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# The 2007-09 Financial Crisis and Bank Opaqueness

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## The 2007-09 Financial Crisis and Bank Opaqueness

### ABSTRACT

Doubts about the accuracy with which outside investors can assess a banking firm's value motivate many government interventions in the banking market. The recent financial crisis has reinforced concerns about the possibility that banks are unusually opaque. Yet the empirical evidence, thus far, is mixed. This paper examines the trading characteristics of bank shares over the period from January 1990 through September 2009. We find that bank share trading exhibits sharply different features before vs. during the crisis. Until mid-2007, large (NYSE-traded) banking firms appear to be no more opaque than a set of control firms, and smaller (NASD-traded) banks are, at most, slightly more opaque. During the crisis, however, both large and small banking firms exhibit a sharp increase in opacity, consistent with the policy interventions implemented at the time. Although portfolio composition is significantly related to market microstructure variables, no specific asset category(s) stand out as particularly important in determining bank opacity.

## **I. Introduction and motivation**

The epicenter of the recent financial market turmoil had been the financial services industry. 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.

However, market participants apparently became unsure about the composition and exposures 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. At the height of the financial crisis, even financial institutions themselves were reluctant to lend to each other, as evidenced by the severe dislocation in the interbank funding market (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 sheet. 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 impaired assets. Furthermore, this kind of information asymmetry could lead outside investors to undervalue the banking firm's equity in a pooling equilibrium, making it expensive for the banking firm 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. First, the Troubled Asset Relief

Program (TARP) buttressed specific banks' capital positions. Later, the Public-Private Investment Program (PPIP) was introduced to help cleanse banking firms' balance sheets. In the spring of 2009, federal regulators undertook a unique Supervisory Capital Assessment Program, or "stress test" to assess the solvency of a set of the largest financial institutions. Market investors apparently viewed the stress tests as reducing uncertainty. Following the release of the stress test results in May of 2009, the banking sector stabilized and several large institutions successfully issued new equity. While some banking firms issued equity to satisfy regulatory requirements upon 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) argued 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 interpreted 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 affect 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. However, the European evidence differs from Morgan's U.S. findings in several ways. Iannotta does not find insurance companies to be more opaque. He also identifies three industries (construction, "energy and utility", and "other") with more splits than the banking industry (see his Table 3), raising some question about the true implication(s) of split bond ratings.

Flannery, Kwan and Nimalendran (2004) (henceforth referred to as FKN) compared banks' and nonbanks' equity market microstructure properties and analysts' earnings forecasts. During the 1990-97 period, they find statistically and economically significant differences between banks' and non-financial firms' microstructure properties only for the NASD-traded firms. Specifically, they find smaller

NASD bank stocks were traded much less frequently than a comparable nonbank, despite having comparable bid-ask spreads. They also find that NASD bank stocks exhibit substantially lower return volatilities and that analysts predict their earnings more accurately. They conclude that the assets of NASD banks were not unusually opaque but simply boring. In contrast, the larger bank stocks (traded in the NYSE/AMEX) 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.<sup>1</sup>

It is important to note that FKN examined banking firms during a relatively tranquil time period. It seems quite plausible that 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. It is therefore important that the sample period for this paper (1990:1 to 2009:9) includes several stressed periods (the early 1990s, LTCM in late 1998, and the recent financial crisis) as well as periods of tranquility (even euphoria!). Furthermore, the Gramm-Leach-Bliley Act of 1999 expanded the scope of permissible BHC activities. During the recent crisis, some of the uncertainty was associated with activities outside banks' traditional lines of business. Thus, the earlier U.S. evidence – mixed as it is – may be less relevant to the current banking system, at least at 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 broad financial conditions? Can we link opacity to specific features of a bank's asset portfolio? To answer these questions, we compare equity market trading patterns of banks and nonbanking firms. A primary idea from the market microstructure literature is that a firm's equity

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<sup>1</sup> A recent paper by Morgan et al. (2010) examines market reactions to various announcements about the 2009 stress test. 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 (apparently) under-capitalized institutions. Their methodology permits no comparison between banking and other firms.

trading properties reflect the nature of information available to market participants. A higher bid-ask spread, for example, is associated with a greater possibility that some traders have information unknown to other traders. A market-maker therefore quotes a higher spread to protect himself from losing money when trading with informed counterparties. The extent to which trades have a permanent effect on a stock's value reflects the relative importance of informed (vs. uninformed) traders in the market (Kyle (1985)). Holding constant the bid-ask spread, trading volume should rise with differences of opinion about a firm's value, and greater opacity may either broaden or narrow differences of opinion.

In this study, we pursue two lines of inquiry. First, we match traded bank holding companies (BHCs) to nonfinancial firms with similar equity values and prices per share, and compare their market microstructure properties over the period 1990:1 through 2009:9. 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 adverse selection spreads are relatively higher, but their price impacts are lower than their nonfinancial control firms. Given their lower trading volume and share price volatility, we conclude that NASD banks also are no more opaque than their control firms during normal periods.

However, during the 2007-09 financial crisis, results of comparing microstructure properties between bank and nonbanks are very different. Both the spreads and price impacts of BHC stocks are significantly higher than nonbanks, consistent with a sharp increase in opacity in banking firms. It thus appears that bank opacity varies over time.

Second, we investigate whether the higher BHC opacity during the financial crisis is related to bank asset holdings. We perform regression analysis to assess whether a bank's portfolio composition has any effects on opacity. While we find asset composition has significantly different effects on bank opacity during the financial crisis, the portfolio source of opacity, however, is somewhat difficult to pin down.

The rest of this paper is organized as follow. Section II discusses information and equity trading properties. Data and descriptive statistics are presented in Section III. Section IV provides the results of the comparisons of market microstructure properties between banking firms and control firms. Section V presents evidence about the effects of bank portfolio composition on measures of bank opaqueness. Section VI concludes.

## **II. Information and equity trading properties**

The motivation for examining market microstructure properties can be found in Demsetz (1968), who demonstrated that a stock's bid-ask spread is systematically related to several of its trading properties. Bagehot (1971) argues that one of these properties should be the potential for 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 (1984) model that estimates the bid-ask spread using the serial covariance of transaction price returns motivated a series of empirical methods for decomposing a stock's bid-ask spread into logically distinct components (see, for example Glosten and Harris (1988), Stoll (1989), George et al. (1991), Huang and Stoll (1994), and Lin et al. (1995)). A stock's bid-ask spread covers several distinct costs of 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 with liquid markets. The cost of holding this inventory includes both the time value of invested capital and a risk premium for bearing nondiversifiable risk. The third spread component reflects a market maker's information asymmetry, and requires a bit more explanation to relate it to the notion of asset opacity.

Market makers effectively write options to traders when they post bid and ask prices. The market maker expects his offer to be "hit" by informed traders more frequently if the bid price is too high or the ask price is too low. The greater the potential supply of private information about a stock,



the larger will be the adverse selection (AS) cost of trading it. 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 two 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. This may be particularly important for banking firms, whose underwriting and loan monitoring abilities affect value but may be difficult for outsiders to observe. Kyle (1985) therefore concludes that a "more opaque" asset should trade with a larger bid-ask spread.

Although the AS component of a stock's bid-ask spread constitutes an ideal measure of information asymmetry, it cannot be observed and must be estimated (with error) by fitting transactions and quote data to a specific model. For robustness, we also use a stock's effective spread (defined below) as measures of adverse selection.<sup>2</sup> This implicitly assumes that market makers have about the same operating costs for all stocks, so cross-sectional variation in their effective spreads captures variation in the adverse selection cost of trading.

Another measure of opacity comes in the form of price impact. The price impact is designed to capture the permanent (as opposed to the transient) component of the price change due to trades. In the Kyle (1985) model the price impact is the coefficient  $\lambda$  which is the ratio of the informed trader's information to noise trader variance. Hence, if there is relatively more information in the informed

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<sup>2</sup> Note that the bid-ask spread's components likely are interrelated with other facets of the stock's trading patterns. For example, if information asymmetry leads to a higher spread, trading volume could fall and hence the market-makers' order processing costs might rise.

agent's trade, then the market maker will adjust the price more aggressively as she extracts more information regarding prices from the trade. Note that in the Kyle model there is no bid/ask spreads. It is more like the NYSE specialist market. Where orders are submitted and the market maker sets the price after seeing the order flow. The price impact measure that we use is not exactly the Kyle lambda (we do not have this for the 1990-92 period). We estimate the absolute price change divided by the volume traded. This is similar to the Amihud(2002) measure and is a proxy for illiquidity and is related to the price impact coefficient  $\lambda$  in Kyle (1985). We argue that an opaque asset would be less liquid, *ceteris paribus*, as less informed traders will be more reluctant to trade; hence in theory our price impact measure would be a good direct measure of opacity.

We also examine two additional trade dimensions whose measurement is more straightforward than the preceding three (direct) measures of opacity. First, trading volume could either rise or fall with asset opacity. In theory, a perfectly opaque asset could be very liquid. 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) should then discourage uninformed traders from holding a 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 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)). So to the extent that more opaque firms are subject to greater differences of opinion, trading volume might be positively related to opacity.

It is an old Wall Street adage that "It takes volume to make prices move." Karpoff (1987) reviews the literature on the relation between volatility and trading volume in financial markets. He

finds that volume is positively related to the (absolute) magnitude of the price change, and, in equity markets, to the price change *per se* (*positive changes are related to higher volume*). He also provides a summary of other research in this field. Bessembinder (1996) investigates the relation between volume and proxies for information flow and divergences in opinions. He finds that volume in individual stocks are related to firm specific information flows consistent with Kyle (1985) model of strategic trading. This suggests that volume should be related to Kyle's measure of price impact which in turn is related to information asymmetry and opacity.

The final measure for opacity we consider is the stock return volatility. There are two origins for stock volatility: *Fundamental volatility* arises from permanent changes in the price due to unexpected changes in the value of the asset. This can again be split into a component that is due to *public information* and another component that arises from the *price discovery that is inferred from the informed trading*. Further, the informed traders will exert pressure on prices through their trading activity and this will change prices during high trading volume days. Hence, the fundamental volatility will be correlated with the AS component of the spread. *Transitory volatility* is due to trading activities by uninformed, liquidity, or noise traders, and market frictions such as bid/ask bounce. The changes in price due to these types of traders are subsequently reversed and hence the volatility is transitory in nature. Transitory volatility is related to the costs of trading for uninformed traders and is likely to be very small in very liquid markets (in our case for large firms). We therefore use return volatility as another indicator of opacity, which could be a particularly good proxy when there is an *episodic volatility* event such as the financial crisis.

To summarize, we measure information opacity using five variables informed by market microstructure theories. They are: (1) the adverse selection component of bid-ask spread, (2) the effective spread, (3) the price impact, (4) trading volume, and (5) stock return variability.<sup>3</sup>

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<sup>3</sup> Equity trading arrangements have changed substantially over the past two decades, in ways that might affect the measured values of microstructure variables. First, in April 2001 the SEC required that NASD and NYSE prices

According to theory, more opaque firms may have a higher reading in one or more of these opacity measure(s), *ceteris paribus*. However, inter-relationships among the microstructure variables complicate their interpretation. For example, trading volume is positively correlated with return volatility (Karpoff (1987), Jones et al. (1994)). Lower turnover is expected to raise a market-makers operating costs by lengthening the amount of time s/he must hold shares in inventory. Low volatility may have the opposite effect, by reducing the risk of inventory positions.<sup>4</sup> While the effects of both turnover and volatility should be reflected in ESPREAD, they should not in theory enter into the computation / estimation of the adverse selection component of spread.

Among the three direct indicators of firm opacity, we have a slight preference for relying on the price impact measure. It is arguably less prone to endogeneity issues, and less model-specific. According to Kyle (1985), trades by informed traders will move the stock price towards its (unobserved) fundamental value, while uninformed (“noise”) trades are not expected to have lasting impact on prices.

### III. Data

We identified a sample of publicly traded bank holding companies (BHCs) that file the Federal Reserve’s Consolidated Financial Statements for Bank Holding Companies (FR Y-9C). We then examined ISSM (for 1990-92) and TAQ (post-1992) transactions data for these BHCs, and eliminated firms with insufficient trades to permit reliable estimates of the firm’s market microstructure properties.<sup>5</sup> In particular, we omitted any BHC-quarter for which the stock had fewer than 100 trades, the average

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be quoted in decimal increments or pennies. Bid-ask spreads fell substantially, as did quoted depth (Bessembinder, 2003). As posted depths fell, however, 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.

<sup>4</sup> The effect of STD depends on the systematic vs. nonsystematic composition of total volatility.

<sup>5</sup> We omit data for the first three months of 1993, when our TAQ dataset had very few bank observations.

quoted spread exceeded 10% of the share's price, or the average share price was less than \$2. We also omit any firm-quarter in which the stock had a split or paid a stock dividend greater than 10%, because research suggests significant microstructure changes following a split (Desai et al. (1998)). The final sample consists of more than 55,000 firm-quarters for NASD banks and 14,500 firm-quarters for NYSE banks.

In order to compare bank stocks' trading characteristics to those of nonfinancial firms, we match each sample BHC with a control firm on the basis of equity market value, share price, and trading venue (NASDAQ or NYSE). 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 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 proper trading venue, determine if its share price is within 25% of the BHC's, and so forth. Each bank stock's control firm is re-selected at the start of each calendar year. We treat the firms that are traded on the NYSE separately from those that are traded on NASD, because the two markets have different trading arrangements.<sup>6</sup>

For each sample firm, we compute five 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. We start with three measures of information asymmetry derived from the stock price's dynamics.

- 1) AS: the adverse selection component of the bid-ask spread (as a proportion of share price), computed using all transactions for the day, as in George et al. (1991).
- 2) ESPREAD<sub>it</sub>: the effective spread for stock *i* reflects trades that occur inside the quoted spread. Specifically,

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<sup>6</sup> 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

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

where  $P_\tau$  = trade price,

$I$  = indicator equal to unity for a bid-initiated trade or zero for an ask-initiated trade (based on Lee and Ready (1991)).

$Q_\tau$  = the average of the bid and ask prices associated with the  $\tau^{\text{th}}$  trade,

$n$  is the number of trades within a day.

3) IMPACT: the permanent effect of a trade on share price Amihud (2002):

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

where  $\Delta P_t = LN(Q_{t+5} - Q_t)$ .

$Q_t$  and  $Q_{t+5}$  are the matched mid-quotes for the trade closest to five seconds prior to and five minutes after the trade.

$Size_t$  is the size of the trade or 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.

IMPACT should reflect the ratio of informed to uninformed traders in the market. Hence, a higher value for  $\lambda$  implies greater information asymmetry or opaqueness in the associated stock (Kyle (1985)).

4) Trading activity (TOVER), measured as the number of shares traded, divided by the average number of shares outstanding during the month.

5) Daily return volatility (%)

$$VOL = (STD) \times \sqrt{n} \times 100$$

where  $STD$  = standard deviation of the continuously compounded returns based on the quote midpoint associated with each trade within a day.

$n$  = the number of trades within a day.

These market microstructure variables' monthly summary statistics are presented in Table 1.

#### IV. Microstructure comparison between BHCs and control firms

We start with a set of monthly comparisons between BHCs and their matched (control) nonfinancial firms for five microstructure variables, over the full sample period (1990-1 through 2009-9).

Although we match on share price and firm market value at the start of each calendar year, the matched variable values can drift apart during the subsequent months. Because share price and firm size can affect some important microstructure variables (e.g. Madhavan (2000), page 205), we control for these effects and estimate the following regression:

$$\Delta M_{ijt} = \delta_0 + \delta_1(\Delta PINV_{it}) + \delta_2(\Delta LNMVEQ_{it}) + \mu_{ijt} \quad (1)$$

Where

$\Delta M_{ijt}$  denotes the  $j^{\text{th}}$  ( $j = \text{AS, ESPREAD, TOVER, VOL, IMPACT}$ ) BHC  $i$ 's 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.

The estimated value of  $\delta_0$  thus measures the mean excess BHC microstructure variable value over its control firm, after controlling for differences in share price and equity market value between the BHC and control. Equation (1) can be estimated as a pooled time series-cross section or as a series of (Fama-MacBeth (1973)) cross-sectional regressions. The panel regression results for the entire sample period and for several noteworthy sub-periods are reported in Table 2. The estimated intercept terms ( $\delta_0$ ) from monthly cross-sectional regressions are presented graphically in Figures 1 - 5, in which the NYSE and NASD sub-samples are examined separately because the market structures differ. In addition, some previous research has indicated that these two groups of BHCs differ in their opacity (FKN).

#### **A. Basic Patterns**

Figures 1A to 5A provide the monthly comparisons for NASD firms by charting the intercept term  $\delta_0$  in equation (1) separately for each of the five opacity measures. Figures 1A and 2A show that the adverse selection components of NASD BHCs' bid-ask spreads tend to be significantly higher than their controls. These differences are statistically significant primarily during the 2007-09 financial crisis. However, the price IMPACT measure in Figure 3A indicates that informed trading is less important for BHC than for their control firms. In Figures 4A and 5A, the price TOVER and VOL of NASD BHCs tend to

be significantly lower than their controls before the 2007-09 financial crisis. We are thus inclined to emphasize the IMPACT implication that NASD BHCs are relatively transparent. The relatively high ESPREAD could reflect the net effect of lower turnover and lower STD on the operating cost component of spreads, while the AS variable is based on a market-maker model that may be less relevant later in our sample period. The time variation in the microstructure variables in Figures 1A – 5A suggests that microstructure comparisons may vary over time, and across financial market conditions. The comparisons for NYSE BHCs and their controls differ somewhat from that of the NASD sub-sample. First, there is no indication in Figures 1B and 2B that NYSE-traded BHC have higher adverse selection costs: both the AS and the ESPREAD monthly differentials in Figures 1B and 2B are (virtually) always indistinguishable from zero.<sup>7</sup> The NYSE banks' price IMPACT measure in Figure 3B also differs insignificantly from zero, except for a few months during the crisis. (We deal explicitly with the crisis period below.) NYSE BHCs' TOVER tends to be somewhat smaller than their controls until the financial crisis, when trading volume increases substantially. NYSE banks' volatility (VOL) tends to be significantly smaller than the controls', and it falls quite substantially in the years preceding the crisis before rising rather sharply after mid-2007.

The basic patterns in Figures 1 – 5 indicate that large BHCs (traded on NYSE) exhibit very similar adverse selection parameters to their nonbank controls; NASD banks have higher AS but similar ESPREAD to their controls until the onset of the crisis. Before the crisis, NASD BHCs also tend to have lower IMPACT, TOVER, and VOL than nonbanks, consistent with our conclusion in FKN that NASD banks are “boring”.<sup>8</sup> More importantly, regarding large BHCs, the basic patterns (before the crisis) suggest the reverse of the fears most commonly expressed about these firms: that large banks are complex and their risk positions change rapidly, making them difficult to understand. Our results thus far indicate

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<sup>7</sup> Note that the NYSE spread measures are considerably smaller than their NASD counterparts'.

<sup>8</sup> The results in Panel F of Table 2 show that the microstructure variables during the subperiod 1990:1 to 1997:12, which is the sampling period in FKN, are broadly similar to the “normal” period in Panel E.



that the larger banks are followed and understood as well as other large firms are; opacity does not appear to be a big issue for them. Beyond these qualitative regularities, Figures 1 – 5 however also indicate a pronounced rise in bank opacity measures late in our study period. We now evaluate relative bank microstructure values during “crisis” and “non-crisis” periods.

#### B. Sub-period Results

The monthly intercept terms plotted in Figures 1 – 5 are free to vary between adjacent months. However, if opacity tends to change slowly, it would be more efficient to limit the month-to-month variation in our estimates. One way to do this is to estimate (1) as a panel regression by pooling over a subset of the months in the 1990-1 to 2009-9 sample period. Table 2 presents the results of these estimations. NASD (NYSE) firm results are shown in the left (right) half of the Table.

Panel A covers all 234 months in the sample period, so the estimated  $\delta_0$  coefficients measure the average excess of the BHC microstructure variables over the controls’ variable values. Given the information in Figures 1 – 5, it is not surprising that the NASD BHCs’ typical adverse selection component (AS or ESPREAD) is 18 – 19 bps higher than the control firms over the full sample period. IMPACT is significantly lower, conflicting with the opacity implications of higher AS and ESPREAD values. BHC TOVER averages 43.3% lower than the NASD control firms’, and VOL is also significantly lower (-16.9%). The NYSE results also conform closely to those presented in the Figures. Over the full sample period, NYSE BHCs’ AS and ESPREAD adverse selection measures exceed those of their peer firms by only a few basis points, although the differences are statistically significant. The average value of IMPACT does not differ significantly between the two groups of firms. Like their NASD counterparts, the NYSE BHCs exhibit significantly lower TOVER and VOL, although these differences are quite a bit smaller for the larger banks.

One of our key research questions is whether bank opacity changes over time and with broad financial market conditions. To address this question, Panels B, C, and D of Table 2 focus on sub-periods of potentially crisis-like conditions. During the 1990 recession, parts of the banking system suffered

severe losses largely due to exposures to commercial real estate; our first subperiod is 1990:1 to 1992:12 in Panel B. Panel C isolates the “LTCM Crisis” from 1998:8 to 1998:12. Finally, Panel D evaluates the opacity measures during the recent financial crisis from 2007:7 to 2009:9. During the first two crisis periods (Panels B and C), NASD banks exhibit somewhat higher adverse selection spreads but lower price IMPACT. Both their TOVER and VOL were significantly below that of their controls. In short, NASD banks exhibit typical microstructure variable values during 1990-92 and 1998. During these same sub-periods, NYSE banks exhibit few significant differences from their controls. IMPACT is significantly smaller in the early 1990s and TOVER is significantly smaller in late 1998. Thus, the evidence from the 1990s does not show NYSE banks to be unusually opaque during the 1990s’ stressed periods.

The recent crisis (2007:7 to 2009:9) is an altogether different situation.

### ***C. The 2007-09 Crisis***

Figures 1 – 5 illustrate a sharp increase in several of the opacity measures during the recent financial crisis. An interesting contrast emerges by comparing the recent crisis months (in Panel D) against the non-crisis months (in Panel E). Although the bank differentials are statistically significant for all microstructure variables in both sub-samples, the AS and ESPREAD differentials’ magnitudes more than double in the crisis months.<sup>9</sup> Furthermore, differential bank IMPACT changes from zero or negative (lower proportion of informed trading) during the normal months to significantly positive (greater informed trading) during the crisis. TOVER and VOL change little between the normal and crisis periods for the NASD banks, but their larger counterparts (on NYSE) move from TOVER and VOL values significantly below those of the controls to significantly higher.

Our comparisons of the opacity measures between banking and control firms show that most of the time, including the 1990 banking crisis and the 1998 LTCM crisis, banking firms do not seem to be more opaque than nonbank nonfinancial firms. Indeed, three of the opacity indicators, IMPACT, TOVER,

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<sup>9</sup> This is despite the fact that decimalization has generally reduced spreads over time. Hence, the baseline expectation would be that recent spreads are smaller than the 1993-2007 average.

and VOL suggest that banks are *less* opaque than nonbanks. However, the 2007-09 financial crisis is very different, and perhaps unique, in terms of banking firms' opacity. The AS, ESPREAD, and IMPACT of banks, both large (NYSE) and small (NASDAQ), are all found to be significantly higher than their controls. There is also evidence that both the TOVER and VOL for banks flip from being significantly below to being significantly above that of control firms.

## **V. 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.<sup>10</sup> We collect quarter-end financial variables from the Federal Reserve's Y-9C from 2003Q1 through 2009Q3, yielding 6,875 NASD and 1,690 NYSE bank-quarters. (The control firms play no role in this part of the analysis.) We also combine the monthly variables underlying Table 2 and Figures 1 – 5 into quarterly averages. 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' differential microstructure variable values changed most dramatically. Accordingly, we define the "normal" period of our sample as 2003Q1 through 2007Q2, and the crisis period as 2007Q3 – 2009Q3. 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 period.

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

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<sup>10</sup> For example, Morgan (2002) found that split ratings were more likely to happen at banks with low capital ratios or large trading portfolios. Flannery et al. (2004) concluded that opacity was related to a BHC's asset portfolio composition.

$$Y_{it} = \alpha_i + \sum_{k=1,5} \beta_k \frac{A_{kit}}{MVEQ_{i,t-1}} + \beta_6 MVLEV_{it} + \gamma_1 PINV_{i,t-1} + \gamma_2 LNMVEQ_{i,t-1} + \sum_y \chi_y Dy + \tilde{\varepsilon}_{it} \quad (2)$$

where  $Y_{it}$  is one of five market measure of the stock's information opacity measures defined above. The daily figures underlying monthly variables in regressions (1) (without the differencing over the control firm) are cumulated to quarterly when estimating (2).

$A_{kit}$  is the book value of assets of type  $k = 1, 5$  held by BHC  $i$  at the end of quarter  $t$ . A residual asset category 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  $TOVER$ .

$Dy$  is a dummy variable equal to unity in year  $y$ , otherwise zero. We include dummy variables for all years in the sample period except 2007.

The specification in (2) is motivated by the idea that outside investors cannot value all bank assets equally well. Each coefficient ( $\beta_k$ ,  $k = 1,5$ ) measures the difference between the  $k^{\text{th}}$  portfolio share's average effect on our opacity variables and the effect of the omitted ("RESIDUAL") portfolio share. A nonzero  $\beta_k$  coefficient is consistent with the banks' asset composition affecting their microstructure properties, such as opacity measures.

Given the prominence of real estate and trading-account securities in the recent crisis, we exhaustively separate bank assets into six categories:<sup>11</sup>

RRELOAN      loans secured by residential real estate,

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<sup>11</sup> An earlier version of this paper included a broader set of asset categories, some flow-related firm characteristics (e.g. profitability), and lagged microstructure variables. The results in Tables 4 and 5 are not qualitatively affected by the addition of those other explanatory variables.

CRELOAN	loans secured by commercial real estate,
LLA	loan loss allowance, a contra asset to the loan account,
TRADE	total trading account securities,
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,
RESIDUAL	the sum of all other assets, which is omitted from the regression in order to avoid perfect multicollinearity among the asset shares.

Leverage (MVLEV) may also affect a bank's microstructure properties, and we again include inverse price and firm size because they account for much of the variation in microstructure variables (Madhavan (2000)). Summary statistics for the variables used in regression (2) are reported in Table 3.

Although (2) is a pooled time series-cross section regression, we estimate the relationship without firm fixed effects, which may be correlated with the firm's business composition and hence mask the effects of specific asset shares on the microstructure variables.<sup>12</sup> Separate estimation results for NASD and NYSE BHC are reported in Tables 4 and 5 respectively, which provide evidence on three related hypotheses:

1. Asset composition (all asset shares, as a group) contributed to measures of firm opacity.
2. The impact of asset composition on opacity differed between the normal and the crisis periods.
3. Individual asset categories contributed to measures of firm opacity.

The first hypothesis has two variants, according to whether we include leverage (MVLEV) in the definition of "asset composition".

For the NASD BHC in Table 4, the hypothesis that asset composition does not affect the microstructure variables is rejected in both time periods for all microstructure variables except IMPACT. We fail to reject the hypothesis that asset composition does not affect IMPACT during the crisis sub-

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<sup>12</sup> Adding firm fixed effects to (2) reduces the number of individual asset shares that carry significant coefficients, but it does not greatly change 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 – 2009Q3 "crisis" period.

period (2007Q3-2009Q3), although we do reject it for the normal sub-period (2003Q1 – 2007Q2). According to the last row in Table 4, we also reject sub-period homogeneity for all five opacity measures. These intertemporal shifts are further illustrated by the year dummies, which are all larger in the later (crisis) years.

The individual asset shares in Table 4 display several interesting features. A higher RRELOAN share insignificantly reduced the three opacity measures during the normal period, when residential real estate was (still) considered a safe, transparent asset class. During the crisis, however, a higher concentration in real estate loans significantly raises AS and ESPREAD, while the IMPACT effect changes from significantly negative to insignificant. RRELOAN also reduces TOVER and VOL during the normal period but not during the crisis. In short, residential real estate became a net contributor to NASD BHC opacity during the crisis. Qualitatively similar effects are associated with commercial real estate. Trading account securities (TRADE) exhibit little effect on the direct opacity measures, but they significantly reduce TOVER and VOL during the pre-crisis period. Apparently, NASD TRADE assets were relatively easy for outsiders to understand. The LLA account shows mixed (contradictory) effects on information asymmetry measures, lowering AS and ESPREAD while raising IMPACT. However, these shifts between the normal and crisis periods are not statistically significant. There is some evidence that a higher LLA reduces TOVER and VOL before the crisis but has the opposite effect during the crisis. OREO tends to raise AS and ESPREAD in both periods but its (positive) effect on IMPACT is significant in the earlier period.

In short, the NASD BHCs' asset composition generally explains their microstructure variables, but the nature of their effect shifts between the normal and the crisis sub-periods. Consistent with conventional wisdom, we find that real estate holdings shifted from being considered relatively safe and transparent to riskier and more opaque during the crisis.

The results for NYSE BHC in Table 5 may be more interesting because some of these firms occupied center stage in the financial meltdown of 2008. Starting with the joint hypotheses whose test

statistics are reported at the bottom of Table 5, we see that the three direct opacity measures (AS, ESPREAD, IMPACT) are significantly affected by asset composition in both sub- periods. We cannot reject the hypothesis (5% confidence level) that TOVER and VOL are unrelated to portfolio composition and leverage in normal times, although the crisis-period results are consistent with these variables reflecting balance sheet composition. All five microstructure variables show signs of being determined differently (in terms of the  $\beta_k$  estimated coefficients) in the normal vs. the crisis periods. As for the NASD banks, the year dummies' coefficients indicate higher values for the first four microstructure variables during the crisis. Surprisingly, the return VOL changes little between the two sub-periods after controlling for asset composition.

Turning to the coefficients on individual asset shares, we find little effect of residential or commercial real estate loans in either the normal or the crisis sub-period. TRADE significantly contributes to firm opacity, as implied by the positive coefficients on all three information asymmetry variables. However, the coefficients on TRADE are quite similar for the two sub-periods, suggesting that large banks' trading accounts were not substantially more difficult for outsiders to value during the crisis. TRADE does not affect share TOVER. Somewhat surprisingly, TRADE tends to reduce return volatility, although this effect is smaller during the crisis period. A higher LLA or OREO tends to reduce the three direct opacity measures, although these effects do not appear to be statistically significant.

In short, the NYSE BHC results in Table 5 broadly resemble those for the NASD BHC in Table 4. Asset composition significantly affects the microstructure variables, but the specific coefficients shift between the normal and crisis sub-periods. Whereas NASD banks exhibited particular effects of real estate holdings, the NYSE banks' most influential balance sheet category was trading accounts assets.

## **VI. Conclusions**

Although many banking policy actions took place during the 2007-09 financial crisis are predicated on the opacity of financial intermediary firms, the question of bank opaqueness has not been resolved in

the banking literature. We have investigated this question using data over a twenty-year period, with particular emphasis on the recent financial crisis. In this paper, we present two lines of inquiry to assess whether banking firms are unusually opaque and how that opacity might be determined. First, we directly compare equity microstructure measures related to asymmetric information or differences of opinion between banks and nonbanks. The evidence indicates most clearly that large banks, traded on the NYSE, are not substantially more difficult to evaluate than their control (nonfinancial, peer) firms, except during the recent financial crisis. During “normal” times, the NYSE bank holding companies exhibit slightly higher adverse selection components in their bid-ask spreads, but lower price impact. Their significantly lower trading activity and return volatility suggest that these large banks do not seem to be opaque. A similar conclusion applies to smaller bank holding companies, traded on NASD. However, the comparisons between banks and nonbanks during the financial crisis period are strikingly different. Bank spreads’ adverse selection components are 200% to 300% of their “normal period” levels, and price impacts significantly exceed those of nonfinancial peer firms. The larger (NYSE) banks also exhibit significantly more volatile returns during the crisis, although volatility and share turnover both remain significantly lower (than peers) even during the crisis. One distinct finding of our analysis is that bank opacity varies substantially through time. Thus, a clear implication is that a researcher’s ability to find evidence that banking firms are opaque depends on the sampling period examined.

Second, having detected time-varying bank opaqueness, we attempt to explain opacity with bank asset composition. Although we again find sharp differences on the effects of asset composition on our opacity measures for the recent crisis period, pinning down the source of bank opaqueness 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.

Regarding policy responses to the financial crisis, our empirical evidence clearly shows that bank opaqueness surged during the crisis. However, whether it is information asymmetry or difference in opinion, or both, that raise bank opacity is less clear cut. Nevertheless, to the extent that bank opacity



contributes to instability, government intervention to lessen information asymmetry or disagreement, including the Supervisory Capital Assessment Program to produce otherwise unavailable information about banks, seems appropriate to foster stability.

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**Table 1: BHC and matched firms' monthly microstructure variables, 1990-1 through 2009-9.**

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*Panel A: Microstructure variables*

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The following five 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.

$TOVER_{it}$  = the number of shares traded, divided by the average number of shares outstanding during the month.

$VOL_{it}$  = the annualized daily standard deviation of the continuously compounded returns between adjacent trades, computed using the quote midpoints.

IMPACT = an estimate of Kyle's (1985) ' $\lambda$ ', which is a price impact measure.

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*Panel B: Control variables*

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$PINV_{it}$  = the inverse of the monthly average share price.

$LNMVEQ_{it}$  = natural log of the month average market value of common equity.

Table 1 (cont'd)

Panel A: Microstructure variables for NASD BHCs and Control

	Bank Holding Companies						Matched (Control) Firms					
	N	Mean	Std. dev.	Min.	Max.	Median	N	Mean	Std. dev.	Min.	Max.	Median
<b>AS</b>	55,028	1.140	1.273	-14.86	9.443	0.884	56,561	1.002	1.278	-9.51	10.40	0.732
<b>ESPREAD</b>	57,518	1.797	1.469	0.000	11.61	1.416	57,637	1.682	1.507	0.000	16.28	1.271
<b>IMPACT</b>	55,752	22.69	20.76	0.000	367.6	17.98	55,141	25.81	21.55	0.000	279.6	21.13
<b>TOVER</b>	58,657	0.161	0.273	0.000	8.954	0.081	58,657	0.595	0.907	0.000	16.84	0.290
<b>VOL</b>	55,226	36.02	43.21	0.000	456.7	22.02	56,672	53.67	50.54	0.000	416.5	36.82
<b>PRICE</b>	58,657	22.59	12.82	2.000	208.7	20.60	58,657	20.87	13.68	0.030	260.4	18.51
<b>MVEQ**</b>	58,657	0.49	1.61	0.000	39.6	0.13	58,657	0.48	1.60	0.000	51.9	0.13

Panel B: Microstructure variables for NYSE BHCs and Control

	Bank Holding Companies						Matched (Control) Firms					
	N	Mean	Std. dev.	Min.	Max.	Median	N	Mean	Std. dev.	Min.	Max.	Median
<b>AS</b>	14,843	0.309	0.560	-2.285	9.272	0.132	14,858	0.296	0.545	-2.494	9.524	0.131
<b>ESPREAD</b>	14,969	0.614	0.768	0.030	11.606	0.313	14,968	0.600	0.767	0.029	12.437	0.310
<b>IMPACT</b>	14,964	14.78	14.75	0.000	145.9	9.33	14,951	14.97	14.62	0.000	217.3	9.87
<b>TOVER</b>	14,969	0.351	0.516	0.003	8.954	0.227	14,969	0.515	0.748	0.001	12.880	0.319
<b>VOL</b>	14,904	62.92	55.36	0.000	374.0	40.92	14,904	71.3	59.91	0.000	470.1	49.03
<b>PRICE</b>	14,969	34.73	32.22	2.010	554.2	28.23	14,969	33.72	30.86	0.140	576.8	27.89
<b>MVEQ**</b>	14,969	9.78	25.68	0.010	268.7	1.68	14,969	9.48	25.13	0.000	327.0	1.66

\*\* reported in millions of dollars

**TABLE 2: Differences in microstructure characteristics of BHCs vs. control firms**

Regression estimates of equation (1):  $\Delta M_{ijt} = \delta_0 + \delta_1(\Delta PINV_{it}) + \delta_2(\Delta LNMVEQ_{it}) + \mu_{ijt}$ , where  $\Delta M_{ijt}$  denotes the  $j^{\text{th}}$  ( $j = \text{AS, ESPREAD, TOVER, VOL, IMPACT}$ ) BHC  $i$ 's 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. All regressions are run with robust standard errors, clustered by firm. \*, \*\*, \*\*\* indicates statistical significance at the 10%, 5%, or 1% confidence level respectively.

**Panel A: Estimates from all SAMPLE months, 1990-1 through 2009-9 (234 months)**

	NASDAQ Firms					NYSE Firms				
	AS	ESPREAD	IMPACT	TOVER	VOL	AS	ESPREAD	IMPACT	TOVER	VOL
Intercept	0.181*** (0.016)	0.192*** (0.021)	-2.756*** (0.259)	-0.433*** (0.012)	-16.871*** (0.490)	0.026** (0.010)	0.039** (0.015)	0.041 (0.331)	-0.164*** (0.025)	-7.690*** (1.228)
$\Delta PINV$	2.097*** (0.317)	3.391*** (0.363)	20.310*** (4.541)	0.370** (0.167)	103.325*** (10.20)	1.866*** (0.524)	3.144*** (0.572)	-6.544 (10.45)	0.705 (0.834)	158.276*** (51.65)
$\Delta LNMVEQ$	-0.442*** (0.034)	-0.664*** (0.046)	-4.424*** (0.496)	0.174*** (0.030)	2.707** (1.303)	-0.156*** (0.033)	-0.291*** (0.045)	-5.965*** (1.440)	0.065 (0.060)	-3.842 (3.197)
R-squared	0.078	0.120	0.023	0.007	0.025	0.102	0.187	0.043	0.001	0.026
N	53,987	56,993	55,142	59,184	54,294	14,744	14,968	14,951	14,975	14,843

**Panel B: Estimates from 1990-1 through 1992-12 (36 months)**

	NASDAQ Firms					NYSE Firms				
	AS	ESPREAD	IMPACT	TOVER	VOL	AS	ESPREAD	IMPACT	TOVER	VOL
Intercept	0.020 (0.034)	0.257*** (0.060)	-1.026 (0.957)	-0.370*** (0.028)	-17.724*** (2.126)	-0.011 (0.011)	-0.003 (0.010)	-1.437** (0.568)	-0.002 (0.030)	-0.261 (1.638)
$\Delta PINV$	-2.896** (1.162)	4.591*** (1.286)	4.262 (18.89)	-0.541** (0.253)	116.065*** (40.15)	-3.083*** (0.327)	4.545*** (0.724)	-42.713 (40.36)	0.049 (0.505)	146.996** (61.51)
$\Delta LNMVEQ$	0.364*** (0.111)	-0.902*** (0.166)	-13.241*** (2.691)	0.113* (0.058)	-18.633** (7.277)	0.049 (0.030)	-0.129 (0.088)	-10.309** (5.006)	0.105 (0.077)	-5.507 (6.455)
R-squared	0.045	0.182	0.056	0.016	0.083	0.198	0.617	0.054	0.014	0.167
N	2,847	4,039	2,226	5,711	2,768	1,502	1,550	1,534	1,551	1,549

Table 2 (cont'd)

Panel C: Estimates from 1998-8 through 1998-12 (5 months)

	NASDAQ Firms					NYSE Firms				
	AS	ESPREAD	IMPACT	TOVER	VOL	AS	ESPREAD	IMPACT	TOVER	VOL
Intercept	0.315*** (0.064)	0.323*** (0.081)	-1.364* (0.715)	-0.342*** (0.033)	-7.536*** (0.844)	0.006 (0.047)	0.030 (0.063)	1.559 (1.315)	-0.204*** (0.058)	-3.103 (2.736)
ΔPINV	3.215** (1.349)	3.828** (1.771)	3.725 (10.53)	-0.527 (0.446)	63.013** (26.49)	3.651** (1.440)	5.589*** (0.605)	-27.167 (16.74)	0.483 (0.632)	95.556** (45.36)
ΔLN MVEQ	-0.537*** (0.119)	-0.720*** (0.153)	-0.603 (1.094)	-0.147 (0.106)	-3.475* (2.001)	-0.136*** (0.051)	-0.354*** (0.051)	-6.915*** (1.911)	-0.015 (0.088)	-5.984 (4.387)
R-squared	0.107	0.113	-0.001	0.010	0.084	0.183	0.286	0.099	0.000	0.085
N	1,358	1,402	1,402	1,409	1,375	406	410	410	414	406

Panel D: Estimates from 2007-7 through 2009-9 (27 months)

	NASDAQ Firms					NYSE Firms				
	AS	ESPREAD	IMPACT	TOVER	VOL	AS	ESPREAD	IMPACT	TOVER	VOL
Intercept	0.500*** (0.051)	0.555*** (0.058)	2.516*** (0.839)	-0.396*** (0.033)	-13.004*** (1.972)	0.083*** (0.019)	0.101*** (0.026)	3.835*** (1.025)	0.112 (0.141)	6.631** (3.087)
ΔPINV	-0.243 (0.843)	-0.048 (1.039)	-13.956 (9.869)	3.412*** (1.118)	157.246*** (35.51)	0.987*** (0.295)	1.273*** (0.392)	-18.130 (13.64)	2.141 (2.516)	49.114 (50.65)
ΔLN MVEQ	-0.275*** (0.099)	-0.348*** (0.118)	-8.256*** (1.446)	0.388** (0.165)	2.740 (4.901)	-0.070 (0.049)	-0.092 (0.067)	-6.323*** (1.669)	0.445 (0.404)	-5.251 (5.359)
R-squared	0.009	0.013	0.014	0.029	0.033	0.045	0.049	0.031	0.009	0.010
N	6,300	6,317	6,317	6,318	6,305	1,490	1,490	1,490	1,490	1,490

Table 2 (cont'd)

Panel E: Estimates from all "normal" months, 1990-1 through 2009-9 (166 months)

	NASDAQ Firms					NYSE Firms				
	AS	ESPREAD	IMPACT	TOVER	VOL	AS	ESPREAD	IMPACT	TOVER	VOL
Intercept	0.152*** (0.015)	0.148*** (0.021)	-3.659*** (0.254)	-0.452*** (0.014)	-17.847*** (0.456)	0.031*** (0.011)	0.048*** (0.017)	-0.279 (0.338)	-0.217*** (0.019)	-10.465*** (1.396)
ΔPINV	3.017*** (0.314)	4.036*** (0.406)	25.729*** (5.267)	0.014 (0.135)	91.144*** (9.325)	3.163*** (0.502)	4.325*** (0.719)	3.545 (12.92)	0.346 (0.453)	228.468** (102.1)
ΔLN MVEQ	-0.482*** (0.036)	-0.661*** (0.052)	-3.444*** (0.564)	0.177*** (0.032)	4.450*** (1.273)	-0.178*** (0.034)	-0.298*** (0.052)	-5.114*** (1.508)	0.038 (0.050)	-1.315 (4.253)
R-squared	0.127	0.140	0.024	0.010	0.022	0.165	0.213	0.037	0.001	0.027
N	43,482	45,235	45,197	45,746	43,846	11,346	11,518	11,517	11,520	11,398

Panel F: Estimates from 1990-1 through 1997-12 (93 months)

	NASDAQ Firms					NYSE Firms				
	AS	ESPREAD	IMPACT	TOVER	VOL	AS	ESPREAD	IMPACT	TOVER	VOL
Intercept	0.074** (0.031)	0.197*** (0.047)	-1.664*** (0.236)	-0.364*** (0.017)	-10.297*** (0.628)	-0.017* (0.009)	-0.005 (0.012)	-1.010*** (0.341)	-0.050** (0.022)	-2.854*** (0.985)
ΔPINV	-0.713 (1.133)	5.972*** (0.978)	12.958* (6.913)	-0.834*** (0.178)	101.179*** (19.749)	-1.033 (1.350)	4.884*** (1.164)	-12.042 (30.203)	0.176 (0.517)	202.862*** (44.669)
ΔLN MVEQ	-0.427*** (0.078)	-0.864*** (0.105)	-2.173*** (0.407)	0.055** (0.028)	-3.689** (1.538)	-0.132 (0.101)	-0.306* (0.155)	-7.383* (3.964)	0.005 (0.040)	-5.369** (2.610)
R-squared	0.020	0.144	0.013	0.013	0.046	0.017	0.298	0.071	0.000	0.186
N	10,862	13,250	11,400	15,379	10,983	3,831	3,916	3,900	3,917	3,885



**Table 3: Summary statistics for the financial variables included in panel regressions**

Quarterly data, 2003Q1 – 2009Q3.

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*Panel A: BHC financial variables*

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The following six balance sheet variables are measured at the end of quarter t and are deflated by the market value of equity at the end of quarter t-1,  $MVEQ_{i,t-1}$ :

$RELOAN_{it}$  = total loans secured by residential real estate.

$CRELOAN$  = total loans secured by commercial real estate.

$LLA_{it}$  = allowance for loan and lease losses.

$TRADE_{it}$  = trading account assets valued at market value or the lower of cost or market.

$OREO_{it}$  = other real estate owned.

$MVLEV_{it}$  = 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.

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*Panel B: Microstructure variables*

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The market microstructure variables defined in Table 1 are summarized here on a quarterly basis for the period 2003Q1 – 2009Q3

**Panel A: Microstructure variables for NASD BHCs and Control**

	Bank Holding Companies						Matched (Control) Firms					
	N	Mean	Std. dev.	Min.	Max.	Median	N	Mean	Std. dev.	Min.	Max.	Median
<b>AS</b>	6,875	0.996	1.088	0.014	9.036	0.643	6,806	0.776	0.975	0.009	10.29	0.441
<b>ESPREAD</b>	6,875	1.340	1.288	0.043	10.41	0.982	6,807	1.092	1.202	0.036	12.76	0.708
<b>IMPACT</b>	6,875	33.95	19.94	1.706	425.5	30.85	6,807	34.30	22.62	0.534	366.0	30.30
<b>TOVER</b>	6,875	0.267	0.403	0.006	8.169	0.143	6,807	0.904	1.491	0.001	39.32	0.498
<b>VOL</b>	6,875	64.19	52.48	5.504	464.6	45.83	6,806	87.86	55.97	0.852	569.0	71.50

**Panel B: Microstructure variables for NYSE BHCs and Control**

	Bank Holding Companies						Matched (Control) Firms					
	N	Mean	Std. dev.	Min.	Max.	Median	N	Mean	Std. dev.	Min.	Max.	Median
<b>AS</b>	1,690	0.213	0.403	-0.027	4.261	0.059	1,690	0.187	0.372	-0.053	5.168	0.051
<b>ESPREAD</b>	1,690	0.389	0.556	0.032	5.855	0.175	1,690	0.353	0.525	0.032	6.166	0.153
<b>IMPACT</b>	1,690	17.25	16.61	2.155	183.4	11.58	1,690	16.30	15.70	0.908	146.9	11.00
<b>TOVER</b>	1,690	0.623	0.837	0.009	11.021	0.363	1,690	0.822	1.109	0.001	13.040	0.548
<b>VOL</b>	1,690	98.80	60.95	8.003	430.4	86.24	1,690	108.9	64.92	6.131	528.4	99.70

Panel C: BHC financial characteristics for NASD and NYSE BHCs

	NASD sample BHC						NYSE sample BHC					
	N	Mean	Std. dev.	Min.	Max.	Median	N	Mean	Std. dev.	Min.	Max.	Median
<b>RRELOAN</b>	6,875	1.546	1.697	0.000	42.60	1.168	1,690	1.677	2.611	0.000	49.40	1.218
<b>CRELOAN</b>	6,875	3.217	3.868	0.000	106.0	2.347	1,690	2.096	8.352	0.000	213.3	1.147
<b>TRADE</b>	6,875	0.015	0.143	0.000	4.756	0.000	1,690	0.192	0.958	0.000	23.632	0.003
<b>LLA</b>	6,875	0.094	0.152	0.000	2.694	0.058	1,690	0.096	0.354	0.000	8.244	0.048
<b>OREO</b>	6,875	0.030	0.143	0.000	4.775	0.004	1,690	0.023	0.163	0.000	3.914	0.003
<b>MVEQ**</b>	6,875	0.620	1.882	0.007	33.49	0.187	1,690	16.36	39.01	0.019	274	2.345
<b>MVLEV</b>	6,875	9.020	7.267	1.324	132.0	7.121	1,690	9.003	17.907	1.077	449.380	6.615

\*\*MVEQ reported in billions of dollars

**Table 4: NASD sub-sample: Balance sheet effects on microstructure variables**

Panel regression results of estimating equation (2) without firm fixed effects, robust standard errors in parentheses.

	04:Q1-07:Q2	07:Q3-09:Q3	04:Q1-07:Q2	07:Q3-09:Q3	04:Q1-07:Q2	07:Q3-09:Q3	04:Q1-07:Q2	07:Q3-09:Q3	04:Q1-07:Q2	07:Q3-09:Q3
	AS		ESPREAD		IMPACT		TOVER		VOL	
RRELOAN	-0.024 (0.026)	0.076*** (0.026)	-0.038 (0.029)	0.086*** (0.029)	-1.709*** (0.506)	-0.603 (0.384)	-0.023* (0.012)	0.017 (0.018)	-2.315*** (0.790)	-0.304 (1.051)
CRELOAN	-0.055*** (0.021)	-0.035* (0.020)	-0.068*** (0.024)	-0.038* (0.023)	-1.046*** (0.403)	0.106 (0.276)	0.027*** (0.010)	0.007 (0.015)	0.772 (0.736)	3.621*** (0.803)
TRADE	0.013 (0.150)	-0.123 (0.214)	-0.035 (0.171)	-0.147 (0.252)	-4.807 (3.237)	0.888 (1.832)	-0.110* (0.063)	0.208* (0.107)	-23.456*** (5.717)	2.078 (6.649)
LLA	-0.909 (0.905)	-0.778** (0.391)	-0.913 (1.041)	-0.718 (0.450)	9.728 (15.872)	8.259 (5.786)	-0.876** (0.434)	0.575 (0.353)	-14.400 (29.126)	28.483* (14.582)
OREO	1.294 (1.282)	1.124** (0.442)	1.535 (1.477)	1.398*** (0.513)	46.552* (27.651)	1.433 (3.111)	-0.216 (0.295)	-0.247** (0.101)	9.896 (27.817)	-4.391 (9.886)
MVLEV	0.038*** (0.013)	0.020 (0.013)	0.041*** (0.015)	0.015 (0.015)	0.242 (0.236)	-0.353* (0.206)	0.009 (0.006)	0.008 (0.007)	-0.275 (0.378)	-1.425*** (0.527)
L_PINV	0.702 (1.118)	-1.705 (1.148)	0.760 (1.323)	-1.890 (1.289)	-4.871 (19.051)	1.198 (17.454)	0.645** (0.313)	-0.272 (0.618)	235.466*** (31.964)	121.440*** (41.435)
L_LNMVEQ	-0.409*** (0.027)	-0.916*** (0.066)	-0.519*** (0.032)	-1.096*** (0.074)	-8.311*** (0.369)	-8.816*** (0.534)	0.099*** (0.008)	0.375*** (0.035)	7.323*** (0.848)	32.806*** (2.755)
D04	0.154*** (0.028)		0.270*** (0.032)		10.104*** (0.626)		-0.062*** (0.013)		1.894 (2.045)	
D05	0.154*** (0.023)		0.236*** (0.027)		6.934*** (0.607)		-0.077*** (0.012)		-8.368*** (2.203)	
D06	0.059*** (0.018)		0.116*** (0.021)		4.398*** (0.540)		-0.073*** (0.010)		-11.270*** (2.188)	
D08		0.449*** (0.046)		0.584*** (0.053)		13.173*** (0.842)		0.155*** (0.023)		36.112*** (2.331)
D09		0.250*** (0.066)		0.381*** (0.074)		15.945*** (1.469)		0.155*** (0.035)		56.775*** (3.920)
Adj-R2	0.619	0.604	0.645	0.628	0.505	0.319	0.337	0.484	0.196	0.367
N	3915	2039	3915	2039	3915	2039	3915	2039	3915	2039
H1A: Pr(all 5 BS=0)	0.037	0.000	0.027	0.000	0.004	0.191	0.000	0.013	0.000	0.000
H1B: Pr(all 6 Fin=0)	0.027	0.000	0.029	0.000	0.006	0.023	0.000	0.000	0.000	0.000
Adj-R2: Just Fin	0.176	0.254	0.169	0.257	0.086	0.069	0.082	0.083	0.049	0.043
Adj-R2: Just MM	0.603	0.567	0.625	0.589	0.444	0.246	0.294	0.384	0.123	0.260
H2: sub-period homogeneity	0.000		0.000		0.000		0.000		0.000	

\*\*\*, \*\*, \* indicate significance at the 1%, 5%, and 10% levels, respectively.

**Table 5: NYSE sub-sample: Balance sheet effects on microstructure variables**

Panel regression results of estimating equation (2) without firm fixed effects, robust standard errors in parentheses.

	04:Q1-07:Q2	07:Q3-09:Q3	04:Q1-07:Q2	07:Q3-09:Q3	04:Q1-07:Q2	07:Q3-09:Q3	04:Q1-07:Q2	07:Q3-09:Q3	04:Q1-07:Q2	07:Q3-09:Q3
	AS		ESPREAD		IMPACT		TOVER		VOL	
RRELOAN	-0.018 (0.028)	-0.017 (0.020)	-0.025 (0.036)	-0.022 (0.026)	-0.475 (0.653)	-0.238 (0.516)	0.033 (0.027)	0.018 (0.053)	7.817 (4.740)	1.684 (1.843)
CRELOAN	-0.024 (0.028)	-0.018 (0.015)	-0.044 (0.035)	-0.024 (0.019)	-1.561** (0.733)	-0.074 (0.372)	0.019 (0.026)	-0.018 (0.042)	4.583 (4.245)	3.969** (1.510)
TRADE	0.335*** (0.082)	0.192*** (0.056)	0.435*** (0.105)	0.259*** (0.072)	6.127*** (1.867)	4.040*** (1.268)	-0.120 (0.116)	0.122 (0.190)	-35.824* (18.058)	-18.129*** (5.031)
LLA	0.594 (1.160)	0.066 (0.230)	1.222 (1.524)	0.086 (0.302)	53.347* (30.940)	-1.158 (7.026)	-1.653 (1.285)	1.814** (0.749)	-214.203 (151.793)	-25.633 (30.849)
OREO	0.725 (1.949)	0.531* (0.278)	1.242 (2.343)	0.733** (0.357)	39.523 (40.982)	13.296** (6.130)	0.197 (2.884)	-1.465* (0.752)	-170.467 (400.635)	-51.718** (20.799)
MVLEV	-0.011 (0.015)	-0.004 (0.006)	-0.013 (0.018)	-0.005 (0.008)	-0.026 (0.281)	-0.022 (0.171)	0.004 (0.019)	0.008 (0.018)	1.858 (2.798)	0.287 (0.790)
L_PINV	1.242 (1.408)	0.210 (1.482)	1.751 (1.772)	-0.263 (1.826)	-42.729 (40.270)	-41.248 (36.049)	1.289 (1.188)	0.209 (2.820)	583.326*** (197.806)	224.999* (124.682)
L_LNMVEQ	-0.116*** (0.016)	-0.195*** (0.044)	-0.184*** (0.021)	-0.282*** (0.056)	-5.166*** (0.358)	-8.392*** (0.933)	0.058*** (0.011)	0.201*** (0.041)	14.049*** (1.889)	2.954 (3.077)
D04	-0.100** (0.041)		-0.130** (0.057)		-8.323*** (2.100)		-0.133*** (0.033)		9.017 (7.101)	
D05	-0.095** (0.039)		-0.081 (0.055)		-4.834** (2.049)		-0.144*** (0.033)		35.086*** (7.929)	
D06	-0.036 (0.023)		0.034 (0.030)		-0.036 (1.341)		-0.113*** (0.026)		53.011*** (7.090)	
D08		0.034 (0.046)		0.021 (0.059)		6.016*** (1.171)		0.467*** (0.069)		38.679*** (4.812)
D09		0.031 (0.073)		0.025 (0.096)		5.656*** (1.779)		0.671*** (0.131)		32.327*** (5.519)
Adj-R2	0.471	0.377	0.570	0.439	0.568	0.614	0.192	0.495	0.298	0.254
N	979	477	979	477	979	477	979	477	979	477
H1A: Pr(all 5 BS=0)	0.000	0.017	0.000	0.010	0.006	0.000	0.370	0.002	0.092	0.000
H1B: Pr(all 6 Fin=0)	0.001	0.001	0.001	0.000	0.004	0.000	0.491	0.001	0.129	0.000
Adj-R2: Just Fin	0.101	0.032	0.142	0.046	0.166	0.172	0.042	0.365	0.026	0.153
Adj-R2: Just MM	0.429	0.339	0.529	0.399	0.491	0.582	0.145	0.300	0.147	0.100
H2: sub-period homogeneity	0.004		0.023		0.000		0.000		0.000	

\*\*\*, \*\*, \* indicate significance at the 1%, 5%, and 10% levels, respectively.

Figure 1A: Intercept term from Monthly Cross Section Regressions  
AS Component of Spread  
NASDAQ sample

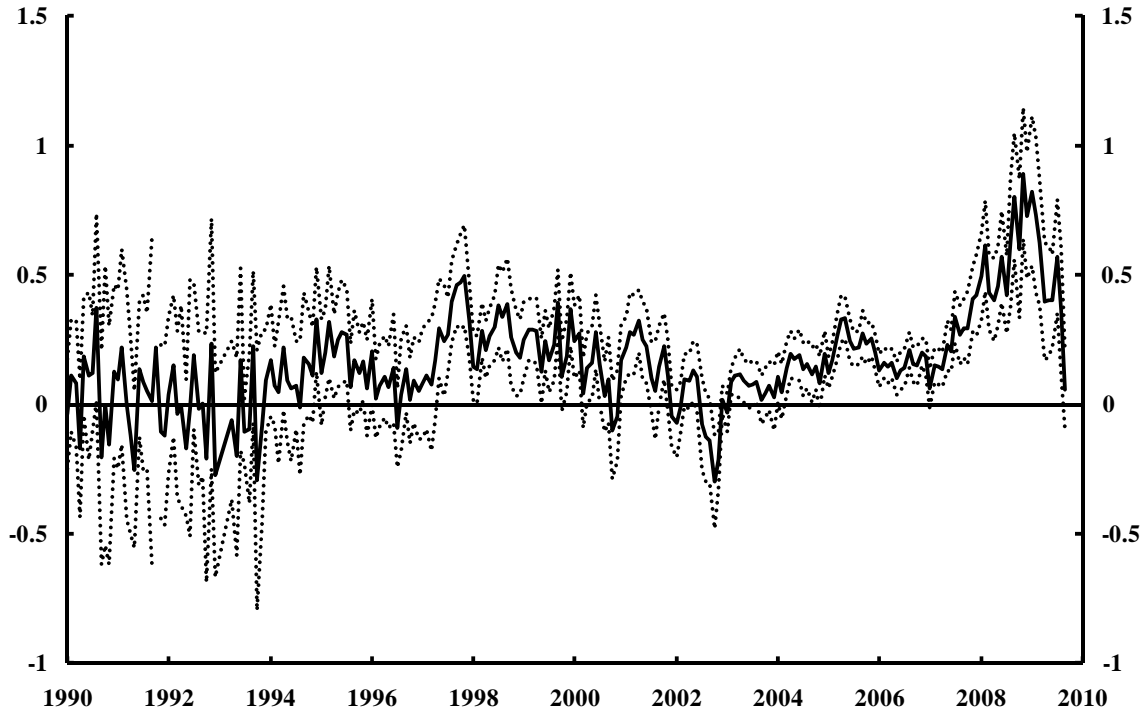
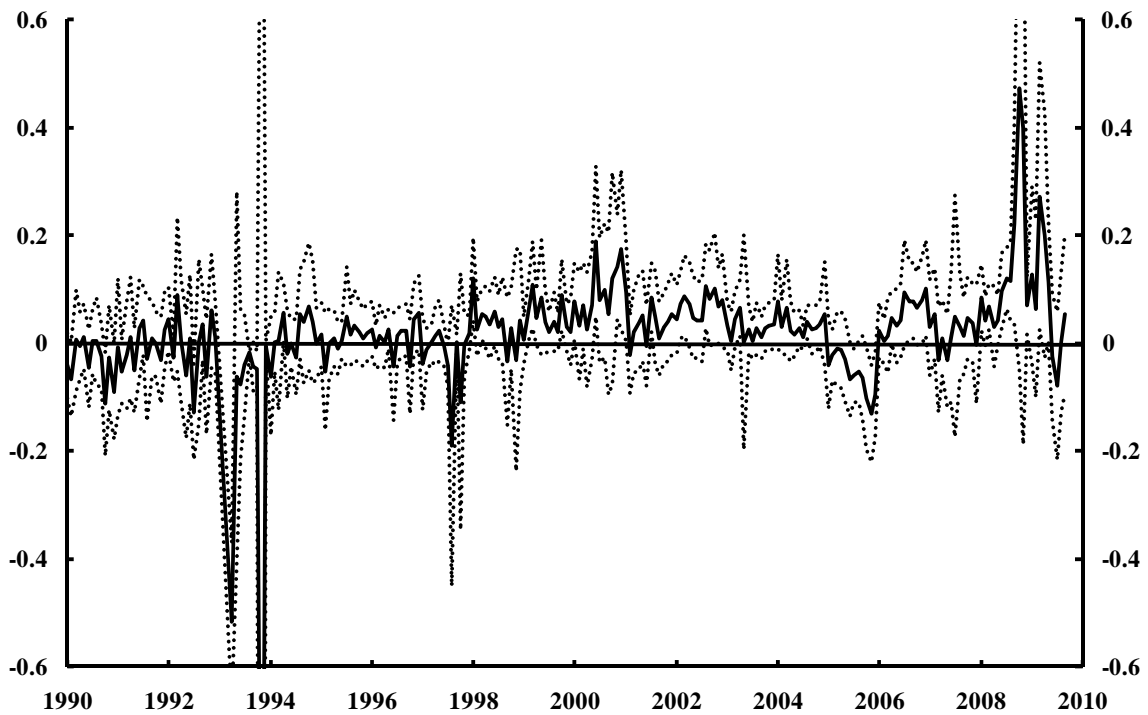
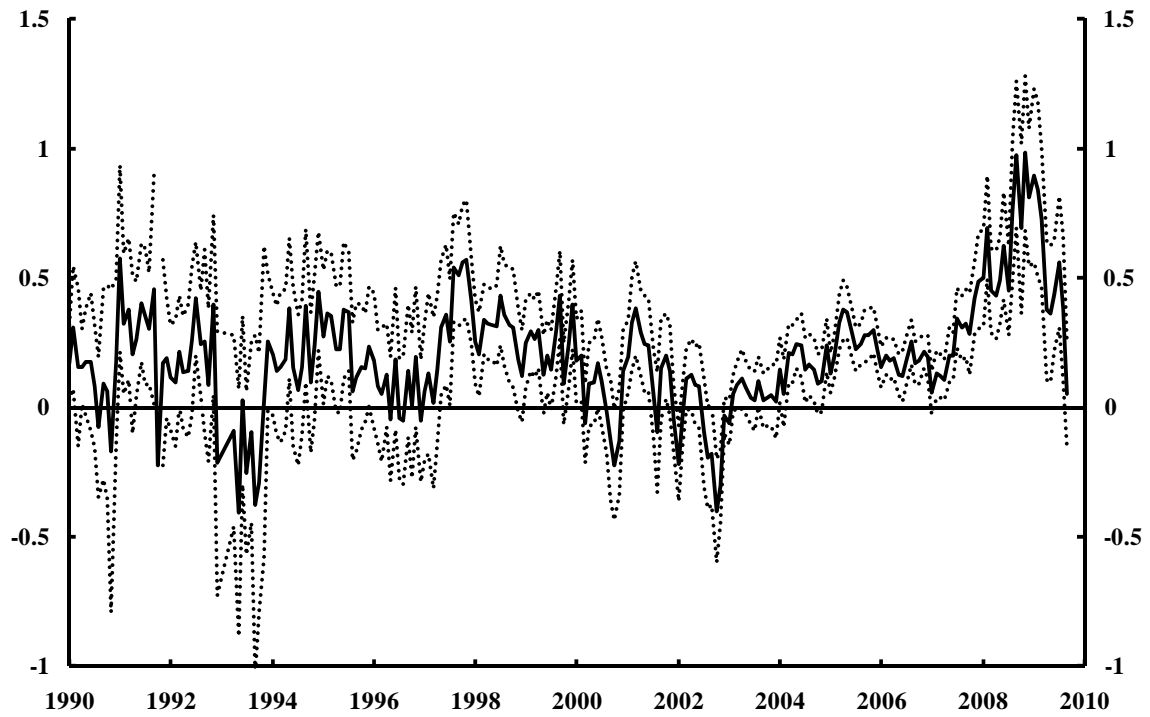


Figure 1B: Intercept term from Monthly Cross Section Regressions  
AS Component of Spread  
NYSE sample



**Figure 2A: Intercept term from Monthly Cross Section Regressions  
Effective Spread (ESPREAD)**  
NASDAQ sample



**Figure 2B: Intercept term from Monthly Cross Section Regressions  
Effective Spread (ESPREAD)**  
NYSE sample

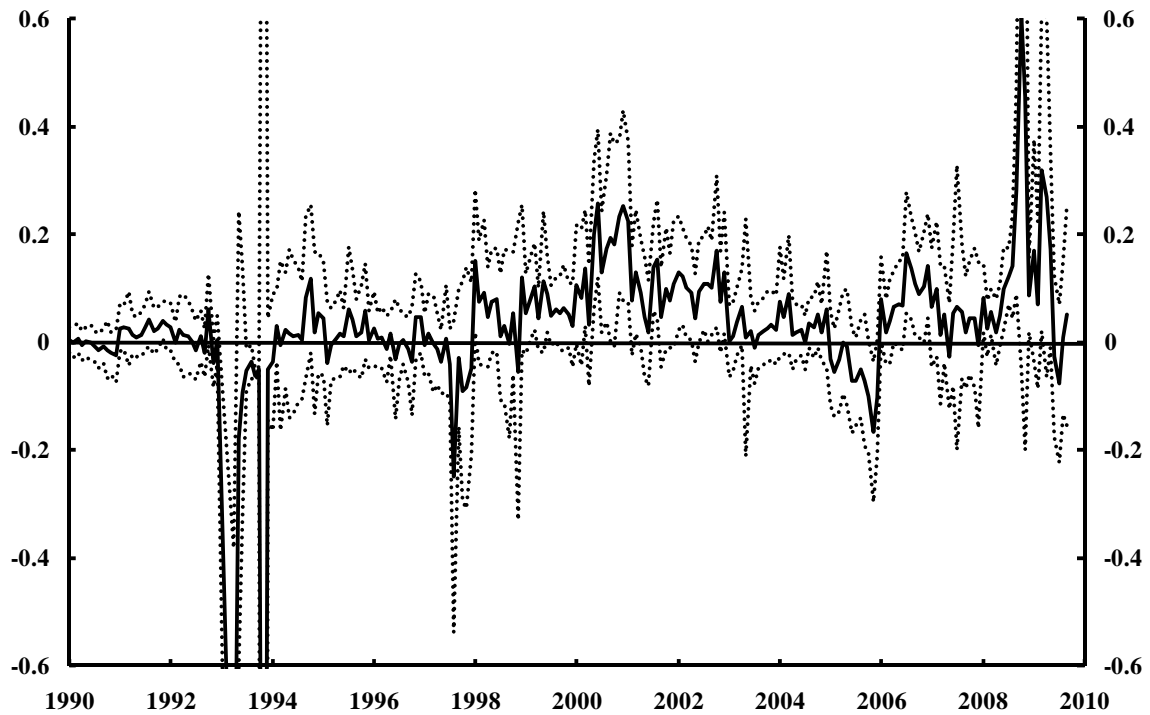


Figure 3A: Intercept term from Monthly Cross Section Regressions  
Price Impact (IMPACT)  
NASDAQ sample

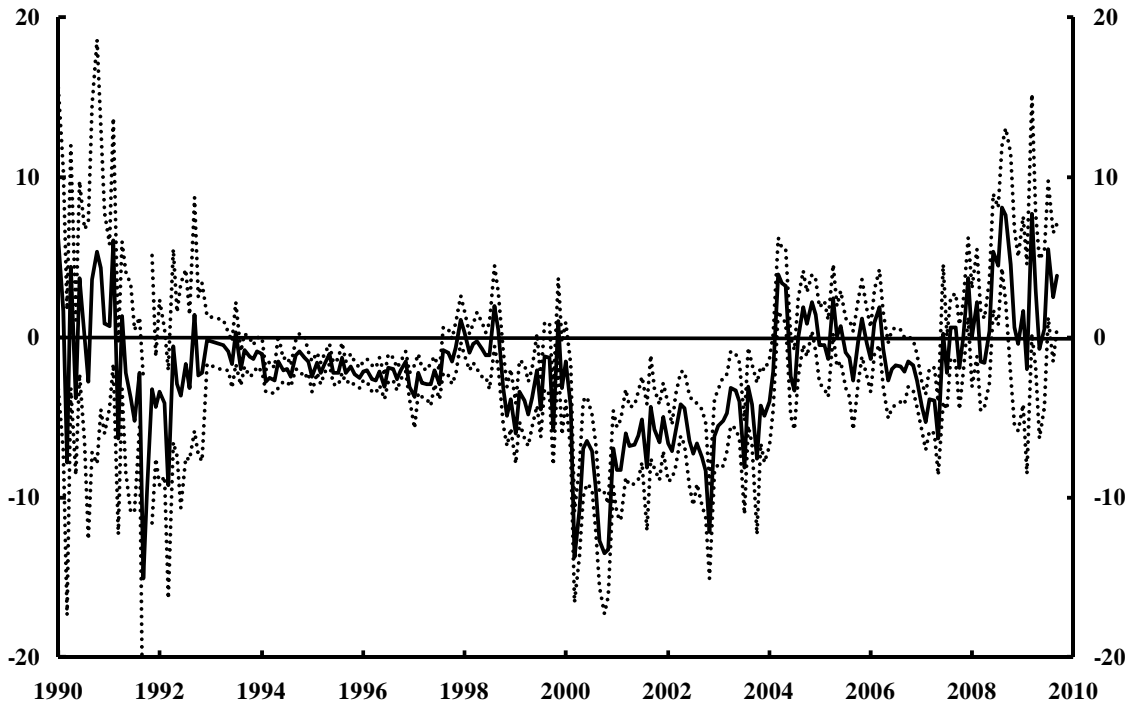
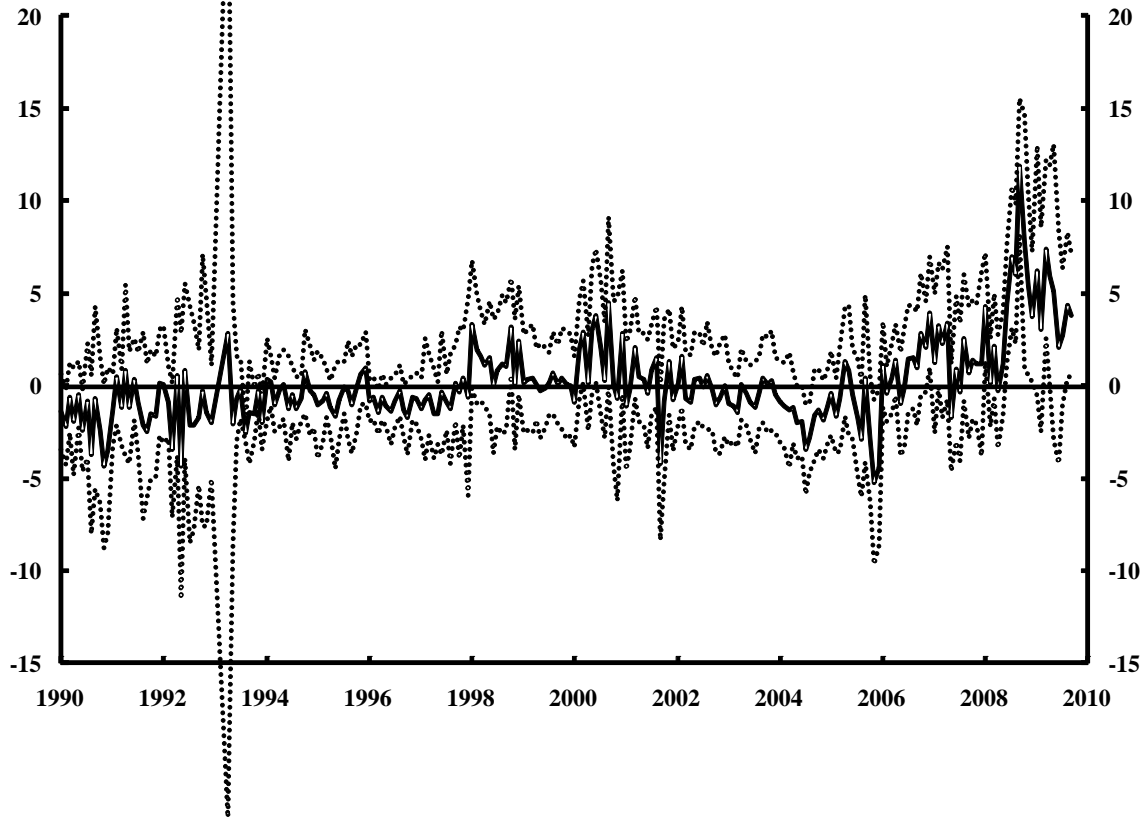
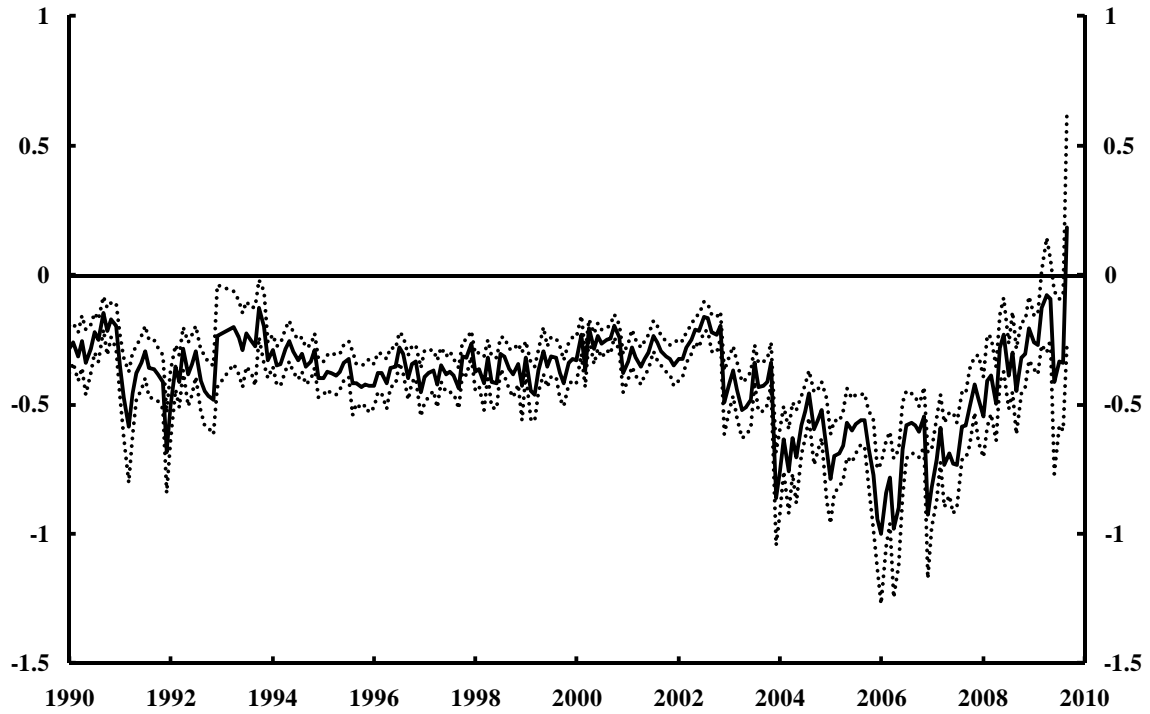




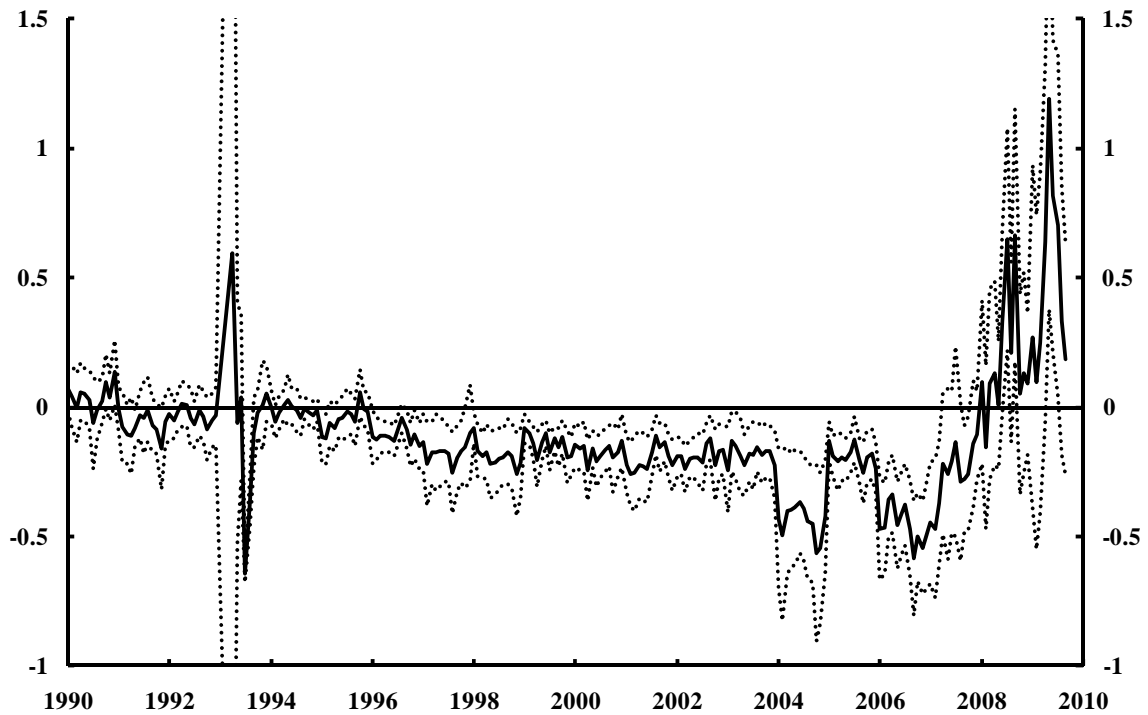
Figure 3B: Intercept term from Monthly Cross Section Regressions  
Price Impact (IMPACT)  
NYSE sample



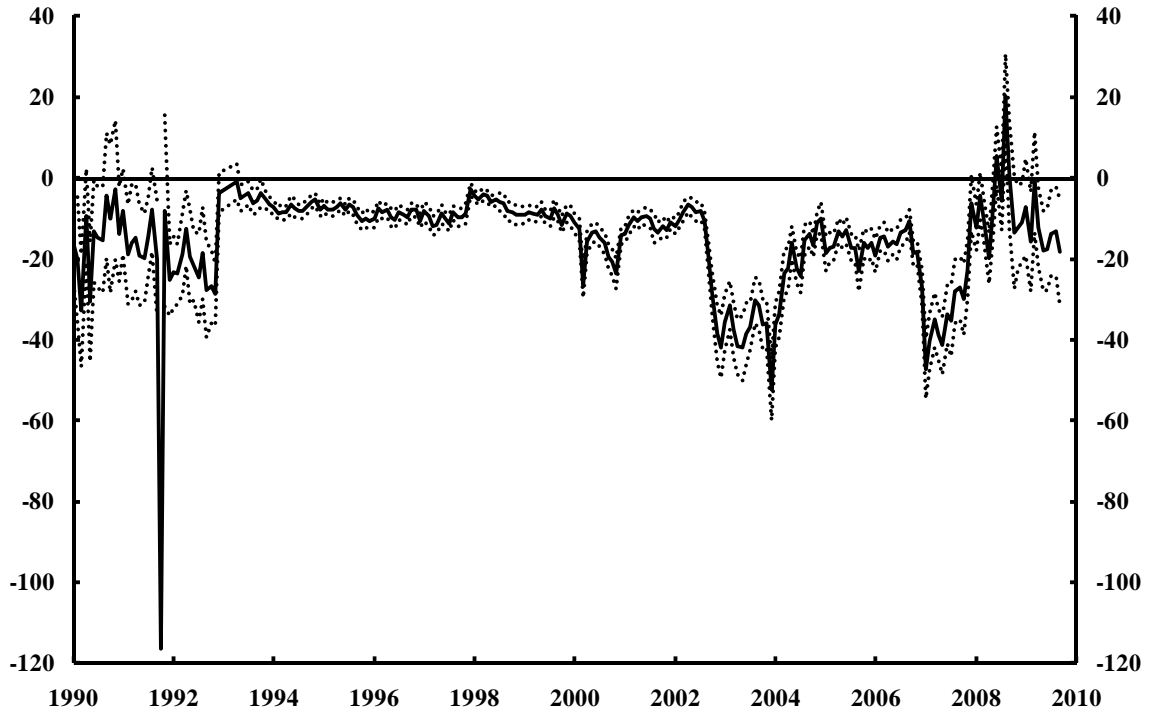
**Figure 4A: Intercept term from Monthly Cross Section Regressions  
Share Turnover (TOVER)**  
NASDAQ sample



**Figure 4B: Intercept term from Monthly Cross Section Regressions  
Share Turnover (TOVER)**  
NYSE sample



**Figure 5A: Intercept term from Monthly Cross Section Regressions  
Standard Deviation of Share Returns (VOL)**  
NASDAQ sample



**Figure 5B: Intercept term from Monthly Cross Section Regressions  
Standard Deviation of Share Returns (VOL)**  
NYSE sample

