentheses that are obtained after controlling for two-dimensional clustering. Similar results are found when we control for conditional heteroskedasticity.

*** statistical significance at the 0.01.
** statistical significance at the 0.05.
* statistical significance at the 0.10 levels.

delay depends on how the variable is calculated. Thus, our results suggest that the effect of bank opacity of the informational efficiency of stock prices is primarily a function of the lending process banks play, which is consistent with finance theory (see Campbell and Kracaw (1980), Berlin and Loeys (1988), Diamond (1989 and 1991), and Kwan and Carleton (1998)).

We also estimate a different specification of Eq. (6) that includes all three opaque assets ratios as independent variables simultaneously. Column [4] shows the results from this estimation. We find that none of the coefficients on the opaque asset ratios are significantly different from zero. However, in unreported tests, we find extremely high variance inflation factors (as high as 27 in some specifications) for these variables suggesting high levels of multicollinearity. Further, the correlation between these three ratio is as high as 0.70.[17] Therefore, we are cautious when drawing meaningful inferences from our tests in Column [4].[18]

3.6. What factors explain the higher delay in banks during the recent financial crisis?

In this final section, we further examine the time-varying nature of price delay. In particular, we examine factors that influence the level of delay for banks during the recent financial crisis. We begin by examining whether the relation between bank price delay and market illiquidity, reported in the previous section, is driven entirely by the financial crisis period. We, therefore, include interaction terms between the three liquidity metrics discussed above and a dummy variable that takes on the value of one for years 2007 and 2008, and zero otherwise. We then estimate the following equation using pooled stock-year data for our sample of banks.

$$\begin{aligned} Delay_{i,t} &= \alpha + \beta_1 Crisis_t + \beta_2 LIQUIDITY_{i,t} + \beta_3 LIQUIDITY_{i,t} \\ &\quad \times Crisis_t + \beta_4 ln(Assets_{i,t}) + \beta_5 ln(LTDebt_{i,t}) \\ &\quad + \beta_6 ln(Equity_{i,t}) + \beta_7 ln(Deposits_{i,t}) + \beta_8 ln(InvSec_{i,t}) \\ &\quad + \beta_9 D/E_{i,t} + \beta_{10} Size_{i,t} + \beta_{11} B/M_{i,t} + \beta_{12} Beta_{i,t} \\ &\quad + \beta_{13} IdioVolt_{i,t} + \beta_{14} Price_{i,t} + \varepsilon_{i,t} \qquad (7) \end{aligned}$$

The dependent variable is again the Hou and Moskowitz (2005) second-stage price delay. The remaining control variables have been defined previously. Since we include the indicator variable *Crisis*, we do not include year fixed effects because doing so would violate the full rank assumption for consistent OLS estimation. We do, however, report *t*-statistics in parentheses that are obtained after controlling for two-dimensional clustering.[19] The results from estimating Eq. (8) are reported in Table 7. Interestingly, we find some evidence that, after controlling for a variety of factors that influence the dependent variable, price delay for banks was higher during the crisis period than during the non-crisis period. The results in Columns [1] and [3] suggest that for our sample of banks only, the crisis period was associated with a higher degree of price delay. In economic terms, the coefficients on *Crisis* in these two columns indicate that delay was 1.4% to 3.5% higher during the crisis period than during the non-crisis period.

of analyst forecasts to the absolute value of the mean forecast. Although we lose 2/3[rds] of our sample because of the lack of analyst coverage, our multivariate results provide some evidence that analyst dispersion and delay are directly related. To the extent that analyst dispersion approximates opacity in the firm's assets, our results again support the idea that opacity is positively related to delay.

[17] For instance, the correlation between *RELoans* and *OtherLoans* is 0.7289. The correlation between *RELoans* and *OtherOpaq* is −0.90.

[18] In additional robustness tests, we estimate Eq. (5) using various combinations of independent variables. We also condition our regressions based on the performance of the bank (in terms of stock return). We find some evidence that our finding that loan opacity leads to less efficiency is driven by banks that had the highest stock return. However, we note that when we include return as an additional independent variable, our general results do not change. We also recognize that during the beginning of the financial crisis, regulation targeting financials may have influenced the efficiency of stock prices. Many of these regulations, such as the 2008 Troubled Asset Relief Program began at the end of 2008. Similarly, the bailout of Lehman occurred during this year. We find results that are similar to those in this study when we do not include the year 2008 in our sample time period.

[19] Similar results are found when we control for conditional heteroskedasticity.

Table 7
Panel regressions – Price delay.

	[1]	[2]	[3]
Intercept	0.4330***	0.3963***	0.4288***
	(11.56)	(8.53)	(11.63)
$Crisis_t$	0.0348***	0.0150	0.0144**
	(4.17)	(0.95)	(1.97)
$Turn_{i,t}$	−0.0105*		
	(−1.72)		
$Spread_{i,t}$		1.1131**	
		(1.99)	
$Illiq_{i,t}$			0.0034***
			(6.03)
$Turn_{i,t} \times Crisis_t$	−0.0471***		
	(−2.62)		
$Spread_{i,t} \times Crisis_t$		2.3798***	
		(5.82)	
$Illiq_{i,t} \times Crisis_t$			0.0001
			(0.11)
$Ln(Assets_{i,t})$	−0.0491	−0.0488*	−0.0556*
	(−1.64)	(−1.69)	(−1.89)
$Ln(LTDebt_{i,t})$	0.0030	0.0026	0.0025
	(1.59)	(1.43)	(1.33)
$Ln(Equity_{i,t})$	0.0155	0.0237	0.0240
	(0.77)	(1.27)	(1.23)
$Ln(Deposits_{i,t})$	−0.0118	−0.0154	−0.0108
	(−0.83)	(−1.11)	(−0.77)
$Ln(InvSec_{i,t})$	−0.0063**	−0.0066**	−0.0070**
	(−2.03)	(−2.20)	(−2.29)
$D/E_{\ i,t}$	0.0043**	0.0046***	0.0049***
	(2.49)	(2.88)	(2.92)
$Size_{\ i,t}$	0.0018***	0.0016***	0.0017***
	(10.19)	(8.51)	(10.11)
$B/M_{\ i,t}$	0.0123***	0.0110***	0.0121***
	(4.48)	(4.37)	(4.50)
$Beta_{\ i,t}$	−0.0006	0.0003	0.0001
	(−0.44)	(0.27)	(0.03)
$IdioVolt_{\ i,t}$	1.0390***	0.0898	0.7548
	(3.35)	(0.21)	(2.36)
$Price_{i,t}$	−0.0001	−0.0001	−0.0001
	(−1.11)	(−1.22)	(−1.58)
Adj. R^2	0.6211	0.6422	0.6290
Year FE	No	No	No

The table reports the results from estimating the following equation using pooled data.

$$Delay_{i,t} = \alpha + \beta_1 Crisis_t + \beta_2 LIQUIDITY_{i,t} + \beta_3 LIQUIDITY_{i,t} \times Crisis_t + \beta_4 ln(Assets_{i,t}) + \beta_5 ln(LTDebt_{i,t}) + \beta_6 ln(Equity_{i,t}) + \beta_7 ln(Deposits_{i,t}) + \beta_8 ln(InvSec_{i,t}) + \beta_9 D/E_{i,t} + \beta_{10} Size_{i,t} + \beta_{11} B/M_{i,t} + \beta_{12} Beta_{i,t} + \beta_{13} IdioVolt_{i,t} + \beta_{14} Price_{i,t} + \varepsilon_{i,t}$$

The dependent variable is the Hou and Moskowitz (2005) second stage measure of price delay ($Delay_{i,t}$). We include the following variables as independent variables. *Crisis* is an indicator variable capturing the financial crisis period 2007–2008. *LIQUIDITY* is one of three liquidity measures. The first is the average daily share turnover or the ratio of volume to shares outstanding (*Turn*), the second is the average daily percentage bid-ask spread (*Spread*), and the third is Amihud's (2002) average daily illiquidity. *Size* is the market capitalization in $billions. Ln*(Assets)* is the natural log of total assets. Ln*(LTDebt)* is the natural log of long-term debt. Ln*(Equity)* is the natural log of shareholder equity. Ln*(Deposits)* is the natural log of deposits. Ln*(InvSec)* is the natural log of investment securities. D/E is the debt-to-equity ratio. All of the balance sheet information is initially denominated in $millions. *B/M* is the book-to-market ratio. *D/E* is the debt-to-equity ratio. *Beta* is the CAPM beta estimate for each firm during the year. *IdioVolt* is the idiosyncratic volatility which is calculated by estimating the standard deviations of residuals from estimating a daily CAPM model. *Price* is the price obtained from CRSP. We report *t*-statistics in parentheses that are obtained after controlling for two-dimensional clustering. Similar results are found when we control for conditional heteroskedasticity.

*** denote statistical significance at the 0.01.
** denote statistical significance at the 0.05.
* denote statistical significance at the 0.10 levels.

We also find that the interaction term between turnover and the crisis indicator variable is significantly negative (estimate = −0.0471, *t*-statistic = −2.62), indicating that banks with lower share turnover experienced higher price delay during the financial crisis. However, we are careful to note that the coefficient on turnover remains significantly negative, albeit at the 0.10 level, suggesting that, during the non-crisis period, banks with less turnover had higher levels of delay. Similar results are found for the relation between bank delay and bid-ask spreads. For instance, in Column [2], we show that the coefficient on the interaction term between *Spread* and *Crisis* is positive and significant (estimate = 2.3798, *t*-statistic = 5.82), as is the coefficient on *Spread* (estimate = 1.1131, *t*-statistic = 1.99). Therefore, banks with wider bid-ask spreads exhibit more price delay in both the financial crisis period and the non-financial crisis period, with the former being more pronounced. Interestingly, in Column [3], we find that the relation between bank delay and Amihud illiquidity is isolated to the non-financial crisis period suggesting that the our findings in Table 5 that price impact is directly associated with higher levels of price delay is not simply an artifact of the financial crisis. In summary, the results in Table 7 provide some evidence that the microstructure proxies for opacity affect delay more so during the financial crisis period vis-à-vis the non-crisis period. However, more importantly, the results in Table 7 indicate that the relation between liquidity measures and price delay hold during the non-crisis period.

We next examine whether the direct relation between real estate loans (and other loans) and price delay is simply an artifact of the recent financial crisis. In particular, we estimate the following equation using pooled stock-year data for our sample of banks.

$$\begin{aligned} Delay_{i,t} = {} & \alpha + \beta_1 OPAQUE_{i,t} + \beta_2 Crisis_{i,t} + \beta_3 OPAQUE_{i,t} \\ & \times Crisis_t + \beta_4 ln(Assets_{i,t}) + \beta_5 ln(LTDebt_{i,t}) \\ & + \beta_6 ln(Equity_{i,t}) + \beta_7 ln(Deposits_{i,t}) + \beta_8 ln(InvSec_{i,t}) \\ & + \beta_9 D/E_{i,t} + \beta_{10} Turn_{i,t} + \beta_{11} Spread_{i,t} + \beta_{12} Illiq_{i,t} \\ & + \beta_{13} Size_{i,t} + \beta_{14} B/M_{i,t} + \beta_{15} Beta_{i,t} + \beta_{16} IdioVolt_{i,t} \\ & + \beta_{17} Price_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{8}$$

The dependent variable is price delay ($Delay_{i,t}$). We include the indicator variable *Crisis* along with the interaction between *Crisis* and the opaque asset ratios ($REloans_{i,t} \times Crisis_t$, $OtherLoans_{i,t} \times Crisis_t$, and $OtherOpaq_{i,t} \times Crisis_t$). As before, we do not include year fixed effects as to avoid violating the full rank assumption for consistent estimation. We do, however, report *t*-statistics in parentheses that are obtained from standard errors that control for two-dimensional clustering. The remaining independent variables have been previously defined. Table 8 reports the results from estimating Eq. (8).

If the direct relation between opaque assets and price delay was entirely driven by the financial crisis, then the interaction estimates are expected to be positive and reliably different from zero while the opaque ratios are expected to produce estimates that statistically close to zero. Columns [1] through [3] show the results when including each of the three interaction estimates. In each of the columns, we do not find that the interaction estimates are reliably different from zero. Further, the estimates for *RELoans*, *OtherLoans*, and *OtherOpaque* still retain their significance, suggesting that the relation between asset opacity and price delay is not simply an artifact of the crisis period. A closer examination of the magnitude of the interaction estimates suggest that the relation between opacity and delay existed during the financial crisis as well as during the non-crisis period. For instance, the total effect of the real estate loan ratio in Column [1] is the sum of $\beta 2$ and $\beta 3$, which is 0.0461. Qualitatively similar results are found in Column [2].

3.7. Multivariate time series tests: impulse response functions

Thus far, we have documented that the stock prices of banks are less efficient than the stock prices of non-banks. We have also found some evidence that, within banks, those that are most opaque tend to be the least efficient. In this subsection, we run a series of additional robustness tests using multivariate time-series

Table 8
Panel regressions – Price delay.

	[1]	[2]	[3]
Intercept	0.3416***	0.3569***	0.4071***
	(7.56)	(7.72)	(7.81)
$Crisis_t$	0.0139**	0.0145**	−0.0041
	(2.03)	(2.13)	(−0.28)
$RELoans_{i,t}$	0.0889***		
	(3.39)		
$OtherLoans_{i,t}$		0.0899***	
		(4.29)	
$OtherOpaque_{i,t}$			−0.0583***
			(−4.08)
$RELoans_{i,t} \times Crisis_t$	−0.0428		
	(−1.28)		
$OtherLoans_{i,t} \times Crisis_t$		−0.0254	
		(−0.79)	
$OtherOpaque_{i,t} \times Crisis_t$			0.0202
			(1.15)
$Turn_{i,t}$	−0.0161**	−0.0161*	−0.0159*
	(−1.97)	(−1.95)	(−1.90)
$Spread_{i,t}$	0.9721*	0.9432*	0.9273
	(1.69)	(1.65)	(1.63)
$Illiq_{i,t}$	0.0008	0.0007	0.0007
	(1.20)	(1.11)	(1.13)
$Ln(Assets_{i,t})$	−0.0150	−0.0208	−0.0123
	(−0.44)	(−0.61)	(−0.36)
$Ln(LTDebt_{i,t})$	0.0008	0.0012	0.0013
	(0.33)	(0.51)	(0.57)
$Ln(Equity_{i,t})$	0.0042	0.0064	0.0004
	(0.19)	(0.28)	(0.02)
$Ln(Deposits_{i,t})$	−0.0295*	−0.0287*	−0.0321*
	(−1.82)	(−1.76)	(−1.96)
$Ln(InvSec_{i,t})$	−0.0040	−0.0031	−0.0030
	(−1.18)	(−0.93)	(−0.91)
$D/E_{\ i,t}$	0.0044**	0.0048**	0.0043**
	(2.23)	(2.40)	(2.23)
$Size_{\ i,t}$	0.0015***	0.0015***	0.0015***
	(8.10)	(8.57)	(8.37)
$B/M_{\ i,t}$	0.0102***	0.0102***	0.0103***
	(3.75)	(3.69)	(3.68)
$Beta_{\ i,t}$	−0.0033	−0.0035	−0.0034
	(−1.61)	(−1.50)	(−1.58)
$IdioVolt_{\ i,t}$	1.6762***	1.6457***	1.6892***
	(3.35)	(3.33)	(3.40)
$Price_{i,t}$	−0.0002**	−0.0001*	−0.0001**
	(−2.11)	(−1.69)	(−2.04)
Adj. R^2	0.4993	0.4995	0.5012
Year FE	No	No	No

The table reports the results from estimating the following equation using pooled data.

$$Delay_{i,t} = \alpha + \beta_1 Crisis_t + \beta_2 OPAQUE_{i,t} + \beta_3 OPAQUE_{i,t} \times Crisis_t + \beta_4 ln(Assets_{i,t}) + \beta_5 ln(LTDebt_{i,t}) + \beta_6 ln(Equity_{i,t}) + \beta_7 ln(Deposits_{i,t}) + \beta_8 ln(InvSec_{i,t}) + \beta_9 D/E_{i,t} + \beta_{10} Turn_{i,t} + \beta_{11} Spread_{i,t} + \beta_{12} Illiq_{i,t} + \beta_{13} Size_{i,t} + \beta_{14} B/M_{i,t} + \beta_{15} Beta_{i,t} + \beta_{16} IdioVolt_{i,t} + \beta_{17} Price_{i,t} + \varepsilon_{i,t}$$

The dependent variable is the Hou and Moskowitz (2005) second stage measure of price delay ($Delay_{i,t}$). We include the following variables as independent variables. *Crisis* is an indicator variable capturing the financial crisis period 2007–2008. *OPAQUE* is one of three ratios that capture opaque assets. The first ratio is the ratio of real estate loans to total assets (*RELoans*), the second is the ratio of all other loans to total assets (*OtherLoans*), and the third is the ratio of other opaque assets (according to Jones et al., 2012) to total assets (*OtherOpaq*). We also include an interaction between *Crisis* and the ratios found in *OPAQUE*. Ln*(Assets)* is the natural log of total assets. Ln*(LTDebt)* is the natural log of long-term debt. Ln*(Equity)* is the natural log of shareholder equity. Ln*(Deposits)* is the natural log of deposits. Ln*(InvSec)* is the natural log of investment securities. D/E is the debt-to-equity ratio. All of the balance sheet information is initially denominated in $millions. *Turn* is the average daily share turnover or the ratio of volume to shares outstanding. *Spread* is the average daily percentage bid-ask spread. *Illiq* is the average daily illiquidity measure according to Amihud (2002). *Size* is the market capitalization in $billions. *B/M* is the book-to-market ratio. *D/E* is the debt-to-equity ratio. *Beta* is the CAPM beta estimate for each firm during the year. *IdioVolt* is the idiosyncratic volatility which is calculated by estimating the standard deviations of residuals from estimating a daily CAPM model. *Price* is the price obtained from CRSP. We report *t*-statistics in parentheses that are obtained after controlling for two-dimensional clustering. Similar results are found when we control for conditional heteroskedasticity.

*** denote statistical significance at the 0.01.
** denote statistical significance at the 0.05.
* denote statistical significance at the 0.10 levels.

analysis to examine how the stock returns of both banks and non-banks (and both opaque banks and non-opaque banks) respond to exogenous shocks to market returns. This examination fits nicely into the framework of our tests, given that delay captures how individual stock prices incorporate market-wide information. In particular, we estimate a vector autoregressive process (VAR) with 10 lags using the following specification.

$$\begin{bmatrix} R^j_{p,t} \\ R_{m..t} \end{bmatrix} = \begin{bmatrix} \alpha_p \\ \alpha_m \end{bmatrix} + \begin{bmatrix} \beta^1_{p,p} & \beta^1_{p,m} \\ \beta^1_{m,p} & \beta^1_{m,m} \end{bmatrix} \begin{bmatrix} R_{p,t-1} \\ R_{m,t-1} \end{bmatrix} + \begin{bmatrix} \beta^2_{p,p} & \beta^2_{p,m} \\ \beta^2_{m,p} & \beta^2_{m,m} \end{bmatrix} \begin{bmatrix} R_{p,t-2} \\ R_{m,t-2} \end{bmatrix} + \cdots + \begin{bmatrix} \beta^{10}_{p,p} & \beta^{10}_{p,m} \\ \beta^{10}_{m,p} & \beta^{10}_{m,m} \end{bmatrix} \begin{bmatrix} R_{p,t-10} \\ R_{m,t-10} \end{bmatrix} + \begin{bmatrix} \varepsilon^j_{p,t} \\ \varepsilon^j_{m,t} \end{bmatrix} \tag{9}$$

Here, the dependent variable is a vector of weekly (Wednesday-to-Wednesday) returns in log price differences for several portfolios. In our first set of tests, the dependent variables include the returns for value-weighted portfolios of either bank or non-bank stocks ($j =$ banks or non-banks) as well as the returns for the CRSP value-weighted index. The independent variables include vectors of lagged dependent variables. Eq. (9) shows, in matrix notation, the specified VAR(10) model (with 10 lags).[20]

From this process, we estimate impulse response functions (IRFs) for the bank and the non-bank portfolios given an exogenous, one standard deviation, shock to the CRSP value-weighted index. Fig. 2 shows the both the orthogonalized IRFs for the portfolios of banks (top left panel) and for non-banks (top right panel).[21] As seen in the figures, the impulse response for the bank portfolio is relatively unstable for approximately 15 weeks. When examining the IRFs for non-banks, we find that the IRFs are relatively stable. To provide some comparison, we estimate the IRFs for a hedge portfolio (the returns for the bank portfolio less the returns for the non-bank portfolio). The bottom panel of Fig. 2 reports the differences in the instability between portfolios caused by the innovations in market returns. These results seem to support our findings in Tables 2 through 4 that indicate that banks respond more slowly than non-banks to exogenous shocks to market returns.

Fig. 3 shows the results when we examine the IRFs of opaque and non-opaque banks. Here, we sort the universe of banks into terciles based on bid-ask spreads. We then form a value-weighted portfolio for stocks with the highest (top third) bid-ask spreads and the lowest (bottom third) bid-ask spreads. Next, we replicate our analysis in Fig. 2 by estimating Eq. (9) using a VAR(10) process. Comparatively, the results in Fig. 3 are similar to those in Fig. 2. For instance, we find that, when viewing each of the panels, the IRFs for opaque banks – as measured by high bid-ask spreads – take longer to revert back to normal after shocks to market returns. These results tend to support our findings in Tables 5 through 8.

Fig. 4 replicates this analysis but examines opaque and non-opaque banks – as measured by loan-to-asset ratios. When exploring the panels in the figure, it is difficult to ascertain which portfolio has the less stable IRFs. In the bottom panel, we find that

[20] The VAR(10) model specified in Eq. (9) seems to be very stable. While we find that causality generally flows from market returns to bank (or non-bank) returns in our Granger causality tests, we do find instantaneous causality in the time-series system. We also find that eigen values testing for unit roots are within normal levels. We note that the choice of using 10 lags is based on the lowest Akaike's information criteria (AIC) although we note that, in unreported tests, we estimate a number of alternative specifications and find qualitatively similar results. Furthermore, we estimate the VARs using sub-time periods. Further, we use daily and monthly returns instead of weekly returns. These unreported tests allow us to draw similar conclusions to those in this study.

[21] Using the orthogonalized IRFs imposes the causal ordering to run from the market index to the bank and non-bank portfolios and insures that the innovations in market returns are exogenous to the impulse responses.

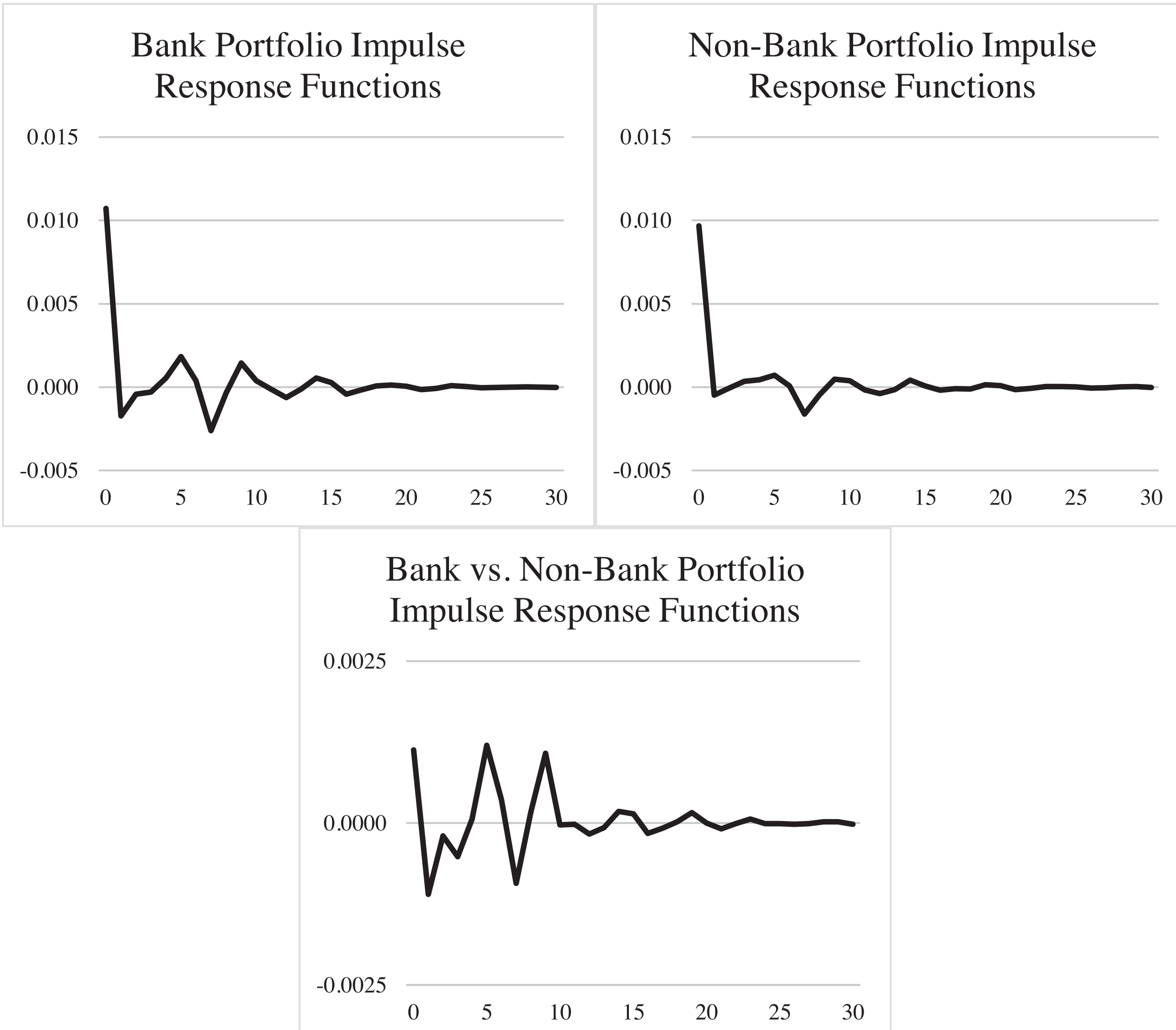

Fig. 2. The figure shows the Impulse Response Functions (IRFs) from Vector Autoregressive process using a value-weighted portfolio of all banks available on CRSP (top left panel) to innovations in the CRSP value-weighted index. The top right panel shows the IRFs for a value-weighted portfolio of non-banks in response to a shock to the CRSP value-weighted index. The bottom panel reports the IRFs from a hedge portfolio (the returns to the bank portfolio less the returns to the non-bank portfolio) to innovations in the CRSP index. The results are estimated using a VAR(10) model with weekly, Wednesday-to-Wednesday returns.

there is some differences between the IRFs of the opaque and non-opaque portfolios. However, these differences are marginal. The results from our sample of banks provides some evidence for the results in the latter tables, but admittedly, the evidence only weakly supports our findings in Sections 3.5 and 3.6.

3.8. Robustness

In a series of robustness tests, we replicate much of our analysis using various measures of Hou and Moskowitz (2005) price delay. As mentioned above, we replicate our analysis using first-stage price delay and find qualitatively similar results to those reported throughout this study. We also estimate two additional measures of delay (D2 and D3 in Hou and Moskowitz (2005)), which capture the magnitude of the slope coefficients in Eq. (1). We, again, find that the conclusions that we are able to draw using these different measures of price delay are similar to those reported in this paper.

In other tests, we include additional risk measures as controls in our analysis. For instance, we estimate and include as controls the loadings on the risk factors in Fama and French (1996) and Carhart (1997). Controlling for the exposures to these different risk factors does not meaningfully influence our results when replicating Tables 3 and 5. We do, however, find that the results in Table 7 change marginally when including additional risk factors, as the statistical significance on the coefficients for *RELoans* and *OtherLoans* weakens.

Finally, we extend our analysis by attempting to identify a significant return premium associated with price delay for both our sample of banks and comparable non-banks. Hou and Moskowitz (2005) show that delay is associated with a positive and significant return premium for their sample of stocks from 1963 to 2001. Using various Fama and MacBeth (1973) regressions with Newey and West (1987) robust standard errors, where the dependent variable is next-year returns and the independent variable of interest is price delay, we do not find significant evidence of cross-sectional return premiums associated with price delay in our sample time period. The lack of significance is likely due to the short time series of our data (yearly observations from 1996 to 2008).

The results from our analysis provide consistency with our general hypothesis that banks, because of the inherent opacity created in the intermediation process, have less efficient stock prices than comparable non-banks. These results have important

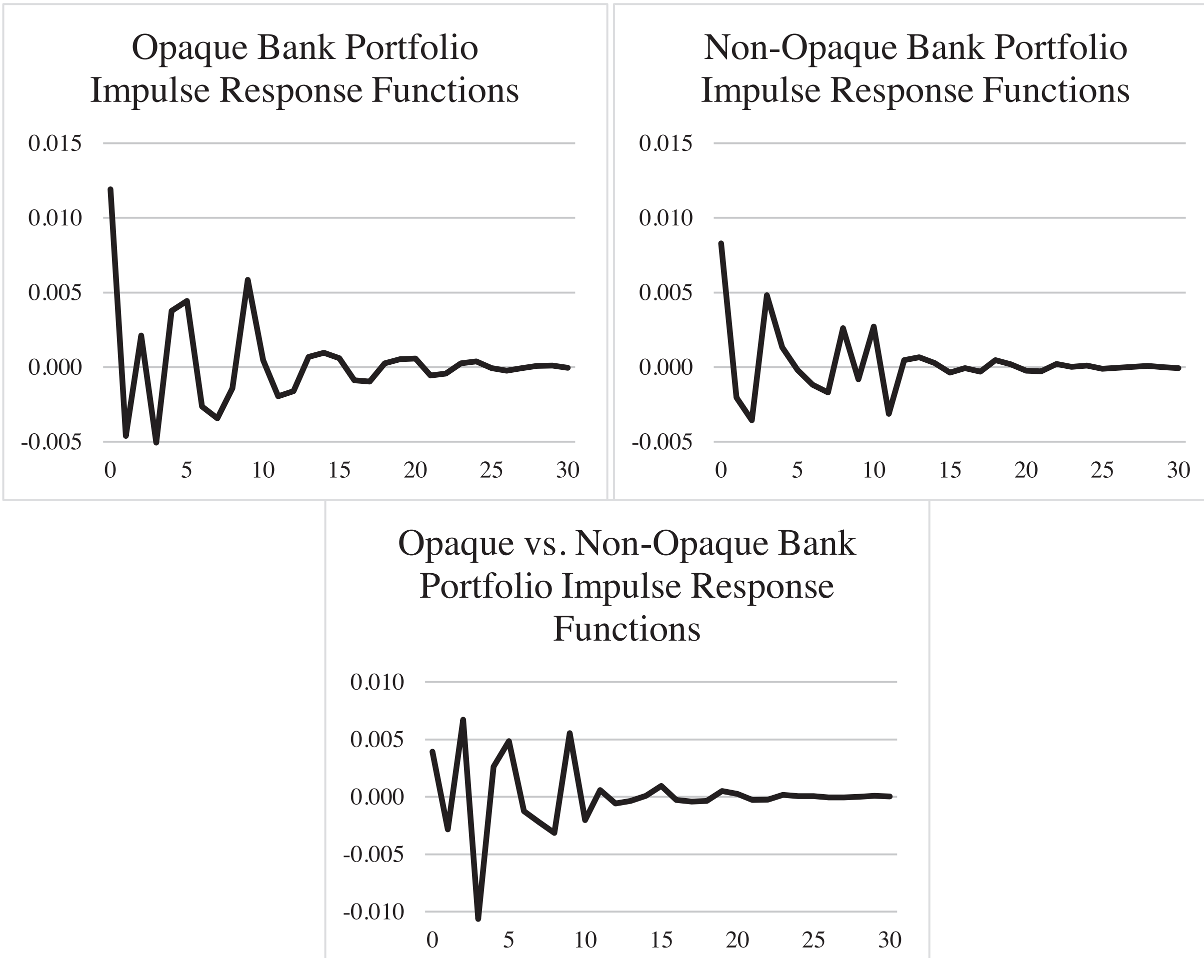

Fig. 3. The figure shows the Impulse Response Functions (IRFs) from Vector Autoregressive process using a value-weighted portfolio of banks with the highest bid-ask spreads (top left panel) to innovations in the CRSP value-weighted index. The top right panel shows the IRFs for a value-weighted portfolio of banks with the lowest (bottom third) bid-ask spreads. The bottom panel reports the IRFs from a hedge portfolio (the returns to the high spread bank portfolio less the returns to the low spread bank portfolio) to innovations in the CRSP index. The results are estimated using a VAR(10) model with weekly, Wednesday-to-Wednesday returns.

implications, given that banks play a pivotal role in the economy For instance, Levine and Zervos (1998) provide cross-country evidence that well-functioning banks are an important determinant of economic growth. More recently, Burgess and Pande (2005) show that the expansion of banks into rural areas of India lead to a marked reduction in the level of poverty. Our findings do not diminish the benefits associated with a well-functioning banking sector. Instead, our results highlight that while the lending mechanism of banks indeed improves a variety of economic outcomes, there may still exist some potential costs associated with the intermediation process. Perhaps a fruitful area for future research might be to model the tradeoffs associated with the intermediation process.

4. Conclusion

The idea that banks are inherently opaque and that the risks associated with financial intermediation are uncertain to outsiders, provides much of the motivation for the regulatory structure in the U.S. financial system (Morgan, 2002). However, prior research has yet to find conclusive evidence that bank opacity adversely affects the market quality of bank stocks (Flannery et al., 2004, 2013). In this study, we contribute to this line of research by exploring the effect of opacity on the efficiency of bank stock prices. To do so, we closely follow Hou and Moskowitz (2005) and estimate a parsimonious measure of the delay with which stock prices incorporate market-wide information. This measure of price delay allows researchers to analyze the informational efficiency of stock prices and, in the context of our study, test whether opacity is associated with the informational efficiency of bank stock prices.

In our first set of tests, we compare the Hou and Moskowitz (2005) measure of delay for a sample of financial institutions (banks) and a matched sample of non-banks. Our univariate and multivariate tests show that delay is both statistically and economically larger for our sample of banks, indicating that stock prices of banks are less efficient than those of non-banks. Second, we find that delay is larger for banks than for non-banks during the recent financial crisis period. Importantly, however, our multivariate tests still show that the delay of banks is higher than the delay of non-banks during the non-crisis period indicating that our first set of results is not simply an artifact of the recent financial crisis. Third, our tests reveal that banks that are most opaque – using either microstructure proxies for informational opacity or opaque asset composition – have significantly higher delay than other banks.

These results provide some support for the idea that the observed differences in delay between banks and non-banks is indeed driven by opacity. Similar to Morgan (2002) and Jones et al., (2012) who contend that bank opacity weakens market discipline and results in greater exposure to contagion, bank runs, and greater levels of systemic risk, our results suggest that because of

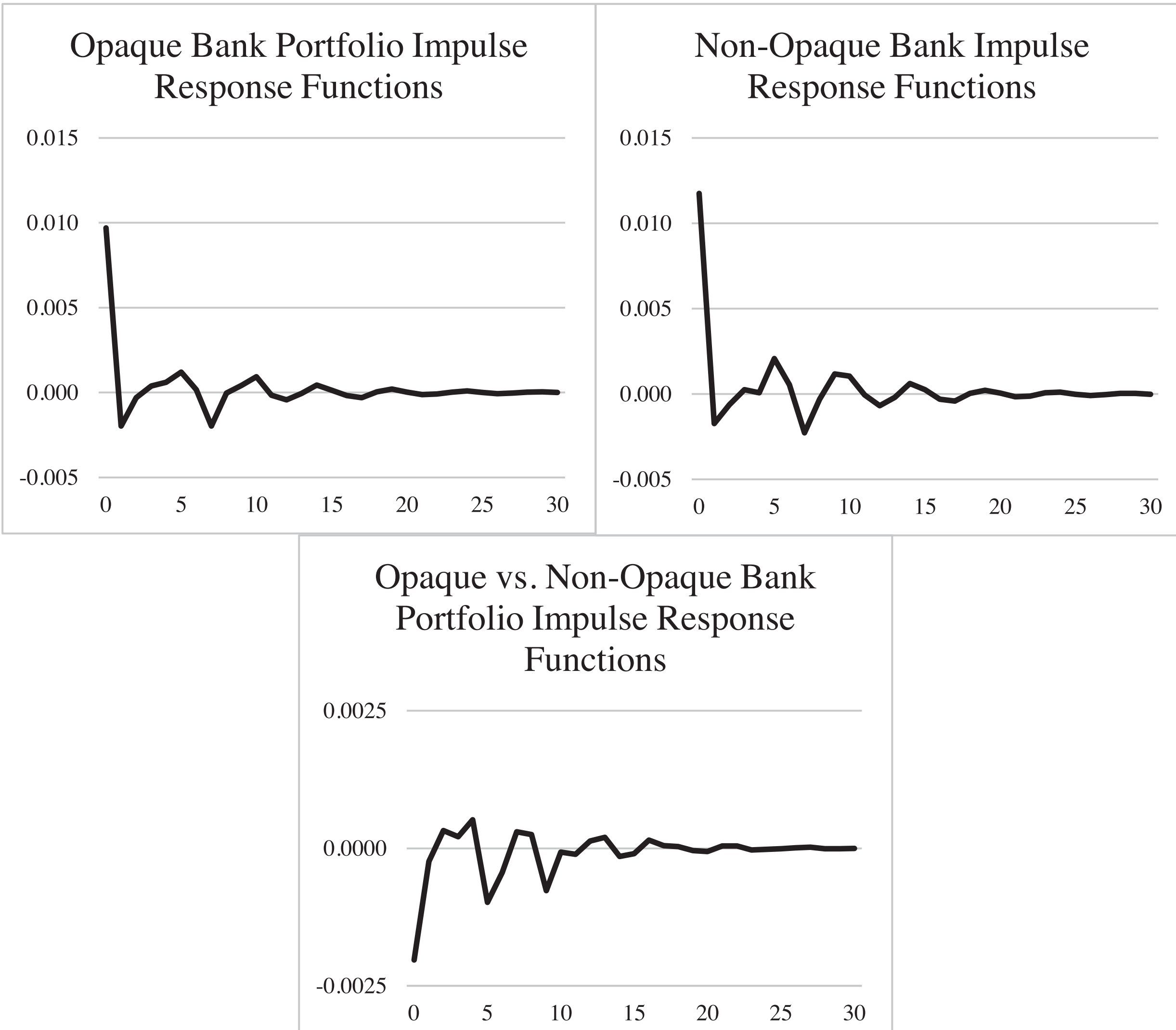

Fig. 4. The figure shows the Impulse Response Functions (IRFs) from Vector Autoregressive process using a value-weighted portfolio of banks with the highest loans-to-asset ratio (top left panel) to innovations in the CRSP value-weighted index. The top right panel shows the IRFs for a value-weighted portfolio of banks with the lowest (bottom third) loan-to-assets ratio. The bottom panel reports the IRFs from a hedge portfolio (the returns to the high L/A bank portfolio less the returns to the low L/A bank portfolio) to innovations in the CRSP index. The results are estimated using a VAR(10) model with weekly, Wednesday-to-Wednesday returns.

weaker market discipline, bank opacity also adversely affects the efficient transmission of information into security prices. Furthermore, our findings may indeed have important regulatory implications. While a well-functioning banking sector is vital to improvements in a number of economic outcomes, future research on the opacity created by the intermediation process may potentially guide regulators on how to create an environment where the risks associated with intermediation are more transparent to outsiders.

References

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Markets 5, 31–56.
Battalio, R., Schultz, P., 2006. Options and the bubble. J. Finance 61, 2071–2102.
Berger, A.N., Udell, G.F., 2004. The institutional memory hypothesis and the procyclicality of bank lending behavior. J. Financ. Intermed. 13, 458–495.
Berlin, M., Loeys, J., 1988. Bond covenants and delegated monitoring. J. Finance 43, 397–412.
Blau, B.M., 2012. Short interest and frictions in the flow of information. Financ Manage. 41, 371–394.
Boyd, J.H., Graham, S.L., Hewitt, R.S., 1993. Bank holding company mergers with nonbank financial firms: effects on the risk of failure. J. Bank. Finance 17, 43–63.
Burgess, R., Pande, R., 2005. Do rural banks matter? Evidence from the Indian social banking experiment. Am. Econ. Rev. 95, 780–795.
Campbell, T., Kracaw, W., 1980. Information production, market signaling, and the theory of intermediation. J. Finance 35, 863–882.
Carhart, M., 1997. On persistence in mutual fund performance. J. Finance 52, 57–82.
Chordia, T., Swaminathan, B., 2000. Trading volume and cross-autocorrelations in stock returns. J. Finance 55, 913–935.
Chung, K.H., Zhang, H., 2014. A simple approximation of intraday spreads using daily data. J. Financ. Markets 17, 94–120.
Copeland, T.E., Galai, D., 1983. Information effects on the bid-ask spread. J. Finance 38, 1457–1469.
Demsetz, R.S., Strahan, P.E., 1997. Diversification, size, and risk at bank holding companies. J. Money Credit Bank. 29, 300–313.
Diamond, D.W., Dybvig, P.H., 1983. Bank runs, deposit insurance, and liquidity. J. Political Econ. 91, 401–419.
Diamond, D.W., 1989. Reputation acquisition in debt markets. J. Political Econ. 97, 828–862.
Diamond, D.W., 1991. Monitoring and reputation: the choice between bank loans and directly placed debt. J. Political Econ. 99, 689–721.
Fama, E.F., French, K.R., 1996. Multifactor explanations of asset pricing anomalies. J. Finance 51, 55–84.
Fishman, M.J., Hagerty, K.M., 1989. Disclosure decisions by firms and the competition for price efficiency. J. Finance 44, 633–646.
Flannery, M.J., Kwan, S.H., Nimalendran, M., 2004. Market evidence on the opacity of banking firms' assets. J Financ. Econ. 71, 419–460.
Flannery, M.J., Kwan, S.H., Nimalendran, M., 2013. The 2007–2009 financial crisis and bank opacity. J. Financ. Intermed. 22, 55–84.
Foos, D., Norden, L., Weber, M., 2010. Loan growth and riskiness of banks. J. Bank. Finance 34, 2929–2940.

Freixas, X., Parigi, B.M., Rochet, J., 2000. Systematic risk, interbank relations, and liquidity provision by the central bank. J. Money Credit Bank. 32, 611–638.
Gerlach, S., Peng, W., 2005. Bank lending and property prices in Hong Kong. J. Bank. Finance 29, 461–481.
Glosten, L.R., Milgrom, P.R., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. J. Financ. Econ. 14, 71–100.
Goodhart, C.A., 1995. Price stability and financial fragility. In: The Central Bank and the Financial System, pp. 263–302.
Greenwood, R., Nagel, S., 2009. Inexperienced investors and bubbles. J. Financ. Econ. 93, 239–258.
Haggard, K.S., Martin, X., Pereira, R., 2008. Does voluntary disclosure improve stock price informativeness? Financ. Manag. 37, 747–768.
Hou, K., Moskowitz, T.J., 2005. Market frictions, price delay, and the cross-section of expected returns. Rev. Financ. Stud. 18, 981–1020.
Jin, L., Myers, S.C., 2006. R 2 around the world: new theory and new tests. J. Financ. Econ. 79, 257–292.
Jones, J.S., Lee, W.Y., Yeager, T.J., 2012. Opaque banks, price discovery, and financial instability. J. Financ. Intermed. 21, 383–408.
Kwan, S., Carleton, W., 1998. Financial contracting and the choice between private placement and publicly offered bonds. Federal Reserve Bank of San Francisco working paper.
Kwan, S.H., Carleton, W.T., 2004. Financial Contracting and the Choice between Private Placement and Publicly Offered Bonds FRB of San Francisco Working Paper.
Kyle, A.S., 1985. Continuous auctions and insider trading. Econometrica 53, 1315–1335.
Laeven, L., Majnoni, G., 2003. Loan loss provisioning and economic slowdowns: too much, too late? J. Financ. Intermed. 12, 178–197.
Levine, R., Zervos, S., 1998. Stock markets, banks, and economic growth. Am. Econ. Rev. 88, 537–558.
Morgan, D.P., 2002. Rating banks: risk and uncertainty in an opaque industry. Am. Econ. Rev. 92, 874–888.
Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Nijskens, R., Wagner, W., 2011. Credit risk transfer activities and systemic risk: how banks became less risky individually but posed greater risks to the financial system at the same time. J. Bank. Finance 35, 1391–1398.
Ofek, E., Richardson, M., 2003. Dotcom mania: the rise and fall of internet stock prices. J. Finance 58, 1113–1138.
Rochet, J., Tirole, J., 1996. Interbank lending and systemic risk. J. Money Credit Bank. 28, 733–762.
Roll, R., Subrahmanyam, A., 2010. Liquidity skewness. J. Bank. Finance 34 (10), 2562–2571.
Senhadji, M.A.S., Collyns, M.C., 2002. Lending Booms, Real Estate Bubbles and the Asian Crisis. International Monetary Fund, pp. 2–20.
Veldkamp, L., 2006. Information markets and the comovement of asset prices. Rev. Econ. Stud. 73, 823–845.
Wall, L.D., 1987. The effect of capital adequacy guidelines on large bank holding companies. J. Bank. Finance 11, 581–600.