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Market Evidence on the Opaqueness of Banking Firms' Assets

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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 strongly indicates that large banks (traded on the NYSE) have very similar trading properties to their matched nonfinancial firms, but smaller banks (traded on NASDAQ) trade much less frequently despite having very similar spreads. We also estimate the impact of portfolio composition on a bank's market microstructure characteristics. Problem (noncurrent) loans tend to raise the frequency with which the bank's equity trades, as well as the equity's return volatility. The implications for regulatory policy and future market microstructure research are discussed.

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I. Introduction

Depository financial intermediaries ("banks") specialize in underwriting and self-financing debt issues which cannot effectively be sold in public markets. Their comparative advantage in this activity may derive from expertise and scale economies in information production (Campbell and Kracaw [1980]). Alternatively, borrowers which are prone to incentive problems may require value-enhancing covenants and monitoring services which public bonds cannot provide (Berlin and Loeys [1988], Diamond [1989, 1991], Smith and Warner [1979], Carleton and Kwan [1998]). Regardless of the specific reasons for banks' lending advantage, conventional wisdom holds that bank loans are, by construction, *informationally opaque*. Bank insiders may possess valuable private information about loan customers' credit condition and the extent of the bank's private monitoring efforts.[1] The recent trend towards securitizing and selling pools of relatively transparent assets to public market investors may have rendered bank balance sheets even more concentrated in informationally opaque assets.

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 unregulated industries, these agency problems are resolved via market-based mechanisms. By contrast, banking firms are typically subject to government supervision and regulation, including on-site examinations and off-site monitoring. These extra-market arrangements are justified in two ways. First, banks' information asymmetries may be so severe that the usual market mechanisms cannot control them very well. Second, and closely related, information asymmetry may subject the banking system to destabilizing runs because banks fund opaque (illiquid) loans with demandable debt:

[1] Private information plays a central role in most theories of financial intermediation (e.g., Diamond [1984], Fama [1985]). Alan Greenspan has summarized the implications of informationally opaque loans for bank valuation:

> 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*

> 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).

If the distinction between the market's valuation of banking and non-banking assets is small, the argument for intrusive banking supervision cannot be based on this type of market failure. Policy makers can perhaps reduce banks' regulatory burden by relying more heavily on market forces to monitor and discipline banks. Conversely, evidence that banking firms are harder than non-banking firms to value would support the role of government supervision. Finally, understanding the opacity of bank assets can help managers and policy makers innovate mechanisms to reduce this opacity, perhaps expanding the role of market prices in resource allocation. In short, the perception that banking assets are unusually opaque has implications both for regulators and for theorists studying models of banks and the capital markets.

Despite the central role of private information and asset illiquidity in theories of the banking firm, the distinction between bank and nonfinancial firms may be less extreme than some models imply. 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? Furthermore, if banks are extremely opaque, how can investors routinely trade the junior (equity) claims on the assets' cash flows for more than 500 U.S. bank holding companies?

This paper investigates whether banking firms' market microstructure features are consistent with their assets being *relatively* opaque. Banks and nonfinancial firms should exhibit different trading characteristics if the banks are more (or less!) difficult for outsiders to understand. The market microstructure literature suggests several dimensions in which this trading behavior might differ, including trading volume, return volatility, bid-ask spreads, and the "adverse selection" component of market makers' spreads. We investigate the market microstructure properties of bank equity using two data sets, each

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loans rather difficult to quantify and to manage. (Greenspan [1996], pages 1-2, emphasis added) derived from a set of approximately 300 U.S. bank holding companies with traded equity. For each holding company, we compute monthly statistics about the stock's bid-ask spread and its other microstructure features, during the period from January 1993 through December 1995. We also identified a set of nonfinancial firms whose market capitalization closely matches that of the banks at each of two dates (January 31, 1993 and June 30, 1995). Our research methodology then has two parts.

First, we compare market microstructure variables for the bank vs. the nonbank samples. We find that large banks (i.e., those traded on the NYSE or AMEX) exhibit microstructure properties closely resembling those of similar-size nonbanks which also trade on the NYSE. In contrast, we find that the smaller (NASDAQ) banks' shares trade much less frequently, despite the fact that their spreads and adverse selection costs closely resemble those of the size-matched nonfinancial firms. The NASDAQ banks also have a substantially lower return volatility. Analyst following provides another potential indicator of information availability.[2] For our size-matched sample of banks and nonfinancial firms, we find that both sets of firms receive the same analyst coverage. Nevertheless, the banks' earnings forecasts are relatively more accurate and less dispersed, implying greater unanimity about bank valuation. Analysts' earnings forecasts are also revised less frequently, suggesting that new information emerges less often for banks than for similar-sized nonfinancial firms.

Second, we use our pooled sample of banking firms to test whether bank asset types differ in their information opacity. For example, if bank loans are more difficult than treasury bills for outsiders to value, we should find larger bid-asked spreads associated with higher loan concentrations. We estimate regressions which explain stock trading volume, return volatility, and bid-ask spreads as a function of bank asset portfolio concentrations. The estimation results indicate that balance sheet composition significantly affects the cost of trading a bank's stock, consistent with the hypothesis that different types of bank assets have differential opacity.

The paper is organized as follows. Section II reviews the literature which has juxtaposed

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[2] For example, Brennan and Subramanyam [1995] show that the number of IBES analysts following a company is inversely related

information and a stock's trading features. Section III describes our data sources, while the following Section compares our banks' market microstructure features to those of a matched sample of similar-sized nonfinancial firms. Section V compares the number of IBES analysts following banks vs. nonbanks, because some researchers (e.g. Brennan and Subramanyam [1995]) contend that analyst following proxies for the extent of private information about a stock. In Section VI we evaluate whether a bank's asset composition affects its equity trading characteristics. If asymmetric information is important in bank operations, institutions which specialize in more opaque loans should exhibit higher spreads, etc. The final Section summarizes our results and discusses their implications for policy reform and subsequent research.

II. Information and Equity Trading Characteristics

The only prior study to evaluate whether banks are relatively opaque is Morgan [1997], who contends that harder-to-value firms are more likely to have split bond ratings. Consistent with this hypothesis, he finds that banking firms are more likely than nonfinancial firms to carry split ratings, and that the probability of a split rating varies with the bank's asset composition. Our paper addresses the same question by evaluating the market microstructure properties of banking firms' common *stock*: trading volume, return volatility, and bid-ask spread and its components.

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. A bid-ask spread has been conceptually divided into three components. The first two -- the order processing component and the inventory holding cost[3] -- reflect a market-maker's standard operating costs. The third component of a bid-ask spread -- the adverse selection (AS) component -- reflects the fact that 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

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to the stock's adverse selection cost of trading.

[3] Market makers hold an inventory of the stock in order to provide traders with immediacy. The inventory cost includes both the time value of invested capital and a risk premium for bearing non-diversifiable risk.

too high (or the ask is too low). The AS spread component compensates the market maker for writing that option. The greater is the potential supply of private information about a stock, the larger should be the adverse selection cost of trading it. In the context of bank opacity, we hypothesize that private information will be more important for firms which are more concentrated in informationally-intensive assets (such as loans).

Numerous researchers have suggested 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]). The economic validity of these decompositions has received at least partial validation in the finance and accounting literature. Brennan and Subrahmanyam [1995] report that a stock's adverse selection trading cost is negatively related to the number of analysts following the firm, suggesting that greater analyst following reduces the proportion of privately informed traders. Krinsky and Lee [1996] find that the adverse selection component significantly widens in 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. Alford and Jones [1996] investigate whether the difference between U.S. and foreign accounting disclosure requirements influences the size of a firm's adverse selection trading cost. Upon finding no significant difference between the stocks of foreign and domestic firms traded on the NYSE, they conclude that the alleged openness of SEC reporting requirements does not make equity securities more transparent to investors.

Most market microstructure research has concerned some aspect of bid-ask spreads; relatively less is known about the other dimensions of a stock's microstructure properties. However, few studies have sought to connect trading characteristics with any dimension of the firm's business activities. This paper relates a bank's spread, trading volume, and the return volatility to its asset composition. While these variables have previously been linked to one another (e.g. Karpoff [1987], Jones, Kaul and Lipson [1994]), their correlation with firms' business properties has not been evaluated. We also compare alternative methodologies for computing the adverse selection component of a stock's bid-ask spread. Surprisingly, alternative decompositions of the same stocks' bid-ask spreads have not previously been compared in the literature. We find distinctly mixed evidence about the comparability of various methods for computing spread decompositions.

III. Data

We identified a set of U.S. bank holding companies whose stock traded on the NYSE, AMEX, or NASDAQ exchanges at any time between January 1993 and December 1995. Using firm names, we matched these publicly-traded banks against the Federal Reserve's quarterly Consolidated Reports of Condition for bank holding companies (FR Y-9C). This yielded a set of 305 banking firms for which we had both stock return and accounting data. We collected the quarterly Y-9C data for 1993-I through 1995-III. Each bank's spread components were estimated using information from the New York Stock Exchange's TAQ (Trade and Quote) database.[4] Using the methods of both GKN [1991] and LSB [1995], we estimated the spread components for each calendar month in our three-year sample period. (The Appendix describes how we computed three measures of adverse selection.) For each month, we also collected from TAQ:

1) TRANS, the number of distinct trades,

2) TURNOVER, the total number of shares traded, divided by the firm's number of shares outstanding, and

3) SDRET, the standard deviation of quote returns, computed as the continuously compounded return based on the quote midpoints

We combined the first and third of these variables to compute a *monthly* return standard deviation: SDMNTH = SDRET $*\sqrt{(\text{TRANS})}$. We eliminated observations which seemed, *ex ante*, likely to produce unrepresentative values. We therefore eliminated any firm-month whose month-end share price was less

[4] The TAQ database contains time stamped trade (price and quantity) and quote quotes (bid price, ask price and the size at each price and time) data for all stocks on the NYSE, AMEX and NASDAQ. It also contains regional transactions reported through the CTS, QTS, and NASDAQ level 1 quote system.

than $2, during which a stock had fewer than 30 trades, or during which the average quoted spread exceeded 30% of the share's price. Finally, we eliminated any stock which had a split greater than 10 percent during the month. Our spread-decomposition methodologies assume that a stock's spread remains constant throughout the estimation period, and previous research has shown that the percentage spread rises after a stock split. Our final bank sample included 270 banks with data for at least one quarter during the period 1993-I and 1995-III.

Table 1 provides summary statistics. Because NYSE/AMEX (henceforth: "NYSE") and NASDAQ stocks have different trading mechanisms, we report separate statistics for banks traded on the two exchanges.[5] NYSE banks are substantially larger, and trade much more frequently. The larger banks also exhibit greater return volatility than their NASDAQ counterparts. Consistent with much previous research, NASDAQ spreads are considerably larger. We also find, as do Affleck-Graves *et al*. (1994), that the Order Processing component of spreads is larger on the NASDAQ than on the NYSE.[6]

To evaluate whether the banking firms exhibit distinctive microstructure characteristics, we matched each sample bank with a similar nonfinancial firm. For each bank, we identified the firm traded on the same exchange (NYSE or NASDAQ) whose equity market value was closest to the bank's.[7] Matched firms were selected (without replacement) from all traded firms except those in the financial industry (SIC code 60) or regulated utilities (code 48-49). This matching process was undertaken for two dates (January 31, 1993 and June 30, 1995), to provide some indication of the comparison's robustness. We computed monthly market microstructure variables for each matched, nonfinancial firm during the first three months of 1993 and the last three months of 1995. When computing these microstructure variables, we applied the same screens to our matched samples as we did for the banks, which left 264 (246) matched nonfinancial firms in 1993

[5] We also report (below) that NASDAQ and NYSE banks exhibit significantly different trading patterns. We attribute these differences primarily to bank size.

[6] Affleck-Graves, *et al.* [1994] attribute this difference in order processing costs to the multiple (NASDAQ) market makers' reduced scale economies. At the same time, they find that NYSE-traded stocks have larger adverse selection and inventory components because(they conjecture) a single specialist must absorb all of the informed trading and inventory risk.

[7] One could reasonably construct a matching sample based on total assets. Given the banks' greater leverage, matching by asset size would have yielded quite different "matched" firms. We chose to match on equity market value because the microstructure literature has primarily focused on this aspect of firm size.

(1995). We collected no accounting information for the matched firms.

IV. Comparing Banks' and Matched Firms' Microstructure Properties

Table 2 reports the summary comparisons of bank and matching firm microstructure variables for March 1993 and December 1995. Panel A includes all available pairs, while Panels B and C describe the sub-samples traded on the NYSE and NASDAQ respectively. A considerable proportion of our sample firms traded too infrequently to be included in the microstructure sample. In March 1993, for example, we have microstructure data for 264 matched firms, but only for 226 banks. The data in Table 2 reflect the intersection of these two sub-samples, which is 205 pairs. The December 1995 microstructure data included 246 banks and 277 nonbanks, with complete data for 225 pairs.

For the overall sample (Table 2, Panel A), the two groups' mean quoted spreads are statistically indistinguishable. However, the *effective* spread provides a better indicator of trading costs, and Row (2) shows that the banks' mean effective spread is significantly lower in 1995. For 1993, a parametric test indicates that the mean effective spreads are identical, but the sign test indicates (at the 10% confidence level) that bank spreads are lower. Rows (3) through (5) report the two groups' adverse selection components, which closely resemble one another in both years. The two groups' mean Neal-Wheatley measures of adverse selection (Row (3)) are statistically and economically indistinguishable, as are the LSB measures (Row (5)). According to the GKN measure of adverse selection (Row (4)) the banks have statistically higher AS trading costs in 1993, though not in 1995.[8] Despite the statistical significance, however, the mean 1993 GKN adverse selection components are economically quite similar: 38.7% of total spread for banks vs. 33.4% for the matched firms.

Despite similar bid-ask spreads, the bank shares trade substantially less than the shares of their size-matched mates. According to Row (6), bank turnover is less than one-third of the nonbanks', and this

[8] Note that the Neal-Wheatley and GKN measures of adverse selection exceed the LSB measures by about a factor of 3. For more detailed comparisons of the two decomposition methods, see the discussion of Table 5 in Section VI below.

difference is highly significant (t-statistics above 6) in both sample years.[9] The average bank also has significantly fewer monthly transactions (Row (7)).[10] In general, trading volume and return volatility are positively correlated (Karpoff [1987]), and this feature appears clearly in our sample. Panel A's Row (8) indicates that the average bank stock has a significantly *lower* standard deviation, and this difference is economically large: bank stock returns are only 50-60% as volatile as their matched nonfinancial firms'.[11]

Because the NYSE vs. the NASDAQ operate with different trading mechanisms, the typical stock's microstructure characteristics might vary between the exchanges. Moreover, Table 1 shows that the NASDAQ banks are much smaller than the NYSE institutions, and small banks have been excluded from some of the riskier financial market activities in which larger banks play a central role. We therefore repeat the Panel A comparisons for each of these subgroups in Panels B and C. It turns out that the differences between banks and nonfinancial firms in Panel A reflect predominantly the NASDAQ firm pairs.

Panel B of Table 2 shows that the NYSE banks' microstructure variables closely resemble those of their matched firms. The only microstructure features exhibiting any statistical difference are Monthly Turnover (according to the parametric test in 1995) and the Monthly SD Return (nonparametric test, 1995). In economic terms, neither statistical difference is very large. Turning to the NASDAQ banks, Panel C shows that their mean Quoted Spread is statistically indistinguishable from that of the matched firms. The mean Effective Spreads are equal in 1993, and significantly *lower* for the banks in 1995.[12] However, the NASDAQ banks' trading volume and return volatility are markedly lower than their matched firms' -- see Rows (6) - (8). These differences are economically substantial. The NASDAQ nonfinancial firms trade four to six times as much as the banks, and exhibit two to three times as much return volatility. The existing

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[9] Recall that Table 2 omits any firm which trades less than 30 times per month. Since this screen eliminated more banks than nonbanks, the indicated trading differences underestimate the true difference between bank and nonbank transactions.

[10] The dollar size of the typical transaction does not substantially differ between the banks and their mates: the average bank transaction trades fewer shares, but the banks tend to have higher share prices. (Not shown.)

[11] Recall that SDMNTH is computed from variations in the mean *quoted* price, and hence incorporates no bid-ask bounce. The banks' lower monthly return volatility reflects significantly less volatility in the quote-to-quote return series (not shown), and significantly fewer monthly transactions (see Row (7)).

[12] The NASDAQ banks' AS Fractions are indistinguishable for two decomposition methods, but not for the GKN method. Even there, however, the economic difference between banks and their matches is not very substantial: 29.8% vs. 23% (in 1993) or 32.2% vs. 28% (in 1995).

literature provides little guidance for interpreting these dramatic differences.

The bank-nonbank differences documented in Panel C may reflect some tendency for firms in the same industry to manifest similar trading characteristics. In other words, Table 2 may not be demonstrating that the NASDAQ banks are somehow special, but only that each industry has its own typical microstructure properties.[13] We investigate this possibility by approximately bifurcating the group of matched firms into the set of manufacturing firms (SIC codes 2 and 3) and the set of all other firm types. This division yields 110 manufacturing firms vs. 95 non-manufacturing firms in 1993 and 121 vs. 104 in 1995. The resulting comparisons (not reported here) reveal virtually no differences in mean spreads between these two broad types of nonfinancial firms.[14] More importantly for our purposes, we also found (again, not reported here) that the bank-nonbank differences in Table 2's Panel A are significant and have the same sign for both the manufacturing and non-manufacturing sub-samples. The NYSE banks are statistically indistinguishable from their nonfinancial mates for both types of comparison firm. The NASDAQ banks' spreads and AS fractions are very similar to both their manufacturing and non-manufacturing mates, but the banks' transactions, turnovers, and monthly return volatilities are significantly lower.

We conclude from Table 2 that the only substantial difference between bank and nonbank microstructure properties lies in the smaller (NASDAQ) banks' propensity to trade less often, despite their very similar bid-ask spreads.[15] This difference appears to reflect some unusual feature of the NASDAQ banks, and does not manifest a broader industry effect. From a public policy perspective, this conclusion implies that the largest, most important, U.S. banking firms -- which trade on the NYSE -- do not appear to be more difficult to value than our size-matched sample of nonbanking firms. On its face, this seems to

[13] Note, however, that the NYSE banks do not reflect the same "industry effect."

[14] The only exception to this statement occurs for the 1993 sample of matched NYSE firms, for which the non-manufacturing firms' 24.8% return volatility significantly exceeded (pr = .01) the manufacturing firms' average of 12.69%. The NYSE banks' mean SDMNTH (16.89%) could not be distinguished (pr=.10, one-tailed test) from either nonfinancial group.

[15] We also conducted multivariate comparisons of banks' and nonbank firms' microstructure characteristics, by regressing each microstructure variable in Table 2 on its likely determinants separately for banks and for nonbanks (not shown). A simple chi-square test then indicated whether the two groups' microstructure variables were similarly determined. In virtually all cases, for both the NYSE and NASDAQ firms, we rejected the hypothesis of equal coefficients for the two groups of firms.

imply that government needs to provide no special oversight services to large banking firms.[16]

The importance of private information for the NASDAQ banks is more difficult to assess. The banks' equal (or lower) spreads suggest that private information is not particularly important for the banks, but their low trading is quite puzzling -- especially *given* the equivalent spreads. Normally, lower trading volume is associated with a higher operating cost component of bid-ask spreads, because dealers must hold larger inventories when customer orders arrive more sporadically. For our banks, however, the total spreads and their AS components are similar to the nonbanks', implying that the operating cost component is likewise similar for the two groups. Although it seems clear that less new information about NASDAQ banks reaches the market, we cannot determine from Table 2 whether this reflects a dearth of value-relevant information about banks, or greater confidentiality for that information. To shed light on this question, we next analyze the analyst following of banks vs. their nonfinancial mates.

V. Bank vs. Nonbank Analyst Following

The number of analysts following a particular stock may reflect their ability to discover valuable information. If banks are unusually difficult to evaluate, we might find significant differences in the number of analysts following them. In cross-sectional equilibrium, the amount of residual private information may be either positively or negatively related to the number of analysts, though Brennan and Subramanyam [1995] present evidence that analysts reduce the incidence of private information.

We collected fiscal-year earnings estimates for each sample bank and its mate, during both 1993 and 1995. In comparing these estimates, we wanted to keep the forecasting horizon consistent across firms, which requires some care.[17] Banks all have December 31 fiscal years, but the nonbanks are less uniform. We therefore selected the nonbank's fiscal yearend closest to December, and "backed up" the appropriate number of months to find the analyst forecasts. For example, in collecting the matched firms' earnings

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[16] At a deeper level, one might argue that banks are equally transparent only *because* government supervisors monitor and discipline them. This is an important policy question, which lies outside the scope of the present paper.

[17] There is some evidence that the number of analysts posting earnings estimates varies with the time to fiscal yearend. We also

expectations for January 1993, we were interested in the fiscal year ending closest to December 1993. For the banks, all these forecasts occurred 11 months before the fiscal yearend. To maintain the same forecast horizon for the nonbanks, we find the fiscal yearend closest to December 1993 and collected the IBES forecasts from 11 months before that fiscal yearend. The same procedure was followed for the other months. For 1993, we collected earnings estimates from 9 through 11 months preceding the fiscal yearend; for 1995, we collected earnings forecasts from 3 through 8 months before the end of the fiscal year.

Table 3 presents the results of our IBES analysis, which was undertaken separately for the NYSE and the NASDAQ sub-samples.[18] We first discuss the NASDAQ results, which are more dramatic. The top portion of Panel B indicates two important facts: fewer banks are followed in IBES, but the average followed bank has effectively the same number of analysts as its nonbank mates. For those firms followed by more than one analyst, we also compared the forecasts' mean standard deviations. We deflated these standard deviations by the firm's mean January share price in order to render different firms' EPS forecasts comparable. Because we have also multiplied the standardized forecast error by 10,000, the reported numbers are expressed in basis points. The bank forecasts are significantly less dispersed than the nonbanks': the mean standard deviation across forecasters' expectations is less than half as large for the banks, a difference which is highly statistically significant in both years and at all “meaningful” forecast horizons.[19] A very similar result occurs (not reported) when we measure analyst dispersion as the difference between the highest and lowest forecast. Still another measure of information arrival is the frequency with which analysts change their earnings forecasts. For both the banks and their mates, we therefore computed the number of earnings forecast changes (per reporting analyst) in each month. For the full sample, the nonbanks' forecasts were 50% to 100% more likely to be revised, and these differences were all statistically significant.

We now require some indication whether the NASDAQ banks' lower return volatility derives from

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wanted the forecasting horizons to be similar for bank and nonbank analysts.

[18] The results for the full sample more closely resembles the NASDAQ results, in Panel B, than the NYSE results.

[19] The longest forecast horizon (11 months) has too few forecasts to provide meaningful comparisons. Presumably, many analysts

fewer innovations in asset value, or from less public dissemination of new developments. At the bottom of Panel B we compare the banks' and matching firms' average forecast errors, measured as the absolute value of actual (future) EPS less the month's median forecast. If banks are relatively opaque and outsiders cannot readily understand changes in their values, their EPS forecast errors should be relatively large. But this is not the case. Bank earnings are much more accurately predicted, particularly in 1995. During 1995, the average nonbank forecast error is *five times* that of the banks, and the differences are highly statistically significant. Since banks and nonbanks attract a similar number of analysts, the bank analysts' superior accuracy suggests that banks are not associated with large amounts of value-relevant, private information. We therefore conclude that the NASDAQ banks' lower trading volumes and return volatilities (reported in Table 2) reflect fewer true changes in value. These banks are not exceptionally opaque. They are boring.

Panel A of Table 3 reports analogous IBES results for the NYSE subsample. The average NYSE bank is followed by more analysts than its size-matched mate, and this difference is statistically significant (at the 5% - 10% level) during 1995. Large banks' earnings are predicted more accurately and with less dispersion, but (unlike the NASDAQ case) these differences are not statistically significant. Although this lack of significance could partly reflect the smaller number of observations, note that the mean forecast errors for banks and nonbanks are much more similar for the NYSE sample than for the NASDAQ firms.[20] As in Table 2, therefore, it appears that NYSE banks are not terribly different from a size-matched sample of nonfinancial NYSE firms.

VI. The Effects of Balance Sheet Composition on Bank Microstructure Variables

Information-based theories of the banking firm suggest that loans are particularly opaque assets. But real-world banks also hold marketable securities and a variety of other asset types. And not all loans have perfect repayment records. We therefore hypothesize that market measures of information asymmetry

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are still concentrating on the most recent year's EPS (which is generally not announced for a few months), and have not yet switched their attention to the coming year's earnings.

[20] Consistent with these observations, the analysts' earnings forecast revisions were always less numerous for the banks, though

about a stock's value reflect the firm's balance sheet composition. In order to test this hypothesis, we estimate fixed effects, pooled regressions of the form:

$$(4) \qquad Y_{it} = \alpha_i + \sum_k \beta_k \frac{A_{kit}}{MVEQ_{it}} + \sum_j \delta_j X_{jit} + \varepsilon_{it}$$

where

Y_{it} is a market measure of the stock's information opacity.

A_{kit} is the book value of assets of type k at bank i at the end of period t.

$MVEQ_{it}$ is the market value of bank i's equity capital at time t (computed as the monthly mean share price times the number of common shares outstanding).

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

The asset categories (A_{kit}) in (4) are deflated by the market value of equity capital ($MVEQ_{it}$) for theoretical reasons. Equity holders – and therefore market makers for the firm's shares – bear the value uncertainty associated with each type of asset in proportion to the amount of that asset *per dollar of bank equity*.[21]

The entire balance sheet is divided into mutually exclusive asset categories:

NETLNS = total loans, net of the allowance for loan and lease losses.

TRADE = 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 = other opaque assets: premises and fixed assets, investments in unconsolidated subsidiaries, customers' liabilities on outstanding acceptances, intangible assets, and the balance sheet category "other assets". [22]

In order to avoid perfect collinearity among the independent variables, we have omitted one asset from (4) –

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these differences were not so statistically significant as for the full sample or for the NASDAQ sub-sample.

[21] Replacing MVEQ with the *book* value of common shares has little effect on the coefficient estimates reported below.

[22] "Other assets" is a portmanteau account which includes, among many other items, accounts receivable, repossessed autos, boats, etc., margin account balances associated with forward and future contracts, and income earned but not collected.

the bank's holdings of informationally "transparent" assets[23]. The $\hat{}_k$ coefficients in (4) therefore measure the impact on Y_{it} of a shift out of the asset k into a transparent asset, or the information opacity of each asset *relative to* that of transparent assets. We test whether different assets have significantly greater information opacity than the transparent securities by comparing the estimated coefficients to zero.[24]

The control variables (X_{jit}) in (4) include:

PINV = the inverse of the bank's average share price during the quarter.

TOBQ = Tobin's q: the ratio of (market value of equity plus book value of liabilities) to book total assets.[25] In the empirical corporate finance literature, a higher value of TOBQ is often taken to indicate a firm with greater growth options, which are more difficult for outsiders to value.

LNMVEQ = the log market value of common equity on the quarter's last trading day.

ROE = the ratio of net current operating earnings to equity capital. Banks with higher earnings may be either easier or more difficult to value.

We evaluate four alternative market measures of asset opaqueness (Y_{it} in (4) above). The first dependent variable is the stock's effective spread (ESPREAD), which should be higher for more informationally opaque assets, *ceteris paribus*. Second, trading frequency may reflect the importance of private information to a stock's valuation. The analysis in Table 3 suggests that NASDAQ banks trade less often because they have less news (which is also manifested in lower return volatilities). In principle, however, low-uncertainty securities could trade *more*, because investors employ such securities for liquidity purposes. (Consider the trading volume of Treasury bills). We use two alternative measures of trade frequency:

TURNOVER = the proportion of outstanding shares traded during the month.

LNTRD = the log of the number of trades during the month.

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[23] Transparent assets include cash and due from balances, federal funds sold and securities purchased under agreements to resell, and investment securities.

[24] It might seem that other bank assets must have positive coefficients in (4), because they are all less transparent than the omitted asset category. However, Myers and Rajan (1998) point out that liquid assets can be quickly re-directed to investments with different values or risks. To the extent that this "re-deployment option" imposes additional information costs on outside investors, other asset classes might carry negative coefficients in (4).

[25] Keeley [1990] used this variable to measure a bank's off-book "charter value."

A stock's return volatility has been used to proxy for the arrival of new information. A stock for which private information is unimportant may have a less variable stock price. We therefore estimate (4) with the dependent variable LSDMNTH = ln(SDMNTH), where SDMNTH is the estimated standard deviation of monthly equity return. Finally, the adverse selection (AS) component of a stock's spread is an obvious dependent variable, provided it can be measured accurately. Theory suggests that the appropriate dependent variable is the AS component as a *proportion* of the stock's market value: uncertainty about the firm's share value should be related to its asset holdings as a proportion of equity capital. Table 6 presents results for three different measures of the AS component. All the microstructure variables were computed on a monthly basis, and the quarterly estimates underlying Tables 4, 5, and 6 are averages of the quarter's three monthly values. (Results using just the quarter's third month's values were similar.)

We present estimation results for two regression specifications for each dependent variable. The first specification disaggregates Net Loans into two categories:[26]

CURLNS = current loans, which are being repaid on a timely basis, and

NCURLNS = non-current loans, which are past due 90 days or more, or have been placed on non-accrual status.

It will be interesting to test whether current loans are more or less opaque than the loans which a bank has publicly identified as troubled. The second regression specification measures all loans as a single, aggregated variable (NETLNS). For both specifications, we test the hypothesis:

H1: All balance sheet ratios' coefficients are jointly zero.

For the first specification, which disaggregates NETLNS into its current and non-current components, we also test

H2: The coefficients on CURLNS and NCURLNS are jointly zero.

H3: CURLNS and NCURLNS carry equal coefficients.

[26] We alternatively divided total loans into consumer vs. nonconsumer loans, which produced broadly similar conclusions about the impact of balance sheet composition on bank microstructure variables.

We first estimated (4) for the full sample of traded banks. When a series of Chow tests strongly rejected the hypothesis that NYSE and NASDAQ banks had the same underlying coefficients, we estimated the models separately for each of these groups, and only these sub-sample results are reported here.

Panel A of Table 4 presents the NYSE results. The first two columns report the coefficient estimates with ESPREAD as the dependent variable in (4). Current loans significantly increase ESPREAD, while noncurrent loans have an insignificant negative effect. (The test statistic for H3 indicates that these two coefficients are not statistically different.) Among the other balance sheet components, OREO significantly raises ESPREAD, and the coefficient on OPAQUE is negative and marginally significant.[27] The hypothesis that asset composition has no explanatory power (H1) is strongly rejected (pr = 0.08%). The control variables' coefficients are consistent with much prior research: stock price (PINV) and firm size (LNMVEQ) both significantly affect ESPREAD. The significant positive coefficient on TOBQ indicates that the extent of a bank's off-balance sheet opportunities importantly affects the cost of trading its stock. The second column of Panel A repeats the same specification, except that the two loan categories have been collapsed into one, NETLNS. This loan coefficient is significantly positive. TRADE now carries a larger coefficient estimate than it does in the first column, and this coefficient is marginally significant. Again, overall portfolio composition significantly influences ESPREAD (H1).

The next four columns evaluate two dimensions of trading frequency, TURNOVER and LNTRD. We have removed PINV from these regressions and added two spread variables. Since spread may be simultaneously determined with the number of transactions, we use a fitted value of the effective spread as our regressor, along with the GKN measure of the AS cost of trade.[28] We now see a clear implication about asset quality: current loans reduce both TURNOVER and LNTRD, while noncurrent loans increase

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[27] Recall that the asset-share coefficients should be interpreted as the impact of a shift *out of* that asset share *into* perfectly elastic securities. The presence of both positive and negative coefficients on asset categories might seem inappropriate, until one recognizes that liquid securities can be converted into a variety of investments. As pointed out above, liquid assets may make a firm more difficult for outsiders to evaluate, because a liquid firm has fewer constraints on its future actions. By contrast, OPAQUE assets (e.g.) are relatively difficult for a bank to re-deploy quickly into other, perhaps riskier, assets.

[28] In order to reduce simultaneity, we instrumentally adjust the effective spread from the quarter's first month. Instruments were the same month's AS Fraction (computed by GKN), inverse share price, LSDMNTH, and LNMVEQ. Similar results occur if the spread variables are omitted from the regression or if the actual value of the first month's ESPREAD replaced the fitted value.

transactions. The two loan types carry significantly different (pr < 0.1%) coefficients in both the TURNOVER and LNTRD regressions. OPAQUE assets also tend to increase trading significantly, consistent with the hypothesis that high trading volume reflects heterogeneous asset valuation. (In all four trade volume regressions, the hypothesis that asset shares all carry zero coefficients is strongly rejected.) TOBQ reduces the number of trades (but not TURNOVER), and ROE is negatively related to trading. Presumably, more profitable banks are less frequently traded because they are easier to understand. Somewhat surprisingly, the coefficient on (the fitted) ESPREAD is significantly positive, perhaps because banks with greater private information have both higher spreads and greater demand for trading. The AS cost of trading has no impact on transactions after controlling for other bank characteristics.

The last two columns of Table 4 report the results of estimating (4) with the log of monthly return volatility as the dependent variable. Noncurrent loans significantly raise return volatility, again consistent with the idea that unusual situations generate new information about value. Moreover, the coefficients on CURLNS and NCURLNS differ significantly from one another at better than the 1% confidence level. None of the other portfolio shares carries a significant coefficient, though we strongly reject the hypothesis that all

portfolio shares carry zero coefficients. Among the control variables, only PINV has a significant effect. When we constrain the coefficients on CURLNS and NCURLNS to be equal (in the rightmost column of Panel A), the loan coefficient becomes indistinguishable from zero and we can no longer reject the hypothesis that portfolio shares have no effect on LSDMNTH. Hence, it seems important to maintain the distinction between current and noncurrent loans.

Overall, Panel A of Table 4 strongly suggests that asset composition affects an NYSE bank's microstructure properties. The estimated coefficients on CURLNS and NCURLNS generally differ from one another, with current loans generating less trade and lower return volatility. More profitable banks are easier to understand, and hence have fewer trades and (marginally) lower return volatility, apparently because they are easier to evaluate.

Panel B of Table 4 reports the results of estimating the same regressions for the NASDAQ firms. Although the results are broadly similar to those for the NYSE banks, coefficient estimates are less precise. In the first two columns, we cannot reject the hypothesis that asset shares have no effect on ESPREAD, though the positive TOBQ effect carries over from the larger institutions. CURLNS reduces both TURNOVER and LNTRD, while NCURLNS has the opposite effect. Although these individual coefficients do not always differ significantly from zero, the hypothesis that current and noncurrent loans have similar effects (H3) is rejected for both TURNOVER (pr = 4.30%) and LNTRD (pr = 9.66%). OREO significantly raises equity trades, presumably because repossessed assets are harder to value. More profitable banks are (again) less likely to trade. In the final two columns of Panel B we find that CURLNS and NCURLNS have significantly different -- and oppositely signed -- effects on SDMNTH, while OREO and TOBQ are correlated with higher return volatility.

In theory, the Adverse Selection cost of trading a firm's stock should be the best measure of information opacity. Since these costs must be estimated with error, however, it may be difficult to reject any null hypothesis. Moreover, little has been established about the properties of alternative spread decomposition methods. We have computed the AS component of our bank spreads using three alternative methods. Before discussing the results of estimating (4) for these dependent variables, we discuss the extent to which the alternative decomposition methods give similar AS cost estimates for the same bank. The top half of Table 5 reports the correlation matrix for the AS costs themselves. We present both the overall correlations – computed from all available firm-date observations – and the range of correlation coefficients for each date computed separately. Although the GKN and NW estimates are quite highly correlated (reflecting their shared basic technique), neither of these variables is very highly correlated with the LSB measure. Still, however, the correlation between ASGKN (ASNW) and ASLSB is positive and significantly different from zero in all quarters except 1995-I.[29]

Alternate decomposition methods might provide consistent *rankings* of the sample banks' AS costs

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[29] Even for that quarter, the correlation between ASLSB and ASGKN (ASNW) is significant at the 12% (9%) level.

without displaying large correlations between the measures. We therefore computed rank correlations in Panel B of Table 5. Again, we present both the overall correlation, and the range of correlations for each of eleven quarter-end dates. While the rank correlations between ASLSB and the other two methods are slightly higher than in Panel A, they remain much smaller than the correlations between ASGKN and ASNW. In short, these alternative decomposition methods do not seem to be measuring the same characteristics of our sample banks.

Table 6 presents the results of estimating regression (4) for three alternative measures of the AS component. Each of the dependent variables measures the Adverse Selection cost of trading, as a fraction of the stock's price per share.[30] A higher Adverse Selection cost denotes more privately-informed trades for the associated security. The left half of Table 6 reports regression results for the NYSE subsample. All three AS measures are significantly affected by the portfolio composition of these banks (H1), but the particular coefficient signs vary across the dependent variables. For ASGKN and ASNW, CURLNS significantly reduce AS costs. TRADE does the same, but is significant only for the GKN decomposition. By contrast, CURLNS significantly *raise* ASLSB! TRADE has a positive effect on ASLSB (which becomes marginally significant for the second specification), and OREO's coefficient is also significantly positive. ROE, which consistently reduces trading volume in Table 4, has no significant effect on AS costs. Reading across the NYSE columns in Table 6, the coefficient signs and significance levels vary dramatically with the dependent variable.

The NASD regressions in Table 6's right half are even more contradictory. Portfolio composition has no significant effect (H1) on either ASNW or ASLSB. For ASGKN, the joint significance of portfolio shares derives from TRADE and (marginally) OREO, though these variables' negative signs are quite surprising.

In sum, Tables 5 and 6 indicate that alternative decomposition methods may differ substantially in their economic content. The reasons for these differences, and their implications for market microstructure

[30] This measure contrasts with the "AS Fractions" reported in Rows (3)-(5) of Table 2, which measure adverse selection as a

empirical work, are important questions for future research.

VII. Summary and Conclusions

This paper combines the literature on bank uniqueness and regulation with that on market microstructure, to assess the extent to which bank stocks' trading behavior suggests that these firms are unusually difficult to value. We have conducted two types of empirical tests.

Section IV compares market microstructure variables for a matched set of banks and (similar-sized) nonbank firms. We find that bank microstructure characteristics vary significantly with their size and the exchange on which they are traded. Large banks (traded on the NYSE) exhibit market microstructure properties which closely resemble the matched nonbanks' characteristics, and IBES analysts cannot predict earnings more reliably for the banks than for the nonbanks. Our results are consistent with the hypothesis that large banking firms are not unusually difficult for investors to value. At least among the largest banks, which account for the economy's most important financial risks, justifying special treatment of banking firms requires some market failure other than extreme information opacity. Moreover, information generated in the (apparently) well-functioning market for NYSE bank stocks may usefully supplement traditional supervisory activities.

By contrast, smaller (NASDAQ) banks trade less than 25% as frequently as nonbanks, *despite* comparable bid-ask spreads. The smaller banks also exhibit substantially lower return volatilities than their size-matched mates, and IBES analysts can predict their earnings much more accurately. We conclude (somewhat tentatively) that these banks are relatively simple firms, about which market investors have rather good information.

We have also tested whether bank asset classes differ in the extent of their information opacity. Using a pooled sample of 270 banking firms over 11 quarters in 1993-1995, we compare each asset category's impact on market microstructure variables to the impact of liquid ("transparent") securities.

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fraction of the quoted or effective bid-ask spread.

Generally, we reject the hypothesis that asset composition has no effect on a bank's spread, trade frequency, and return volatility. Non-delinquent ("current") loans raise a stock's effective spread and reduce its trading volume. "Noncurrent" loans have no significant effect on effective spread, but significantly raise trading volume. OREO appears to be a high-information-cost asset, since it raises equity trading and return volatility. We also find some evidence that Tobin's Q measures a bank's information asymmetry, and that more profitable banks are more uniformly valued by market investors – presumably because private information is less valuable about obviously profitable institutions.

Finally, we have compared three empirical methods for extracting the "adverse selection" component from a stock's bid-ask spread. (Although numerous methods for undertaking this decomposition have been used in the literature, we believe that ours is the first explicit comparison of methods for a sizeable set of stocks.) Our results indicate that the information content of the differently-computed adverse selection components are not very highly correlated with one another. Moreover, no one method seems to provide a superior characterization of sample firms' economic properties. The implications of these findings for empirical research in market microstructure are left for future research.

Appendix:
Computing the Adverse Selection Component of Spread

The bid-ask spread must cover order processing, inventory holding and adverse selection costs.[31] Three classes of statistical models have been proposed to estimate these spread components. In the first class of models, inferences are made 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 regression to decompose the spread (Glosten and Harris [1988] and Madhavan, Richardson and Roomas [1996]). The third class of models does not decompose quoted bid-ask spreads, but uses data about order flow and trade direction to estimate a measure of market depth, which is related to the market maker's adverse selection problem (Hasbrouck [1991a, 1991b], Hausman, Lo and MacKinlay [1992], and Foster and Viswanathran [1993]).

We employ two methods to estimate the adverse selection component of a bid-ask spread: that of George, Kaul, and Nimalendran [1991] (implemented two different ways), and that of Lin, Sanger and Booth [1995].[32] For all estimations, we include only BBO (best bid and offer) eligible quotes in our analysis. We also follow Lee and Ready's [1991] recommendation that the quote associated with each transaction is the one in effect five seconds earlier which are. Utilizing three alternative estimates of the spreads' AS component should make our findings more robust. Moreover, we are unaware of any empirical attempts to compare empirical estimates of a spread's components.

<u>Method I - George, Kaul, and Nimalendran [1991]</u>

Three important assumptions underlay the spread decomposition method of George, Kaul, and Nimalendran (GKN). First, they decompose the spread into only two components (adverse selection and

[31] Models that emphasize inventory holding costs include Demsetz (1968), Stoll (1978), Amihud and Mendelson (1980), and Ho and Stoll (1981, 1983). Models that discuss the importance of adverse selection include Bagehot (1971), 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.

order processing), because they assume that the inventory component is small enough to ignore.[33] Second they assume that the sequence of buy and sell orders is serially uncorrelated: regardless of the most recent order's type, the probability of "buy" and a "sell" on the next order both equal 0.5. Finally, they assume that the quoted spread is constant across transactions.

GKN compute two different return series for each stock – one based on transaction prices and the other based on quote midpoints. By differencing these two return measures, they remove the effect of unanticipated returns (which cause a large fraction of the quote volatility), which substantially increases efficiency. Let R_{it}^{T} be the return to stock i at time t, based on transaction prices. Correspondingly, define R_{it*}^{Q} as the return to security i at time t*, based on the midpoint of the bid and ask quotes. The time subscripts on these returns differ because GKN assume that the quotes are updated following each transaction. Hence $t* > t$. Next define $R_{it}^{D} = R_{it}^{T} - R_{it*}^{Q}$ as the difference in returns based on the transaction prices and quote midpoints for security i at time t. S_i is the quoted spread, and π_i is the fraction of the quoted spread due to order processing costs. (Of course, this makes $[1-\pi_i]$ the fraction due to adverse selection costs.) GKN show that

(A-1) $$\pi_i S_i = 2\sqrt{-[\mathrm{Cov}(R_{it}^{D}, R_{it-1}^{D})]}\ .$$

GKN use daily data and end-of-day prices to estimate spread components, while here we use intra-day transaction prices and quotes.

Method II – Neal and Wheatley [1998]

[33] 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

Neal and Wheatley [1998] implement GKN's methodology in a slightly different manner. In particular, they allow the proportional spread to vary through time, and they do not impose the restriction that the probability of a buy or sell is 0.5. Under these conditions, the following regression model can be used to estimate the adverse selection component of the spread.

$$2RD_t = \pi_0 + \pi_1(s_{qt}Q_t - s_{qt-1}Q_{t-1}) + \varepsilon_t,$$

where s_{qt} is the quoted proportional spread at time t, Q_t is a +1/-1 buy/sell indicator variable, RD_t is the difference between the transaction price based return and the quote based return, and ε_t is an error term. The above model is estimated using OLS and the estimate of $(1-\pi_1)$ gives the fraction of the spread due to adverse selection.

Method III - Lin, Sanger and Booth [1995]

Lin, Sanger and Booth (LSB) employ a regression method to estimate the proportion of the *effective* spread that can be attributed to adverse selection. Their approach is based on Stoll [1989] and Huang and Stoll [1994]. The main idea is that quote revisions will reflect the adverse selection component of the spread, while changes in transaction prices will reflect order processing costs and bid-ask bounce. As in the GKN model, LSB assume that the market maker's inventory cost is zero. 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).

Let

P_t = transaction price at time t,
Q_t = quote midpoint,
$Z_t = P_t - Q_t$, one half the effective spread,
λ = proportion of the effective spread due to adverse selection, and
$\delta=(\theta +1)/2$ = order persistence parameter.

The adverse selection and order persistence parameters are estimated from the following pair of equations:

(A-2) $$Q_{t+1} - Q_t = \lambda Z_t + \varepsilon_{t+1},$$

(A-3) $$Z_{t+1} = \theta Z_t + \eta_{t+1}$$

In this model, ε_{t+1} and η_{t+1} are noise terms, while λ measures the fraction of the *effective* spread which is due to the market-maker's adverse selection costs. By contrast, GKN's $(1-\pi_i)$ measures adverse selection costs as a fraction of the *quoted* spread.

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Table 1: Summary Statistics for Microstructure Variables, by Exchange

This table reports the average and median values for bank microstructure variables, grouped by the exchange. The averages are based on the pooled time series (quarter) and firm observations. The GKN measure is estimated using the George, Kaul and Nimalendran [1991] methodology applied to transactions data. The LSB measures are obtained using the Lin, Sanger and Booth [1995] methodology. We omitted banks whose stock price was less than \$2, whose effective spread was greater than 30%, which had fewer than 31 trades during the month, or which undertook a stock split or stock dividend equal to more than 10% of the stock's initial value.

Mean [Median]

Variable		NYSE/AMEX	NASDAQ
Number of Observations		598	1648
Market Value (\$ M)		3,860 [2,242]	428 [203]
Number of Trades (per month)		3,425 [2,120]	457 [173]
Shares Traded x 10^{-3} (per month)		7,360 [3,763]	774.4 [229.1]
Price (\$)		36.7 [32.0]	24.5 [23.9]
Monthly Return Standard Deviation (%)		12.6 [9.99]	4.22 [3.32]
Quoted Spread (% of quote midpoint)		1.47 [1.16]	3.26 [2.78]
GKN Measure	Adverse selection (%)	0.91 [0.75]	1.03 [0.75]
	Order Processing (%)	0.56 [0.38]	2.24 [1.93]
Effective Spread (% of quote midpoint)		0.68 [0.45]	2.42 [2.12]
LSB Measure	Adverse Selection (%)	0.25 [0.14]	0.05 [0.03]
	Order Processing (%)	0.42 [0.30]	2.37 [2.07]

Table 2: Comparisons of Microstructure Variables, Banks vs. Size-Matched Firms

Mean values of microstructure variables for the bank sample and their matched, nonfinancial firms. Numbers in brackets are t-statistics for the hypothesis that the Banks' mean value equals the Matches' mean value.

Variable definitions:

(1) Quoted Spread: The average quoted spread for all transactions during the quarter's third month.

(2) Effective Spread = $\frac{2}{T}\sum\left|P_t - Q_t\right|, where P_t = \text{Trade Price, and } Q_t = \frac{Ask_t + Bid_t}{2}$

(3) AS Fraction of Spread, Neal-Wheatley application of GKN method: Proportion of the quoted bid-ask spread which is attributable to the adverse selection component, using Neal and Wheatley's [1998] implementation of the GKN decomposition method.

(4) AS Fraction of Spread, GKN: Proportion of the quoted bid-ask spread which is attributable to the adverse selection component, using the GKN decomposition method.

(5) AS Fraction of Spread, LSB: Proportion of the effective bid-ask spread which is attributable to the adverse selection component, using the LSB decomposition method.

(6) Monthly Turnover: Proportion of outstanding common shares traded during the quarter's third month.

(7) Number of Transactions: Number of transactions in which the firm's shares were traded during the quarter's third month.

(8) Monthly SD or Return: Monthly standard deviation of the equity return, computed using the center of bid and ask prices (to avoid bid-ask bounce).

(9) MV of Equity: Market value of outstanding common shares.

Table 2, Panel A: All available firm pairs

	1993 # Obs	1993 Banks	1993 Matches	1993 Difference	1993 % Positive	1995 # Obs	1995 Banks	1995 Matches	1995 Difference	1995 % Positive
(1) Quoted Spread	205	3.24%	3.18%	0.06%	44.39%	225	2.60%	2.89%	-0.30%	45.33%
				[0.386]	[-1.606]				[-1.837]	[-1.400]
(2) Effective Spread	205	2.27%	2.27%	0.00%	43.90%	225	1.84%	2.10%	-0.25%	41.33%
				[0.035]	[-1.746]				[-2.450]	[-2.600]
(3) AS Fraction of Quoted Spread, Neal-Wheatley	205	37.63%	37.24%	0.39%	48.78%	225	38.16%	38.16%	0.01%	49.33%
				[0.332]	[-0.349]				[0.006]	[-0.200]
(4) AS Fraction of Quoted, Spread, GKN	205	38.68%	33.44%	5.24%	58.05%	225	38.83%	36.61%	2.21%	53.78%
				[4.176]	[2.305]				[1.559]	[1.133]
(5) AS Fraction of Effective Spread, LSB	205	10.09%	9.41%	0.68%	53.66%	225	9.45%	9.02%	0.43%	55.56%
				[0.972]	[1.048]				[0.754]	[1.667]
(6) Monthly Turnover (# sh traded / # sh outst)	205	5.19%	15.47%	-10.28%	28.29%	225	4.05%	17.28%	-13.23%	18.22%
				[-7.726]	[-6.216]				[-8.586]	[-9.533]
(7) Number of Transactions	205	1,229	2,341	-1,112	25.85%	225	1,269	3,376	-2,107	18.22%
				[-4.343]	[-6.914]				[-5.699]	[-9.533]
(8) Monthly SD Return	205	7.48%	12.28%	-4.79%	22.44%	225	5.49%	11.40%	-5.90%	12.89%
				[-3.960]	[-7.892]				[-7.308]	[-11.133]
(9) MV of Equity ($ million)	205	$1,260	$1,117	$143	72.68%	225	$1,566	$1,505	$61	63.11%
				[3.996]	[6.495]				[0.730]	[3.933]

Table 2, Panel B: NYSE/AMEX firm pairs

	1993					1995				
	# Obs	Banks	Matches	Difference	% Positive	# Obs	Banks	Matches	Difference	% Positive
(1) Quoted Spread	50	1.58%	1.84%	-0.26%	42.00%	51	1.22%	1.66%	-0.43%	41.18%
				[-1.423]	[-1.131]				[-1.195]	[-1.260]
(2) Effective Spread	50	0.68%	0.82%	-0.14%	48.00%	51	0.48%	0.56%	-0.08%	49.02%
				[-1.328]	[-0.283]				[-1.283]	[-0.140]
(3) AS Fraction of Quoted Spread, Wheatley-Neal	50	61.41%	63.47%	-2.06%	46.00%	51	62.82%	65.62%	-2.80%	41.18%
				[-0.556]	[-0.566]				[-1.200]	[-1.260]
(4) AS Fraction of Quoted, Spread, GKN	50	66.12%	65.61%	0.51%	44.00%	51	61.62%	65.95%	-4.32%	47.06%
				[0.296]	[-0.849]				[-1.239]	[-0.420]
(5) AS Fraction of Effective Spread, LSB	50	33.93%	31.67%	2.27%	56.00%	51	34.18%	31.00%	3.18%	62.75%
				[0.853]	[0.849]				[1.675]	[1.820]
(6) Monthly Turnover (# sh traded / # sh outst)	50	7.00%	8.16%	-1.16%	50.00%	51	5.21%	7.63%	-2.42%	39.22%
				[-0.923]	[0.000]				[-2.060]	[-1.540]
(7) Number of Transactions	50	3,766	3,750	16	52.00%	51	3,783	3,837	-54	39.22%
				[0.026]	[0.283]				[-0.124]	[-1.540]
(8) Monthly SD Return	50	16.89%	17.27%	-0.38%	50.00%	51	11.07%	12.56%	-1.49%	31.37%
				[-0.084]	[0.000]				[-0.535]	[-2.661]
(9) MV of Equity ($ million)	50	$3,872	$3,462	$410	72.00%	51	$5,180	$5,062	$118	68.63%
				[2.983]	[3.111]				[0.328]	[2.661]

Table 2, Panel C: NASDAQ firm pairs

	1993 # Obs	1993 Banks	1993 Matches	1993 Difference	1993 % Positive	1995 # Obs	1995 Banks	1995 Matches	1995 Difference	1995 % Positive
(1) Quoted Spread	155	3.77%	3.61%	0.16%	45.16%	174	3.00%	3.26%	-0.26%	46.55%
				[0.810]	[-1.205]				[-1.424]	[-0.910]
(2) Effective Spread	155	2.79%	2.74%	0.05%	42.58%	174	2.24%	2.55%	-0.31%	39.08%
				[0.334]	[-1.847]				[-2.304]	[-2.881]
(3) AS Fraction of Quoted Spread, Wheatley-Neal	155	29.96%	28.78%	1.18%	49.68%	174	30.94%	30.11%	0.83%	51.72%
				[1.170]	[-0.080]				[0.868]	[0.455]
(4) AS Fraction of Quoted, Spread, GKN	155	29.83%	23.06%	6.76%	62.58%	174	32.15%	28.02%	4.13%	55.75%
				[4.374]	[3.133]				[2.753]	[1.516]
(5) AS Fraction of Effective Spread, LSB	155	2.40%	2.22%	0.17%	52.90%	174	2.20%	2.57%	-0.38%	53.45%
				[0.471]	[0.723]				[-0.793]	[0.910]
(6) Monthly Turnover (# sh traded / # sh outst)	155	4.61%	17.83%	-13.22%	21.29%	174	3.71%	20.11%	-16.40%	12.07%
				[-8.033]	[-7.149]				[-8.640]	[-10.007]
(7)Number of Transactions	155	410	1,886	-1,476	17.42%	174	533	3,241	-2,709	12.07%
				[-5.432]	[-8.113]				[-6.000]	[-10.007]
(8) Monthly SD Return	155	4.45%	10.67%	-6.22%	13.55%	174	3.86%	11.05%	-7.19%	7.47%
				[-9.969]	[-9.076]				[-11.518]	[-11.220]
(9) MV of Equity	155	$418	$361	$57	72.90%	174	$506	$462	$44	61.49%
				[5.333]	[5.703]				[1.779]	[3.032]

Table 3, Panel A: NYSE Banks and Matched Firms

Months Before FYE	Banks' Mean Value	Number of Banks	Matches' Mean Value	Number of Marches	T-stat: Equal Mean Values?
Number of Analysts Forecasting Current Fiscal Year's EPS					
1993					
11	13.67	9	12.00	2	0.14
10	18.09	47	17.40	42	0.29
9	18.38	47	17.70	43	0.31
1995					
8	19.07	54	15.25	56	1.99
7	18.89	55	15.32	56	1.88
6	18.84	55	15.65	55	1.67
5	18.80	55	15.52	56	1.72
4	18.86	56	15.54	56	1.71
3	19.04	56	15.64	56	1.73
Cross-sectional SD of analyst forecasts, divided by January Share Price, times 10,000					
1993					
11	21.11	8	1.10	1	2.64
10	40.13	42	87.13	39	-1.62
9	36.97	43	84.48	42	-1.82
1995					
8	26.25	50	36.63	51	-1.40
7	27.02	50	33.73	51	-1.00
6	24.75	49	33.33	51	-1.29
5	24.99	48	31.00	51	-0.90
4	23.78	49	28.26	51	-0.77
3	24.60	49	26.69	51	-0.32
Absolute EPS Forecast Error, divided by January share price, times 10,000					
1993					
11	51.75	8	305.89	2	-0.83
10	149.48	45	257.65	39	-1.58
9	146.09	45	257.78	41	-1.64
1995					
8	58.42	49	100.60	51	-1.09
7	54.24	49	91.09	51	-1.02
6	53.31	49	89.12	51	-0.96
5	51.53	49	79.78	51	-0.77
4	50.66	50	69.79	51	-0.55
3	50.85	50	62.85	51	-0.35

Table 3, Panel B: NASDAQ Banks and Matched Firms

Months Before FYE	Banks' Mean Value	Number of Banks	Matches' Mean Value	Number of Marches	T-stat: Equal Mean Values?
Number of Analysts Forecasting Current Fiscal Year's EPS					
1993					
11	4.46	13	8.00	2	-0.69
10	5.33	121	7.38	105	-2.53
9	5.21	128	6.20	151	-1.43
1995					
8	5.43	145	5.46	174	-0.06
7	5.40	146	5.49	175	-0.17
6	5.32	148	5.49	177	-0.29
5	5.18	153	5.49	177	-0.56
4	5.25	154	5.44	178	-0.34
3	5.28	158	5.39	178	-0.20
Cross-sectional SD of analyst forecasts, divided by January Share Price, times 10,000					
1993					
11	42.69	9	37.17	1	0.24
10	27.05	85	56.25	95	-1.78
9	25.32	87	54.67	130	-2.33
1995					
8	21.31	106	62.93	144	-3.91
7	23.07	106	69.04	149	-3.73
6	22.24	108	62.63	149	-4.10
5	20.69	108	63.80	148	-4.27
4	18.45	109	59.09	152	-4.12
3	18.15	112	56.53	147	-3.50
Absolute EPS Forecast Error, divided by January share price, times 10,000					
1993					
11	211.10	13	12.39	1	1.92
10	149.29	112	176.35	102	-0.64
9	132.18	119	200.17	140	-1.76
1995					
8	48.08	125	398.11	154	-5.46
7	45.45	125	373.72	157	-5.45
6	42.66	126	338.52	158	-5.42
5	52.11	131	289.05	159	-4.74
4	52.02	131	257.84	161	-4.30
3	50.19	134	228.48	161	-4.21

Table 4: Equity Trades and Bank Balance Sheet Composition

We estimate the fixed-effect, pooled regression

$$(4)\quad Y_{it} = \alpha_i + \sum_k \beta_k \frac{A_{kit}}{MVEQ_{it}} + \sum_j \delta_j X_{jit} + \varepsilon_{it}$$

for a sample of 270 bank holding companies over the quarters 1993-I through 1995-III, where the dependent variable is either:

ESPREAD = the stock's average effective spread during the quarter's three months, computed as

$$\frac{2}{T}\sum \left|P_t - Q_t\right|, \textit{ where, } P_t = \text{Trade Price, and } Q_t = \frac{Ask_t + Bid_t}{2}$$

LNTRD = the natural log of the number of trades during the quarter's three months.

TURNOVER = average proportion of outstanding shares traded during the quarter's three months.

LSDMNTH = natural log of (Standard deviation of monthly equity return). We first computed the standard deviation of quote returns from the midpoint of each quote's bid and ask, then computed LSDMNTH as ln(SDRET*(NTRANS$^{0.5}$)).

Independent variables (A_{kit}) are:

NETLNS = total loans, net of the allowance for loan and lease losses (=CURLNS+NCUNLNS).

CURLNS = current loans

NCURLNS = loans on non-accrual status or past due more than 89 days

TRADE = assets held in trading accounts

OREO = other real estate owned

OPAQUE = other opaque assets

$MVEQ_{it}$ is the market value of bank i's equity capital at time t.

Control variables (X_{jit})include:

PINV = the inverse of the stock's quarterly average price

LNMVEQ = the log market value of common equity

TOBQ = the ratio of (market value of equity plus book value of liabilities) to book total assets.

ROE = return on equity

ESPREAD1 = the fitted value of the bank's effective spread during the quarter's first month, from an instrumental variables regression.

The omitted balance sheet category is "transparent" assets. Market measures are averages of separately-estimated monthly measures from the quarter's three months. Accounting information is for quarter-end. Coefficient estimates have been multiplied by 1000, except for the TURNOVER regressions. Heteroskedasticity-consistent (White) t-statistics are reported in brackets.

H1: All balance sheet ratios' coefficients are jointly zero.
H2: The coefficients on CURLNS and NCURLNS are jointly zero.
H3: CURLNS and NCURLNS carry equal coefficients.

Table 4, Panel A: Regressions Explaining Microstructure Properties of NYSE Banks

	EFFECTIVE SPREAD		TURNOVER		LNTRD		LSDMNTH	
NETLNS		0.3104		-6.237		-26.12		-21.12
		[3.914]		[-4.910]		[-2.111]		[-1.227]
CURLNS	0.3167		-6.194		-27.16		-25.16	
	[3.96]		[-5.091]		[-2.234]		[-1.415]	
NCURLNS	-1.038		125.2		939.5		1629	
	[-0.821]		[3.347]		[3.274]		[2.998]	
TRADE	0.0755	0.1144	6.995	3.207	86.91	59.04	98.47	49.62
	[1.016]	[1.782]	[2.958]	[1.311]	[3.823]	[2.463]	[1.330]	[0.657]
OREO	9.719	8.704	-92.79	11.62	-233.6	544	-305.5	1046
	[3.190]	[3.141]	[-1.839]	[0.316]	[-0.543]	[1.486]	[-0.480]	[1.905]
OPAQUE	-0.7472	-0.8207	20.35	32.26	129.1	211.2	6.762	145
	[-1.742]	[-1.861]	[1.807]	[3.101]	[1.082]	[1.827]	[0.035]	[0.769]
PINV	99.68	100.8	--	--	--	--	11710	10330
	[8.730]	[8.881]					[4.458]	[3.996]
TOBQ	19.4	19.11	-0.8795	28.62	-1965	-1733	435.8	684.2
	[4.435]	[4.413]	[-0.012]	[0.374]	[-2.126]	[-1.887]	[0.361]	[0.555]
LNMVEQ	-1.656	-1.611	8.938	3.354	1029	986.8	152.3	75.62
	[-4.732]	[-4.615]	[1.466]	[0.594]	[10.240]	[9.852]	[1.117]	[0.563]
ROE	0.7412	0.9149	-50.7	-68.66	-314.5	-445.7	-332.9	-567.3
	[0.838]	[1.035]	[-4.001]	[-4.506]	[-2.167]	[-2.852]	[-1.457]	[-1.785]
ESPREAD1			4152	4002	73540	72300		
			[2.248]	[2.052]	[4.328]	[4.102]		
AIGKN1			198.8	198	2038	2032		
			[1.380]	[1.391]	[1.061]	[1.069]		
H1	0.08%	0.03%	0.00%	0.00%	0.00%	0.43%	0.43%	14.88%
H2	0.03%		0.00%		0.07%		0.33%	
H3	28.29%		0.05%		0.08%		0.23%	
N	598	598	598	598	598	598	598	598
$\overline{R}^2$	0.974	0.974	0.786	0.774	0.975	0.974	0.570	0.558

Table 4, Panel B: Regressions Explaining Microstructure Properties of NASD Banks

	EFFECTIVE SPREAD		TURNOVER		LNTRD		LSDMNTH	
NETLNS		0.7179		-2.229		-13.18		-59.85
		[1.193]		[-1.869]		[-0.840]		[-3.219]
CURLNS	0.6444		-3.066		-22.07		-67.85	
	[1.021]		[-2.425]		[-1.421]		[-3.363]	
NCURLNS	2.762		21.05		224.6		234.9	
	[0.467]		[1.830]		[1.538]		[1.373]	
TRADE	0.7128	0.6644	-0.7128	-1.188	43.38	38.64	129.8	122.6
	[0.497]	[0.458]	[-0.116]	[-0.197]	[0.514]	[0.462]	[0.795]	[0.752]
OREO	1.477	2.007	39	43.12	559.6	602.3	412.7	468.5
	[0.211]	[0.310]	[2.328]	[2.656]	[2.856]	[3.224]	[2.382]	[2.834]
OPAQUE	1.079	1.119	-23.38	-23.52	-9.752	-11.83	166.5	170.9
	[0.382]	[0.392]	[-1.797]	[-1.805]	[-0.071]	[-0.086]	[1.12]	[1.028]
PINV	107.9	109.2	--	--	--	--	4002	4119
	[2.332]	[2.343]					[2.679]	[2.807]
TOBQ	50.95	52.63	19.29	39.06	-530.4	-324.8	4984	5209
	[2.886]	[2.938]	[0.305]	[0.642]	[-0.682]	[-0.423]	[4.278]	[4.509]
LNMVEQ	-12.73	-12.85	13.44	12.9	876.2	870.6	-678.9	-690.3
	[-10.140	[-10.32]	[1.976	[1.891]	[9.696]	[9.572]	[-7.775]	[-7.906]
ROE	-2.735	-3.24	-29.51	-34.43	-323.6	-374.5	-152.1	-212.9
	[-0.605]	[-0.777]	[-2.358]	[-2.761]	[-2.279]	[-2.583]	[-0.878]	[-1.307]
ESPREAD1			1128	1226	-4823	-3820		
			[1.578]	[1.710]	[-0.567]	[-0.432]		
AIGKN1			-982.8	-1057	3447	2683		
			[-1.604]	[-1.722]	[0.454]	[0.342]		
H1	51.59%	43.82%	0.04%	0.11%	0.41%	2.54%	0.34%	0.20%
H2	44.58%		2.58%		13.71%		0.33%	
H3	72.87%		4.30%		9.66%		9.01%	
N	1648	1648	1648	1648	1648	1648	1648	1648
$\overline{R}^2$	0.888	0.888	0.678	0.677	0.926	0.926	0.516	0.516

Table 5: Comparing Alternative Spread Decompositions

Comparison of three AS estimates for a sample of 270 bank holding companies:

ASGKN = adverse selection cost of trading a stock, using George, Kaul, and Nimalendran's [1991] method of decomposing the quoted spread, as a percentage of the stock's price.
ASNW = adverse selection cost of trading a stock, using Neal and Wheatley's [1998] implementation of the George, Kaul, and Nimalendran, as a percentage of the stock's price.
ASLSB = adverse selection cost of trading a stock, using Lee, Sanger, and Booth's [1995] method of decomposing the effective spread, as a percentage of the stock's price.

All three spreads are expressed as a proportion of the stock's price (center of bid and ask quotes), and are the average of three month's estimates within the quarters 1993-I through 1995-III. The Appendix describes the specific computational methods employed. Within each cell, the first number is the correlation for the full sample. We also computed the correlations separately for each quarter, and the bracketed pair of numbers indicates the minimum and maximum values obtained.

Panel A: Simple Correlation Coefficients

	ASGKN	ASNW	ASLSB
ASGKN	1.00		
ASNW	0.95 *** [0.94 – 0.97]	1.00	
ASLSB	0.27 *** [0.11 –0.42]	0.25 *** [0.12 – 0.41]	1.00

Panel B: Pearson Rank Correlation Coefficients

	ASGKN	ASNW	ASLSB
ASGKN	1.00		
ASNW	0.93 *** [0.92 – 0.94]	1.00	
ASLSB	0.36 *** [0.22 –0.51]	0.32 *** [0.22 – 0.40]	1.00

*** = significantly different from zero, 1% confidence level.

Table 6: Adverse Selection Costs and Bank Balance Sheet Composition

We estimate the fixed-effect, pooled regression

$$(4)\quad Y_{it} = \alpha_i + \sum_k \beta_k \frac{A_{kit}}{MVEQ_{it}} + \sum_j \delta_j X_{jit} + \varepsilon_{it}$$

for a sample of 270 bank holding companies over the quarters 1993-I through 1995-III, where the dependent variable is either:

ASGKN = George, Kaul, and Nimalendran's [1991] adverse selection cost of trading a stock, divided by the stock's price per share.
ASNW = GKN measure, as computed by Neal and Wheatley [1998].
ASLSB = Lin, Sanger, and Booth's [1995] adverse selection cost of trading a stock, divided by the stock's price per share.

Independent variables and other notes are defined in Table 4.

H1: All balance sheet ratios' coefficients are jointly zero.
H2: The coefficients on CURLNS and NCURLNS are jointly zero.
H3: CURLNS and NCURLNS carry equal coefficients.

Table 6: Adverse Selection Costs and Bank Balance Sheet Composition

	Banks trading on NYSE						Banks trading on NASD					
	ASGKN		ASNW		ASLSB		ASGKN		ASNW		ASLSB	
NETLNS		-0.3232		-0.4919		0.2111		0.2711		0.5577		-0.01104
		[-2.001]		[-3.288]		[2.971]		[1.056]		[1.984]		[-0.119]
CURLNS	-0.3143		-0.4824		0.2213		0.2688		0.5982		-0.02651	
	[-1.963]		[-3.283]		[3.047]		[1.090]		[2.247]		[-0.280]	
NCURLNS	-1.039		0.1745		-0.9709		0.5047		-0.5819		0.5398	
	[-0.393]		[0.068]		[-0.646]		[0.153]		[-0.162]		[0.652]	
TRADE	-0.5638	-0.5415	-0.1186	-0.1367	0.05911	0.09337	-3.293	-3.302	-0.8558	-0.8354	-0.3402	-0.354
	[-2.153]	[-2.317]	[-0.930]	[-1.234]	[0.878]	[1.861]	[-3.475]	[-3.493]	[-1.016]	[-1.005]	[-0.847]	[-0.877]
OREO	1.055	0.3353	1.181	1.531	6.587	5.663	-6.641	-6.527	-2.896	-3.022	-0.5418	-0.4213
	[0.268]	[0.096]	[0.270]	[0.412]	[2.426]	[2.332]	[-1.875]	[-1.914]	[-0.834]	[-0.957]	[-0.712]	[-0.600]
OPAQUE	1.02	0.9693	0.9897	1.063	-0.07336	-0.1182	-0.14	-0.1012	-1.55	-1.511	0.3667	0.3797
	[1.078]	[1.083]	[1.093]	[1.225]	[-0.133]	[-0.215]	[-0.095]	[-0.069]	[-1.118]	[-1.092]	[1.190]	[1.198]
PINV	157.7	158.5	150.8	150.6	13.04	14.15	98.84	99.24	68.17	68.13	8.82	9.105
	[5.529]	[5.538]	[5.529]	[5.410]	[0.969]	[1.030]	[5.333]	[5.373]	[3.279]	[3.194]	[0.737]	[0.764]
TOBQ	9.146	9.012	-4.371	-4.318	11.88	11.58	25.8	25.88	19.3	18.26	0.9836	1.399
	[1.211]	[1.202]	[-0.656]	[-0.652]	[3.661]	[3.616]	[2.152]	[2.143]	[2.060]	[1.838]	[0.454]	[0.653]
Ln(MVEQ)	-2.612	-2.562	-2.695	-2.702	-1.063	-1.021	-5.047	-5.074	-4.255	-4.234	-0.2569	-0.2823
	[-3.078]	[-3.088]	[-3.078]	[-3.144]	[-4.218]	[-3.966]	[-4.603]	[-4.688]	[-5.125]	[-5.220]	[-1.408]	[-1.519]
ROE	0.4307	0.5404	1.358	1.274	0.9459	1.096	-4.063	-4.137	-5.793	-5.586	0.5318	0.4105
	[0.287]	[0.367]	[0.923]	[0.909]	[0.918]	[1.129]	[-1.551]	[-1.710]	[-2.072]	[-2.135]	[0.752]	[0.658]
H1	4.67%	2.65%	0.14%	0.06%	2.06%	1.98%	0.30%	0.14%	21.03%	20.39%	70.65%	56.62%
H2	14.50%		0.39%		0.58%		53.39%		8.00%		79.18%	
H3	78.26%		79.56%		42.55%		94.35%		74.42%		50.23%	
N	598	598	598	598	598	598	1648	1648	1648	1648	1648	1648
$\bar{R}^2$	0.869	0.869	0.915	0.915	0.891	0.891	0.817	0.817	0.863	0.863	0.290	0.289