Market Evidence on the Opaqueness of Banking Firms' Assets

by

Mark J. Flannery *

Simon H. Kwan **

M. Nimalendran *

ABSTRACT

We assess the market microstructure properties of U.S. banking firms' equity, to determine whether they exhibit more or less evidence of asset opaqueness than similar-sized nonbanking firms. The evidence indicates that large bank holding companies (BHC), traded on the NYSE, have very similar trading properties to their matched nonfinancial firms. In contrast, smaller BHCs, traded on NASDAQ, trade *much less* frequently despite having very similar spreads. We also find empirical support for the hypothesis that BHC asset categories differ in their opacity. Analysis of IBES earnings forecasts indicates that banking assets are not unusually opaque; they are simply boring. The implications for regulatory policy and future market microstructure research are discussed.

Comments and suggestions were kindly offered by George Benston (the referee), Mark Carey, Thomas Gehrig, Charles Goodhart, Roger Huang, Stephen Kane, Don Morgan, Matt Spiegel, Shawn Thomas, Rene Stulz, and seminar participants at DePaul, Indiana, Iowa, Houston, Humboldt, and Miguel Hernandez Universities, and INSEAD. We thank John Banko, Bart Danielsen, Kasturi Rangan and Katie Thomas for their help in constructing the data sets. Data on analyst coverage were provided by I/B/E/S Inc. (now a part of Thomson Financial), under a program to encourage academic research.

August, 2002

* Department of Finance, Box 117168, Graduate School of Business Administration, University of Florida, Gainesville, FL 32611-7168.

** Economic Research Department, Federal Reserve Bank of San Francisco, 101 Market Street, San Francisco, CA 94105.

Market Evidence on the Opaqueness of Banking Firms' Assets

I. Introduction

All firms suffer from some degree of information asymmetry between insiders and outside investors, and researchers have extensively studied the resulting corporate control problems (e.g., Jensen and Meckling [1976], Myers and Majluf [1984], Harris and Raviv [1991]). In most industries, these agency problems are resolved via market-based mechanisms (Fama and Jensen [1983]), but government regulation plays an unusually prominent role for financial firms. Financial regulation can be justified in several ways, but one motivation reflects the assertion that bank assets are unusually difficult for outside investors to value. Effective market discipline relies on investors' ability to receive timely and accurate information about firms and to take appropriate actions. If outsiders cannot value bank assets accurately, how can the usual market mechanisms adequately control bank managers and shareholders? A coherent evaluation of the role for government regulation in the financial sector therefore requires an empirical comparison of banks' and nonbanks' informational opacity.

The conventional wisdom, that bank loans are *informationally opaque,* has been justified on a variety of theoretical grounds (e.g., Campbell and Kracaw [1980]), Berlin and Loeys [1988], Diamond [1989, 1991], Kwan and Carleton [1998]). These theories maintain that bank insiders may possess valuable private information about loan customers' credit condition or the bank's monitoring efforts. Federal Reserve Board chairman Alan Greenspan typifies this view when he says that

> bank loans are customized, privately negotiated agreements that, despite increases in availability of price information and in trading activity, still quite often lack transparency and liquidity. *This unquestionably makes the risks of many bank loans rather difficult to quantify and to manage.* (Greenspan [1996], pages 1-2, emphasis added)

The possibility that poorly informed creditors may subject the banking system to destabilizing runs underlies one prominent economist's argument that financial stability requires the government (or the central bank) to operate as a lender of last resort:

> Since no one actually knows the "true" value of such nonmarketable loans, the fact that the value of a subset of such loans has been found to be impaired at a bank or banks is bound to throw doubt on the position and solvency of other banks believed to have made similar kinds of loans. (Goodhart [1988], page 100).

Clearly, then, asset transparency and the optimal bank governance mechanisms are closely related.

However, loan illiquidity and private information about specific borrowers don't *necessarily* make banks more difficult to value than nonfinancial firms are. Just as many bank loans do not trade in active secondary markets, neither do many assets of nonfinancial firms: e.g., plant and equipment, patents, managers' human capital, or accounts receivable. How can outside investors accurately value the public securities issued by *these* firms? Benston and Kaufman [1988] argue that banks are easier to value:

> market value accounting is much more feasible and inexpensive for financial institutions to adopt than for most other enterprises. Unlike nonfinancial firms, banks have relatively small investments in assets for which current market values are difficult to measure. (page 48)

Numerous event studies conclude that investors can fairly accurately discriminate troubled banks from healthy institutions, even during a financial crisis (for example, Jordan, Peek, and Rosengren [2000], Musumeci and Sinkey [1990], and Calomiris and Mason [1997]), and the market prices for uninsured bank debts seem to reflect appropriate bank-specific information (see the survey in Flannery [1998]). Finally, we usually think of opaque assets as illiquid, but investors routinely trade the junior (equity) claims on asset cash flows for more than 500 U.S. bank holding companies.

Bank assets *may* be illiquid and hard to value, but government regulations tend to mitigate their opaqueness. Banks and bank holding companies regularly report detailed financial information, which becomes available to public investors. Government supervisory practices reinforce this required information release, by checking the accuracy of reported information via periodic on-site examinations and continuous off-site surveillance.[1] Bank supervisors frequently publicize their own sense of the industry's condition, and formal enforcement actions directed at individual banks have been publicly available since 1989. More recently, both U.S. banking regulators and the Basel Committee on Banking Supervision have made concerted efforts to improve transparency in banking, largely as a means of promoting more effective market discipline over large financial firms. Thus, even if banking firms were *intrinsically* opaque, it remains an empirical question whether

[1] Flannery and Houston [1999] report that market and book valuations are more closely correlated for quarters in which a holding company was inspected by Federal Reserve supervisors, suggesting that investors place more confidence in examiner-approved financial statements.

supervised banks are more or less opaque than nonbanks.

If banks are relatively difficult for outsiders to understand, the literature on equity market microstructure indicates that their shares should exhibit distinctive trading characteristics, such as their bid-ask spreads, the "adverse selection" component of those spreads, and perhaps trading volume or return volatility. Moreover, equity analysts should have greater difficulty forecasting a more opaque firm's earnings, *ceteris paribus*. Starting from these two premises, we examine whether banking firms' equity market features are consistent with their assets being *relatively* more opaque during the period 1990-1997. First, we assemble a matched sample of traded bank holding companies (BHC) and unregulated, nonfinancial firms. (For convenience, we sometimes refer to these holding companies as "banks" or "banking firms.") BHCs traded on the NYSE or AMEX are relatively large, and their microstructure properties closely resemble those of their control group. The smaller, NASDAQ-traded BHCs' bid-ask spreads closely resemble those of their control group, but the BHCs' trading volume and return volatility are *much lower*.

Next, we confirm the relationship between the microstructure variables and the concept of informational opacity by testing whether a BHC's asset composition affects its bid-ask spreads, trading volume or return volatility. (For example, if outsiders have more difficulty valuing bank loans than treasury bills, we should find larger bid-ask spreads associated with higher loan concentrations.) The regression estimates indicate that balance sheet composition significantly affects the cost of trading a BHC's stock, consistent with the hypothesis that bank assets differ in their opacity. Despite its statistical significance, the explanatory power of balance sheet composition in these regressions is quite small, and comparable to the explanatory power of traditional market microstructure variables.

We then replicate the regression analysis using analyst forecasts of BHC earnings as indicators of asset opacity, in place of the microstructure variables. We hypothesize that more opaque firms will have less accurate and more dispersed earnings forecasts. The earnings forecast data help to distinguish between two plausible reasons for the BHCs' low return volatility and infrequent trading. First, BHC asset values may be stable and readily understood, providing little reason for investors to trade. Second, BHC asset values may be volatile, but few trades occur because relevant information arrives to the market only at infrequent intervals. During these long, information-less intervals the measured return volatility should be low. When we examine annual earnings forecasts for BHCs vs. those for control firms, the results mirror what we find for the market microstructure variables. The larger (NYSE) BHCs quite closely resemble their non-BHC counterparts, but the NASDAQ BHCs do not. *Fewer* analysts follow small BHCs than the control firms, but these analysts forecast BHC earnings *more accurately*. The analysts' significantly lower forecast errors for NASDAQ BHCs imply that these firms are comparatively easy to understand. Finally, we find evidence that a BHC's asset composition significantly affects the features of analysts' earnings forecasts, again consistent with the hypothesis that BHC assets differ in the extent of their opacity.

The paper is organized as follows. Section II reviews the relationship between information and a stock's trading features. Section III describes our data set and presents summary statistics. We then compare BHC microstructure characteristics to those of the control firms in Section IV. In Section V, we estimate the impact of BHC asset composition on equity trading characteristics. Section VI analyzes several dimensions of IBES earnings forecasts for BHCs vs. those for the control sample, and across BHCs with different asset compositions. The IBES results basically confirm our conclusions from the microstructure measures of bank opacity. The final Section summarizes our results and discusses their implications for supervisory policy and subsequent research.

II. Information and Equity Trading Characteristics

Ours is not the only paper that examines market data to determine whether banking firms are relatively opaque. Morgan [2002] contends that bond rating agencies (such as Moodys or S&P) are more likely to disagree in their assessments of harder-to-value firms. He therefore 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, but also that a BHC's asset composition significantly affects the probability of a split rating. Morgan and Stiroh [2001] reach a similar conclusion when they evaluate the impact of bank balance sheet composition on the rates offered on an institution's new subordinated debentures. Our paper addresses the same question by evaluating the market microstructure properties of banks' common *stock* and analysts' ability to forecast the returns to common shareholders. [2]

Demsetz [1968] first demonstrated that a stock's spread was systematically related to several of its trading properties, and Bagehot [1971] argued that one of these properties should be the potential for differentially (privately) informed traders. Using a sample of more than 300 stocks traded over-the-counter, Benston and Hagerman [1974] concluded that inter-dealer competition, price volatility, share price, and order flow all significantly affected a stock's spread. Kyle's [1985] model of the market maker's information problem motivated a series of empirical methods for de-composing a stock's bid-ask spread into logically distinct components (e.g., Stoll [1989], Glosten and Harris [1988], George, Kaul, and Nimalendran [1991], Huang and Stoll [1994], Lin, Sanger, and Booth [1995]). An order processing component of the bid-ask spread and an inventory holding cost reflect a market maker's standard operating costs.[3] The spread's adverse selection (AS) component is a bit more complex.

Market makers effectively write options to traders when they post bid and ask prices. The market maker expects his offers to be "hit" by informed traders only if the bid is too high or the ask is too low. The greater is the potential supply of private information about a stock, the larger will be the adverse selection cost of trading it. Some researchers have examined the information content of a stock spread's AS component. Brennan and Subrahmanyam [1995] report that a stock's adverse selection spread is negatively related to the number of analysts following the firm, suggesting that greater analyst following reduces the importance of privately informed traders. Krinsky and Lee [1996] find that the adverse selection 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.

To identify the effects of asset opacity on a bank's equity trading features, we must define "opaque." We take asset opacity to mean that investors cannot value the asset very accurately, *but (perhaps) insiders or*

---

[2] Although we primarily discuss a stock's bid-ask spread in this section, the spread, return volatility, and trading volume are all inter-related. See the discussion in Section V, following equation (3).

[3] Market makers hold an inventory of the stock in order to provide traders with immediacy. The inventory cost includes

specialists can. This information asymmetry underlies Kyle's [1985] conclusion that a "more opaque" asset trades with a larger bid-ask spread.[4] Asset opacity could either raise or lower trading volume. *Ceteris paribus*, a higher spread (trading cost) would discourage uninformed traders from holding this stock (as in 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 needn't collapse if opinionated investors wish to trade frequently with one another because they disagree about the implications of news for the stock's value (Harris and Raviv [1993]). Finally, asset opacity may depress equity's return volatility over limited periods of time. To see this effect, suppose the "true" value of an opaque asset changes frequently, but the accumulated impact of these changes becomes public only occasionally. Between information arrival dates, the asset's price volatility will be low. When some information finally reaches the market, however, the asset's price should move to reflect its true value. Eventually, therefore, measures of return volatility are unaffected by an asset's opacity. The question is whether short-period return volatilities reflect true changes in asset value.

A firm's asset opacity should also affect financial analysts' earnings forecasts. For more opaque firms, analysts' forecasts may be less accurate and more dispersed. IBES data on analyst earnings forecasts further permit us to evaluate the impact of asset opacity on the number of analysts following a firm, and on the frequency with which earnings forecasts are revised.

We base our empirical work on the assumption that informationally opaque assets will tend to have larger analyst forecast errors and higher bid-ask spreads (reflecting higher AS costs of trading). Return volatility should be unaffected by opacity, and we remain agnostic about the impact of asset opacity on a stock's trading volume.

---

both the time value of invested capital and a risk premium for bearing non-diversifiable risk.

[4] In theory, a perfectly opaque asset could be very liquid. It would trade with no adverse selection 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 (e.g. 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 assets' value will seriously reduce its liquidity. The market maker would be forced to raise her spread, and uninformed traders would expect to suffer an information-based loss in trading the asset (Gorton and Pennacchi [1990]).

III. Data

We began with a list of firms whose SIC code suggested that they were banks or bank holding companies (SIC 6021-6025, 6710-6712), and whose common equity traded on the NYSE, AMEX, or NASDAQ at any time between January 1990 and December 1997. Since almost all traded banking firms are bank holding companies, we discarded any firm that did not file the Federal Reserve's Consolidated Financial Statements for Bank Holding Companies (FR Y-9C).[5] For these BHCs, we collected quarter-end financial variables from the Y-9C, and transactions level stock information from the Institution for the Study of Securities Markets (ISSM, 1990-1992) and the NYSE's Trade and Quote (TAQ) data (after 1992). The financial data provide indicators of asset opacity, while the transactions data permit us to measure several indicators of equity market depth: trading volume, stock price volatility, bid-ask spreads, and the spreads' adverse selection components.

We used the ISSM-TAQ transactions data to compute several quarterly measures of each firm's equity-trading characteristics. Table 1 provides more detailed definitions of the following variables.

1) Bid-ask spreads, averaged over all transactions in the quarter:
    a. the quoted bid-ask spread (QSPREAD)
    b. the effective spread (ESPREAD), which reflects trades that occur inside the quoted spread
    c. the spread's adverse selection component (AS).

2) Trading activity, measured alternately as
    a. VOL, the number of shares traded during the quarter.
    b. NUMTRD, the number of distinct trades during the quarter.
    c. TOVER, the number of shares traded, divided by the number of shares outstanding.
    d. TRDSZE, the average number of shares traded in a each transaction during the quarter.

3) Return volatility, the annualized standard deviation of the continuously compounded returns between adjacent trades, computed using the quote midpoints (STD).

We eliminated observations that seemed likely to produce unrepresentative values: any firm-quarter for

[5] Under U.S. law, any firm that controls a bank is supervised as a "bank holding company." Bank "control" is defined as holding more than 25% of a bank's equity shares or the ability to elect at least two directors. Most U.S. BHC own primarily commercial bank assets, and their non-bank subsidiaries tend to deal in financial markets (e.g. a consumer financing subsidiary). Selected non-banking activities have also been permissible for many years, but nonbank subsidiaries constitute a large proportion of total assets for only a few BHC.

which the average share price was less than $2, the stock had fewer than 100 trades, or the average quoted spread exceeded 10% of the share's price.[6] We also omitted any firm-quarter in which the stock split or paid a stock dividend greater than 10 percent, because research has revealed significant microstructure changes following a split (Desai, Nimalendran and Venkataraman [1998]). The final sample consists of more than 5,100 observations on 320 BHCs with financial data and market microstructure variables available for at least part of the 1990-1997 sample period.[7] The sample BHCs are traded in two very different market environments. Both NYSE and AMEX firms are traded through a single specialist, while NASDAQ firms are traded via dealer quotes. We combine the 58 firms traded on NYSE or AMEX exchanges into a single "NYSE sample," which is composed predominantly of NYSE-traded BHCs. The "NASDAQ sample" includes 262 BHCs that traded for at least part of the 1990-1997 period.

We also collect fiscal-year earnings forecasts from IBES. The first meaningful forecasts come ten months before the fiscal yearend, because few analysts post a forecast for the next fiscal year until the firm has announced its most recent yearend results. For each of the ten months preceding a fiscal yearend, we collect the number of analysts posting earnings estimates, the median and standard deviation of posted forecasts, and the year's actual earnings.[8] We standardize different firms' earnings forecasts by deflating the standard deviation of posted forecasts and the forecast errors by the firm's share price at the start of the fiscal year. We then multiplied the standardized forecast error by 10,000, yielding basis points as the unit of measurement for the forecasts.

Table 1 defines the microstructure and financial variables used in our subsequent analysis, and presents summary statistics.

---

[6] Omitting observations with a spread larger than 30%, instead of 10%, leaves the number of NYSE observations unchanged but adds 91 additional observations for the NASD banks. Results are not sensitive to this variation in the spread cutoff.

[7] The number of observations varies slightly for different dependent variables, primarily due to variations in availability of microstructure data.

[8] All banks have December 31 fiscal years, but the nonbanks are less uniform. In order to compare bank and nonbank earnings estimates with similar forecasting horizons, we selected the nonbank's fiscal year end closest to December and "backed up" the appropriate number of months to find the analyst data.

IV. Comparing Microstructure Variables: BHCs vs. Other Traded Firms

In order to compare BHCs' stock-trading characteristics to those of firms that are regulated primarily by market forces, we matched each sample BHC with a control firm on the basis of equity market value, share price, and trading venue (NASDAQ, AMEX, or NYSE).[9] Each BHC's control firm is re-selected at the start of each calendar year. Potential control firms were selected from the set of all firms on the CRSP tape that survived the entire calendar year, except financial firms (SIC code 6000-6999) or regulated utilities (SIC code 4800-4900). We first selected the firm whose equity market value was closest to the BHC's. If that firm's stock price was also within 25% of the BHC's stock price, we used this as our nonfinancial control firm. Otherwise, we selected the next-closest equity value match from the proper trading venue, determined if its share price was within 25% of the BHC's, and so forth. We collected no accounting information for the control firms.

Table 2 summarizes the microstructure variables for the two samples of BHCs and their matching control firms. We report the BHC and control samples' mean values for each variable, and the statistical significance of their difference. We also show median values for each group and a non-parametric test of the hypothesis that the BHCs' median value equals the controls' median. The large number of observations in our sample helps make even relatively small BHC-control differences statistically significant. To assess the economic importance of these differences, we compute a proportional ("Prop'al") difference for each bank-nonbank pair, equal to the difference between the two firms' values (the bank's value minus the control firm's value), divided by their mean value.

The first two rows in Table 2 confirm that the control group's market value and price closely resemble the BHCs'. The Table's first row (MVEQ) also illustrates the large size difference between the NASDAQ and NYSE BHC sub-samples: the typical NYSE-traded BHC is 10 – 15 times larger than its NASDAQ counterpart. The next four rows describe bid-ask spreads and their components. Relatively opaque firms might be expected to have larger adverse selection (AS) costs of trading, and larger spreads would discourage trading. However, all

[9] Choosing "similar sized" control firms on the basis of asset values (rather than *equity* market values) would have yielded control firms with substantially higher equity market values than their associated banks. We wished to avoid this situation because the microstructure literature primarily contains results for firms with similar equity market values, and we wished to

four spread measures in Table 2 exhibit mean and median values that are *lower* for the banks. While the spread differences are not overwhelming, they are generally statistically significant.[10] This is our first indication that banking firms are not unusually opaque to market investors.

The next row in Table 2 (STD) indicates that the NASDAQ-traded BHCs' return volatility is less than half that of the control firms, and these two series have significantly different mean and median values. Once again, the larger (NYSE-traded) BHC exhibit differences that are qualitatively similar but much less economically substantial. The apparent differences between NYSE and NASDAQ BHCs are further illustrated by the fact that the larger BHCs' return volatility is more than triple that of their smaller counterparts.

The next four rows describe the stocks' trading activity. A typical NASDAQ BHC's equity trades *much* less frequently than its control'. Using either shares traded during the quarter (VOL) or the number of distinct trades (NUMTRD), the mean NASDAQ control firm trades nearly five times as much as its matching BHC. Since we have matched BHCs and their controls on the basis of equity market value and price, each firm in a pair has a similar number of shares outstanding, and so the difference between nonbank and BHC turnover (TOVER) is similarly large. Finally, average trade size is also significantly smaller for the NASDAQ BHCs.

The larger (NYSE) banking firms in Panel B of Table 2 resemble their control firms much more than the NASDAQ BHC do. Mean trading volume (VOL), number of trades (NUMTRD), and trade size (TRDSZE) do not differ between the two groups. Only the mean value of TOVER is significantly smaller for the banks. Comparing the medians of these same series, BHC trading is significantly smaller, but the bank-nonbank differences are much less substantial in economic terms than they are for the NASDAQ sample.

One possible explanation for the BHCs' low trading activity is that BHC stocks have lower float (i.e., the number of outstanding shares held by investors willing to trade the stock). If the BHCs are more tightly controlled, their shares may trade less even if investors view the two sets of firms as otherwise comparable.

---

rely on that literature to interpret Table 2.

[10] Our sub-sample spread properties resemble earlier results in the literature. For example, we find that NASDAQ spreads substantially exceed NYSE spreads. Consistent with Affleck-Graves *et al*. [1994] we also find that the Order Processing component of spreads is larger on the NASDAQ, while the AS component is larger on the NYSE (where a single specialist must absorb all of the informed trading and inventory risk).

To evaluate this possibility, we collected insider and 5% owner data for each BHC and its match from Compact Disclosure, for yearend 1990 and yearend 1995. At both dates, BHC ownership was substantially *less* concentrated than the controls'. Because ownership features were similar in both years, Table 3 reports only the 1995 information. The first two lines in Table 3 describe sample means and medians for all 405 BHC-control pairs with available ownership data.[11] (If either firm in a pair lacked data, we omitted both firms from this analysis.) For the full sample, control firms have roughly twice the insider holdings and twice the blockholders (defined as 5% owners which may, of course, include some insiders). These differences are highly statistically significant. The remainder of Table 3 separates the BHC-control pairs on the basis of their stocks' trading location. We find that the full sample's large differences are primarily due to the NASDAQ firms, which differ from their controls with a very high level of statistical confidence. By contrast, the *median* insider blockholdings of NYSE-traded BHCs and their control firms are statistically indistinguishable. The NYSE BHCs' *mean* insider holdings are significantly lower than the controls', but the difference is much smaller than for the NASDAQ-traded firms. Consistent with the data in Table 3, the last row in Table 2 indicates that institutional investors hold a significantly smaller proportion of BHC shares, and this difference is (again) more substantial for the NASDAQ BHCs.

The fact that BHC shares are more widely held than control firm shares *compounds* the question why BHC shares trade less frequently. However, the BHCs' low institutional ownership (see the last row of Table 2) is consistent with the hypothesis that gathering the information required to monitor BHC performance is not unusually costly.

We conclude from Tables 2 and 3 that the NYSE BHCs quite closely resemble the control sample. We find no microstructure indications that these BHCs are substantially *more* opaque. On its face, this seems to imply that government supervision of large banking firms must be justified on grounds other than information asymmetry. However, as we note in the concluding section, the large BHCs' transparency may reflect government monitoring and discipline services.

[11] Table 3 contains more bank observations than the other tables because we gathered shareholder information even for

The implications of Tables 2 and 3 for the NASDAQ firms are less obvious. Despite somewhat lower spreads and spread components, these BHCs have lower trading activity. Do extreme information asymmetries cause NASDAQ BHCs to trade so much less frequently? If so, why do the bid-ask spreads not reflect these asymmetries? The NASDAQ banking firms also exhibit relatively low return volatility, which suggests relatively stable asset value. This fact is consistent with the evidence that BHCs have fewer blockholders and lower institutional holdings: less volatile firms require less concentrated ownership to control agency problems. Section VI demonstrates that analyst earning forecasts also imply that BHCs are relatively easy to value. First, however, Section V explores the determinants of BHC microstructure variables.

V. The Effects of Balance Sheet Composition on BHC Microstructure Variables

If microstructure variables reflect opacity, they should vary systematically across BHCs with different balance sheet compositions.[12] For example, loans may be harder for outside investors to value than investment securities. We test the hypothesis that a BHC stock's microstructure features reflect the information asymmetries impounded in its asset portfolio by estimating fixed effect, pooled regressions, in which end-of-quarter accounting variables are aligned with average microstructure variables from all transactions during the preceding calendar quarter.[13]

$$Y_{it} = \alpha_i + \sum_{k=1,5} \beta_k \frac{A_{kit}}{MVEQ_{i,t-1}} + \sum_{j=1,4} \gamma_j X_{jit} + \sum_{p} \omega_p M_{pi,t-1} + \sum_{\tau=91,97} \delta_\tau D_\tau + \varepsilon_{it} \qquad (3)$$

where

Y_{it} is a market measure of the stock's information opacity, measured alternatively as the effective spread, the stock return's (log) standard deviation, or share turnover.[14]

banks lacking sufficient other information to be included in the subsequent regressions.

[12] Banking data may be uniquely suited to this type of test because the reported asset categories are relatively homogeneous across BHC. Similar tests for a large set of nonfinancial firms would be weakened by the variety of assets held across different industries.

[13] Estimating (3) via OLS (without firm fixed effects) yields similar coefficient estimates on the variables of interest, but in all cases an F test rejects the hypothesis that the fixed effects all equal zero.

[14] Although the most natural dependent variable for (3) would seem to be the adverse selection (AS) component of spread, AS is estimated with error and little is known about the properties of alternative spread decomposition methods. Estimation

A_{kit} is the book value of assets of type k (k = 1, 5) held by BHC i at the end of quarter t.

$MVEQ_{i,t-1}$ is the market value of BHC i's common equity at the end of the preceding quarter (which ends at time (t-1)).

$M_{pi,t-1}$ is a set of microstructure variables for the stock.

X_{jit} is the value of control variable j at BHC i at the end of quarter t.

D_τ is a dummy variable equal to unity in year τ, and zero otherwise.

All regressions include firm fixed effects, whose estimated values are not reported in the tables. We estimate separate models for the NYSE and NASDAQ BHC samples because Chow tests rejected the hypothesis that they share the same coefficient values.

Each banking firm's assets are separated into six (exhaustive) categories (A_{kit}) at the end of quarter t:

NETLNS = total loans, net of the allowance for loan and lease losses plus customers' liabilities on outstanding acceptances.[15]

LLA = loan loss allowance, a contra asset to the loan account.[16]

TRADE = the fair value of assets held in trading accounts (including treasuries, agencies, state and local bonds, CDs, commercial paper and bankers acceptances).

OREO = other real estate owned. This account primarily includes real estate taken in settlement of problem loans, though some real estate investments (other than bank premises) are also included.

OPAQUE = the book value of bank premises and fixed assets, plus other opaque assets: investments in unconsolidated subsidiaries, intangible assets, and the balance sheet category "other assets".[17]

TRANSP = easily valued ("transparent") assets: the sum of cash, marketable securities, interbank balances, federal funds sold, and securities purchased under agreement to resell ("RPs").

---

results presented in the Appendix indicate that some specific conclusions tend to depend on how a stock's AS component is computed. We therefore express our main "spread" results in terms of ESPREAD.

[15] We also experimented with decomposing NETLNS into components like foreign vs. domestic loans or current vs. delinquent loans. As in Table 4, bank balance sheet composition significantly affected microstructure variables, but the coefficients on various NETLNS components provided little intuition about the opacity of the different loan types. Results are available from the authors.

[16] LLA is meant to capture the loan portfolio's quality. An alternative indicator – the provision for loan losses – was included in place of LLA and in addition to LLA. The provision variable never carried a significant coefficient, nor did its inclusion affect the significance of our hypothesis test statistics.

[17] The Y-9C report provides no further breakdown for these asset categories. Over the entire sample, OPAQUE included a mean (median) proportion of 39% (40%) premises, 0.7% (0%) investments in unconsolidated subsidiaries, 14% (11%) intangible assets, and 47% (45%) "Other assets." This last category is an aggregation of many items, including accounts receivable, repossessed autos, boats, and other collateral, margin account balances associated with forward and future contracts, and income earned but not collected.

Each asset category is deflated by the lagged market value of equity capital ($MVEQ_{i,t-1}$) because equity traders experience valuation uncertainty in proportion to their equity claim on the BHC.[18] We omitted TRANSP from the asset share variables in (3), and therefore interpret the β_k coefficients as measuring the impact on Y_{it} of a shift into asset k from TRANSP.

Whereas the above stock variables capture the opacity of the banking firm's assets-in-place, the valuation of a banking firm also depends on its income flows, leverage, and the composition of banking versus nonbanking activities. The control variables (X_{jit}) in (3) capture other BHC characteristics that might affect an outsiders' ability to value the firm. They are:

$PROFIT_{it}$ = the ratio of annualized net income during the quarter ending at t, to equity's market value at the end of the quarter ending at (t-1).

$FEES_{it}$ = the ratio of net fee income during the quarter ending at t, to equity's market value at the end of the quarter ending at (t-1).

$MVLEV_{it}$ = market value 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).

$HIGH\text{-}CB_{it}$ = a dummy variable equal to unity if the BHC's subsidiary commercial bank assets exceed the sample median proportion of total BHC assets.

The dependent variable in (3) will be one of the firm's microstructure characteristics. The market microstructure literature has established that a firm's spread, trading volume, trade size, and asset return volatility are closely inter-related. For example, a large bid-ask spread tends to depress trading volume, which in turn makes it more difficult for a market-maker to manage her inventory. Higher volatility also raises inventory-holding costs (and hence bid-ask spreads), but trading volume is positively correlated with return volatility (Karpoff [1987], Jones, Kaul and Lipson [1994]). Causation may also run the other way, as thinner trading or more return volatility tends to increase the market maker's operating costs, and hence equilibrium spreads. Although a fully-specified structural model would ideally describe all microstructure variables simultaneously, a good set of instruments for these variables is virtually impossible to specify. Accordingly, we lag these

[18] Replacing MVEQ with the book value of common shares or with total assets (book value) yields very similar conclusions for NASDAQ banks and broadly similar conclusions for NYSE banks (whose market values include a larger proportion of

microstructure variables one quarter when estimating (3). [19]

Two lagged microstructure variables are always included in regression (3):

$PINV_{it}$ = the inverse of the BHC's average share price during the quarter ending at t. For low-priced shares, the minimum tick size may constrain spreads, biasing upward the market maker's required compensation for insider trading (opacity). The inverse of share price captures the tendency for this effect to diminish as share price rises.

$LNMVEQ_{it}$ = the log of the market value of BHC equity at the end of the quarter ending at t. If analysts more closely follow larger firms, these firms' stock should have lower spreads and (therefore) perhaps higher trading volumes. [20]

The other components of $M_{pi,t-1}$ vary with the regression's dependent variable, which is either ESPREAD, LNSTD, or TOVER (defined below).

When the dependent variable is ESPREAD (the stock's proportional effective spread), other microstructure control variables are

$LNSTD_{it}$ = the natural log of the annualized standard deviation of equity returns during the quarter ending at t.

$TRDSZE_{it}$ = the average number of shares per transaction during the quarter ending at t. Larger trades are generally thought to reflect more inside information.

$Ln(VOL_{it})$ = the log of the total number of shares traded during the quarter ending at t. [21]

More volatile stocks are more expensive for a market maker to hedge in his inventory, while higher trading volume makes it easier to manage the inventory and reduces per-share operating costs. Holding volume constant, larger TRDSZE may indicate more informed counterparties, which cause the market maker to quote wider spreads to offset greater adverse selection.

When *LNSTD* is the dependent variable in (3), the lagged microstructure control variables are ESPREAD and

$TOVER_{it}$ = turnover: shares traded during the previous quarter, divided by the number of shares outstanding at the end of the preceding quarter.

---

off-balance-sheet activities).

[19] Hasbrouck [1991] uses a VAR model to infer that lagged trading information affects spreads.

[20] Size might alternatively be considered a bank characteristic, along with the portfolio share variables or the control variables (X_{jit}). By omitting LNMVEQ(-1) from the "bank characteristics" vector, we bias our tests against finding that bank characteristics significantly affect stock trading properties.

[21] The results are effectively unchanged when we replaced TRDSZE and ln(VOL) with share turnover (TOVER).

Finally, we use TOVER as our preferred measure of trading activity, and include lagged values of ESPREAD and LNSTD among its microstructure controls.

In addition to the significance of individual coefficients, we test whether each set of explanatory variables jointly influences a BHC's microstructure properties.

H1: All five balance sheet ratios' coefficients (β_k) jointly equal zero.

H2: All nine BHC financial variables' coefficients (β_k and γ_j) jointly equal zero.

H3: All microstructure variables' coefficients (ω_p) jointly equal zero.

H4: All seven year-dummy coefficients (δ_τ) jointly equal zero.

Finally, we compare the economic significance of various variable sets – in particular the balance sheet ratios vs. the lagged microstructure variables – by examining the marginal contribution of each set to the regression's $\overline{R}^2$. This requires that we run (and display) three specifications of (3) for each dependent variable: one includes only the microstructure variables, one includes only the financial information, and the third includes both sets of explanatory variables. (All specifications include the year dummies.)

Panel A of Table 4 presents the NASDAQ results. We clearly reject the hypothesis (H1) that balance sheet composition has no effect on ESPREAD (pr < .02) in both specifications (I) and (III). Presumably, a BHC's balance sheet composition influences its bid-ask spread because asset categories vary in their information opacity. In the full model estimated in column (III), the only individual asset that significantly affects ESPREAD is net loans (NETLNS), consistent with the loan portfolio being a source of value uncertainty. Beyond the balance sheet's composition, we find that more profitable firms (PROFIT) and BHC relying more on noninterest income (FEES) have significantly lower spreads (the FEES coefficient is nearly significant at the 5% confidence level). More highly levered firms concentrate their valuation uncertainties into a smaller volume of equity claims, which is reflected in the significantly positive (10% level) coefficient on MVLEV. Finally, ESPREAD is significantly larger for BHC that concentrate in commercial banking assets (HIGH-CB), suggesting that BHC leave their least transparent assets in their banking subsidiaries when they form other subsidiaries.[22]

In specifications (II) and (III), we strongly reject the hypothesis that the microstructure variables are jointly zero (H3). As reported elsewhere in the literature, discrete tick sizes tend to make proportional spreads larger for lower-priced stock (higher PINV). ESPREAD also responds to inventory risks: greater trading volume (Ln(VOL)) lowers the spread and return volatility (LNSTD) raises it. Finally, ESPREAD is significantly positively related to average trade size (TRDSZE), which is often interpreted as an indicator of informed trading.

Despite these statistically significant coefficients on the portfolio composition and microstructure variables, neither information set contributes greatly to the regression's explanatory power. The portfolio and microstructure variables each explain about the same proportion of the variation in ESPREAD. The bottom section of Table 4A reports that regressing ESPREAD on the firm fixed effects and year dummies alone yields an $\overline{R}^2$ ("R^2: FE, Years") of 0.749. The $\overline{R}^2$ statistic for specification (I) indicates that the balance sheet ratios add 4.5 percentage points of explanatory power ($\overline{R}^2$ = .794). Specification (II) adds the lagged microstructure variables to the fixed effects and year dummies, to produce 5.2 percentage points of additional explanatory power ($\overline{R}^2$ = .801). In the specification (III), both sets of coefficients variables jointly differ from zero (pr < .02 for both H1 and H3), but the $\overline{R}^2$ statistic (0.813) only slightly exceeds its value in (I) and (II). It thus appears that the balance sheet and market microstructure variables *incorporate very similar information* about ESPREAD.

The middle three regressions in Table 4A explain a stock's return volatility, LNSTD. The portfolio variables (H1) and microstructure variables (H3) each add significant explanatory power when included alone (in columns (IV) and (V)). However, when both sets of explanatory variables are combined (column (VI)), the balance sheet variables become insignificant (pr = .13) and no individual asset type carries a significant coefficient.[23] A greater reliance on fee income (RFEES) raises volatility. HIGH-CB lowers return volatility, consistent with the notion that banking assets are relatively stable. The financial and microstructure sets of

---

[22] This result is not robust to an alternative way of measuring BHC that concentrate in banking assets (the simple proportion of BHC assets in its banking subsidiaries). However, none of the other variables or hypotheses is substantially affected by the inclusion or exclusion of either of these concentration measures.

[23] Still, a bank's condition does affect LNSTD: the set of nine "financial" variables remains jointly significant (pr < .001).

explanatory variables for LNSTD affect explanatory power in much the same way as they do for ESPREAD. The set of fixed effects and year dummies explains 54.0% of the variation in LNSTD ("R^2: FE,Yrs"). Adding either the BHC financial variables (in column (IV)) or the microstructure variables (in column (V)) raises $\overline{R}^2$ only slightly (to 55.6% and 55.8% respectively). Combining both variable sets into a single regression (VI) adds very little ($\overline{R}^2$=56.6%). As for ESPREAD, we conclude that a BHC's portfolio composition provides largely the same information about return volatility as the lagged microstructure variables.

The last three regressions in Table 4A explain the proportion of shares traded (TOVER). The financial and microstructure variables carry jointly significant coefficients (H1, H2), but we again find that the marginal contribution of either variable set to $\overline{R}^2$ is very small.

Table 4B reports estimation results for the NYSE subsample. The balance sheet's composition and the firm's microstructure characteristics significantly affect all three dependent variables. As we found for the NASDAQ sample, however, neither group of variables adds much explanatory power to the regression and it appears that they explain similar aspects of the three dependent variables. Despite these broad similarities, the NYSE regressions contain fewer statistically significant coefficients, perhaps because there are fewer data points. In a few cases, the large and small BHCs exhibit opposite sensitivities to a variable. For example, trading account assets (TRADE) significantly raise share turnover for NYSE BHCs, but lower it for their smaller counterparts. The fact that some balance sheet assets have opposite effects in the NASDAQ and NYSE samples again suggests that these two groups of institutions differ quite substantially.

The results in Table 4 confirm that a BHC stock's trading properties are determined by its asset composition and financial characteristics, which reflect the degree of opaqueness underlying its operations. This provides empirical support for using the microstructure properties in Section IV to compare opaqueness between BHCs and nonbanks. We also found that a stock's trading properties are interrelated, confirming what has been reported in the microstructure literature. Although the marginal explanatory power of BHC financial characteristics over microstructure variables in explaining a stock's trading properties is not large, the fact that the financial variables remain significant even after controlling for microstructrure characteristics supports the hypothesis that asset composition matters.

VI. Analyst Earnings Forecasts

Outside analysts' earnings forecasts provide an independent measure of firm opacity. *Ceteris paribus*, larger analyst forecast errors or disagreement implies that the firm is harder to understand.

A. BHC versus Nonbank Earnings Estimates

Table 5 presents our IBES data analysis separately for the NASDAQ and the NYSE sub-samples. To save space, we report only four months' data for each variable: 10, 7, 4, and 1 month before the fiscal yearend. The NASDAQ BHCs in Table 5A are followed by significantly fewer analysts at all forecast horizons. Among the BHC-nonbank pairs with multiple analysts, the median forecast dispersions (cross-sectional standard deviations) are statistically indistinguishable for BHCs vs. nonbanks. Banks also have smaller mean dispersions at all four forecast horizons, although the difference is statistically significant only 7 and 4 months before the fiscal year end. The third panel of Table 5A indicates that bank analysts revise their forecasts significantly *less* often. Depending on the forecast horizon, nonbank forecast revisions exceed the BHCs' revisions by as much as 50%. Finding fewer analyst revisions is consistent with the NASDAQ BHCs' lower return volatility in Table 2: firms whose apparent condition changes less often should have less variable earnings forecasts.

The key question is whether infrequent information arrival means that BHC values are stable, or merely that many value changes remain hidden from the market. The last four rows of Table 5A answer this question by comparing the mean and median absolute forecast errors for BHCs vs. control firms. These forecast errors decline as the year proceeds, but the BHC forecasts are always more accurate than the nonbank analysts' forecasts. In all cases except one, the forecast errors are significantly ($pr < .05$) lower for BHCs. The only instance of statistically indistinguishable mean forecast errors occurs one month before the fiscal year end, and even then the BHCs' median forecast error remains significantly smaller.

Some commentators suggest that analysts predict BHC earnings more accurately because BHCs can better manage their accounting earnings to meet analyst expectations (e.g. Robb [1998]). This would reduce the relevance of a BHC's accounting earnings to investors, perhaps rendering the BHC more opaque. However, we do not find this hypothesis to be a good explanation for the results in Table 5A. Artificial earnings management seems more relevant for short-term forecasts: with only a few months left in the fiscal year, managers know more about the need to realize discretionary income or expenses in order to camouflage fundamental changes in firm value. Table 5A indicates that the BHC and nonbank forecast errors converge as the year progresses, but the BHCs' relative accuracy *worsens* as the fiscal year end approaches. For example, the BHCs' mean forecast error rises from 65% of the controls' ten months before year end to 79% of the controls' one month out.[24]

The BHCs' lower forecast errors in Table 5A suggest that analysts find them easier to understand than the typical control firm. The fact that bank analysts post fewer revised forecasts further suggests that news arrives less frequently for BHCs than for the controls. We therefore conclude that the NASDAQ BHCs' lower trading volumes and return volatilities (reported in Table 2) reflect fewer changes in true value. NASDAQ BHCs are not opaque. They are boring.

Table 5B reports IBES results for the NYSE BHCs. Unlike the NASDAQ case, significantly *more* analysts follow NYSE BHCs. The BHC earnings forecasts exhibit *greater* cross-sectional variation, but the difference is statistically significant only for the 7-month-ahead forecasts. The NYSE BHCs qualitatively resemble their NASDAQ counterparts only in their relatively infrequent forecast revisions. Most importantly, NYSE bank analysts' forecast errors are statistically *indistinguishable* from the nonbank forecast errors.[25] Overall, the results in Table 5B indicate no reason to conclude that large BHCs are more opaque than their control firms.

B. Asset Composition and IBES Earnings Forecasts

We can learn more about the opacity of banking firms by evaluating how their balance sheet compositions affect the properties of analyst earnings forecasts. Once again, the idea is that portfolio composition should affect earnings forecasts if some types of BHC assets are more difficult for outsiders to evaluate. We

---

[24] We thank Jon Garfinkel for this observation.

[25] At all forecast horizons, the NYSE median forecast errors are insignificantly smaller and the mean forecast errors are insignificantly larger.

estimate a regression model like (3) to explain IBES variables:[26]

$$IBES_{it} = \alpha_i + \sum_{k=1,5}\beta_k \frac{A_{kit}}{MVEQ_{i,t}} + \omega LNMVEQ_{i,t-1} + \sum_{j=1,4}\gamma_j X_{jit} + \sum_{\tau=91,97}\delta_\tau D_\tau + \sum_{m=1,3} DQ_m + \varepsilon_{it} \tag{4}$$

where $IBES_{it}$ is alternatively

$NEST_{it}$ = Number of analysts posting an earnings forecast for the firm's current fiscal year.

CSD_{it} = Cross-sectional standard deviation of analysts' forecast, computed only for firms with more than one analyst.

REV_{it} = Number of analysts revising their forecast during the month, as a percentage of the number of analysts following the firm.

FE_{it} = Median absolute EPS forecast error, divided by the share price at the start of the fiscal year, multiplied by 10,000 (to measure the forecast error in basis points).

Because each of the resulting IBES series combines earnings forecasts with different horizons, we added dummy variables to identify the first three calendar quarters of each year:

$DQ_m = 1$ $(m = 1, 2, 3)$ for the year's m^{th} quarter, = 0 otherwise.

We omit the market microstructure variables from regression (4), but retain BHC size (LNMVEQ) as a potentially important influence on BHC earnings forecasts.[27]

Table 6 presents the estimation results separately for the NASDAQ and NYSE samples. The test statistics for hypotheses H1 and H2 indicate that the BHC's financial variables significantly affect all four dimensions of the NASDAQ BHCs' earnings estimates. However, comparison of the $\overline{R}^2$ statistics indicates that the economic significance of these financial variables is substantial only for the two most natural indicators of firm opacity: forecast dispersion (CSD) and errors (FE). The effects of asset composition on opacity can be seen in these two regressions. Year dummies and fixed effects alone explain about 21% of the variation in CSD ("R^2: FE, Yrs"). Adding the firm's financial variables nearly doubles the regression's $\overline{R}^2$ to 37.9%. The FE regression's $\overline{R}^2$ also rises substantially when we add the financial variables -- from 42% ("R^2: FE, Yrs") to

---

[26] We associate the monthly IBES data with the quarterly financial data by pairing each quarter's financial data with the IBES observation closest to that quarter end. Specifically, financial data for the first quarter or each fiscal year were associated with the 10-month-ahead earnings variables; the second quarter's financial data were paired with the 7-month-ahead earnings variables; and so forth.

62.2%. The individual coefficient estimates in these two regressions indicate that NETLNS significantly increase both CSD and FE. LLA raises uncertainty in both cases, but the effect is statistically significant only for CSD. PROFIT, FEES, and MVLEV all reduce analyst uncertainty, although the statistical significance of these coefficients varies between the two regressions. Finally, the proportion of BHC assets in commercial bank subsidiaries (HIGH-CB) significantly reduces CSD, FE and REV, consistent with the hypothesis that banking assets are relative easy to value.

Going beyond the statistical significance, the economic effects of the balance sheet variables are sometimes quite large for CSD and FE. For example, a one-standard-deviation increase in NETLNS raises CSD by 0.70 standard deviations and a simultaneous one-sigma increase in *each* of the five balance sheet categories raises CSD by 1.35 standard deviations. FE is most sensitive to NETLNS: a one-sigma change in NETLNS changes FE by 0.72 standard deviations. Increasing all five balance sheet variables by one standard deviation raises FE by 0.82 standard deviations.

The right half of Table 6 presents NYSE results. Financial variables significantly affect three out of four IBES variables for these larger BHCs (the exception being revision frequency, REV). As for the NASDAQ BHCs, however, financial information substantially increases the regression's $\overline{R}^2$ only for CSD and FE. We find that different variables affect the opacity of larger vs. smaller BHCs: NASDAQ BHCs' CSD varies significantly with NETLNS, LLA and TRADE, but only OREO affects significantly the NYSE sample's CSD. Similarly, FE varies with NETLNS, ROE, and HIGH-CB in both samples, but TRADE enters only for the smaller BHCs. Again, the economic significance of these effects is substantial. For example, a 1-sigma increase in OREO raises CSD by 0.41standard deviations and a 1-sigma increase in NETLNS raises forecast error (FE) by 0.93 standard deviations.

Overall, Table 6 suggests that banking firms' financial characteristics affect outsiders' ability to understand their value, consistent with the hypothesis that different types of assets differ in their degree of opacity. Nevertheless, Table 5 shows that BHCs are not absolutely more difficult to understand than a set of

[27] Including the lagged microstructure variables in (4) does not change the conclusions reported in the text.

control firms: smaller BHCs' earnings are significantly easier to forecast, while outsiders forecast large BHCs' earnings about as accurately as they forecast earnings for the large BHCs' control firms.

VII. Summary and Conclusions

We have combined the literatures on bank uniqueness and market microstructure to assess whether bank stocks' trading behavior indicates that they are unusually difficult to value. Our basic conclusion is that bank stocks are *not* unusually opaque, although the details differ between small and large institutions.

Our empirical tests evaluate two proxies for firm opacity, the stock's market microstructure properties and analysts' ability to forecast firm earnings. We construct a matched set of BHCs and (similar-sized, similarly-priced) control firms trading in the same market (either NASDAQ or NYSE-Amex). We find statistically and economically significant differences between the two groups only for the smaller (NASDAQ) firms.

The smaller (NASDAQ) banking firms differ quite substantially from their control sample. They trade much less frequently than comparable nonbanks *despite* having comparable bid-ask spreads. The NASDAQ BHCs' comparatively low concentrations of insider and block owners make their trading differences even more striking than the raw data imply. The smaller BHCs also exhibit substantially lower return volatilities than their control firms, and IBES analysts can predict their earnings more accurately. The combination of low volatility and low earnings forecast errors implies that market investors have rather good information about these BHCs. Opacity is not a prominent feature of these banking firms.

The larger BHCs (traded on the NYSE/AMEX exchanges) exhibit trading activity, return volatility and bid-ask spreads comparable to their controls'. The NYSE sample's IBES forecast errors are statistically indistinguishable from those of their controls. Relatively infrequent revisions to BHC earnings forecasts (Table 5) are consistent with their slightly lower return volatility (Table 2). NYSE BHCs also have less concentrated ownership, although the differences are small and not generally statistically significant (Table 3). Overall, our results support the hypothesis that investors can evaluate large banking firms as readily as they evaluate the nonfinancial control firms

We also sought evidence that a BHC's financial characteristics determine its microstructure properties and analyst earnings forecasts. Since theory predicts that BHC assets will differ in their information asymmetries, a failure of balance sheet ratios to explain at least some of the variation in our opacity proxies would cast doubt on their usefulness. Using a quarterly, pooled sample of banking firms, we assess various asset categories' impact on market microstructure variables. In Table 4, we nearly always reject the hypothesis that asset composition has no effect on a BHC's stock spread, return volatility or share turnover, consistent with the hypothesis that asset categories differ in their opacity. However, the information about BHC opacity in financial variables seems to be largely replicated in the BHC stock's market microstructure variables. Neither of these variable sets adds substantial explanatory power to a simple regression that includes only fixed effects and year dummies.

BHC financial characteristics add substantial explanatory power in regressions that explain two of our four IBES variables. In particular, the financial variables sharply increase the $\overline{R}^2$ statistic for the two IBES variables that seem most closely associated with BHC opacity: the size of earnings forecast errors ("FE" in Table 6) and the dispersion of analyst expectations ("CSD").

As a byproduct of our primary investigations, we compare (in the Appendix) two empirical methods for extracting the "adverse selection" component from a stock's bid-ask spread. Our results indicate that the information content of these two adverse selection measures may be quite different, and neither method provides a clearly superior characterization of the BHCs' economic properties. The implications of these findings for empirical research in market microstructure are left for future study.

What implications does this analysis carry for bank regulatory issues? Taken at face value, BHC microstructure characteristics suggest that unusually opaque bank assets cannot justify special supervision of banking firms. The equity market evidence suggests that, if there is any differential opacity, BHCs are probably *easier* to evaluate than other types of firms. At a deeper level, however, banking firms are highly regulated, and special government supervision may somehow *cause* the BHCs' transparency. If BHCs are intrinsically opaque, government regulations and banking supervision have reduced that opacity. Further regulatory efforts to improve

BHC transparency must be justified by some differential social cost of opacity. Perhaps, for example, the systemic effects of banking firms' remaining opacity are more costly than those of nonbanks.

In the end, how much transparency is enough? Policymakers must balance the marginal benefits of further transparency against the regulatory burden imposed on financial firms. Our evidence of a well-functioning BHC equity market conforms to other recent findings that the market evaluates a bank's condition quite effectively. While it is entirely legitimate to ask for more market discipline, and hence more transparency in banking due to the special roles of banks in our economy, it may be more fruitful to think about how we can harvest existing market based information more effectively to supplement traditional supervisory activities.

Appendix: Adverse Selection Costs of Trading

A market-maker's bid-ask spread must cover her order processing, inventory holding and adverse selection costs.[28] Three classes of statistical models have been used to decompose observed bid-ask spreads. The first class of models makes economic inferences on the basis of the serial covariance properties of quotes and transaction prices (Roll [1984], Choi, Salandro and Shastri [1988], Stoll [1989], George, Kaul and Nimalendran [1991], and Lin, Sanger and Booth [1995]). The second class of models uses a trade direction indicator to decompose the spread (Glosten and Harris [1988] and Madhavan, Richardson and Roomas [1997]). The third class of models uses data about order flow and trade direction to estimate market depth, which should be lower for stocks with more severe adverse selection problems (Hasbrouck [1991a, 1991b], Hausman, Lo and MacKinlay [1992], and Foster and Viswanathan [1993]).

Van Ness *et al*. [2001] examine the economic validity of these models by comparing adverse selection (AS) estimates to one another and to "corporate finance" indicators of opacity, such as analyst forecast properties, return volatility, leverage, and institutional holdings. They conclude that most of the AS estimates are poorly correlated with alternate indicators of asymmetric information, and speculate that "these adverse selection components are merely noisy measures of spread." (page 96). Our own analysis is more limited. We compare the results from two, closely related, decomposition techniques for our bank holding company data.

Method I - George, Kaul, and Nimalendran [1991]

George, Kaul, and Nimalendran (GKN) decompose a stock's quoted spread into only two components (adverse selection and order processing), because they assume that the inventory component is small enough to ignore.[29] Their method also assumes that the quoted spread is constant across transactions, that the bid and ask quotes are updated after each transaction, and that the sequence of buy and sell orders is serially uncorrelated.

[28] Models that emphasize inventory holding costs include Demsetz (1968), Benston and Hagerman (1974), Stoll (1978), Amihud and Mendelson (1980), and Ho and Stoll (1981, 1983). Models that discuss the importance of adverse selection include Bagehot (1971), Benston and Hagerman (1974), Copeland and Galai (1983), Glosten and Milgrom (1985), Kyle (1985), Easley and O'Hara (1987), Admati and Pfleiderer (1988), and Subrahmanyam (1991). O'Hara (1995) provides an excellent review of both adverse selection and inventory cost models.

[29] Stoll (1989) documents that the inventory cost component is a small fraction of the total spread (less than 10%), and Madhavan and Smidt (1991) find that inventory effects are economically and statistically insignificant.

GKN compute two return series for each stock – one based on transaction prices and the other based on quote midpoints. Differencing these two return series cancels out unanticipated returns, which permits a more efficient estimate of the spread components:

(A-1) $$R_t^D = R_t^T - R_{t*}^Q$$

where R_t^T is the percentage change in transaction prices between the last trade and the trade at time t,

R_{t*}^Q is the percentage change in the midpoint of the bid and ask prices following the last trades at time t and time (t-1).

GKN show that the adverse selection component of a quoted spread (AS) is

(A-2) $$AS = s - 2\sqrt{-[Cov(R_t^D, R_{t-1}^D)]}\,.$$

where s is the average proportional quoted spread.

Neal and Wheatley [1998] modify GKN's methodology to let the proportional spread vary through time, and they do not restrict the probability of a buy or sell to be 0.5. Under these conditions, the following regression model can be used to estimate the adverse selection component of the spread.

(A-3) $$2R_t^D = \pi_0 + \pi_1(s_{qt}Q_t - s_{qt-1}Q_{t-1}) + \varepsilon_t\,,$$

where s_{qt} is the quoted proportional spread at time t, Q_t is a +1/-1 buy/sell indicator variable, and ε_t is an error term. The model (A-3) can be estimated using OLS: the estimate of $(1-\hat{\pi}_1)$ gives the fraction of the spread due to adverse selection, which we multiply by the most recent quoted spread to get the variable AS-GKN in Table A-1.

Method II - Lin, Sanger and Booth [1995]

Lin, Sanger and Booth (LSB) also assume that the market maker's inventory cost is zero, and hence produce only two spread components: order processing and adverse selection. Their regression model estimates the proportion of a stock's *effective* spread that can be attributed to adverse selection. (Recall that GNK compute adverse selection as a proportion of the *quoted* spread.) The main idea is that quote revisions reflect the market maker's response to adverse selection, while changes in transaction prices reflect order processing costs and bid-ask bounce. (See also on Stoll [1989], Huang and Stoll [1994].) Unlike GKN, however, LSB estimate an order persistence parameter, which measures the probability that a buy (sell) order will be followed by another buy (sell).

LSB estimate the adverse selection and order persistence parameters from the following pair of equations:

(A-4) $$Q_{t+1} - Q_t = \lambda Z_t + \varepsilon_{t+1},$$

(A-5) $$Z_{t+1} = \theta Z_t + \eta_{t+1}$$

where $Z_t = P_t - Q_t$, one half the effective spread,

P_t = transaction price at time t,

Q_t = quote midpoint,

λ = proportion of the effective spread due to adverse selection,

$\delta = (\theta + 1)/2$ = order persistence parameter, and

ε, η = noise terms.

The estimated value of λ measures the market-maker's adverse selection costs as fraction of the *effective* spread. We multiply λ by the most recent effective spread to get the variable AS-LSB in Table A-1.

Empirical Results

We calculated both adverse selection measures using only BBO (best bid and offer) eligible quotes, and following Lee and Ready's [1991] recommendation that each transaction should be associated with the quote in effect five seconds earlier. Table 1 clearly indicates that these two measures (AS-GKN and AS-LSB) imply very different adverse selection costs of trade!

To determine how these measures relate to balance sheet composition and other microstructure variables, we estimated a regression of the form (3) for each adverse selection measure, over each exchange sub-sample. The regression results in the left half of Table A-1 indicate that the two AS measures are explained by similar variables in the NASDAQ subsample. Both AS measures are significantly affected by portfolio composition (H1), market microstructure (H3), and time (H4). Some of the individual explanatory variables affect both AS-GKN and AS-LSB similarly. In particular, NETLNS (OPAQUE) carries significantly positive (negative) coefficients in both NASDAQ regressions. The other explanatory variables of interest show coefficients that differ in significance or sign between the two regressions. The regressions $\overline{R}^2$ statistics are lower than those reported for ESPREAD in Table 4A, as might be expected if the spread decompositions are noisy.

The right half of Table A-1 presents a far less consistent comparison of the two AS measures for NYSE BHCs. The asset share coefficients are less strongly significant here (H1 is rejected with probability 17.8% for AS-GKN and 3.9% for AS-LSB). The two AS measures provide very different impressions of which NYSE BHC characteristics affect opacity. One variable, firm size (LNMVEQ(-1)), significantly affects the two AS measures in opposite directions.

While these results are not inconsistent with our "primary" estimates in Table 4, their ambiguity gives us pause about the information content of these decompositions. Van Ness *et al*. (2001) share these reservations, concluding that they "cannot say whether these models are capturing uncertainty due to information problems, or some other costs." (page 96). Accordingly, we utilize ESPREAD as our primary estimate of adverse selection costs.

References

Admati, A., and P. Pfleiderer, 1988, “A Theory of Intraday Patterns: Volume and Price Variability,” *Review of Financial Studies* 1, 3-40.

Amihud, Y., and H. Mendelson, 1980, “Dealership Market: Market Making with Inventory,” *Journal of Financial Economics* 8, 31-53.

Affleck-Graves, John, Shantaram P. Hegde, and Robert E. Miller, “Trading Mechanisms and the Components of the Bid-Ask Spread”, *Journal of Finance* 49(4) (September 1994), pp. 1471-1488.

Akerlof, George A. “The Market for ‘Lemons’: Quality Uncertainty and the Market Mechanism,” *Quarterly Journal of Economics* v84 n3 Aug. 1970, pp. 488-500

Bagehot, Walter (pseud.) [1971], “The Only Game in Town,” *Financial Analysts Journal* 27, 12-14, 22

Benston, George J., and Robert L. Hagerman, 1974, “Determinants of Bid-Asked Spreads in the Over-the-Counter Market,” *Journal of Financial Economics 1*, 353-364.

Benston, George J. and George G. Kaufman, “Risk and Solvency Regulation of Depository Institutions: Past Policies and Current Options,” Salomon Brothers Center *Monograph Series in Finance and Economics* (1988-1).

Berlin, Mitchell and Jan G. Loeys, “Bond Covenants and Delegated Monitoring”, *Journal of Finance* (June 1988), 397-412.

Brennan, Michael and A. Subramanyam, “Investment Analysis and Price Formation in Securities Markets”, *Journal of Financial Economics* July 1995, pp. 361-381.

Calomiris, Charles W., and Joseph Mason, "Contagion and Bank Failures During the Great Depression: The June 1932 Chicago Banking Panic", *American Economic Review* 87, December 1997, 863-883.

Campbell, Tim, and William Kracaw, 1980, “Information production, market signaling, and the theory of intermediation,” *Journal of Finance* 35, 863-882.

Choi, J. Y.,D. Salandro, and K. Shastri, 1988,."On the Estimation of Bid-Ask Spreads: Theory and Evidence," *Journal of Financial and Quantitative Analysis* 23, 219-230.

Copeland, T., and D. Galai, 1983, “Information Effects and the Bid-Ask Spread,” *Journal of Finance* 38, 1457-1459.

Demsetz, H., 1968, “The Cost of Transacting,” *Quarterly Journal of Economics* 82, 33-53.

Desai, Anand, M. Nimalendran and S. Venkataraman, 1998, "Changes in Trading Activity Following Stock Splits and Their Effect on Volatility and the Adverse-Information Component of the Bid-Ask Spread." *The Journal of Financial Research* 21(2), 159-183.

Diamond, Douglas W., 1989, “Reputation Acquisition in Debt Markets,” *Journal of Political Economy* 97, 828-862.

_____, 1991, "Monitoring and Reputation: The Choice between Bank Loans and Directly Placed Debt," *Journal of Political Economy* 99, 689-721.

Easley, D., and M. O'Hara, 1987, "Price, Trade Size, and Information in Securities Markets," *Journal of Financial Economics* 19, 69-90.

Fama, Eugene F., and Michael C. Jensen, 1983, "Separation of Ownership and Control," *Journal of Law and Economics*, 26(2)

Flannery, Mark J., "Using Market Information in Prudential Bank Supervision: A Review of the U.S. Empirical Evidence" *Journal of Money, Credit and Banking* (August 1998, Part I), pp. 273-305.

Flannery, Mark J., and Joel F. Houston, [1999], "The Value of a Government Monitor for Firms with Hard-to-Value Assets" *Journal of Money, Credit and Banking* (February), pp. 14-34.

Foster, F. Douglas and S. Viswanathan. "Variations In Trading Volume, Return Volatility, And Trading Costs: Evidence On Recent Price Formation Models," *Journal of Finance*, 1993, v48(1), pp. 187-212.

George, T.J., G. Kaul, and M. Nimalendran, 1991, "Estimation of the Bid-Ask Spread and Its Components: A New Approach," *Review of Financial Studies* 4, 623-656.

Glosten, L., and L. Harris, 1988, "Estimating the Components of the Bid-Ask Spread," *Journal of Financial Economics* 21, 123-142.

Glosten, L., and P. Milgrom, 1985, "Bid, Ask, and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders," *Journal of Financial Economics* 13, 71-100.

Goodhart, C. A. E., *The Evolution of Central Banks* (Cambridge: The MIT Press, 1988).

Gorton, Gary, and George Pennacchi, Financial-Intermediaries And Liquidity Creation, *Journal of Finance* 45: (1) 49-71 March 1990.

Greenspan, Alan, "Remarks" at Financial Markets Conference of the Federal Reserve Bank of Atlanta, Coral Gables, Florida, February 23, 1996.

Harris, M. and A. Raviv, 1991, "The Theory of Capital Structure," *Journal of Finance* 46, 297-355.

________ , 1993, **"**Differences Of Opinion Make A Horse Race," *Review Of Financial Studies,* 6: (3) 473-506.

Hasbrouck, J., 1991a, "Measuring the Information Content of Stock Trades," *Journal of Finance* 46, 179-207.

Hasbrouck, J., 1991b, "The Summary Informativeness of Stock Trades: An Econometric Analysis," *Review of Financial Studies* 4(3), 571-594.

Hausman, J. A., A. Lo, and A.C. MacKinley, 1992, "An Ordered Probit Analysis of Transaction Stock Prices," *Journal of Financial Economics* 31, 319-330.

Ho, T. and H. Stoll, 1981, "Optimal Dealer Pricing Under Transactions and Return Uncertainty," *Journal of Financial Economics* 9, 47-73.

Ho, T. and H. Stoll, 1983, “The Dynamics of Dealer Markets Under Competition,” *Journal of Finance* 38, 1053-1074.

Huang, Roger D. and Hans R. Stoll, “Market Microstructure And Stock Return Predictions,” *Review of Financial Studies*, 1994, v7(1), 179-213.

Jensen, M. and W. Meckling, 1976, “Theory of the Firm: Managerial Behavior, Agency Costs, and Ownership Structure,” *Journal of Financial Economics* 4, 305-360.

Jones, Charles M., Gautam Kaul and Marc L. Lipson. “Information, Trading, And Volatility,” *Journal of Financial Economics*, 1994, v36(1), 127-154.

Jordan, John S., Joe Peek and Eric S. Rosengren, 2000, “The market reaction to the disclosure of supervisory actions: Implications for bank transparency,” *Journal of Financial Intermediation*, v.9 (3), pp. 298-319.

Karpoff, Jonathan M. “The Relation Between Price Changes And Trading Volume: A Survey,” *Journal of Financial and Quantitative Analysis*, 1987, v22(1), 109-126.

Krinsky, Itzhak and Jason Lee, “Earnings Announcements and the Components of the Bid-Ask Spread”, *Journal of Finance* 51(4) (September 1996), pp. 1523-1535.

Kwan, Simon, and Willard Carleton, “Financial Contracting and the Choice Between Private Placement and Publicly Offered Bonds”, Federal Reserve Bank of San Francisco working paper (March 1998).

Kyle, A. S., 1985, “Continuous Auctions and Insider Trading,” *Econometrica* 53, 1315-1335.

Lee, C. M. C., and M. J. Ready,"Inferring Trade Direction from Intraday Data," *Journal of Finance*, 1991, v46, pp. 733-746.

Lin, J., G. Sanger and G. Booth, “Trade Size and Components of the Bid-Ask Spread,” *Review of Financial Studies* 8 (4) (Winter 1995), pp. 1153-1184.

Madhavan, A., M. Richardson, and M. Roomans, 1997 "Why do Security Prices Fluctuate? A Transaction-Level Analysis of NYSE Stocks," *Review of Financial Studies* 10, 1035-1064.

Madhavan, A., and S. Smidt, 1991, "A Bayesian Model of Intraday Specialist Pricing," *Journal of Financial Economics* 30, 99-134.

Morgan, Donald P., “"Rating Banks: Risk and Uncertainty in an Opaque Industry," *American Economic Review*, September 2002 (forthcoming).

Morgan, Donald P. and Kevin J. Stiroh, 2001, “Market Discipline of Banks: The Asset Test”, *Journal of Financial Services Research* 20(2/3), pp. 195-208.

Musumeci, James J. and Joseph F. Sinkey, 1990, “The international debt crisis, investor contagion, and bank security returns in 1987: The Brazilian experience,” *Journal of Money, Credit, and Banking*, v. 22 (2), pp. 209-220.

Myers, Stewart, and Nicolas Majluf, 1984, “Corporate Investment and Financing Decisions When Firms Have Information that Investors Do Not Have,” *Journal of Financial Economics* 13, 187-222.

Neal, Robert, and Simon W. Wheatley, "Adverse Selection and Bid-ask Spreads: Evidence From Closed-End Funds*", Journal of Empirical Finance* 1 (1998), pp. 121-149.

O'Hara, M., 1995, *Market Microstructure Theory*. (Oxford: Blackwell Publishers).

Robb, Sean W. G., 1998, "The Effect of Analysts' Forecasts on Earnings Management in Financial Institutions", *Journal of Financial Research* 21(3), pp. 315-332.

Roll, R., 1984, "A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market," *Journal of Finance* 39(4), 1127-1139.

Subrahmanyam, A., 1991, "Risk Aversion, Market Liquidity, and Price Efficiency," *Review of Financial Studies* 4, 417-442.

Stoll, H. R., 1978, "The Supply of Dealer Services in Securities Markets," *Journal of Finance* 33, 1133-1151.

________, 1989, "Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests," *Journal of Finance* 44, 115-134.

Van Ness, Bonnie F., Robert A. Van Ness, and Richard S. Warr, 2001 "How Well do Adverse Selection Components Measure Adverse Selection?", *Financial Management* 30, 77-98.

Table 1: BHC Microstructure and Financial Variables, Sample Statistics

Quarterly observations during 1990-1997

Microstructure Variables

$VOLUME_{it}$ = number of shares (in millions) traded during the quarter ending at t.

$NUMTRD_{it}$ = number of trades during the quarter ending at t.

$TOVER_{it}$ = share turnover: number of shares traded during the quarter ending at t, divided by the number of shares outstanding at the end of the preceding quarter (time t-1).

$TRDSZE_{it}$ = the average number of shares per transaction during the quarter ending at t.

STD_{it} = the annualized standard deviation of return across all trades during the quarter ending at t. "Return" is computed using the center of bid and ask prices at each trade and is measured in percent. STD = $2*std\sqrt{T}$, where "std" is the standard deviation of the returns across all "T" trades in the quarter.

The following four <u>spread</u> <u>measures</u> are averaged over all trades during quarter ending at t, and are expressed as a percentage of price per share:

$QSPREAD_{it}$ = average quoted spread in effect for transactions during the quarter ending at t.

$ESPREAD_{it}$ = average effective spread for transactions during the quarter ending at t, defined as $\frac{2}{T}\sum_{\tau=1}^{T}\left|\left(\frac{P_\tau - Q_\tau}{Q_\tau}\right)\right|$, where P_τ = trade price, Q_τ = the average of the bid and ask prices associated with the τ^{th} trade and T = the number of trades during the quarter.

$AS\text{-}GKN_{it}$ = George, Kaul, and Nimalendran's [1991] average adverse selection cost of trading stock i during quarter t (as computed by Neal and Wheatley [1998]), as a percentage of the price per share. (See Appendix for details.)

$AS\text{-}LSB_{it}$ = Lin, Sanger and Booth's [1995] average adverse selection cost of trading stock i during quarter t, as a percentage of the price per share. (See Appendix for details.)

BHC Financial Characteristics

$MVEQ_{it}$ = market value of common equity at the end of the quarter ending at t.

$LNMVEQ_{it}$ = the natural log of $MVEQ_{it}$.

$PRICE_{it}$ = price per share at the end of the quarter ending at t.

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

$NETLNS_{it}$ = total loans, net of the allowance for loan and lease losses, plus customers' liabilities to bank for outstanding acceptances

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

$OPAQUE_{it}$ = the book value of bank premises and fixed assets, plus other hard-to-value assets: investments in unconsolidated subsidiaries, intangible assets, and the balance sheet category "other assets".

$PROFIT_{it}$ = annualized net income during the quarter ending at t, as a proportion of *$MVEQ_{it}$*.

$FEES_{it}$ = annualized noninterest income during the quarter ending at t, as a proportion of *$MVEQ_{it}$*.

$MVLEV_{it}$ = the sum of liabilities' book value 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).

$HIGH\text{-}CB_{it}$ = a dummy variable equal to unity if the BHC's subsidiary commercial bank assets exceed the sample median proportion of total BHC assets.

Earnings Forecast (IBES) Variables

(averaged over 1, 4, 7, and 10 months preceding fiscal yearend)

$NEST_{it}$ = Number of analysts posting an earnings forecast for the firm's current fiscal year.

CSD_{it} = Cross-sectional standard deviation of analysts' forecast, computed only for firms with more than one analyst.

REV_{it} = Number of analysts revising their forecast during the month, as a percentage of the number of analysts following the firm.

FE_{it} = Median absolute EPS forecast error, divided by share's price at the start of the fiscal year, multiplied by 10,000 (to measure the forecast error in basis points).

Additional variables evaluated in Table 2

$OP\text{-}GKN_{it}$ = order processing component of spread, % of price per share (based on GKN decomposition discussed in the Appendix).

OWN = institutional ownership, as a proportion of total shares outstanding (available only through yearend 1996).

Table 1 (continued)

	Panel A: NASDAQ Sample BHC						Panel B: NYSE Sample BHC					
	N	Mean	Std. Dev.	Minimum	Maximum	Median	N	Mean	Std. Dev.	Minimum	Maximum	Median
						Microstructure Variables						
VOLUME	3,938	2.24	4.86	0.03	101.50	0.66	1,197	20.54	29.74	0.05	281.99	9.63
NUMTRD	3,938	1433.6	2,914	100	56,134	493	1,197	10,052	13,345	100	110,320	5,130
TOVER	3,938	0.13	0.14	0.00	1.77	0.08	1,197	0.16	0.12	0.01	0.91	0.13
TRDSZE	3,938	1,382	627	258	5,245	1,266	1,197	1,759	775	235	5,375	1,700
STD	3,869	12.33	9.04	0.39	182.8	10.4	1,197	47.84	63.33	5.93	707.4	32.2
QSPREAD	3,938	3.13	1.85	0.30	9.95	2.79	1,197	1.35	1.04	0.19	9.64	1.04
ESPREAD	3,938	2.41	1.42	0.22	8.67	2.16	1,197	0.67	0.57	0.09	4.86	0.47
AS-GKN	3,923	0.66	0.62	0.00	7.32	0.48	1,168	0.95	0.84	0.01	6.87	0.70
AS-LSB	3,938	0.07	0.11	0.00	2.07	0.03	1,197	0.12	0.29	0.00	2.14	0.01
LNMVEQ	3,938	12.16	1.25	8.83	16.13	12.10	1,197	14.24	1.80	8.88	17.93	14.56
PRICE	3,938	$24.65	$12.66	$2.00	$118.75	$23.50	1,197	$38.48	$36.48	$2.25	$415.00	$32.00
						BHC Financial Characteristics						
NETLNS	3,938	6.281	4.342	0.641	52.691	5.105	1,197	7.373	5.971	0.803	52.823	5.657
LLA	3,938	0.123	0.145	0.016	1.714	0.083	1,197	0.200	0.261	0.013	2.967	0.115
TRADE	3,938	0.034	0.188	0.000	3.397	0.000	1,197	0.485	1.424	0.000	12.396	0.013
OREO	3,938	0.062	0.168	-0.148	2.656	0.014	1,197	0.077	0.169	-0.051	1.839	0.020
OPAQUE	3,938	0.449	0.389	0.059	6.459	0.358	1,197	0.699	0.701	0.116	5.609	0.471
PROFIT	3,938	0.084	0.103	-2.407	0.753	0.089	1,197	0.088	0.160	-2.939	0.443	0.099
FEES	3,938	0.126	0.120	0.010	1.565	0.092	1,197	0.232	0.231	0.010	2.395	0.159
MVLEV	3,938	10.57	6.49	2.47	89.30	8.87	1,197	12.35	8.64	2.50	81.03	9.72
HIGH-CB	3,938	0.493	0.500	0	1	0	1,197	0.498	0.500	0	1	0
						Earnings Forecast (IBES) Variables						
NEST	3,111	5.21	4.95	1	36	4	1,092	19.75	10.68	1	44	22
REV	3,111	26.93	30.07	0	100	20	1,092	32.98	23.65	0	100	30
FE	3,111	124.39	369.22	0	4,860.57	34.17	1,092	177.55	471.45	0	4,806.01	36.26
CSD	2,455	51.44	335.56	0	13,907	20.38	1,030	65.93	156.76	0	2,255.8	28.62

Table 2: Comparing BHC vs. Control Firm Microstructure Properties

Variables are defined in Table 1.

	Panel A: NASDAQ Sample, 1990-1997							Panel B: NYSE Sample, 1990-1997						
		MEANS			MEDIANS				MEANS			MEDIANS		
	N	Bank	Control	Prop'al Difference	Bank	Control	Prop'al Difference	N	Bank	Control	Prop'al Difference	Bank	Control	Prop'al Difference
MVEQ	3,938	385.0	383.8	0.31%	158.2	159.9	-1.05%	1,197	3,867.7	3,721.6	3.85%	1,963.8	1,938.0	1.33%
PRICE	3,938	$23.58	$22.01	6.89% ***	$22.25	$20.00	10.65% ***	1,197	$36.50	$35.91	1.64%	$31.25	$29.88	4.48%
QSPREAD	3,938	3.13%	3.52%	-11.49% ***	2.79%	2.70%	3.33%	1,190	1.35%	1.63%	-18.71% ***	1.04%	1.19%	-13.72% ***
ESPREAD	3,938	2.41%	2.73%	-12.45% ***	2.16%	2.08%	4.13%	1,193	0.67%	0.75%	-11.47% ***	0.47%	0.51%	-8.98% ***
OP-GKN	3,819	2.47%	2.81%	-12.79% ***	2.22%	2.24%	-0.56% ***	1,162	0.41%	0.42%	-2.16%	0.23%	0.23%	-3.53%
AS-GKN	3,819	0.66%	0.71%	-7.83% ***	0.48%	0.44%	8.21% ***	1,162	0.95%	1.22%	-25.55% ***	0.70%	0.84%	-18.74% ***
STD	3,820	12.33%	27.81%	-77.16% ***	10.37%	24.50%	-81.07% ***	1,190	47.84%	53.89%	-11.88% **	32.22%	38.29%	-17.23% ***
VOL	3,938	2.24	11.37	-134.11% ***	0.66	3.43	-135.65% ***	1,193	20.54	19.98	2.74%	9.63	11.38	-16.73% **
NUMTRD	3,938	1,434	7,152	-133.21% ***	493	1,859	-116.14% ***	1,193	10,052	10,774	-6.94%	5,130	5,931	-14.48% **
TOVER	3,938	0.138	0.630	-128.33% ***	0.088	0.362	-121.93% ***	1,193	0.175	0.222	-23.91% ***	0.147	0.160	-8.06% ***
TRDSZE	3,938	1,382	1,812	-26.92% ***	1,266	1,637	-25.54% ***	1,193	1,760	1,797	-2.09%	1,700	1,758	-3.31%
OWN	3,112	0.225	0.400	-56.13% ***	0.196	0.384	-64.83% ***	995	0.416	0.519	-22.01% ***	0.447	0.548	-20.30% ***

"Prop'al Difference" is computed as the bank's value less the control firm's value, divided by the average of the two firm's values.

Table 3: Insider and Block Holdings of Bank and Control Firm Stocks, Yearend 1995.

Data are percentages of total shares outstanding. "Insider" and "5% Owner" holdings are not mutually exclusive.

	Insider Holdings			5% Owners' Holdings		
	Banks	Controls	Difference [t-stat], (p-val)	Banks	Controls	Difference [t-stat], (p-val)
	Full Sample, Nobs = 405					
Mean	13.72	26.24	-12.52 [t = 8.71]	21.08	39.86	-18.78 [t = 10.76]
Median	8.70	19.84	-8.23 (p<.0001)	14.32	35.39	-18.02 (p<.0001)
	NASDAQ Firms, Nobs = 319					
Mean	14.95	29.06	-14.11 [t = 8.45]	19.61	42.99	-23.38 [t = 12.01]
Median	9.53	23.73	-10.52 (p<.0001)	13.23	39.07	-22.15 (p<.0001)
	NYSE Firms, Nobs = 86					
Mean	9.16	15.76	-6.60 [t = 2.49]	26.52	28.25	-1.72 [t = 0.51]
Median	3.21	4.83	-0.04 (p=.295)	16.41	22.52	-3.95 (p=.118)

Table 4: Equity Trades and Bank Balance Sheet Composition

We estimate the fixed-effect, pooled regression

$$Y_{it} = \alpha_i + \sum_{k=1,5} \beta_k \frac{A_{kit}}{MVEQ_{i,t-1}} + \sum_{j=1,4} \gamma_j X_{jit} + \sum_{p} \omega_p M_{pi,t-1} + \sum_{\tau=91,97} \delta_\tau D_\tau + \varepsilon_{it} \qquad (3)$$

for a sample of 320 bank holding companies over the quarters 1990-I through 1997-IV, where the dependent variable is either:

ESPREAD$_{it}$ = the stock's effective spread, as a percentage of quoted price per share.
LNSTD$_{it}$ = natural log of *STD*$_{it}$ which is the annualized standard deviation of equity return during the quarter.
TOVER$_{it}$ = share turnover: number of shares traded during the previous quarter, divided by the number of shares outstanding at the end of the preceding quarter.

Balance sheet variables (A_{kit}) are measured on the last day of each quarter and are deflated by the prior quarter's equity market value ($MVEQ_{i,t-1}$):
NETLNS = total loans, net of the allowance for loan and lease losses, plus customers' liabilities to bank for outstanding acceptances
LLA = allowance for loan and lease losses
TRADE = assets held in trading accounts valued at market value or the lower of cost or market.
OREO = other real estate owned
OPAQUE = book value of premises and fixed assets plus other hard-to-value assets

Other BHC features that may affect opacity (X_{jit}) are:
PROFIT$_{it}$ = annualized net income during the quarter ending at t, as a proportion of $MVEQ_{i,t-1}$.
FEES$_{it}$ = annualized noninterest income during the quarter ending at t, as a proportion of $MVEQ_{i,t-1}$.
MVLEV$_{it}$= the sum of liabilities' book value 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).
HIGH-CB$_{it}$ = a dummy variable equal to unity if the BHC's subsidiary commercial bank assets exceed the sample median proportion of total BHC assets.

Lagged microstructure variables in $M_{pi,t-1}$ include various combinations of the dependent variables ($ESPREAD_{it}$, $LNSTD_{it}$,$TOVER_{it}$) and
PINV$_{it}$ = the inverse of the stock's average quarterly price during the quarter ending at t.
TRDSZE$_{it}$ = the average number of shares per transaction during the quarter ending at t.
VOLUME$_{it}$= number of shares traded during the quarter ending at t, in millions.

Hypotheses of interest:

H1: All five balance sheet ratios' coefficients (β_k) jointly equal zero.
H2: All nine financial variables' coefficients (β_k and γ_j) jointly equal zero.
H3: All microstructure variables' coefficients (ω_p) jointly equal zero.
H4: All seven year-dummy coefficients (δ_τ) jointly equal zero.

Explanatory power of variable groups:

R^2: Just FE: Adjusted R^2 statistic for a regression of the dependent variable on just the firm fixed effects.
R^2: FE, Yrs: Adjusted R^2 statistic for a regression of the dependent variable on the firm fixed effects and seven year dummies.
R^2: FE, MM: Adjusted R^2 statistic for a regression of the dependent variable on the firm fixed effects and the lagged market microstructure variables.

Table 4, Panel A: Microstructure Properties of NASDAQ Banks

	ESPREAD						*LNSTD*						*TOVER*					
	(I)		(II)		(III)		(IV)		(V)		(VI)		(VII)		(VIII)		(IX)	
NETLNS	0.042	2.311			0.049	3.209	0.006	0.872			0.001	0.138	0.010	3.156			0.010	3.331
LLA	0.827	2.059			0.096	0.281	0.202	1.364			0.179	1.224	-0.185	-2.764			-0.172	-2.759
TRADE	0.070	1.026			0.005	0.068	-0.055	-1.491			-0.048	-1.331	-0.044	-4.743			-0.042	-4.616
OREO	0.165	0.616			-0.207	-0.856	0.343	4.022			0.113	1.293	0.056	1.200			0.080	1.631
OPAQUE	-0.256	-2.238			-0.125	-1.461	-0.023	-0.567			-0.017	-0.514	0.008	0.564			0.005	0.424
PROFIT	-0.028	-0.120			-0.352	-1.990	-0.057	-0.771			-0.006	-0.075	0.004	0.133			0.003	0.101
FEES	-0.667	-1.666			-0.640	-1.939	0.287	2.142			0.342	2.631	0.102	2.004			0.092	1.857
MVLEV	0.042	2.815			0.025	1.923	0.000	-0.045			0.007	1.294	-0.005	-2.411			-0.005	-2.557
HIGH-CB	0.090	2.759			0.080	2.537	-0.062	-2.874			-0.066	-3.117	0.001	0.133			0.002	0.439
PINV(-1)			10.654	10.724	7.860	7.869			3.426	7.679	2.262	5.011			-0.356	-3.578	-0.397	-3.128
LNMVEQ(-1)			-0.022	-0.300	0.114	1.655			0.218	5.375	0.280	6.748			-0.025	-2.568	-0.027	-2.516
TOVER(-1)									0.345	4.131	0.398	4.750						
LNSTD(-1)			0.188	6.086	0.172	5.729									0.016	4.288	0.016	4.177
ESPRD(-1)									0.043	3.958	0.038	3.444			-0.001	-0.207	-0.002	-0.417
TRDSZE(-1)			0.090	2.841	0.120	3.660												
Ln(VOL(-1))			-0.342	-11.174	-0.328	-10.883												
D91	-0.153	-2.377	-0.264	-3.959	-0.160	-2.698	-0.253	-7.789	-0.274	-8.308	-0.257	-7.983	0.012	1.549	0.008	1.025	0.014	1.780
D92	-0.181	-2.769	-0.317	-5.052	-0.100	-1.611	-0.245	-7.092	-0.319	-10.191	-0.290	-8.419	0.030	3.585	0.026	3.220	0.034	4.177
D93	-0.215	-3.254	-0.329	-4.789	-0.053	-0.778	-0.785	-20.179	-0.921	-24.782	-0.879	-21.529	0.033	3.486	0.039	4.238	0.049	5.093
D94	-0.289	-4.528	-0.216	-2.778	0.019	0.259	-0.832	-23.204	-1.023	-26.326	-0.977	-23.725	0.043	4.671	0.054	5.714	0.067	6.680
D95	-0.683	-10.386	-0.591	-7.164	-0.368	-4.684	-0.885	-24.155	-1.093	-25.517	-1.047	-23.597	0.042	4.402	0.057	5.532	0.069	6.416
D96	-0.899	-12.968	-0.589	-6.319	-0.388	-4.310	-0.571	-14.968	-0.814	-16.572	-0.792	-15.711	0.105	10.556	0.120	9.854	0.131	10.837
D97	-1.236	-16.463	-0.993	-9.507	-0.784	-7.770	-0.012	-0.274	-0.276	-4.609	-0.264	-4.337	0.073	6.693	0.083	5.917	0.095	6.680
Mean LHS	2.412		2.412		2.412		1.604		1.604		1.604		0.129		0.129		0.129	
Adj. R^2	0.794		0.801		0.813		0.556		0.558		0.566		0.552		0.548		0.557	
Nob	3,938		3,938		3,938		3,985		3,985		3,985		3,938		3,938		3,938	
H1: Pr(All 5 BS = 0)	0.007		n/a		0.015		<0.001		n/a		0.130		<0.001		n/a		<0.001	
H2: Pr(All 9 Fin = 0)	<0.001		n/a		<0.001		<0.001		n/a		<0.001		<0.001		n/a		<0.001	
H3: Pr(All MM = 0)	n/a		<0.001		<0.001		n/a		<0.001		<0.001		n/a		<0.001		<0.001	
H4: Pr(All years=0)	0.000		<0.001		<0.001		<0.001		<0.001		<0.001		<0.001		<0.001		<0.001	
R^2: Just FE	0.612		0.612		0.612		0.257		0.257		0.257		0.506		0.506		0.506	
R^2: FE, Years	0.749		0.749		0.749		0.540		0.540		0.540		0.543		0.543		0.543	
R^2: FE, MM	0.787		0.787		0.787		0.275		0.275		0.275		0.523		0.523		0.523	

For each specification, the left column reports the coefficient estimate and the right column reports heteroskedasticity-consistent (White) t-statistics. Shaded t-statistics indicate statistical significance at the 5% confidence level. TRDSZE coefficients have been multiplied by 1,000.

Table 4 Panel B: Microstructure Properties of NYSE Banks

	ESPREAD						*LNSTD*						*TOVER*					
	(I)		(II)		(III)		(IV)		(V)		(VI)		(VII)		(VIII)		(IX)	
NETLNS	-0.007	-0.536			0.005	0.388	0.050	2.813			0.062	3.250	0.003	0.503			0.005	0.833
LLA	-0.180	-1.407			-0.425	-3.227	-0.007	-0.033			-0.207	-0.928	0.026	0.476			0.020	0.368
TRADE	-0.050	-3.148			-0.042	-2.567	0.052	1.168			0.062	1.351	0.019	3.517			0.018	3.358
OREO	0.457	2.968			0.245	1.474	0.576	3.150			0.336	1.940	-0.068	-1.449			-0.079	-1.704
OPAQUE	-0.146	-4.088			-0.118	-3.441	-0.005	-0.079			0.047	0.762	-0.015	-1.113			-0.012	-0.860
PROFIT	-0.285	-1.709			-0.420	-1.955	0.396	2.985			0.262	1.936	-0.049	-1.049			-0.072	-1.691
FEES	-0.313	-2.872			-0.175	-1.608	-0.467	-2.069			-0.292	-1.256	-0.004	-0.077			0.002	0.049
MVLEV	0.046	4.467			0.032	2.863	-0.003	-0.178			-0.023	-1.412	0.001	0.243			-0.002	-0.420
HIGH-CB	0.036	2.096			0.030	1.816	0.066	1.577			0.060	1.467	0.000	0.011			0.002	0.285
PINV(-1)			7.401	7.112	4.358	4.235			1.530	1.181	1.971	1.633			-0.150	-0.463	-0.125	-0.555
LNMVEQ(-1)			-0.030	-0.815	0.039	1.156			-0.136	-2.092	-0.046	-0.656			-0.045	-3.339	-0.041	-2.974
TOVER(-1)									0.496	1.994	0.451	1.794						
LNSTD(-1)			0.080	4.916	0.064	4.414									0.006	1.003	0.006	0.928
ESPRD(-1)									0.373	4.668	0.249	3.236			0.012	0.876	0.001	0.070
TRDSZE(-1)			-0.030	-2.064	0.000	0.262												
Ln(VOL(-1))			-0.034	-1.570	-0.031	-1.569												
D91	-0.042	-1.168	-0.124	-2.883	-0.091	-2.494	-0.052	-0.996	-0.153	-2.664	-0.125	-2.346	-0.004	-0.410	-0.013	-1.373	-0.011	-1.191
D92	-0.113	-3.129	-0.211	-6.882	-0.131	-3.792	-0.198	-3.818	-0.313	-6.165	-0.227	-4.350	0.014	1.468	0.013	1.235	0.019	2.012
D93	-0.111	-2.843	-0.271	-7.924	-0.147	-3.775	-0.052	-0.733	-0.210	-2.949	-0.082	-1.106	0.020	1.728	0.029	1.867	0.034	2.491
D94	-0.126	-3.118	-0.247	-5.878	-0.148	-3.296	-0.105	-1.679	-0.197	-2.968	-0.104	-1.453	0.014	1.451	0.040	3.092	0.036	3.163
D95	-0.209	-5.643	-0.356	-8.995	-0.247	-5.899	-0.175	-2.956	-0.241	-3.150	-0.175	-2.428	0.023	2.330	0.054	3.670	0.048	3.657
D96	-0.286	-7.259	-0.387	-8.139	-0.302	-6.470	0.057	0.795	0.003	0.032	0.065	0.758	0.107	8.580	0.148	7.575	0.142	7.807
D97	-0.333	-7.354	-0.427	-7.696	-0.350	-6.316	0.093	1.270	0.096	0.925	0.144	1.342	0.053	4.353	0.104	4.816	0.099	4.904
Mean LHS	0.670		0.670		0.670		2.888		2.888		2.888		0.162		0.162		0.162	
Adj. R^2	0.869		0.844		0.883		0.512		0.511		0.528		0.623		0.618		0.628	
Nob	1197		1197		1197		1197		1197		1197		1197		1197		1197	
H1: Pr(All 5 BS = 0)	<0.001		n/a		<0.001		0.010		n/a		0.027		<0.001		n/a		<0.001	
H2: Pr(All 9 Fin = 0)	<0.001		n/a		<0.001		<0.001		n/a		<0.001		<0.001		n/a		<0.001	
H3: Pr(All MM = 0)	n/a		<0.001		<0.001		0.001		<0.001		<0.001		n/a		0.001		0.046	
H4: Pr(All years=0)	<0.001		<0.001		<0.001		<0.001		<0.001		<0.001		<0.001		0.000		<0.001	
R^2: Just FE	0.624		0.624		0.624		0.400		0.400		0.400		0.540		0.540		0.540	
R^2: FE, Years	0.748		0.748		0.748		0.444		0.444		0.444		0.604		0.604		0.604	
R^2: FE, MM	0.831		0.831		0.831		0.480		0.480		0.480		0.554		0.554		0.554	

For each specification, the left column reports the coefficient estimate and the right column reports heteroskedasticity-consistent (White) t-statistics. Shaded t-statistics indicate statistical significance at the 5% confidence level. TRDSZE coefficients have been multiplied by 1,000.

Table 5: Equity Analyst Followings and Earnings Forecasts
Panel A: NASDAQ Sample, 1990-1997

Month before Fiscal Year End	Number of Obs.	Means			Medians		
		Banks	Non-Banks	H0: Means are Equal,* p-value	Banks	Non-Banks	H0: Medians are Equal,* p-values
NEST: Number of Analysts							
10	497	5.8	6.6	.002	4.0	5.0	<.001
7	754	5.6	6.1	<.001	4.0	5.0	<.001
4	779	5.3	6.2	<.001	4.0	5.0	<.001
1	794	5.6	6.2	<.001	4.0	5.0	<.001
CSD: Cross-sectional Standard Deviation of Analyst Forecast							
10	375	40.8	52.5	.11	22.8	24.0	.17
7	553	42.6	52.7	.05	21.6	22.8	.51
4	563	37.1	49.6	.04	20.4	20.1	.62
1	580	39.4	44.4	.41	16.6	17.2	.89
REV: Percentage of Analysts Revising Forecast during the Month							
10	497	25.1	31.8	.002	17.6	27.3	<.001
7	754	24.4	37.7	<.001	16.7	33.3	<.001
4	779	28.3	41.6	<.001	22.2	40.0	<.001
1	794	29.8	42.9	<.001	25.0	40.0	<.001
FE: Standardized Forecast Errors (Absolute EPS Forecast Errors/Initial Share Price)*10,000							
10	455	155	239	.007	47	78	<.001
7	684	152	240	.001	44	68	<.001
4	712	126	169	.024	33	45	<.001
1	733	90	114	.147	20	25	.005

* Mann-Whitney sign rank test.

Table 5, Panel B - NYSE Sample, 1990-97

Month before Fiscal Year End	Number of Obs.	Means			Medians		
		Banks	Non-Banks	H0: Medians are Equal, * p-values	Banks	Non-Banks	H0: Medians are Equal, * p-values
NEST: Number of Analysts							
10	239	21.0	16.1	<.001	22.0	16.0	<.001
7	274	20.2	15.2	<.001	22.0	15.0	<.001
4	276	20.4	15.0	<.001	22.0	15.0	<.001
1	282	20.0	14.7	<.001	22.0	14.0	<.001
CSD: Cross-sectional Standard Deviation of Analyst Forecast							
10	230	67.7	70.0	.80	30.8	34.3	.64
7	263	72.1	57.2	.09	34.2	29.4	.03
4	262	59.9	50.8	.41	26.1	24.4	.26
1	261	55.8	44.7	.28	21.9	21.7	.10
REV: Percentage of Analysts Revising Forecast during the Month							
10	239	29.9	34.7	.016	26.7	33.3	.012
7	274	31.7	35.6	.06	29.2	30.6	.04
4	276	35.4	41.4	.002	33.3	40.0	.002
1	282	34.3	44.2	<.001	30.0	42.8	<.001
FE: Standardized Forecast Errors (Absolute EPS Forecast Errors//Initial Share Price)*10,000							
10	230	211	232	.64	66	73	.41
7	261	176	182	.86	45	54	.31
4	265	134	137	.97	31	37	.22
1	271	97	84	.54	16	23	.25

* Mann-Whitney sign rank test.

Table 6: Effect of Bank Characteristics on Earnings Expectations Properties

$$IBES_{it} = \alpha_i + \sum_{k=1,5}\beta_k \frac{A_{kit}}{MVEQ_{i,t-1}} + \omega LNMVEQ_{i,t-1} + \sum_{j=1,4}\gamma_j X_{jit} + \sum_{\tau=91,97}\delta_\tau D_\tau + \sum_{m=1,3} DQ_m + \varepsilon_{it} \qquad (4)$$

where $IBES_{it}$ alternately equals number of IBES forecasters (NEST), cross-sectional standard deviation of forecasts (CSD), proportion of forecasters revising their forecast during the month (REV) and the standardized forecast error (FE). See Table 1 for more detailed definitions.

	NASDAQ, 1990-1997								NYSE, 1990-1997							
	NEST		CSD		REV		FE		NEST		CSD		REV		FE	
NETLNS	0.19	5.90	53.94	3.12	0.64	0.82	60.97	4.64	0.97	7.13	1.11	0.11	-0.61	-0.62	73.17	2.22
LLA	-2.09	-3.36	1200.64	2.50	-7.94	-0.49	302.42	0.74	1.63	1.13	200.19	1.36	-10.35	-1.20	-406.60	-1.57
TRADE	-0.38	-1.61	99.54	2.23	-8.17	-3.01	-102.52	-2.14	0.04	0.17	-16.84	-1.37	-0.19	-0.11	28.71	0.69
OREO	-0.06	-0.13	252.95	0.72	-10.49	-1.02	156.58	0.67	3.66	3.01	378.31	2.68	-8.52	-0.65	337.68	0.61
OPAQUE	-0.24	-1.42	-43.31	-0.72	-3.82	-1.40	-31.07	-0.40	0.28	0.65	-49.86	-1.19	1.93	0.61	152.84	1.65
PROFIT	-0.02	-0.05	-582.43	-0.65	-10.03	-0.96	-1566.45	-5.45	2.56	2.41	-207.17	-0.85	-10.57	-1.33	-768.98	-2.25
FEES	-5.73	-8.44	-1164.32	-5.17	27.00	1.81	-422.72	-1.25	2.66	2.08	-238.55	-2.13	4.13	0.34	-1092.59	-2.48
MVLEV	0.05	1.87	-37.51	-3.60	-0.23	-0.42	-20.02	-1.71	-0.77	-7.41	9.44	1.17	0.66	0.77	-29.18	-1.02
HIGH-CB	-0.81	-1.00	-132.90	-2.03	-30.49	-2.66	-257.68	-3.23	0.92	0.51	-85.78	-0.95	-13.50	-0.59	-1064.62	-3.46
LNMVEQ(-1)	1.66	10.60	61.01	1.67	1.76	0.52	172.71	3.02	3.33	7.48	-8.64	-0.49	4.89	1.60	59.36	0.84
D91	0.50	2.74	-42.11	-0.91	-0.70	-0.24	-172.39	-3.94	0.35	0.90	-4.28	-0.26	-0.83	-0.29	-182.43	-2.13
D92	0.64	3.45	-147.59	-2.54	4.44	1.38	-300.53	-6.59	0.21	0.49	6.32	0.27	1.44	0.43	-346.38	-3.98
D93	1.93	10.31	-164.97	-2.46	1.96	0.56	-313.92	-6.07	1.08	2.36	19.27	0.72	0.83	0.22	-400.78	-3.92
D94	2.43	12.64	-178.74	-2.72	-7.58	-2.08	-405.73	-7.41	1.29	2.68	18.97	0.76	-15.42	-4.04	-436.54	-4.33
D95	2.55	12.51	-201.71	-2.81	-10.00	-2.63	-429.60	-7.27	1.35	2.70	17.08	0.69	-26.41	-7.03	-561.33	-5.21
D96	2.56	11.55	-235.10	-2.79	-6.84	-1.50	-498.86	-7.20	-0.55	-0.91	24.97	0.82	-21.84	-4.86	-585.37	-4.79
D97	2.48	9.97	-270.60	-2.81	-6.38	-1.21	-570.27	-7.11	-2.50	-3.41	24.73	0.70	-23.98	-4.66	-607.31	-4.46
DQ1	-0.22	-2.99	47.14	1.77	-5.83	-3.64	117.17	8.06	0.12	0.59	10.28	1.06	-3.50	-1.92	157.40	4.33
DQ2	-0.07	-0.94	33.04	2.29	-5.77	-3.90	107.80	7.10	0.21	0.96	17.99	2.11	-2.21	-1.28	141.83	4.44
DQ3	0.00	-0.07	33.78	1.33	-2.81	-1.98	60.57	4.99	0.27	1.40	10.93	1.30	1.22	0.70	69.07	2.56
Mean LHS	5.22		53.28		26.94		135.21		19.75		65.93		32.98		177.55	
Adj. R^2	0.929		0.379		0.103		0.622		0.951		0.634		0.305		0.395	
Nob	3,140		2,466		3,140		3,140		1,092		1,030		1,092		1,092	
H1: Pr(All 5 BS = 0)	<0.001		<0.001		0.029		<0.001		<0.001		<0.001		0.625		<0.001	
H2: Pr(All 9 Fin = 0)	<0.001		<0.001		0.002		<0.001		<0.001		<0.001		0.470		<0.001	
H3: Pr(All years=0)	<0.001		0.001		<0.001		<0.001		<0.001		0.937		<0.001		<0.001	
R^2: Just FE	0.864		0.182		0.085		0.324		0.923		0.141		0.169		0.191	
R^2: FE, Years	0.922		0.209		0.100		0.420		0.935		0.243		0.305		0.318	

For each specification, the left column reports the coefficient estimate and the right column reports heteroskedasticity-consistent (White) t-statistics. Shaded t-statistics indicate statistical significance at the 5% confidence level.

Table A-1: Adverse Selection Costs and Bank Balance Sheet Composition

We estimate the quarterly, fixed-effect, pooled regression

$$Y_{it} \quad = \quad \alpha_i + \sum_k \beta_k \frac{A_{kit}}{MVEQ_{i,t-1}} + \sum_p \omega_p M_{pi,t-1} + \sum_j \gamma_j X_{jit} + \sum_\tau \delta_\tau D_\tau + \varepsilon_{it} \qquad (3)$$

for a sample of 320 bank holding companies from 1990-I through 1997-IV, where the dependent variable is either:

AS-GKN = George, Kaul, and Nimalendran's [1991] adverse selection cost of trading a stock, as computed by Neal and Wheatley [1998], divided by the stock's price per share.

AS-LSB = Lin, Sanger, and Booth's [1995] adverse selection cost of trading a stock, divided by the stock's price per share.

Independent variables are defined in Table 4.

Hypotheses of interest:

H1: All five balance sheet ratios' coefficients (β_k) jointly equal zero.
H2: All nine financial variables' coefficients (β_k and γ_j) jointly equal zero.
H3: All microstructure variables' coefficients (ω_p) jointly equal zero.

Explanatory power of sets of variables:

R^2: Just FE: Adjusted R^2 for a regression of the dependent variable on just the firm fixed effects.

R^2: FE, Years: Adjusted R^2 for a regression of the dependent variable on the firm fixed effects and seven year dummies.

R^2: FE, MM: Adjusted R^2 for a regression of the dependent variable on the firm fixed effects and the lagged market microstructure variables.

Table A-1 (continued): Adverse Selection Costs and Bank Balance Sheet Composition

	NASDAQ 1990-1997				NYSE, 1990-1997			
	AS-GKN		AS-LSB		AS-GKN		AS-LSB	
NETLNS	0.021	2.486	0.005	2.584	-0.029	-0.969	0.004	0.444
LLA	0.187	0.801	-0.049	-1.178	-0.055	-0.187	-0.202	-2.854
TRADE	-0.067	-1.487	-0.012	-1.840	-0.032	-0.825	-0.020	-2.012
OREO	-0.115	-0.954	-0.006	-0.289	0.314	1.064	-0.003	-0.046
OPAQUE	-0.124	-3.088	-0.029	-3.010	-0.102	-1.161	-0.030	-1.875
PROFIT	0.117	0.941	0.028	1.461	-0.488	-1.335	0.010	0.195
FEES	-0.069	-0.373	0.052	1.779	-0.275	-1.137	-0.038	-0.721
MVLEV	0.912	0.116	-0.451	-0.317	43.90	1.561	8.37	1.289
HIGH-CB	0.022	1.045	0.004	0.803	0.055	1.360	0.010	1.265
PINV(-1)	2.065	3.527	0.223	2.640	-0.425	-0.228	1.444	2.848
LNSTD(-1)	0.070	3.637	0.011	2.406	0.072	2.566	0.005	0.865
LNMVEQ(-1)	0.058	1.250	0.041	3.815	-0.196	-2.394	0.066	3.200
TRDSZE(-1)	0.057	3.110	0.0004	0.115	0.043	1.475	0.007	-0.716
Ln(VOL(-1))	-0.142	-7.820	-0.012	-3.740	0.023	0.479	-0.025	-2.052
D91	0.076	1.845	-0.042	-3.353	-0.549	-7.199	0.014	0.960
D92	0.117	2.627	-0.025	-1.688	-1.003	-14.181	0.047	2.240
D93	-0.097	-2.123	-0.127	-8.787	-0.755	-9.240	0.035	1.532
D94	-0.070	-1.430	-0.135	-8.483	-0.719	-8.753	0.045	1.708
D95	-0.138	-2.622	-0.141	-8.520	-0.817	-9.574	0.017	0.678
D96	-0.142	-2.393	-0.147	-8.061	-0.915	-9.366	0.001	0.030
D97	-0.208	-3.072	-0.104	-5.215	-0.946	-7.025	-0.007	-0.182
Mean LHS	0.660		0.067		0.945		0.116	
Adj. R^2	0.618		0.302		0.716		0.845	
Nob	3,923		3,938		1,168		1,197	
H1: Pr(All 5 BS = 0)	0.001		0.005		0.178		0.039	
H3: Pr(All MM = 0)	0.001		0.007		< 0.001		0.055	
H4: Pr(All years = 0)	< 0.001		< 0.001		< 0.001		0.004	
R^2: Just FE	0.505		0.120		0.466		0.833	
R^2: FE, Years	0.594		0.294		0.659		0.836	
R^2: FE, MM	0.608		0.215		0.617		0.840	

For each specification, the left column reports the coefficient estimate and the right column reports heteroskedasticity-consistent (White) t-statistics. Shaded t-statistics indicate statistical significance at the 5% confidence level. TRDSZE and MVLEV coefficients have been multiplied by 1,000.