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The 2007–2009 financial crisis and bank opaqueness

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ABSTRACT

Doubts about the accuracy with which outside investors can assess a banking firm's value motivate many government interventions in the banking market. Although the available empirical evidence is somewhat mixed, the recent financial crisis has reinforced a common assessment that banks are unusually opaque. This paper examines bank equity's trading characteristics during "normal" periods and two "crisis" periods between 1993 and 2009. We find only limited (mixed) evidence that banks are unusually opaque during normal periods. However, consistent with theory, crises raise the adverse selection costs of trading bank shares relative to those of nonbank control firms. A bank's balance sheet composition significantly affects its equity opacity, but we cannot detect specific balance sheet categories that have robust effects.

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1. Introduction and motivation

The financial services industry lay at the epicenter of the recent financial market turmoil. The end of the credit and housing boom in 2006 revealed earlier excesses in financial markets that eventually led to swollen mortgage delinquencies and the eruption of financial market turmoil in August of 2007. During the credit boom, asset values were inflated in an environment of unusually low risk spreads, increased financial leverage, and a proliferation of complex financial instruments that proved to be fragile under stress. As market forces corrected these excesses, the simultaneous re-pricing of risks, deleveraging, and massive write-downs by financial institutions unleashed powerful forces across financial markets. This process would have been painful enough if financial institutions had been reasonably transparent.

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However, market participants apparently became unsure about the composition of some financial institutions' portfolios, and the true economic value of some assets in those portfolios. This solvency uncertainty led investors to lose confidence in the banking system. The interbank lending market "froze" at the height of the financial crisis, as even sophisticated financial institutions were reluctant to lend to each other (Kwan, 2009). Some researchers argue that borrowing impediments reflected uncertainty about counterparty solvency (e.g. Heider et al., 2010; Pritsker, 2010) – that is, bank opacity.

Policy makers were concerned about credit flows being disrupted by the substantial amount of impaired assets clogging banking firms' balance sheets. One obstacle to removing impaired assets from banking firms' balance sheets was the substantial disagreement between insiders and outsiders about the economic value of those assets. Furthermore, this kind of information asymmetry could lead outside investors to undervalue the average banking firm's equity in a pooling equilibrium, making it expensive for banking firms to raise capital and exacerbating the underinvestment problem (Myers and Majluf, 1984). In an effort to maintain credit flows to the real sector, the U.S. government implemented unprecedented policies to stabilize the financial sector, such as the Troubled Asset Relief Program (TARP) and the Public–Private Investment Program (PPIP). Federal regulators then undertook a unique Supervisory Capital Assessment Program (SCAP) in the spring of 2009. This "stress test" was designed to assess the solvency of the largest financial institutions. Market investors apparently viewed the tests as reducing uncertainty: following the release of the stress test results in May, the banking sector stabilized and several large institutions successfully issued new equity. While some banking firms issued shares to satisfy regulatory requirements related to the stress test findings, others voluntarily raised a cushion of new equity capital.

Although the possibility that banking firms are "opaque" has played a central role in the current financial crisis, existing empirical evidence on the opaqueness of banking firms is mixed. Morgan (2002) argues that bond rating agencies (including Moody's and Standard and Poor's) are more likely to disagree in their assessments of harder-to-value firms. He interprets a "split" bond rating, when the two main rating agencies rate the same bond differently, as a sign of opacity. Morgan not only finds that banking firms are more likely than nonfinancial firms to carry split ratings during his 1983–1993 sample period, but also that a bank holding company's asset composition significantly affects the probability of a split rating. Iannotta (2006) undertakes a similar analysis for bonds issued in Europe from 1993 through 2003, and also concludes that bank bonds are more likely to carry split ratings. Iannotta concludes that the probability of a split rating increases with a bank's equity capital ratio, while Morgan finds the reverse in his sample.

Flannery et al. (2004) (henceforth referred to as FKN) compare banks' and nonbanks' equity market microstructure properties and analysts' earnings forecasts during the 1990–1997 period. They find no statistically significant differences between banks' and non-financial firms' microstructure properties for NYSE/AMEX-traded firms. These larger banks' stocks resemble their control firms in trading activity, return volatility, and bid-ask spreads. On average, investors seem to evaluate large banking firms as readily as they evaluate nonfinancial firms. In contrast, the assets of (smaller) NASD banks were not unusually opaque but simply "boring." Specifically, the NASD bank stocks trade much less frequently than a comparable nonbank, despite having comparable bid-ask spreads. They also find that NASD bank stocks exhibit relatively low return volatilities and that analysts predict their earnings more accurately.

Three more recent papers evaluate the relative opacity of banks without relying on credit ratings. Hirtle (2006) investigates the impact of the Sarbannes-Oxley requirement that corporate CEOs attest to the accuracy of reported financial statements. Such certification might improve the reliability of financial statements, reducing opacity. Although the typical affected firm showed no stock price reaction when CEOs first certified financial statements (Bhattacharya et al., 2007; Griffin and Lont, 2005), Hirtle finds a significantly positive stock price effect for 40 large banking organizations. She interprets these abnormal returns as reflecting reduced opacity for banks, consistent with the hypothesis that banks are relatively opaque. Jones et al. (2012) examine the effect of bank mergers on the market value of non-merging firms. They argue that merger prices should provide new information about the value of opaque banks, and find positive abnormal returns for the most opaque non-merging banks when 80 mergers are announced between 2000 and 2006. A recent paper by Morgan et al. (2010)

examines market reactions to various announcements about the 2009 SCAP. They conclude that banks are neither totally opaque nor totally transparent. The market correctly identified which firms would be judged to have sufficient capital, but was somewhat surprised by the announced magnitudes of capital required for the (predictably) under-capitalized institutions. Their methodology permits no direct comparison between banking and other firms.[1]

Bannier et al. (2010) investigate why unsolicited credit ratings tend to be lower (i.e., to imply worse credit quality) than solicited ratings. They assume that a rating agency is less certain about the appropriate rating for an unsolicited rating because it receives no "inside information" when producing an unsolicited rating. They further hypothesize that a rating agency suffers a larger cost by over-rating firms about which it is uncertain (as opposed to under-rating them). Accordingly, unsolicited ratings tend to be biased downwards. To test this hypothesis, Bannier et al. (2010) use assigned ratings to predict future defaults. Their evidence about industrial firms is mixed, but they do find a downward bias for banks' unsolicited ratings. They further hypothesize that the downward bias resulting from rating agency risk aversion ("conservativeness") should be more substantial if the rated firm is harder to understand. Using three measures of bank opacity, Bannier et al. find "tentative, but not conclusive, evidence that the downward bias is, indeed, more pronounced when bank opaqueness is high." (p. 265)

Morgan (2002) reports that insurance company bonds are more likely to carry split ratings than bank bonds, and two recent papers study the stock trading properties of insurance companies. Zhang et al. (2009) examine how NYSE-traded insurance companies' portfolio composition affects the bid-ask spreads on their equity from 1996 to 2004. They find no significant effect of asset composition on the adverse-selection component of the bid-ask spread. However, Zhang et al. (2009) note that insurance products differ in their opacity and that long-tail, property–casualty claims (such as workers' compensation or medical malpractice) may be particularly difficult for outsiders to evaluate. They conclude that "insurers underwriting more opaque [lines of business] are subject to higher adverse selection costs." (p. 317) Park and Xie (2011) examine how insurance companies' multi-tranche structured security-holdings (such as RMBS, CMBS, ABS, and CDOs) affect their quoted bid-ask spreads from 1998 to 2008. They conclude that privately-sponsored, multi-tranche securities significantly raise quoted spreads, but only during the 2005–2008 sub period.

The two papers focused most directly on U.S. bank opacity (Morgan, 2002; FKN et al., 2004) require some updating. Banks might become more opaque during broad financial crises, and indeed much of the governments' interventions during the recent crisis were predicated on the market's presumed inability to distinguish sound from unsound institutions. Morgan's (2002) sample period includes the turbulent 1980s; FKN examine banking firms during a relatively tranquil time period. Both samples predate the expanded activities permitted by the Gramm-Leach-Bliley Act of 1999. The sample period for this paper (1993 through 2009) includes two stressed periods (LTCM in 1998 and the recent financial crisis) as well as periods of tranquility (even euphoria!). Furthermore, some of the recent crisis' uncertainty was associated with activities outside banks' traditional lines of business – activities newly permitted by the Gramm-Leach-Bliley Act.[2] Thus, the earlier U.S. evidence – mixed as it is – may be less relevant to the current banking system, at least for the largest, most complex institutions.

This paper re-evaluates the question of banking firms' opaqueness in the current environment. We are interested in three main questions: Are banks relatively opaque? Does bank opacity change over time and with financial market conditions? Can we link opacity to specific bank characteristics? To answer these questions, we compare equity market trading patterns of banks and matched nonbanking firms. [3] Opacity is related to information availability. If all investors know all the relevant information about an asset, it trades readily with a small bid-ask spread. Likewise, an asset can be very liquid if

[1] Other studies also find evidence of bank opacity during normal times: Jones et al. (2012) and Haggard and Howe (2007).

[2] Myers and Rajan (1998) argue that access to liquid funds increases a firm's opacity because outsiders cannot know how those funds might be deployed in the portfolio. By 2007, some of the largest U.S. banks were operating large proprietary trading accounts, whose risk positions could change frequently. These investment opportunities were less important before Gramm–Leach-Bliley.

[3] Even if banking firms are not unusually opaque, policy makers might still be concerned about opacity combined with banks' unusual leverage or their unusual reliance on short-term funding.

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no investor knows its fundamental value (Dang et al., 2010). As a practical matter, opacity corresponds to the extent of asymmetric information, and the market microstructure literature specifies that a firm's equity trading properties should reflect the information available to market participants. We primarily examine three facets of stock trading properties. First, a higher bid-ask spread is associated with a greater possibility that some traders have information unknown to other traders (Bagehot, 1971). A market-maker therefore quotes a wider spread to protect himself from losing money when trading with (unidentified) informed counterparties. A second indicator of informed trading is the extent to which trades have a permanent effect on a stock's price (Kyle, 1985). Price changes are less likely to reverse when informed trading is more prominent. Both spreads and the price impact should be positively related to asset opacity. Trading volume – our third microstructure feature – may either rise or fall with opacity. Trade should rise with differences of opinion about a firm's value, holding constant the bid-ask spread. Greater opacity may either broaden or narrow differences of opinion.

The rest of this paper is organized as follow. Section 2 discusses information and equity trading properties. Data and descriptive statistics are presented in Section 3. Section 4 compares the market microstructure properties of banking firms against nonfinancial control firms with similar market values, share prices, and trading venue over the period 1993 through 2009. During normal (non-stressed) times, larger banks (traded on the NYSE) seem no more opaque than their nonfinancial control firms. The evidence is slightly mixed for smaller BHCs (traded on NASD). Their spread measures are significantly higher than their nonfinancial control firms, but their price impacts are significantly lower. Given that NASD banks have lower return volatilities and trading volume, the spread results do not necessarily imply that NASD banks are more opaque than their control firms during normal periods.

However, during the crisis periods – particularly the 2007–2009 financial crisis – the banks' microstructure properties diverge from those of the nonbanks. Both the spreads and price impacts of BHC stocks are significantly higher than nonbanks, consistent with a sharp increase in banking firms' relative opacity. It thus appears that bank opacity varies over time. In Section 5, we use quarterly financial data about BHCs to examine whether a bank's portfolio composition affects its opacity. While we find asset composition has significantly different effects on bank opacity during the financial crisis, the portfolio source of opacity is difficult to pin down. Section 6 concludes.

2. Information and equity trading properties

The motivation for examining market microstructure properties derives from Demsetz' (1968) examination of equity bid-ask spreads. Bagehot (1971) argues that the bid-ask spread should reflect the importance of differentially (privately) informed traders. Benston and Hagerman (1974) study a sample of more than 300 stocks traded over-the-counter, and conclude that interdealer competition, price volatility, share price, order flow, and insider trading all significantly affect a stock's bid-ask spread. Roll's (1984) use of transaction prices' serial correlation to estimate the bid-ask spread motivated a series of empirical methods for decomposing the spread into logically distinct components (for example Glosten and Harris, 1988; Stoll, 1989; George et al., 1991; Huang and Stoll, 1994; Lin et al., 1995).

A stock's bid-ask spread must compensate for several distinct costs of market-making operations. First, the spread must be large enough to cover the cost of processing customer orders. Second, the market-maker holds an inventory of stock in order to provide traders liquidity and the cost of holding this inventory includes both the time value of invested capital and a risk premium for bearing nondiversifiable risk. Third, the spread must compensate for the market maker's information asymmetry, which is related to the notion of asset opacity. [4]

2.1. Information asymmetry and opacity

When market makers post bid and ask prices, they effectively write options to traders. The market maker expects his offer to be "hit" by informed traders more frequently if the bid price is too high or

[4] Some of the bid-ask spread's components are likely interrelated. For example, if information asymmetry leads to a higher spread, trading volume could fall and hence the market-makers' order processing costs might rise, raising the spread still further.

the ask price is too low. In order to break even, the market maker charges a wider spread on stocks with greater potential for adverse selection (AS). These securities are therefore more expensive to trade. Brennan and Subramanyam (1995) report that a stock's AS component is negatively related to the number of analysts following the firm, suggesting that greater analyst coverage reduces the importance of privately informed traders. Krinsky and Lee (1996) find that the AS component significantly widens for the 2 days prior to a company's earnings announcement, consistent with the hypothesis that market makers are more susceptible to informed trading when earnings are known to insiders, but not yet announced. Differentially informed traders, who threaten the market maker's profits, should be more important at firms for which it is more difficult to find reliable public information about asset value. If investors in general cannot value a firm's assets very accurately, perhaps insiders or specialized traders can. Kyle (1985) therefore concludes that a "more opaque" asset should trade with a larger bid-ask spread. This may be particularly important for banking firms, whose underwriting and loan monitoring decisions may be difficult for outsiders to observe.

2.2. Price impact and opacity

Another measure of opacity comes from the typical price impact of a trade – the permanent (as opposed to transient) component of the price change induced by a trade. According to Kyle (1985), trades by informed traders will move a stock price towards its (unobserved) fundamental value, while uninformed ("noise") trades are not expected to affect prices permanently. In other words, more private information (opacity) raises a stock's price impact. In Kyle's model, insiders have information about an asset's future payoffs, which are distributed $N(0, \sigma_i^2)$ If informed traders can predict the asset's return perfectly and the noise or liquidity traders' order flow is distributed $N(0, \sigma_u^2)$, then an asset's price impact (opacity) will be

$$\lambda = \frac{1}{2}\left(\frac{\sigma_i}{\sigma_u}\right) \tag{1}$$

In words, the typical price effect is more persistent for more opaque assets – those with more uncertain returns (higher σ_i). The greater price impact occurs because the market maker adjusts price more aggressively as she extracts more information from the typical trade in a stock with more, informed traders.[5]

2.3. Trading volume and opacity

An old Wall Street adage says that "It takes volume to move prices." Karpoff (1987) reviews the literature on return volatility and trading volume, and finds that volume is positively related to the (absolute) magnitude of the price change. In equity markets, volume is also related to the price change *per se*: positive changes are related to higher volume. Bessembinder et al. (1996) finds that volume in individual stocks is related to firm specific information flows, consistent with Kyle's (1985) model of strategic trading. How might volume be related to information asymmetry and opacity? It seems that trading volume could either rise or fall with asset opacity.

In theory, a perfectly opaque asset could be very liquid (Dang et al., 2010). It would trade with no AS component to its bid-ask spread because the market maker need not fear a winner's curse. A low spread would attract greater trading volume (say, for liquidity purposes), further reducing the market maker's break-even spread. However, this scenario is easily disturbed. Any possibility that some trader may possess private information about the asset's value could seriously reduce its liquidity. Higher spreads (due to AS) would then discourage uninformed traders from holding the stock (Gorton and Pennacchi, 1990), making it more difficult for informed traders to hide their information. In the limit, the market for opaque shares could break down entirely, as in Akerlof (1970). However, the market

[5] Kyle's model can be extended to the case where the insider only receives a "signal" about the asset's future value of the asset. If σ_s is the volatility of the insider's signal error, the Kyle measure of illiquidity becomes $\lambda = \frac{1}{2}\left(\frac{\sigma_i}{\sigma_u}\right)\left(\frac{\sigma_i}{\sqrt{\sigma_i^2+\sigma_s^2}}\right)$. Note that λ unambiguously increases with the amount of public uncertainty (σi).

need not collapse if opinionated investors wish to trade frequently with one another because they disagree about the correct value of the underlying assets (Harris and Raviv, 1993). If more opaque firms are subject to greater differences of opinion, trading volume should be positively related to opacity.

2.4. Financial market conditions and opacity

Our long time series (17 years) permits us to compare firms' trading properties during "normal" and "crisis" periods. But what *is* a crisis period? We think it fair to categorize crisis market conditions as a sudden fall in firms' asset values and a sudden increase in uncertainty about asset returns.

Kyle's asset opacity measure can be combined with Merton's (1974) model of a levered firm to illustrate how a financial crisis affects a stock's opacity.[6] Let A' be the market value of the firm's underlying assets and let σ be the volatility of the rate of return on these assets. Define B as the promised payment on the firm's debt, to be made in T years. The discounted promised payment for the debt is $P = Be^{-rT}$, where r is the constant risk-free interest rate. Define $A = A'/p$ as the ratio of the market value of assets to the debt's present discounted value. Similarly, let $E = E'/P$, where E' is the market value of equity. Essentially A and E can be thought of as the market values of the firm's assets and equity when the value of debt is normalized to one. Since equity is a call option on the firm's assets where the exercise price is the normalized payoff on the debt ($1), it follows that,

$$E = AN(d_1) - N(d_2) \tag{2}$$

where $d_1 = \left[LN(A) + \frac{1}{2}\sigma^2 T\right]/(\sigma\sqrt{T}),\ d_2 = d_1 - \sigma\sqrt{T}$, $N(\cdot)$ is the standard normal CDF.

Merton shows that the standard deviation of the rate of return on equity is

$$\sigma_E = \frac{A}{E}N(d_1)\sigma \tag{3}$$

Now suppose that an insider has private information about the value of the firm's underlying assets but trading takes place only in the firm's equity. From (1), a measure of the equity's illiquidity is then

$$\lambda = \frac{1}{2}\left(\frac{\sigma_E}{\sigma_u}\right) = \frac{1}{2}\left(\frac{A}{E}\right)N(d_1)\left(\frac{\sigma}{\sigma_u}\right) = \left(\frac{A}{E}\right)N(d_1)\lambda \tag{4}$$

In words, the illiquidity (opacity) of the firm's stock (λ_E) is proportional to the illiquidity of its assets λ. Eqs. (3) and (4) imply two comparative static properties of a firm's equity liquidity measures. First, equity's opacity rises as the firm's asset value falls:

$$\frac{\partial \lambda_E}{\partial A} = \frac{\lambda}{E^2\sigma\sqrt{T}}[n(d_2)N(d_1) - n(d_1)N(d_2) - \sigma\sqrt{T}N(d_1)N(d_2)] < 0 \tag{5}$$

where $n(\cdot)$ is the standard normal pdf.[7] Second, equity's lambda (price impact) increases with public uncertainty about asset values:

$$\frac{\partial \lambda_E}{\partial \sigma} = \frac{An(d_1)}{2\sigma_u E^2}\left[E\left(\frac{N(d_1)}{n(d_1)} - d_1\right) - \sigma\sqrt{T}N(d_2)\right] \leqslant 0 \quad \text{for } A \leqslant 1 \tag{6}$$

A proof of (6) is available upon request. During a financial crisis, both forces are at work. A bank's asset value fall as loan defaults rise. Greater macroeconomic uncertainty combines with the increased importance of default, to raise uncertainty about future asset returns. Equity's price impact (λ_E) thus rises in a crisis. In addition, less-informed traders will be more reluctant to trade when uncertainty (σ) is up or asset value (A) is down, expanding equilibrium bid-ask spreads.[8]

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[6] We thank the editor, George Pennacchi, for providing a detailed framework for linking Kyle's lambda to asset opacity.

[7] Galai and Masulis (1976) derive the result (5): their equation (8) on page 58 is comparable to our equation (4). They derive the equivalent of our equation (5) on page 76.

[8] An alternative perspective on bank assets recognizes that banks primarily own debts issued by other firms. If a financial crisis reduces the value of borrowers' assets or increases uncertainty about their asset returns, loans or asset backed pools will become less liquid by (5) and (6) respectively.

To summarize, bank shares' microstructure properties reflect the opacity of bank assets. Theory indicates that more opaque firms' equity trades should have higher spreads and price impacts during a crisis.

3. Data

We identify a sample of publicly traded bank holding companies (BHCs) that file the Federal Reserve's quarterly Consolidated Financial Statements (FR Y-9C). We then examine transactions data for these BHCs in the NYSE's daily Trade and Quote (TAQ) dataset. We eliminate firms with insufficient trades (fewer than 100 per month) to permit reliable estimates of the firm's market microstructure properties. As is customary in microstructure studies, we also omit bank stocks in months for which they had a low average share price (<$2), a high average spread (>10% of share price over the quarter), or a substantial split or stock dividend (>10% of share price). (Desai et al. (1998) find significant microstructure changes following a split.) Finally, we omit data for the first 3 months of 1993, when our TAQ dataset had very few bank observations. We compute daily spread, IMPACT, and turnover measures for each remaining firm, and average those daily values to produce monthly microstructure measures.

In order to compare bank stocks' monthly trading characteristics to those of nonfinancial firms, we match each sample BHC with a control firm on the basis of characteristics known to affect microstructure variables (Madhavan, 2000).

1. Share price.
2. Size (market value of equity).
3. Trading venue (NASD vs. NYSE).[9]

Potential control firms are selected from the set of all CRSP firms that survived the entire calendar year, except financial firms (SIC code 6000-6999) or regulated utilities (SIC code 4800-4900). We first select the firm whose market value is closest to the BHC's. If that firm's share price is also within 25% of the BHC's share price, we use this as our nonfinancial control firm. Otherwise, we select the next-closest equity value match from the same trading venue, determine if its share price is within 25% of the BHC's, and so forth. Each bank's control firm is re-selected at the start of each calendar month. The final sample consists of more than 45,000 firm-months for NASD banks and 13,000 firm-months for NYSE banks.

For each BHC and control firm, we compute four market microstructure variables related to opacity. Each variable is computed using all the trades from a given day, and the daily values are averaged to give monthly observations.

- AS: the adverse selection component of the bid-ask spread (as a proportion of share price), as in George et al. (1991).

Although the AS component of a stock's bid-ask spread constitutes an ideal measure of information asymmetry, it must be estimated (with error) by fitting transactions and quote data to a specific model.[10] For robustness, we also use a stock's *effective* spread as an alternative proxy for adverse selection.

[9] We treat the firms that are traded on the NYSE separately from those traded on NASD, because the two markets have different trading arrangements. Each NYSE stock has an assigned market-maker who must maintain orderly, two-sided trading in the stock. NASD brokers can enter (or withdraw) quotes without exchange-imposed restrictions. In addition, FKN find that these two groups of BHCs differ in their opacity.

[10] Livingston et al. (2007) examine the association between split bond ratings and seven alternative proxies for opacity: firm size, market-to-book ratio, intangible assets, number of analysts following the firm's stock, standard deviation of analysts' earnings forecasts, bond maturity, and the bid-ask spread's adverse selection (AS) component. They find mixed evidence about the meaning of AS. In univariate tests, only the AS component does not differ significantly between the groups with vs. without a split rating (see their Table I). They also estimate probit models of split ratings, which include all seven proxies at the same time (Table II), and again the AS coefficients are insignificant. When they separate bonds with the same initial rating from both agencies into groups that did, or did not, subsequently become split-rated, the AS component was significantly larger at issuance for the group that eventually became split-rated. See their Table IV.

$$\text{ESPREAD} = \sum_{n} \frac{2 * \frac{(Q_\tau - P_\tau)*I + (P_\tau - Q_\tau)*(1-I)}{Q_\tau}}{n}$$

where P_τ is the trade price, Q_τ the average of the bid and ask prices associated with the τth trade, I the indicator equal to unity for a bid-initiated trade or zero for an ask-initiated trade (based on Lee and Ready, 1991) and n is the number of trades within a day.

Using ESPREAD to proxy for adverse selection costs implicitly assumes that market makers have about the same operating costs for all stocks, so cross-sectional variation in their effective spreads largely reflects variation in the adverse selection cost of trading.

- IMPACT: the permanent effect of a trade on share price as measured in Amihud (2002):

$$\hat{\lambda} = \left(\frac{1}{n} \sum_{n} \frac{|\Delta P_t|}{Size_t} \right) * 10^6$$

where $\Delta P_t = LN(Q_{t+s} - Q_t)$. Q_t and Q_{t+5} are the matched mid-quotes for the trade closest to 5 s prior to and 5 min after the trade. $Size_t$ is the size of the trade (number of shares traded). n is the number of trades within a day.

The variable is scaled by 10^6 to avoid reporting a large number of leading zeros in its summary statistics. A higher value for λ (IMPACT) implies greater information asymmetry or opacity in the associated stock.

- TOVER: trading activity measured as the number of shares traded, divided by the average number of shares outstanding during the month.

For each stock, we also calculate the daily standard deviation of continuously compounded returns (based on the quote midpoint associated with each trade within a day). Because higher return volatility increases the market-maker's risk of holding inventory, and hence increases the equilibrium spread, the monthly average of daily returns volatilities (STD) serves as a control in some regressions.

Equity trading arrangements have changed substantially over the past two decades, in ways that might affect the measured microstructure variables. First, in April 2001 the SEC required that NASD and NYSE prices be quoted in decimal increments or pennies. Bid-ask spreads fell substantially, as did quoted depth (Bessembinder, 2003). As posted depths have fallen, limit orders have become a much more important part of the market's liquidity. Second, trading volumes have exploded, in part due to shrinking spreads (transaction costs), and in part due to the entry of hedge funds, "flash" traders, and other suppliers of liquidity. We control for these structural changes using time dummies and matched control firms when evaluating bank microstructure variables.

Table 1 reports microstructure variables' monthly summary statistics for BHC and their control firms. Panel A describes the NASD sub-sample; Panel B describes NYSE-traded firms. To compare the information content of our opacity proxies, we computed for each sample the correlations among the four monthly opacity measures. Table 2 reports the mean (median) monthly correlations among AS, ESPREAD, IMPACT, and TOVER. For each sample, the mean correlations are reported in the lower diagonal and medians are in the upper diagonal. Not surprisingly, AS and ESPREAD are quite highly correlated on both exchanges and in all periods. The correlation tends to be somewhat higher during crisis periods, but not dramatically so. IMPACT is also positively correlated with the two spread measures. TOVER is negatively correlated with AS on both exchanges, and with ESPREAD on the NYSE. It is always positively correlated with IMPACT, and with ESPREAD on the NYSE. We conclude that each opacity measure contains some unique information. Among the three direct indicators of firm opacity (AS, ESPREAD, IMPACT), we have a slight preference for relying on the price impact measure, because it is arguably less prone to endogeneity issues and less model-specific.

4. Microstructure comparison between BHCs and control firms

We start by comparing BHCs' monthly microstructure variables with those of their matched (control) nonfinancial firms, via the following regression

$$\Delta M_{ijt} = \delta_0 + \delta_1(\Delta PINV_{it}) + \delta_2(\Delta \mathrm{LNMVEQ}_{it}) + \delta_3 \Delta STD_{it} + \mu_{ijt} \quad (7)$$

where ΔM_{ijt} is the BHC i's value for its jth market microstructure value (j = AS, ESPREAD, IMPACT, and TOVER) in month t, less that of its matching nonfinancial firm; $\Delta PINV_{it}$ the inverse of the average share price for BHC i in month t, less that of its control firm; $\Delta LNMVEQ_{it}$ the log of BHC i's average equity market value in month t, less that of its control firm; and ΔSTD_{it} is the BHC i's return standard deviation during month t, less that of its control firm.

Although we match BHC and control firms on share price and market value monthly, these matches are imperfect. So we control for these differences in (7). In addition, we control for differences in return volatility (STD) because the banks may be particularly volatile during crisis periods, which would tend to raise their bid-ask spreads. Estimating (7) provides a good estimate of δ_0, the mean excess BHC microstructure variable value over its control firm's value. Eq. (7) can be estimated as a series of cross-sectional regressions or as a pooled time series-cross section.

We start with cross-sectional estimates of (7), to provide an overview of the data's implications. Figs. 1–4 plot the estimated intercept terms (δ_0) from monthly cross-sectional regressions, along with their 95% confidence intervals. The panel regression results for the entire sample period and for two "crisis" sub-periods are reported in Table 3 below.

4.1. Basic patterns from monthly cross-section regressions

Figs. 1A–4A plot the NASD firms' monthly estimated intercept terms (δ_0) from Eq. (7) separately for each of the four opacity measures. The first two figures show that the NASD BHCs' spreads (AS, ESPREAD) are usually indistinguishable from their controls'. Both spread measures become significantly larger for the BHCs around 1998 and after 2008.[11] Spreads thus seem to rise for NASD BHCs during times of financial distress. The price IMPACT results in Fig. 3A show only a few significant differences for NASD firms, but the BHCs' relative IMPACT (relative opacity) rises during 2009, consistent with the spread results in Figs. 1A and 2A. Fig. 4A indicates that BHC TOVER is generally significantly lower than the controls' TOVER, with the difference becoming particularly large after about 2004. The time variation in the microstructure variables in Figs. 1A–4A suggests that NASD BHCs' opacity varies over time, but not too greatly.

Comparisons for NYSE BHCs and their controls in Figs. 1B–4B differ somewhat from that of the NASD sub-sample. First, Figs. 1B and 2B provide no indication in that NYSE-traded BHCs have higher adverse selection costs: both the AS and the ESPREAD differentials are (almost) always indistinguishable from zero. Likewise, the NYSE banks' price IMPACT measure in Fig. 3B differs insignificantly from their controls' in nearly all months. During the crisis we see some larger BHC IMPACT values, but the differences are rarely distinguishable from zero. (We deal explicitly with the crisis period below.) Finally, Fig. 4B indicates that NYSE BHCs' TOVER tends to be smaller than their controls' until the financial crisis. Starting in 2008, the TOVER differential becomes much more variable, but (in most months) it remains indistinguishable from zero.

To summarize, Figs. 1A–4A indicate that NASD banks are not unusually opaque except perhaps during crisis periods, while the larger BHCs (traded on NYSE) always exhibit similar opacity measures to their nonbank controls. Evidence that large banks became more opaque during the crisis seems statistically quite weak from the cross-sectional regressions. However, the intercept terms plotted in Figs. 1B–4B are free to vary between adjacent months. If opacity tends to change slowly, it would

[11] Specifically, the AS intercept terms plotted in Figure 1A are significantly positive for all but 4 (scattered) months during the interval November 1997 – September 2000 and continuously starting July 2007. Similarly, the ESPREAD intercept terms in Figure 2A are significantly positive for all but 3 (scattered) months between September 1997 and April 2000, and again from December 2006 – yearend 2009 (with three scattered exceptions).

Table 1
BHC and matched firms' monthly microstructure variables, 1993–1994 through 2009–2012.

Microstructure variables
The following four market microstructure measures are computed daily and then averaged over all days of the month. Definitions are provided in the text

AS_{it}	Average adverse selection cost of trading stock, as a percentage of the share price
$ESPREAD_{it}$	Average effective spread for transactions, as a percentage of the share price
$IMPACT_{it}$	An estimate of Kyle's (1985) 'λ', which is a price impact measure
$TOVER_{it}$	The number of shares traded, divided by the average number of shares outstanding during the month

Control variables

$PINV_{it}$	The inverse of the monthly average share price
$LNMVEQ_{it}$	Natural log of the month average market value of common equity
STD_{it}	The annualized daily standard deviation of the continuously compounded returns between adjacent trades, computed using the quote midpoints

	Bank holding companies						Matched (control) firms					
	N	Mean	Std. dev.	Min.	Max.	Median	*N*	Mean	Std. dev.	Min.	Max.	Median
Panel A: Microstructure variables for NASD BHCs and Controls												
AS	45,938	1.417	1.140	0.019	7.489	1.132	45,938	1.260	1.148	0.000	8.008	0.925
ESPREAD	46,377	1.519	1.221	0.036	10.741	1.231	46,377	1.403	1.271	0.033	12.926	1.044
IMPACT	46,368	22.441	20.525	0.000	321.868	17.794	46,368	25.334	21.128	0.000	369.708	20.739
TOVER	46,480	0.191	0.312	0.004	8.954	0.101	46,480	0.688	1.852	0.000	119.037	0.339
PINV	46,480	0.060	0.047	0.005	0.711	0.047	46,480	0.064	0.051	0.006	0.831	0.050
LNMVEQ	46,480	12.260	1.281	9.115	17.494	12.108	46,480	12.255	1.285	9.126	17.756	12.112
STD	46,048	39.416	46.461	0.000	437.864	23.721	46,048	59.109	54.365	0.000	446.738	40.450
PRICE	46,480	23.200	12.470	1.410	186.240	21.270	46,480	21.860	12.010	1.200	165.040	19.880
Panel B: Microstructure variables for NYSE BHCs and Controls												
AS	13,570	0.781	0.918	0.004	6.285	0.443	13,570	0.750	0.881	0.000	8.008	0.461
ESPREAD	13,619	0.536	0.650	0.030	7.892	0.302	13,619	0.587	0.817	0.028	10.071	0.300
IMPACT	13,619	13.063	13.574	0.057	270.401	8.151	13,619	13.195	13.385	0.000	163.964	8.510
TOVER	13,621	0.380	0.537	0.005	8.954	0.248	13,621	0.553	0.723	0.001	24.041	0.349
PINV	13,629	0.043	0.039	0.005	0.575	0.033	13,629	0.045	0.041	0.006	0.649	0.034
LNMVEQ	13,629	14.470	2.065	9.441	18.727	14.599	13,629	14.441	2.063	9.296	18.656	14.606
STD	13,576	66.913	57.491	3.973	433.295	44.725	13,576	73.466	61.811	0.000	451.752	50.897
PRICE	13,629	34.800	21.050	1.740	186.240	30.530	13,629	33.450	19.970	1.540	165.040	29.440

Table 2
Correlation matrix of monthly microstructure variables, 1993–1994 through 2009–2012. This table reports the mean and median values of monthly correlations among the four market microstructure variables used in the analysis. Means are in the lower diagonal and medians in the upper diagonal of each matrix.

	NASD sample BHCs					NYSE sample BHCs			
	AS	ESPREAD	IMPACT	TOVER		AS	ESPREAD	IMPACT	TOVER
Panel A: Mean (median) monthly correlations of daily values, full period									
AS	1.0	(0.917)	(0.149)	(−0.235)	AS	1.0	(0.665)	(0.250)	(−0.271)
ESPREAD	0.876	1.0	(0.164)	(−0.230)	ESPREAD	0.587	1.0	(0.507)	(−0.163)
IMPACT	0.104	0.138	1.0	(0.077)	IMPACT	0.234	0.503	1.0	(0.178)
TOVER	−0.215	−0.219	0.083	1.0	TOVER	−0.184	−0.111	0.170	1.0
Panel B: Mean (median) monthly correlations of daily values, crisis periods (1998:7–1998:12, 2007:7–2009–12)									
AS	1.0	(0.941)	(0.307)	(−0.286)	AS	1.0	(0.818)	(0.434)	(−0.091)
ESPREAD	0.887	1.0	(0.364)	(−0.224)	ESPREAD	0.695	1.0	(0.747)	(0.110)
IMPACT	0.309	0.366	1.0	(0.122)	IMPACT	0.340	0.618	1.0	(0.394)
TOVER	−0.248	−0.218	0.113	1.0	TOVER	−0.051	0.115	0.310	1.0
Panel C: Mean (median) monthly correlations of daily values, normal period									
AS	1.0	(0.906)	(0.136)	(−0.279)	AS	1.0	(0.665)	(0.272)	(−0.270)
ESPREAD	0.864	1.0	(0.127)	(−0.279)	ESPREAD	0.571	1.0	(0.557)	(−0.238)
IMPACT	0.081	0.113	1.0	(−0.012)	IMPACT	0.245	0.531	1.0	(0.057)
TOVER	−0.251	−0.266	−0.006	1.0	TOVER	−0.216	−0.183	0.048	1.0

be more efficient to limit the month-to-month variation in our estimates by estimating (7) as a panel regression with a single coefficient vector over a subset of the months within the sample period.

4.2. Panel regression results

To evaluate whether bank opacity changes over time and with broad financial market conditions, we estimate the following panel regression model by interacting the regression coefficients in (7) with two crisis dummies:

$$\Delta M_{ijt} = \left(\delta_0 + \sum_1^2 \delta_{0k} D_k\right) + \left(\delta_1 + \sum_1^2 \delta_{1k} D_k\right)(\Delta \mathrm{PINV}_{it}) + \left(\delta_2 + \sum_1^2 \delta_{2k} D_k\right)(\Delta \mathrm{LNMVEQ}_{it}) + \left(\delta_3 + \sum_1^2 \delta_{3k} D_k\right)\Delta \mathrm{STD}_{it} + \mu_{ijt} \tag{8}$$

- D_1 = 1 during the LTCM Crisis (1998:8 through 1998:12), zero otherwise;
- D_2 = 1 during the recent financial crisis (2007:7 through 2009:12), zero otherwise.

The estimated δ_0 coefficient measures the average excess of the BHC microstructure variables over the controls' variable values for all "normal" periods. Our primary interest in (8) is the δ_{0k} coefficients that indicate the microstructure measures' mean differential value during the crisis periods. We permit the coefficients on share characteristics ($\Delta PINV$, etc.) to vary between normal and crisis periods in order to obtain unbiased estimates of the intercept term.

The left and right halves of Table 3 present the panel regression results for NASD and NYSE firms respectively. Given the preponderance of positive (although insignificant) intercepts in Figs. 1A–4A, it is not surprising that the NASD BHCs' spread measure (AS or ESPREAD) averages 8–9 bps higher than the control firms' during normal times. This mean difference is statistically significant, but small compared to the NASD BHCs' AS (ESPREAD) overall average of 1.4% (1.5%). However, the significantly negative δ_0 coefficient on IMPACT is inconsistent with the spread results. NASD BHC TOVER averages 25.7% lower than the control firms'.[12] During normal periods, therefore, we find contradictory evidence

[12] Recall that, theoretically, TOVER could be either positively or negatively related to opacity.

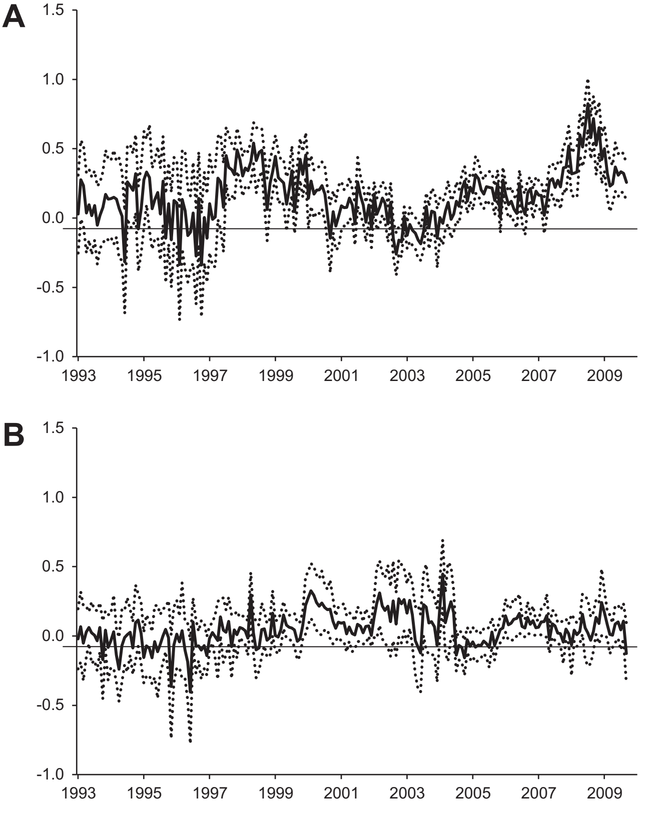

Fig. 1. (A) Intercept term from monthly cross-section regressions, NASD sample, dependent variable = AS. Estimated intercept term (solid line) and bounds of 95% confidence interval (dashed lines). (B) Intercept term from monthly cross-section regressions, NYSE sample, dependent variable = AS. Estimated intercept term (solid line) and bounds of 95% confidence interval (dashed lines).

about the relative opacity of NASD banking firms. The right half of Table 3 indicates that NYSE BHCs on average have a marginally significantly higher AS than their control firms. However, neither the BHCs' relative ESPREAD nor their IMPACT differs statistically from zero. Consistent with Fig. 4B, the large BHCs' TOVER is also significantly smaller than that of the control firms during normal times. The sum of the evidence thus does not clearly indicate that NYSE banking firms are significantly more opaque during normal times.

The results are quite different during the crisis periods.

Consider first the LTCM crisis (August–December of 1998). For NASD banks, the coefficient on D_1 is positive for the AS, ESPREAD, and IMPACT regressions, indicating heightened opacity during the last five months of 1998.[13] The NASD banks' TOVER during this crisis is indistinguishable from their relatively low TOVER during normal times. In contrast, the NYSE results present a mixed view of their relative opacity: significantly lower AS and ESPREAD but significantly higher IMPACT. Relative to sample mean values, these effects are smaller than for the NASD firms. Like the NASD BHCs, NYSE banks' TOVER is not significantly different during this crisis. The findings seem to suggest that, perhaps surprisingly, the LTCM period was more stressful for smaller than for larger banks.

[13] The crisis dummies are relative to the intercept term, δ_0, which measures the average difference between banks and control firms over the non-crisis period.

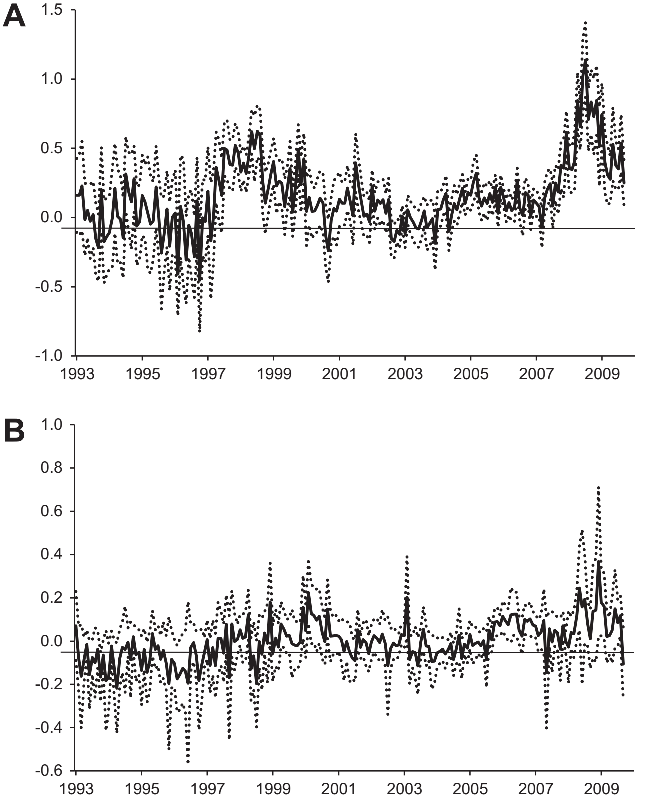

Fig. 2. (A) Intercept term from monthly cross-section regressions, NASD sample, dependent variable = ESPREAD. Estimated intercept term (solid line) and bounds of 95% confidence interval (dashed lines). (B) Intercept term from monthly cross-section regressions, NYSE sample, dependent variable = ESPREAD. Estimated intercept term (solid line) and bounds of 95% confidence interval (dashed lines).

Turning to the recent financial crisis from 2007:7 through 2009:12, the coefficients on D_2 indicate highly significant increases in opacity for both NASD and NYSE banks. ESPREAD and IMPACT are significantly higher during the crisis for all banks, and AS is significantly higher for NASD banks. The magnitudes of the crisis-period increases are large, compared to their normal-period values: Among the NASD banks, AS rises from 0.09 above their control firms to 0.39 (=0.094 + 0.296) for AS, from 0.09 to 0.47 for ESPREAD, and −0.74 to 5.28 for IMPACT. For NYSE banks, ESPREAD rises from −0.02 to 0.07 and IMPACT rises from −0.01 to 3.60. Note that the NYSE banks appear to be *less* affected by the crisis than their smaller counterparts – despite the popular attention paid to mispricing and the alleged effect of short-selling on the largest banking firms.

Overall, the findings in Table 3 confirm that banking firms' opacity increases during banking or financial crisis, as predicted by theory. The degree of the surge in bank opacity during crisis seems to be directly related to the severity of the crisis, as evidenced by the large increases in our opacity measures during the financial crisis of 2007–2009.

5. Effects of portfolio composition on microstructure variables

Given the intertemporal shifts in the BHCs' relative opacity, we now investigate whether our opacity measures are correlated with specific bank balance sheet features. (The control firms play no role in this part of the analysis.) We collect quarter-end financial variables from the Federal Reserve's Y-9C

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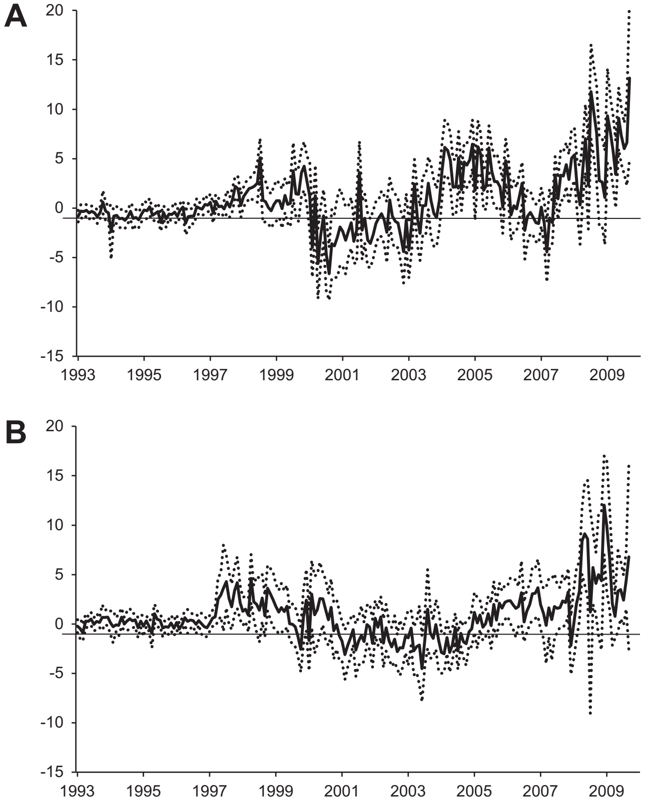

Fig. 3. (A) Intercept term from monthly cross-section regressions, NASD sample, dependent variable = IMPACT. Estimated intercept term (solid line) and bounds of 95% confidence interval (dashed lines). (B) Intercept term from monthly cross-section regressions, NYSE sample, dependent variable = IMPACT. Estimated intercept term (solid line) and bounds of 95% confidence interval (dashed lines).

from 2003QI through 2009Q4, yielding 7693 NASD and 1908 NYSE bank-quarters. We combine the monthly variables from Table 1 into quarterly averages, to match the quarterly balance sheet data. If bank assets or activities differ in their transparency, the quarterly opacity measures should vary systematically with a bank's financial variables. A chronology of crisis events suggests that widespread challenges in the banking sector first emerged at the end of July 2007, and our findings in the previous section show that this is when the banks' relative microstructure values changed most dramatically. Accordingly, we define the "normal" period of our sample as 2003Q1 through 2007Q2, and the crisis period as 2007Q3–2009Q4. We estimate a pooled regression model for each of these two time periods and test whether their coefficient values changed between the normal and the crisis periods.

The following regression model aligns the end-of-quarter financial variables with average microstructure variables from all transactions during the calendar quarter.

$$M_{it} = \alpha + \sum_{k=1,10} \beta_k \frac{A_{kit}}{MVEQ_{i,t-1}} + \beta_6 MVLEV_{it} + \gamma_1 PINV_{i,t-1} + \gamma_2 LNMVEQ_{i,t-1} + \gamma_3 \mathrm{STD}_{i,t-1} + \sum_y \chi_y Dq + \tilde{\varepsilon}_{it} \tag{9}$$

where M_{it} is one of the four measures of the stock's information opacity: AS, ESPREAD, IMPACT, and TOVER, expressed as the quarterly average of daily values.

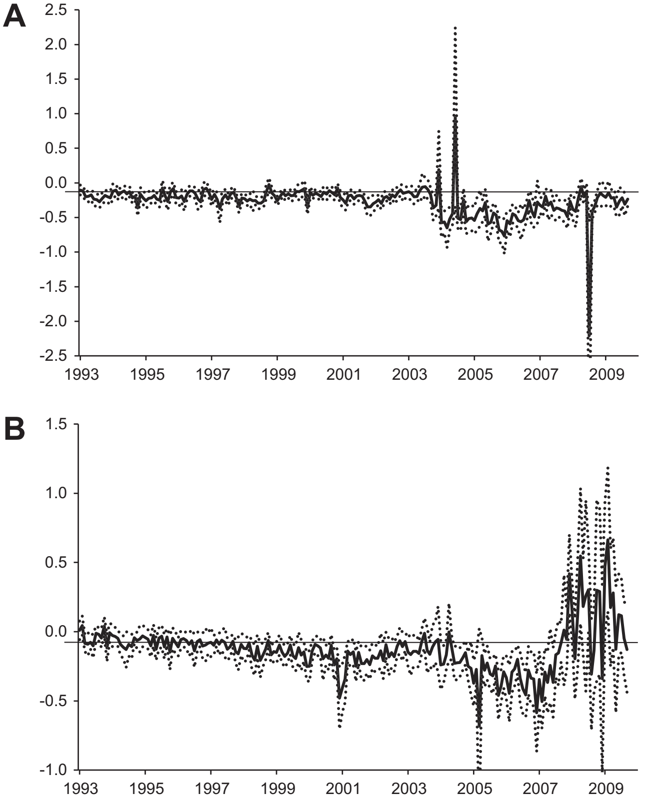

Fig. 4. (A) Intercept term from monthly cross-section regressions, NASD sample, dependent variable = TOVER. Estimated intercept term (solid line) and bounds of 95% confidence interval (dashed lines). (B) Intercept term from monthly cross-section regressions, NYSE sample, dependent variable = TOVER. Estimated intercept term (solid line) and bounds of 95% confidence interval (dashed lines).

- A_{kit} is the book value of assets of type k = 1, 10 held by BHC i at the end of quarter t. The set of transparent assets (including cash, interbank balances, federal funds sold, and securities purchased under agreement to resell) is omitted from the specification to avoid perfect multicollinearity.
- $MVEQ_{i,t-1}$ is the market value of BHC i's common equity at the end of the preceding quarter (which ends at time $t-1$). Each asset category is deflated by the lagged market value of equity capital, $MVEQ_{i,t-1}$ because equity investors experience valuation uncertainty in proportion to their equity claim on the BHC.
- $MVLEV_{it}$ is market-valued leverage, the sum of liabilities' book value at t plus equity's market value at the end of quarter $t-1$, divided by equity's market value at $t-1$.
- $PINV_{it}$ is the inverse of the BHC's average share price during the quarter ending at $t-1$. For low-priced shares, any fixed component of the spread would raise the market maker's required compensation for insider trading (opacity). PINV should capture this tendency.
- $LNMVEQ_{it}$ is the natural log of the market value of BHC equity at the end of the quarter ending at $t-1$. If analysts follow larger firms more closely, these firms' stocks should have lower spreads and therefore perhaps higher TOVER.
- STD_{it} is the annualized daily standard deviation of the continuously compounded returns between adjacent trades, computed using the quote midpoints.
- Dq is a set of dummy variables separately identifying each quarter in the sample except 2007-Q2 and 2007-Q3.

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Table 3
Differences in microstructure characteristics of BHCs vs. control firms, 1993–1994 through 2009–2012. Regression estimates of Eq. (8): $\Delta M_{ijt} = (\delta_0 + \sum_1^2 \delta_{0k} D_k) + (\delta_1 + \sum_1^2 \delta_{1k} D_k)(\Delta PINV_{it}) + (\delta_2 + \sum_1^2 \delta_{2k} D_k)(\Delta LNMVEQ_{it}) + (\delta_3 + \sum_1^2 \delta_{3k} D_k)\Delta STD_{it} + \mu_{ijt}$ Where ΔM_{ijt} denotes the ith BHC's jth (j = AS, ESPREAD, IMPACT, TOVER) market microstructure value in month t less that of its matching nonfinancial firm; $\Delta PINV_{it}$ = the inverse of the average share price for BHC i in month t less that of its control firm; $\Delta LNMVEQ_{it}$ = the log of BHC i's average equity market value in month t less that of its control firm; ΔSTD_{it} = quarterly average of daily return standard deviations; $D_1 = 1$ when t is from 1998:8 through 1998:12, zero otherwise; $D_2 = 1$ when t is from 2007:7 through 2009:12, zero otherwise. All regressions are run with robust standard errors, clustered by firm.

	NASD firms				NYSE firms			
	ΔAS	$\Delta ESPREAD$	$\Delta IMPACT$	$\Delta TOVER$	ΔAS	$\Delta ESPREAD$	$\Delta IMPACT$	$\Delta TOVER$
Intercept	0.094***	0.086***	−0.743***	−0.288***	0.050*	−0.021	−0.011	−0.183***
	(0.017)	(0.017)	(0.196)	(0.018)	(0.028)	(0.014)	(0.239)	(0.016)
D_1	0.375***	0.467***	3.287***	0.025	−0.075*	−0.068**	1.810**	0.022
	(0.055)	(0.058)	(0.574)	(0.024)	(0.045)	(0.034)	(0.764)	(0.027)
D_2	0.296***	0.388***	6.020***	−0.072**	0.006	0.091***	3.615***	0.207**
	(0.036)	(0.043)	(0.575)	(0.036)	(0.033)	(0.028)	(0.901)	(0.081)
$\Delta PINV$	3.142***	6.112***	47.872***	−6.476***	5.629***	10.244***	−23.477	−1.312
	(0.926)	(0.954)	(10.812)	(0.801)	(2.152)	(2.176)	(23.473)	(0.887)
$D_1 * \Delta PINV$	−6.418	−4.240	−102.839***	5.321**	4.956	−0.069	−37.643	−3.466
	(4.552)	(4.876)	(33.418)	(2.108)	(3.030)	(5.552)	(168.077)	(2.172)
$D_2 * \Delta PINV$	−4.715***	−7.072***	−107.962***	3.838*	−6.878***	−11.312***	−46.147	8.261***
	(1.283)	(1.312)	(23.491)	(2.008)	(2.176)	(2.279)	(32.841)	(2.042)
$\Delta LNMVEQ$	−0.565***	−0.560***	−5.855***	0.362**	−0.317***	−0.289***	−7.395***	−0.011
	(0.142)	(0.138)	(1.358)	(0.151)	(0.084)	(0.091)	(1.918)	(0.073)
$D_1 * \Delta LNMVEQ$	−0.355	−0.180	5.167**	−0.331*	−0.141	−0.031	1.208	−0.037
	(0.264)	(0.212)	(2.001)	(0.196)	(0.142)	(0.209)	(5.455)	(0.140)
$D_2 * \Delta LNMVEQ$	−0.029	−0.140	−8.615*	−1.307*	0.036	−0.024	−1.526	0.767**
	(0.237)	(0.232)	(4.773)	(0.703)	(0.139)	(0.179)	(4.028)	(0.387)
ΔSTD	−0.001***	0.001***	0.144***	0.012***	−0.000	0.001***	0.067***	0.004***
	(0.000)	(0.000)	(0.005)	(0.001)	(0.000)	(0.000)	(0.006)	(0.000)
$D_1 * \Delta STD$	0.013***	0.021***	0.349***	0.000	−0.001	−0.002	0.109*	0.004***
	(0.003)	(0.004)	(0.040)	(0.002)	(0.002)	(0.002)	(0.055)	(0.002)
$D_2 * \Delta STD$	−0.004***	−0.004***	0.033***	−0.004**	−0.000	−0.001***	0.012	0.003***
	(0.000)	(0.000)	(0.010)	(0.002)	(0.000)	(0.000)	(0.012)	(0.001)
Adj-R^2	0.042	0.048	0.143	0.060	0.017	0.066	0.141	0.111
N	45,938	46,048	46,048	46,048	13,562	13,576	13,576	13,576

* Indicates significance (two-tailed test) at the 10% levels.
** Indicates significance (two-tailed test) at the 5% levels.
*** Indicates significance (two-tailed test) at the 1% levels.

The specification (9) captures the idea that outside investors cannot value all bank assets equally well. Each coefficient (β_k, k = 1, 10) measures the difference between the kth portfolio share's effect on our opacity variables and the effect of the omitted ("transparent") portfolio share. A nonzero β_k coefficient is consistent with the banks' asset composition affecting their microstructure properties. We exhaustively separate bank assets into 11 categories:

- RRELOAN loans secured by 1–4 family residential properties,
- CRELOAN loans secured by all other real estate, except farmland,
- CONLOAN loans to individuals for household, family, and other personal expenditures,
- OTHLOAN all other loans,
- LLA loan loss allowance, a contra asset to the loan account,
- TRADE total trading account securities,
- AFS marketable securities available-for-sale,
- HTM marketable securities held to maturity,
- OREO other real estate owned, including primarily real estate taken in settlement of problem loans, though some real estate investments by the bank (other than bank premises) are also included,

- OPAQUE the sum of: book value of bank premises and fixed assets, investments in unconsolidated subsidiaries, intangible assets (such as mortgage service right and core deposit intangibles), and the balance sheet category "other assets" (such as accounts receivable, repossessed autos, boats, and other collateral, margin account balances associated with forward and future contracts, and income earned but not collected)
- TRANSPARENT cash, interbank balances, federal funds sold, and securities purchased under agreement to resell

Note that these 11 asset categories exhaust the balance sheet.

Since the 2007–2009 financial crisis was set off by the bursting of the housing bubble, we pay special attention to balance sheet variables that capture a banking firm's exposure to the housing market, as well as to the so-called toxic assets. In addition to OREO and OPAQUE, we separate the real estate loan portfolio into RRELOAN that is secured by residential properties, including both first-lien mortgages and home equity line of credit, and CRELOAN.[14] As the financial crisis deepened, mortgage-related assets in banking firms' trading book and banking book were particularly vulnerable to information asymmetry and valuation uncertainty/disagreement.[15] We use three balance sheet variables – TRADE, AFS, and HTM – to capture a banking firm's securities holding.

In (9), leverage (MVLEV) is included for two reasons. First, it may affect a bank's microstructure properties. Second, previous researchers have found conflicting implications of leverage for firm opacity.[16] We also include three control variables used in regression (7), which are known to account for much of the variation in microstructure properties (Madhavan, 2000): firm size (LNMVEQ), the share price's inverse (PINV), and stock return volatility (STD). Quarterly summary statistics for the variables used in regression (9) are reported in Table 4.

We are interested in whether specific balance sheet categories are reliably related to opacity measures. In addition, the last four rows of these tables report test statistics for the following hypotheses:

H1. Asset composition (all asset shares, as a group) does not significantly contribute to measures of firm opacity.

H2. Asset composition and leverage (MVLEV) do not significantly contribute to measures of firm opacity.

H3. Price, firm size, and return volatility do not significantly contribute to measures of firm opacity.

H4. All regression coefficients are homogeneous across two sub-periods: 2003Q1–2007Q2 and 2007Q3–2009Q4.

Eq. (9) is estimated separately for the NASD and NYSE BHCs, using pooled time-series cross-section data. We report results that both exclude (Tables 5A and 5B) and include (Tables 6A and 6B) firm fixed effects.

The NASD BHC results in Table 5A reveal some interesting effects of individual asset classes on opacity measures. During the normal period from 2003Q1 to 2007Q2, residential real estate loan has an insignificant effect on AS, significantly negative effect on ESPREAD, and significantly negative effect on IMPACT, indicating that more residential real estate lending lowers the firm's opacity measures prior to the financial crisis. This suggests that during the normal period, investors considered residential mortgages and home equity loans to be easily understood and relatively transparent. However, during the financial crisis, which was largely triggered by the bursting of the housing

[14] Real estate loans that are secured by farm lands are included in OTHLOAN, which also includes all other agricultural loans.

[15] These include mortgage-backed securities and their derivative products, as well as structured investment vehicles that were previously off-balance sheet but bought back to the sponsoring banking firms' book during the crisis.

[16] Morgan (2002) and Iannotta (2006) find that split ratings are more likely for banks with lower capital ratios or higher capital ratios, respectively. FKN find mixed results about how capitalization affects opacity.

Table 4
Summary statistics for the financial variables included in the panel regressions, quarterly data, 2003Q1–2009Q4.

BHC financial variables
The following 10 balance sheet variables are measured at the end of quarter *t* and are deflated by the market value of equity at the end of the prior quarter:

RRELOAN	Loans secured by 1–4 family residential properties
CRELOAN	Loans secured by all other real estate, except farmland
CONLOAN	Loans to individuals for household, family, and other personal expenditures
OTHLOAN	All other loans
LLA	Loan loss allowance, a contra asset to the loan account
TRADE	Total trading account securities
AFS	Marketable securities available-for-sale
HTM	Marketable securities held to maturity
OREO	Other real estate owned, including primarily real estate taken in settlement of problem loans, though some real estate investments by the bank (other than bank premises) are also included
OPAQUE	The sum of: book value of bank premises and fixed assets, investments in unconsolidated subsidiaries, intangible assets (such as mortgage service right and core deposit intangibles), and the balance sheet category “other assets” (such as accounts receivable, repossessed autos, boats, and other collateral, margin account balances associated with forward and future contracts, and income earned but not collected)
MVLEV	Sum of liabilities’ book values at the end of quarter t plus equity’s market value at the end of quarter $t-1$, divided by equity’s market value at $t-1$

Microstructure (dependent) and control variables
These variables are defined in Table 1, which reports their monthly average values across 1993–2009. The variables’ quarterly averages are summarized here for the period 2003Q1–2009Q4

	NASD sample BHCs ($n = 7693$)					NYSE sample BHCs ($n = 1908$)				
	Mean	Std. dev.	Min.	Max.	Median	Mean	Std. dev.	Min.	Max.	Median
BHC financial characteristics										
RRELOAN	1.589	1.709	0.000	40.483	1.192	1.674	2.340	0.000	40.483	1.234
CRELOAN	3.194	3.709	0.000	58.926	2.284	1.843	3.697	0.000	58.926	1.141
CONLOAN	0.314	0.508	0.000	12.270	0.177	0.412	0.714	0.000	12.270	0.219
OTHLOAN	1.180	1.274	0.000	18.146	0.860	1.208	1.576	0.000	18.146	0.864
LLA	0.099	0.158	0.001	2.694	0.059	0.089	0.199	0.001	2.694	0.049
TRADE	0.013	0.115	0.000	3.570	0.000	0.122	0.353	0.000	3.960	0.002
AFS	1.534	1.514	0.001	26.460	1.156	1.508	2.126	0.016	31.604	1.042
HTM	0.187	0.511	0.000	12.324	0.010	0.309	0.787	0.000	12.324	0.012
OREO	0.031	0.129	0.000	2.548	0.004	0.024	0.144	0.000	2.548	0.003
OPAQUE	0.601	0.579	0.070	7.643	0.440	0.737	0.899	0.070	10.683	0.523
MVLEV	9.255	7.536	1.283	122.479	7.217	8.646	8.825	1.283	122.479	6.714
Microstructure (dependent) variables										
AS	1.327	1.182	0.024	6.003	0.967	0.544	0.891	0.010	4.892	0.181
ESPREAD	1.357	1.300	0.043	9.074	0.989	0.396	0.566	0.032	5.855	0.175
IMPACT	34.122	19.066	2.454	215.340	31.020	17.173	16.534	2.454	155.600	11.414
TOVER	0.263	0.395	0.014	7.399	0.139	0.597	0.740	0.014	7.399	0.362

Control variables										
PINV	0.062	0.054	0.011	0.479	0.047	0.047	0.043	0.011	0.468	0.036
LNMVEQ	12.273	1.255	8.979	17.327	12.096	14.602	2.099	9.847	18.696	14.649
STD	64.243	51.923	7.600	377.478	46.115	96.394	58.211	7.600	368.558	85.053
PRICE	22.860	11.750	2.090	89.080	21.360	31.800	17.830	2.140	89.080	28.130
MVEQ[a]	0.596	1.829	0.008	33.491	0.179	12.394	24.319	0.019	131.646	2.301

[a] Reported in billions of dollars.

Table 5A
NASD sub-sample: Balance sheet effects on microstructure variables, without firm fixed effects. Panel regression results of estimating Eq. (9) without firm fixed effects, robust standard errors in parentheses, quarterly time effect coefficients not reported.

	AS		ESPREAD		IMPACT		TOVER	
	03:Q1–07:Q2	07:Q3–09:Q4	03:Q1–07:Q2	07:Q3–09:Q4	03:Q1–07:Q2	07:Q3–09:Q4	03:Q1–07:Q2	07:Q3–09:Q4
RRELOAN	−0.062	0.062***	−0.079**	0.076**	−1.612**	−0.744*	−0.012	0.007
	(0.041)	(0.018)	(0.036)	(0.031)	(0.697)	(0.399)	(0.010)	(0.013)
CRELOAN	−0.115**	−0.007	−0.110***	0.002	−1.323*	−0.566	0.020*	0.013
	(0.046)	(0.019)	(0.039)	(0.026)	(0.681)	(0.363)	(0.011)	(0.014)
CONLOAN	−0.073	0.062	−0.069	0.131	−0.547	0.562	−0.042**	0.008
	(0.078)	(0.062)	(0.066)	(0.106)	(1.112)	(1.092)	(0.020)	(0.024)
OTHLOAN	−0.065	−0.020	−0.058	−0.046	−0.806	−0.731	−0.002	0.047**
	(0.048)	(0.026)	(0.044)	(0.045)	(0.840)	(0.454)	(0.013)	(0.019)
LLA	0.082	0.012	−0.162	−0.199	7.708	6.405	−0.199	0.319
	(0.876)	(0.274)	(0.761)	(0.423)	(14.465)	(5.000)	(0.296)	(0.263)
TRADE	−0.016	−0.117	−0.064	−0.001	−4.103	0.745	−0.086	0.210
	(0.252)	(0.183)	(0.196)	(0.326)	(3.323)	(2.301)	(0.053)	(0.139)
AFS	−0.036	0.021	−0.041	0.017	−0.413	0.270	0.001	−0.007
	(0.042)	(0.022)	(0.036)	(0.034)	(0.595)	(0.420)	(0.009)	(0.015)
HTM	−0.093	0.084*	−0.100*	0.054	−1.017	−1.607	0.030	0.031
	(0.059)	(0.050)	(0.051)	(0.082)	(0.931)	(1.164)	(0.026)	(0.032)
OREO	1.574	0.452***	1.649	1.187***	52.849**	3.710	−0.196	−0.216***
	(1.347)	(0.173)	(1.204)	(0.367)	(24.298)	(2.629)	(0.266)	(0.083)
OPAQUE	−0.132	−0.098	−0.125	−0.094	−0.098	−1.815	0.003	0.244***
	(0.093)	(0.074)	(0.085)	(0.111)	(1.542)	(1.453)	(0.033)	(0.063)
MVLEV	0.079**	−0.004	0.077**	−0.003	0.596	0.155	0.004	−0.012
	(0.038)	(0.014)	(0.032)	(0.021)	(0.544)	(0.273)	(0.008)	(0.010)
PINV(−1)	−1.196	−1.325*	1.507	0.001	−42.139**	−47.381***	0.404*	−0.316
	(1.058)	(0.794)	(1.012)	(1.156)	(16.548)	(16.658)	(0.232)	(0.545)
LNMVEQ(−1)	−0.530***	−0.756***	−0.463***	−0.784***	−8.481***	−12.712***	0.080***	0.306***
	(0.035)	(0.059)	(0.030)	(0.066)	(0.406)	(0.790)	(0.008)	(0.036)
STD(−1)	−0.001*	−0.008***	−0.001	−0.010***	0.133***	0.096***	0.001***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.011)	(0.013)	(0.000)	(0.000)
N	5351	2342	5351	2342	5351	2342	5351	2342
Adj-R^2	0.614	0.749	0.618	0.735	0.469	0.454	0.338	0.545
Adj-R^2: Just Fin	0.161	0.244	0.179	0.287	0.087	0.065	0.091	0.187
Adj-R^2: Just MM	0.553	0.647	0.580	0.604	0.402	0.335	0.266	0.420
H1: Pr(all 10 BS = 0)	0.130	0.001	0.067	0.000	0.130	0.065	0.000	0.003

H2: Pr(all 11 Fin = 0)	0.140	0.002	0.082	0.000	0.156	0.007	0.000	0.000
H3: Pr(all 3 MM = 0)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
H4: sub-period homogeneity	0.000	0.000	0.000	0.000				

* Indicates significance at the 10% levels.
** Indicates significance at the 5% levels.
*** Indicates significance at the 1% levels.

Table 5B
NYSE sub-sample: Balance sheet effects on microstructure variables, without firm fixed effects. Panel regression results of estimating Eq. (9) without firm fixed effects, robust standard errors in parentheses, quarterly time effect coefficients not reported.

	AS		ESPREAD		IMPACT		TOVER	
	03:Q1–07:Q2	07:Q3–09:Q4	03:Q1–07:Q2	07:Q3–09:Q4	03:Q1–07:Q2	07:Q3–09:Q4	03:Q1–07:Q2	07:Q3–09:Q4
RRELOAN	−0.027	0.007	−0.052*	0.010	−1.138**	0.363	0.035	−0.038
	(0.047)	(0.014)	(0.030)	(0.016)	(0.527)	(0.401)	(0.023)	(0.042)
CRELOAN	−0.114**	−0.004	−0.076***	−0.002	−1.742***	0.214	0.010	0.005
	(0.054)	(0.014)	(0.028)	(0.016)	(0.576)	(0.352)	(0.022)	(0.037)
CONLOAN	−0.072	0.031	0.050	0.031	0.756	1.690	−0.117	−0.059
	(0.167)	(0.040)	(0.074)	(0.045)	(1.606)	(1.232)	(0.077)	(0.105)
OTHLOAN	−0.062	0.001	−0.070*	0.005	−1.853**	−0.385	−0.047	0.077
	(0.088)	(0.018)	(0.042)	(0.021)	(0.875)	(0.459)	(0.048)	(0.055)
LLA	0.428	−0.295	1.051	−0.221	66.194**	−7.735	0.508	1.837***
	(3.053)	(0.261)	(1.331)	(0.272)	(31.198)	(7.479)	(1.041)	(0.509)
TRADE	0.546***	0.128**	0.425***	0.149**	5.785***	3.101**	−0.019	0.277
	(0.168)	(0.056)	(0.116)	(0.064)	(2.099)	(1.424)	(0.107)	(0.212)
AFS	−0.040	−0.001	−0.045	0.005	−0.179	−0.109	0.031	0.019
	(0.050)	(0.012)	(0.029)	(0.015)	(0.502)	(0.359)	(0.029)	(0.038)
HTM	−0.141**	−0.088**	−0.138***	−0.087**	−1.870*	−1.629*	0.088*	−0.000
	(0.063)	(0.033)	(0.042)	(0.035)	(0.960)	(0.852)	(0.049)	(0.059)
OREO	−0.681	0.661**	0.445	0.580*	16.493	8.778	−0.195	−1.600**
	(4.037)	(0.290)	(1.580)	(0.306)	(43.215)	(5.715)	(1.624)	(0.775)
OPAQUE	−0.134	0.012	−0.074	0.032	−4.355**	0.065	0.057	0.257
	(0.163)	(0.034)	(0.098)	(0.037)	(2.104)	(1.000)	(0.082)	(0.168)
MVLEV	0.034	0.000	0.036*	−0.006	0.623	0.064	−0.021	−0.024
	(0.032)	(0.006)	(0.019)	(0.007)	(0.419)	(0.148)	(0.019)	(0.016)
PINV(−1)	−3.662*	0.509	2.202*	1.254	−46.355	−41.316	0.340	0.859
	(1.926)	(1.110)	(1.293)	(1.246)	(30.991)	(29.393)	(0.837)	(1.750)
LNMVEQ(−1)	−0.316***	−0.279***	−0.178***	−0.282***	−4.733***	−8.631***	0.046***	0.156***
	(0.036)	(0.035)	(0.020)	(0.042)	(0.317)	(0.847)	(0.011)	(0.036)
STD(−1)	−0.002***	−0.006***	−0.000	−0.006***	0.023***	−0.046	0.001***	0.002*
	(0.000)	(0.001)	(0.000)	(0.002)	(0.007)	(0.028)	(0.000)	(0.001)
N	1354	554	1354	554	1354	554	1354	554
Adj-R^2	0.464	0.639	0.578	0.583	0.562	0.660	0.314	0.574
Adj-R^2: Just Fin	0.197	0.138	0.212	0.104	0.213	0.196	0.131	0.460
Adj-R^2: Just MM	0.391	0.541	0.497	0.477	0.472	0.563	0.208	0.308
H1: Pr(all 10 BS = 0)	0.000	0.001	0.000	0.005	0.001	0.015	0.222	0.000

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H2: Pr(all 11 Fin = 0)	0.000	0.000	0.000	0.000	0.001	0.000	0.260	0.000
H3: Pr(all 3 MM = 0)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
H4: sub-period homogeneity	0.003	0.000	0.000	0.000				

[*] Indicates significance at the 10% levels.
[**] Indicates significance at the 5% levels.
[***] Indicates significance at the 1% levels.

Table 6A
NASD sub-sample: Balance sheet effects on microstructure variables, with firm fixed effects. Panel regression results of estimating Eq. (9) with firm fixed effects, robust standard errors in parentheses, quarterly time effect coefficients not reported.

	AS		ESPREAD		IMPACT		TOVER	
	03:Q1–07:Q2	07:Q3–09:Q4	03:Q1–07:Q2	07:Q3–09:Q4	03:Q1–07:Q2	07:Q3–09:Q4	03:Q1–07:Q2	07:Q3–09:Q4
RRELOAN	−0.083*	0.010	−0.018	0.049*	−0.391	−0.252	0.025	0.008
	(0.050)	(0.019)	(0.042)	(0.026)	(0.951)	(0.454)	(0.021)	(0.015)
CRELOAN	0.012	0.019	0.027	0.016	0.182	0.269	0.004	−0.024
	(0.049)	(0.017)	(0.042)	(0.024)	(0.797)	(0.349)	(0.016)	(0.017)
CONLOAN	−0.022	0.014	−0.094	0.055	−3.224	1.340	0.023	0.046
	(0.125)	(0.048)	(0.121)	(0.074)	(2.647)	(0.951)	(0.037)	(0.050)
OTHLOAN	−0.045	−0.032	0.008	−0.118**	2.688**	0.180	0.008	0.054*
	(0.072)	(0.030)	(0.054)	(0.046)	(1.107)	(0.562)	(0.026)	(0.032)
LLA	0.558	−0.002	−0.117	−0.039	−41.455*	3.647	0.375	0.380*
	(1.072)	(0.204)	(0.871)	(0.371)	(24.362)	(4.145)	(0.439)	(0.223)
TRADE	−0.295***	−0.402***	−0.271**	−0.306	−2.460	−2.750	−0.006	0.234
	(0.099)	(0.100)	(0.106)	(0.232)	(3.613)	(2.910)	(0.033)	(0.270)
AFS	−0.008	−0.007	−0.013	0.011	−0.129	0.234	0.030	−0.016
	(0.038)	(0.028)	(0.031)	(0.044)	(0.635)	(0.445)	(0.020)	(0.015)
HTM	−0.039	0.037	−0.041	0.035	−0.055	−1.171	0.024	−0.009
	(0.063)	(0.062)	(0.052)	(0.088)	(1.151)	(1.679)	(0.020)	(0.039)
OREO	2.375*	0.276	1.954*	0.913***	26.501	−2.668	0.173	−0.118*
	(1.408)	(0.177)	(1.119)	(0.247)	(24.961)	(3.226)	(0.355)	(0.063)
OPAQUE	−0.065	−0.140*	−0.132	−0.141	−1.801	−2.631*	−0.034	0.171**
	(0.115)	(0.073)	(0.097)	(0.113)	(2.213)	(1.516)	(0.049)	(0.072)
MVLEV	0.012	−0.006	0.007	−0.007	0.392	−0.050	−0.008	−0.004
	(0.033)	(0.013)	(0.027)	(0.017)	(0.531)	(0.239)	(0.015)	(0.007)
PINV(−1)	−4.471***	3.236***	−1.981	2.781**	−118.110***	−32.918**	0.643*	−1.514***
	(1.348)	(0.710)	(1.218)	(1.205)	(26.805)	(15.022)	(0.347)	(0.555)
LNMVEQ(−1)	−0.644***	−0.608***	−0.511***	−0.910***	−8.212***	−6.416***	0.121***	0.000
	(0.072)	(0.112)	(0.066)	(0.150)	(1.545)	(2.384)	(0.030)	(0.071)
STD(−1)	0.002***	−0.002***	0.002***	−0.004***	0.135***	0.094***	−0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.010)	(0.011)	(0.000)	(0.000)
N	5351	2342	5351	2342	5351	2342	5351	2342
Adj-R^2	0.797	0.890	0.802	0.860	0.589	0.581	0.675	0.793
Adj-R^2: Just Fin	0.737	0.824	0.752	0.765	0.445	0.349	0.606	0.780

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Adj-R^2: Just MM	0.756	0.836	0.776	0.775	0.529	0.463	0.636	0.761
H1: Pr(all 10 BS = 0)	0.027	0.000	0.189	0.000	0.231	0.463	0.605	0.264
H2: Pr(all 11 Fin = 0)	0.038	0.000	0.246	0.000	0.301	0.526	0.551	0.189
H3: Pr(all 3 MM = 0)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.017
H4: sub-period homogeneity	0.000	0.000	0.000	0.000				

* Indicates significance at the 10% levels.
** Indicates significance at the 5% levels.
*** Indicates significance at the 1% levels.

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Table 6B

NYSE sub-sample: Balance sheet effects on microstructure variables, with firm fixed effects. Panel regression results of estimating Eq. (9) with firm fixed effects, robust standard errors in parentheses, quarterly time effect coefficients not reported.

	AS		ESPREAD		IMPACT		TOVER	
	03:Q1–07:Q2	07:Q3–09:Q4	03:Q1–07:Q2	07:Q3–09:Q4	03:Q1–07:Q2	07:Q3–09:Q4	03:Q1–07:Q2	07:Q3–09:Q4
RRELOAN	0.036	0.005	−0.018	0.009	−0.804	−0.093	0.028	0.011
	(0.129)	(0.009)	(0.032)	(0.011)	(0.967)	(0.302)	(0.025)	(0.040)
CRELOAN	0.074	0.039***	0.008	0.014	−0.984	0.503*	0.004	−0.051
	(0.078)	(0.011)	(0.039)	(0.009)	(1.103)	(0.289)	(0.029)	(0.037)
CONLOAN	−0.209	0.017	−0.044	−0.037	4.615	−0.552	−0.061	0.049
	(0.495)	(0.034)	(0.080)	(0.032)	(4.734)	(0.815)	(0.071)	(0.073)
OTHLOAN	−0.213	−0.005	−0.185***	−0.008	−4.919**	−0.781	0.012	0.056
	(0.179)	(0.017)	(0.060)	(0.021)	(2.204)	(0.510)	(0.038)	(0.054)
LLA	1.372	−0.281	2.316	−0.066	91.619*	−3.257	0.656	1.154*
	(4.625)	(0.185)	(1.514)	(0.208)	(51.859)	(3.974)	(0.711)	(0.669)
TRADE	0.030	−0.074*	0.084	−0.065	−2.866	−3.536**	0.066	0.883***
	(0.182)	(0.042)	(0.121)	(0.065)	(2.821)	(1.558)	(0.056)	(0.307)
AFS	0.087	−0.000	−0.007	−0.005	0.208	−0.219	0.023	−0.043
	(0.088)	(0.011)	(0.026)	(0.012)	(0.927)	(0.475)	(0.027)	(0.041)
HTM	0.243	−0.012	−0.064*	−0.037	−3.640***	0.557	0.107**	−0.124
	(0.167)	(0.022)	(0.036)	(0.025)	(1.172)	(0.906)	(0.042)	(0.083)
OREO	−12.534*	−0.101	−1.632	−0.037	−1.128	−4.636	1.518	−0.133
	(7.455)	(0.157)	(1.432)	(0.184)	(48.138)	(8.473)	(1.254)	(0.766)
OPAQUE	0.128	−0.026	0.021	−0.038	−1.776	−0.736	0.093*	0.210
	(0.237)	(0.018)	(0.100)	(0.027)	(2.739)	(0.549)	(0.056)	(0.154)
MVLEV	0.003	0.002	0.026	0.003	0.659	0.256	−0.031*	−0.024*
	(0.040)	(0.005)	(0.021)	(0.005)	(0.493)	(0.202)	(0.016)	(0.013)
PINV(−1)	2.513	1.232	0.622	0.863	−41.816	−15.586	−1.481	−0.116
	(2.205)	(0.744)	(0.802)	(0.877)	(33.345)	(24.948)	(0.955)	(2.010)
LNMVEQ(−1)	0.352*	−0.079	−0.087	−0.336**	−4.359*	−5.809*	−0.084	−0.531**
	(0.179)	(0.065)	(0.083)	(0.150)	(2.342)	(3.130)	(0.069)	(0.215)
STD(−1)	0.000	−0.002**	0.001***	−0.002**	0.038***	0.019	0.000	0.002**
	(0.001)	(0.001)	(0.000)	(0.001)	(0.007)	(0.026)	(0.000)	(0.001)
N	1354	554	1354	554	1354	554	1354	554
Adj-R^2	0.644	0.916	0.804	0.877	0.705	0.845	0.760	0.811
Adj-R^2: Just Fin	0.589	0.898	0.790	0.845	0.639	0.746	0.720	0.737
Adj-R^2: Just MM	0.583	0.891	0.792	0.848	0.668	0.792	0.699	0.649

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H1: Pr(all 10 BS = 0)	0.686	0.000	0.019	0.000	0.009	0.000	0.043	0.000
H2: Pr(all 11 Fin = 0)	0.687	0.000	0.030	0.000	0.013	0.000	0.030	0.000
H3: Pr(all 3 MM = 0)	0.219	0.085	0.006	0.073	0.000	0.029	0.239	0.001
H4: sub-period homogeneity	0.564		0.002		0.000		0.000	

* Indicates significance at the 10% levels.
** Indicates significance at the 5% levels.
*** Indicates significance at the 1% levels.

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bubble, residential real estate lending has a significantly positive effect on both AS and ESPREAD. While RRELOAN remains significantly negative in the IMPACT regression, the point estimate fells by more than one-half.

OREO, which includes repossessed real estate assets, is insignificant in explaining both the AS and the ESPREAD before the crisis, but significantly positive during the crisis. OREO has a significantly positive effect on IMPACT during the normal period, but it carries an insignificant coefficient during the crisis period. Commercial real estate loans (CRELOAN) CRELOAN has a significantly negative effect on AS, ESPREAD, and IMPACT before the crisis, which seems surprising. During the crisis, CRELOAN no longer serves to reduce NASD bank opacity.

Other balance sheet variables exhibit no strong effects on NASD banks' opacity. Yet balance sheet composition matters: the hypothesis that asset composition does not affect the microstructure variables of NASD banks is rejected for all four opacity measures during the later (crisis) period, and for ESPREAD and TOVER during the normal period. The last row in Table 4 indicates that the hypothesis of sub-period homogeneity is rejected for all four opacity measures, consistent with the theory of asset opacity.

Some of the results for NYSE BHC in Table 5B look qualitatively similar to the NASD results. Residential real estate lending (RRELOAN) tends to reduce ESPREAD and IMPACT before the financial crisis, but becomes insignificant after the housing bubble burst. OREO also raises AS and ESPREAD during the financial crisis, even though it has insignificant effect during the normal period. Similar to NASD BHC, we also find CRELOAN reduces AS, ESPREAD, and IMPACT during the normal period, but becomes insignificant during the crisis. However, results for NYSE BHC securities holdings differ from the NASD banks'. TRADE has a significantly positive effect on all three NYSE BHC opacity measures (AS, ESPREAD, and IMPACT), during both the normal period and the crisis period. Conversely, the hold-to-maturity securities in NYSE BHCs' banking book (composed mostly of Treasuries and agency debts) carry significantly negative coefficients in both subperiods. The effects of investment securities on opacity, therefore, seem qualitatively similar before and during the crisis.

At the bottom of Table 5B, the hypothesis that the balance sheet composition does not matter is rejected for AS, ESPREAD, and IMPACT, for both time periods; it is rejected for TOVER during the crisis. The hypothesis of sub-period homogeneity is also rejected by the data. We conclude from Tables 5A and 5B that balance sheet composition affects banking firms' opacity differently before and during the financial crisis. While pinning down the source of opacity is challenging, the way that the balance sheet effects changed during the financial crisis is consistent with the significant role of residential housing in this crisis. Although large, complex financial institutions occupied center stage in the financial meltdown of 2008, our estimated balance sheet effects on opacity do not vary qualitatively between the NYSE and NASD subsamples.

Tables 6A and 6B reports the results of estimating equation (9) with firm fixed-effects, which reduce the number of balance sheet variables carrying significant coefficients (relative to Tables 5A and 5B). Presumably, some banks operated with relatively stable portfolio compositions. (As one example, trading account securities significantly raise opacity measures in Table 5B, but their significance is eliminated by the firm fixed effects in Table 6B.) The overall findings, however, are qualitatively similar; the presence or absence of fixed effects has no great effect on our conclusions about the joint significance of asset shares or the hypothesis that there was no shift in regression coefficients between the pre-crisis period and the 2007Q3–2009Q4 "crisis" period.

6. Conclusions

In the banking literature, the fragility of a banking firm's liability structure can give rise to a "runs" equilibrium if outsiders become uncertain about the bank's solvency. Opaque, difficult-to-value assets increase the possibility of runs because they create uncertainty about how other depositors will evaluate solvency. Theory indicates that a fall in bank asset values will increase the opacity of its equity. If opacity increases when bank equity cushions decline, banks are doubly exposed to the possibility of destabilizing runs. Many of the policy actions implemented during the 2007–2009 financial crisis were intended to head off the runs motivated by potentially self-fulfilling beliefs about bank solvency.

Our analysis shows that this is not a remote, theoretical possibility. Over our 17-year sample period (1993–2009), banks are not qualitatively more opaque than matched nonfinancial firms during "normal" time periods: both our (smaller) NASD banks and our (larger) NYSE banks exhibit somewhat larger spreads but lower price impact. Evidence about the banks' relative opacity is thus mixed for normal time periods. We identified two "crisis" periods–the LTCM crisis in late 1998 and the recent financial crisis (starting in mid-2007). During these periods, the NASD banks' spreads and price impact measures increased substantially, consistent with a rise in their relative opacity. The NYSE banks exhibit unmitigated increases in both spreads and price impact during the recent crisis, but their microstructure response to the LTCM crisis is mixed: their spreads fell significantly while their impact measure rose. Somewhat surprisingly, therefore, the LTCM crisis seems to have affected smaller banks more prominently than larger ones. The general pattern of time-varying relative bank opacity is troubling, since it suggests a reduction in bank stability during crisis periods, even beyond the obvious deterioration in bank balance sheet values.

We also regress banks' market microstructure measures on bank balance sheet composition in an effort to assess whether some asset classes are measurably more opaque than others. We do find that asset composition affects opacity measures, but identifying the specific asset classes causing this sensitivity is challenging. The exact mechanism and the channels through which bank opaqueness manifests into market microstructure characteristics therefore remain an important area for further research.

One clear implication of our analysis is that a researcher's ability to find evidence that banking firms are opaque depends on the sample period examined. More importantly, our results suggest some specific policy actions that might stabilize the banking system at crucial times. First, the central bank's lending facility has a crucial role in responding to bank runs. Runs are encouraged by cyclical increases in asset opacity. If the central bank confirms, by lending, that the bank appears solvent, private claimants may choose not to run. Second, to the extent that capital and transparency substitute for one another in forestalling runs, banks should be encouraged to maintain sufficient capital that their solvency is not questioned in a crisis. Note that this recommendation somewhat contradicts Basel's contra-cyclical capital ratios, which are designed to assure that banks continue lending even during downturns. Further research is needed to determine how to balance these two forces on the banking system. Finally, our results suggest that regulators should continue encouraging banks to become more transparent about their exposures and their method of assessing risks. If transparency can be maintained even in crisis situations, the danger of runs against truly solvent banks will be severely reduced. Our results indicate that being transparent during normal times is not sufficient, however: banks must take steps to assure that transparency persists even as asset values (and hence equity ratios) fall.

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