International Review of Accounting, Banking and Finance

Vol 4, No.1, Winter 2012 Pages 51~72

IRABF

Are Banks Opaque?

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Abstract: We use the Jin and Myers (2006) model to examine the relative opacity of banks. Our results show that banks have less firm-specific information in their equity returns than industrial matching firms, consistent with banks being more opaque than industrial firms. We also provide new evidence on the opacity of specific bank assets. We find that higher proportions of agricultural and consumer loans are related to lower levels of bank opacity. Our results are robust to inclusion of various controls, consideration of differential fundamental cash flow risk between banks and industrial firms, and the stock exchange on which shares trade.

JEL: G21

Key Words: Banks, Opacity of Banks

1. Introduction

One rationale for the regulation and protection of banks rests on the assumption that banks are opaque, that outsiders cannot observe the risks involved in financial intermediation. Such opacity exposes banks and the financial system to runs and contagion, in which even healthy banks fall victim because opacity prevents outsiders from being able to distinguish between sound institutions and unsound ones. Thus, the logic goes, government regulation, the discount window as lender of last resort, and deposit insurance are necessary to protect healthy banks and the banking system (Morgan (2002), Flannery et al. (2004)).

But are banks really more opaque than industrial firms? To address this question, Morgan (2002) examines the ratings of new bonds issued by banks and industrial firms. If a firm is completely transparent, then the two major rating agencies should reach the same conclusion regarding the default risk of any given bond issued by the firm. However, if a firm is opaque, rating agencies must use partial information to arrive at a rating, creating the possibility of disagreement between the two agencies. Therefore, disagreement between the agencies (a “split” bond rating) is an indication of firm opacity. Morgan finds that banks are more likely to receive such "split" ratings than industrial firms, consistent with banks being more opaque than industrial firms.

Flannery et al. (2004) also empirically examine the differences in opacity between banks and industrial firms, using analyst and microstructure data to arrive at the conclusion that banks are no more opaque than industrial firms. In fact, they find that analysts forecast bank earnings more accurately than industrial firm earnings.

Given the mixed evidence, the issue of bank opacity remains an open question. In this paper, we revisit this issue using the theoretical model of Jin and Myers (2006), which links a firm's opacity to its stock price movements. We also re-interpret the analyst forecast findings of Flannery et al. (2004) given the theoretical model of Jin and Myers (2006).

Jin and Myers (2006) define firm opacity (opaqueness) as reduced firm information available to outside investors, and argue that opacity affects the division of risk bearing between firm insiders and outside equity holders. Outside investors, in the presence of limited firm-specific information, replace unknown firm-specific information with its expected value, conditioned on the information available to them. Thus, Jin and Myers (2006) contend that the stock returns of opaque firms are less likely to reflect firm-specific information and more likely to reflect market (and perhaps industry) information.

Veldkamp (2006) reaches a similar conclusion about the impact of firm opacity on the information content of stock returns. In her model, investors rely on common information signals in the absence of firm-specific information. Veldkamp notes that information "is a non-rival good with a high fixed cost of discovery and a low marginal cost of replication" (p. 824). As a result, information that has value for pricing many assets will be economically feasible to produce because such information can be sold to many different investors. Conversely, firm-specific information that is only valuable for pricing the stock of one firm is not likely to be produced due to the high fixed costs and smaller base of potential customers for such information. Thus, investors are more likely to use common information than firm-specific information to value opaque firms, resulting in the returns of such firms reflecting more market and industry information and less firm-specific information.

Theory suggests that banks are opaque because of the nature of their assets. Studies by Campbell and Kracaw (1980), Berlin and Loeys (1988), and Diamond (1991) all lead to the conclusion that bank loans are opaque. Therefore, bank assets, which are composed primarily of bank loans, are also opaque. Previous studies examine the opacity of different types of assets, such as loans, assets held in trading accounts, and premises and fixed assets, but no previous study examines the opacity of individual loan types.[1] In this study, we perform an analysis to determine which types of loans impact bank opacity.

We use coefficients of determination from asset pricing model regressions (a measure of stock "synchronicity" or co-movement) to provide evidence consistent with banks being more opaque than matching industrial firms. Ceteris paribus, bank returns contain less firm-specific information than matching firm returns. We also re-interpret the analyst findings of Flannery et al. (2004) in light of the Jin and Myers (2006) model. If managers of opaque firms only release information that varies with market and industry conditions, then their earnings will be easier to predict than the earnings of transparent firms, which vary with market, industry, and firm-specific information.

Using stock returns and Federal Reserve (FR) Y-9C financial statement information for our sample of publicly traded bank holding companies, we determine which assets, and specifically which loan types, are related to bank opacity. We find that higher proportions of agricultural and consumer loans are related to lower levels of bank opacity.

The rest of the paper is organized as follows: Section 1 summarizes the current knowledge on bank opacity. Section 2 provides a review of the stock synchronicity literature and summarizes the Jin and Myers (2006) and Veldkamp (2006) models. Section 3 presents hypotheses and empirical predictions. Section 4 describes the data and methods used, and Section 5 examines our results. Section 6 concludes.

2. The Opacity of Bank Assets

As Flannery et al. (2004) state, conventional wisdom says that bank loans are informationally opaque. This conventional wisdom is consistent with several theoretical works. Campbell and Kracaw (1980) posit that one reason borrowers use bank loans is that they have confidential information that they do not wish to disclose to the public. Berlin and Loeys (1988) discuss the choice between public bonds and bank loans. Both forms of debt are characterized by information asymmetry between borrowers and lenders, although banks partially overcome this asymmetry through costly monitoring. Diamond (1991) posits a difference in information asymmetry between commercial paper and bank loans. Commercial paper is a contract with terms and loan-granting decisions based only on public information, including the borrower's track record. Bank loans are granted based on public information plus information gathered by banks through costly monitoring. Borrowers with excellent credit ratings will choose to issue commercial paper because they can borrow less expensively in the open market due to their reputation for repayment. However, firms without such a reputation (e.g., new firms) will turn to banks for their borrowing needs.

[1] Morgan and Stiroh (2001) examine the relation between proportions of different loan types and yield spreads on new bond issues. This analysis captures differences in yield spreads due to differences in the riskiness of the underlying assets, not necessarily yield spread differences due to differences in opacity.

In all of these models, bank insiders have more information about bank loans than do equity investors or depositors, making bank loans informationally opaque by definition. Loans form a sizeable portion of the assets of banks. At the end of our sample period, the average bank holding company's loans accounted for 64.44 percent of its assets.[2] Thus, bank assets are opaque due to the opacity of loans.

The empirical evidence on the opacity of bank assets is mixed. If banks assets are truly opaque, investors and depositors will not be able to distinguish troubled financial institutions from healthy ones. However, several studies find that investors and depositors can identify troubled banks, even during financial crises. Musumeci and Sinkey (1990) examine the 1987 Brazilian debt moratorium and find that "the market reacted rationally and penalized banks in direct proportion to their exposure to Brazilian debt." Calomiris and Mason (1997) examine the 1932 Chicago banking panic and find that, although depositors were temporarily confused about bank asset quality, "the panic did not produce significant social costs in terms of failures among solvent banks."

Flannery et al. (2004) use microstructure data and analyst estimate data to show that large banks (defined as those traded on NYSE and AMEX) exhibit similar microstructure properties to large non-financial firms, leading the authors to conclude that the assets of large banks and the assets of large non-financial firms are similar in opacity. NASDAQ banks have similar bid-ask spreads, but have lower trade volume and return volatility than non-financial firms of similar size and stock price. Flannery et al. (2004) interpret the latter findings as the assets of NASDAQ banks being "boring." All three of these studies indicate that bank assets are relatively transparent.

At least one study provides evidence that bank assets are opaque. Morgan (2002) uses "split ratings" from bond rating agencies as a measure of opacity, and finds that banks are more likely to carry split ratings than non-financials, which he interprets as indicating that bank assets are more opaque than the assets of non-financials. The logic behind this interpretation is that, ceteris paribus, a transparent firm's bonds should receive identical ratings from the two major bond rating agencies because information regarding the firm is readily available. However, if the firm is opaque, rating agencies might reach different conclusions about the prospects of the firm based on the limited available information.

2. The Information Content of Stock Returns

Several studies seek to explain the relation between information asymmetry (opacity) and R^2 from asset pricing regressions. Roll (1988) in his "R^2" Presidential Address to the AFA, discusses the large proportion of stock price movement that cannot be attributed to systematic factors (in essence, $1 - R^2$ from an asset pricing model regression), and posits that lower market model R^2s reflect greater activity on the part of informed traders.

[2] Consolidated Financial Statements for Bank Holding Companies – FR Y-9C, United States Federal Reserve, December 31, 2002. We use the financial reports of 2,028 bank holding companies in the determination of the average percent of assets represented by loans.

Bushman et al. (2004) find that stocks exhibit lower R^2 in countries with a freer press and a more developed financial analysis industry. Durnev et al. (2003) find that firms with lower R^2 exhibit a higher association between current returns and future earnings, consistent with lower R^2 firms exhibiting lower opacity. Piotroski and Roulstone (2004) find that stock return synchronicity is inversely related to insider trades, which are assumed to impound firm-specific information into equity prices. Thus, firms with more firm-specific information in their returns exhibit lower R^2 for asset pricing model regressions. As a result, we are able to use R^2 for asset pricing model regressions as a proxy for the opacity of a firm.

Morck et al. (2000) provide international evidence of higher R^2 in poor economies than in rich economies, and posit that stronger public investor property rights in rich economies promote informed arbitrage, which allows the incorporation of firm-specific information into asset prices. Jin and Myers (2006) develop an alternative model to explain the findings of Morck et al. (2000). Jin and Myers (2006) explain how control rights and information affect the division of risk bearing between inside managers and outside investors. In their model, insiders capture a portion of the firm's operating cash flows. The limits to capture are based on outside investors' perception of the value of the firm. Information asymmetry exists between insiders and outside investors. Outside investors are unable to observe firm-specific news perfectly, which allows insiders to capture a portion of the unexpected positive earnings on good news.

When firm-specific news is bad, insiders have an incentive to pass along, or even to exaggerate, the bad news so they can maintain or increase the proportion of firm earnings that they capture. Outside investors recognize the incentive for insiders to announce bad news (whether it be true or not) and, as a result, bad news only becomes credible when insiders pass it along at a cost to themselves. As a result, insiders must reduce their capture of the firm's cash flows in bad times to avoid costly reporting of bad news.

Because insiders report neither good nor bad firm-specific news, insiders bear most of the firm-specific risk, and outsiders bear mostly systematic risks. Thus, the stock price for a firm with high opacity tends to vary with systematic factors, consistent with insiders bearing the firm-specific risk. Such an opaque firm will display a higher R^2 in asset pricing model regressions. Jin and Myers test this prediction using stock returns from 40 stock markets from 1990 to 2001, finding strong positive relations between R^2 and several measures of opacity.

Veldkamp (2006) develops a model in which investors rely on common information signals in the absence of firm-specific information. Veldkamp notes that information "is a non-rival good with a high fixed cost of discovery and a low marginal cost of replication" (p. 824). As a result, information that has value for pricing many assets will be economically feasible to produce since such information can be sold to many different investors. Conversely, firm-specific information that is only valuable for pricing the stock of one firm is not likely to be produced due to the high fixed costs and smaller base of potential customers for the information. Thus, investors are more likely to use common information than firm-specific information to value opaque firms, resulting in the returns of such firms reflecting more market and industry information and less firm-specific information. Haggard et al. (2008) test Veldkamp's model using voluntary disclosure data and find that firms with better disclosure display lower stock price synchronicity, consistent with a positive relation between R^2 and firm opacity.

Ours is not the first paper to use R^2 to examine banks. Demsetz and Strahan (1997) use R^2 as a proxy for diversification. As a firm becomes more diversified, it bears less idiosyncratic risk and should, therefore, experience a higher R^2 in market model regressions. Demsetz and Strahan use R^2 across banks to show that larger BHCs are more diversified. We examine R^2 for both banks and industrial firms. In general, we know that banks are involved in one general pursuit: banking. Industrial firms are far more likely to be diversified than banks. We use the number of reported segments for each firm (bank and industrial) as a proxy for diversification, so our analysis controls for the diversification differences between banks and industrial firms.

Even if the reported segments proxy does not totally control for the diversification differences between banks and industrial firms, the thought process behind Demsetz and Strahan would predict a lower R^2 for banks, given their lack of diversification compared to industrial firms. Our finding is that, after introducing control variables, R^2 is higher for banks than for industrial firms. Therefore, the diversification interpretation of R^2 means that our findings of higher R^2 for banks is actually conservative, since R^2 for banks remains higher despite the lowering of R^2 resulting from banks' lack of diversification.

A criticism of our analysis based on this alternate interpretation of R^2 might be valid for our analysis of the relation between bank assets and opacity, as banks holding certain types of assets might tend to be less diversified. However, these less-diversified banks are likely to also differ in size compared to better diversified banks. Using the relation between size and diversification uncovered by Demsetz and Strahan (1997), we include the market value of equity in all regressions in an attempt to control for differences in diversification between banks.

3. Hypotheses and Empirical Predictions

H1. Banks are more opaque than matched firms in other industries.

Conventional wisdom holds that bank assets are more informationally opaque (less transparent) than assets of industrial firms. Given the positive relation between R^2 and opacity posited by the recent literature, we predict higher asset pricing regression R^2 for banks than for a matching set of non-regulated industrial firms.

H2. Banks traded on NASDAQ are more opaque than matching firms.

Flannery et al. (2004) conclude that NASDAQ banks are not more opaque than their industry counterparts; they are merely "boring." Their conclusion is based on NASDAQ banks trading much less often than industrial matching firms despite having similar bid-ask spreads, and the fact that IBES analyst earnings forecasts are more accurate for NASDAQ banks than for matching industrial firms.

The low levels of trading and accurate analyst forecasts are also consistent with a lack of firm-specific information in returns. If banks are opaque, then little firm-specific news exists upon which to trade, resulting in low trading frequency. Also, if opacity allows managers to "manage" earnings, then the reported earnings of the firm will most likely move in step with other firms in the industry, and not include firm-specific information (see Kirschenheiter and Melumad (2002)). Such earnings are easier for analysts to forecast than earnings containing large amounts of firm-specific information, resulting in more accurate analyst earnings forecasts for more opaque firms.

If the conclusion of Flannery et al. (2004) is valid, then multivariate regressions of opacity measures on independent variables including an indicator for NASDAQ firms and an indicator for banks should produce estimated coefficients on these two indicators that cancel out or at least sum to a number not statistically significantly different from zero. However, if such banks are more opaque than their industrial counterparts as we predict, then the estimated coefficient on the bank indicator should be positive and significant and the estimated coefficient on the NASDAQ indicator should be either be positive, not significantly different from zero, or if negative and statistically significant, of a smaller magnitude than the positive coefficient on the bank indicator. We also perform regressions including the interaction of these two indicators to examine the difference in opacity between NASDAQ and non-NASDAQ banks.

H3. Firm-level opacity of banks depends on the composition of their assets.

Morgan (2002) uses "split ratings" from bond rating agencies as a measure of opacity, and finds that the composition of bank assets significantly affects the probability of a split rating. Flannery et al. (2004) define types of bank assets that are more opaque. We predict a positive relation between R^2 values from asset pricing model regressions including industry returns and the proportion of a bank's assets represented by these "opaque" assets. We also examine the impact of different types of loans on R^2 to determine the differences in opacity between different types of loans.

4. Data and Methods

We follow Flannery et al. (2004) in the selection of banks and matching firms. In addition to their requirements, we also require our firms to have data present in the Compustat quarterly data. We use Compustat quarterly data and institutional ownership data from Compact Disclosure to create additional control variables suggested by Piotroski and Roulstone (2004). As a result, our study has a smaller sample size. Using a sample period of 1993-2002 leaves us with 243 bank holding companies, which we will refer to interchangeably as BHCs or banks.

We select matching firms from the Center for Research in Security Prices (CRSP) data (excluding financial firms (SIC code 6000-6999) and regulated utilities (SIC code 4800-4900)) on the basis of stock exchange, market value of equity and share price. We re-select each bank's matching firm at the start of each calendar year. Matching firms must survive the entire calendar year. We match firms first by exchange, then by market equity. If the share price of the industrial firm is within 25 percent of the bank's share price, we then choose the industrial firm as a match. If not, we select the next-closest market equity firm and subject it to the same share price test until we find an appropriate matching firm listed on the same stock exchange as the bank.

We also follow Flannery et al. (2004) in the elimination of "observations that seem likely to produce unrepresentative values." (p. 425) Specifically, we omit any firm-year (bank or match) for which the average share price is less than \$2 or the stock has fewer than 400 trades. We obtain share price and number of trades from CRSP. Our final sample consists of 1,186 bank-year observations and an equal number of matching industrial firm-year observations.

For each calendar year, we calculate R^2 measures for all banks and matching firms through regression of excess weekly returns on the excess market return. We also perform the same regression including an additional industry excess return factor. We define industries using 2-digit SIC codes, calculate value-weighted weekly industry excess returns, and include lagged values of all regressors. Piotroski and Roulstone (2004) include the lagged values of regressors "since the presence of informed parties can impact the timing of the market and industry information's incorporation into prices" (page 1123). Specifically, we calculate the R^2 measures for the following regressions:

$$BETARSQ: \quad RET_{i,t} = \alpha + \beta_1 MARET_{i,t} + \beta_2 MARET_{i,t-1} \tag{1}$$

$$BETAINDRSQ: \quad RET_{i,t} = \alpha + \beta_1 MARET_{i,t} + \beta_2 MARET_{i,t-1} + \beta_3 INDRET_{i,t} + \beta_4 INDRET_{i,t-1} \tag{2}$$

Also following Piotroski and Roulstone (2004), we log transform both of these measures as follows:

$$SYNCHB = \log\left(\frac{BETARSQ}{1 - BETARSQ}\right) \tag{3}$$

$$SYNCHBI = \log\left(\frac{BETAINDRSQ}{1 - BETAINDRSQ}\right) \tag{4}$$

Log transformation changes the R^2 variable, bound by zero and one, into a continuous variable with a more normal distribution (Piotroski and Roulstone (2004)).

A potential criticism of using R^2 to investigate differences in opacity between banks and industrial firms is that the cash flow risks of these two sets of firms are different, perhaps resulting in differences in R^2 between the banks and industrial firms that are unrelated to differences in opacity. Jin and Myers (2006) control for differences in cash flow risks by including measures of return volatility (variance) and return kurtosis in their analysis. Accordingly, we create these proxies and include them in every regression model with R^2 as the dependent variable.

We use control variables suggested by Piotroski and Roulstone (2004) and Flannery et al. (2004) to demonstrate the robustness of our findings to inclusion of items previously shown to be related to opacity or R^2. These variables are:

DIVERS =	revenue-based Herfindahl index of firm diversification using business segments reported in Compustat segment data, available from 1996.
HERF =	revenue-based Herfindahl index of 2-digit SIC industry-level concentration using Compustat annual data.
NIND =	the average number of firms used to calculate the weekly industry return index.
STDROA =	annual standard deviation of quarterly return on assets (ROA) from Compustat.
RETCORR =	Spearman correlation between weekly market returns and value-weighted industry returns.
FUNDCORR =	the logarithmic transformation of the R^2 from a regression of the firm's quarterly return on assets (ROA) on a value-weighted index of ROA. FUNDCORR is calculated each year using the previous twelve quarterly observations.
REV =	number of analysts revising their forecast during the month divided by the number of analysts following the firm.
ΔINST =	the absolute change in the number of shares held by institutions, as a fraction of all shares outstanding.
MVE =	the market value of equity in thousands of dollars at the beginning of the year, calculated by multiplying share price by the number of shares outstanding from CRSP.
TRDSZE =	average number of shares per transaction during the calendar year (in thousands).
NEST =	number of analysts posting an earnings forecast for the firm's current fiscal year.
CSD =	cross-sectional standard deviation of analysts' forecasts, computed only for firms with more than one analyst.
FE =	median absolute EPS forecast error, divided by share's price at the start of the fiscal year, and multiplied by 10,000 (to measure forecast error in basis points).
SHRTURN =	annual share volume divided by shares outstanding (from CRSP) multiplied by 1000.
log(.) =	the log of *MVE*, *NIND*, *MB*, and *TRDSZE* or the log of one plus *REV*, *ΔINST*, *INST*, *SHRTURN*, *NEST*, *CSD*, *FE*, and *HERF*.

To control for differences in R^2 stemming from differences in cash flow risk, we follow Jin and Myers (2006) and control for the following variables:

WKRETVAR =	the variance of weekly firm stock returns.
WKRETKURT =	the kurtosis of weekly firm stock returns.

We also control for leverage (the proportion of assets funded by debt) due to the large difference in this attribute between banking and industrial firms.

We follow Palia (2001) and Fama and French (2002) in taking steps to preserve sample size in the presence of missing data. For most variables with a sizable proportion of observations missing (*ΔINST, NEST, CSD, REV* and *FE*), we set missing observations equal to zero and create an indicator value equal to one if the variable has been set to zero and equal to zero otherwise. For *DIVERS*, we set missing observations equal to one and create an indicator value equal to one if *DIVERS* has been set to one and equal to zero otherwise. We treat *DIVERS* differently than other control variables because of the way in which we define *DIVERS*. A value of one for *DIVERS* represents an undiversified firm, whereas a value of zero represents an infinitely diversified firm. Firms with no data in the Compustat segment dataset are likely to be undiversified. We include the indicator for a variable with missing data in all regressions in which the control variable is used. Thus, the coefficient on the indicator variable accounts for variation between observations with and without data for the control variable.

Following Flannery et al. (2004) we create the following variables for the composition of each bank's portfolio of assets:

TRADE =	the fair value of assets held in trading accounts (includes government debt, CDs, commercial paper, and bankers acceptances), normalized by the market value of equity.
OPAQUE =	the book value of bank premises and fixed assets, plus investments in unconsolidated subsidiaries, intangible assets, and "other assets," normalized by the market value of equity.
HIGH_CB =	an indicator equal to one if the BHC's subsidiary commercial bank assets (summed from individual bank call reports) *exceed* the sample median proportion of total BHC assets.

Following Beatty et al. (2002), we create variables to represent the composition of each bank's loan portfolio as follows:

LOANAG =	percent of loan portfolio accounted for by agricultural loans.
LOANCI =	percent of loan portfolio accounted for by commercial and industrial loans.
LOANDEP =	percent of loan portfolio accounted for by loans to depository institutions.
LOANIND =	percent of loan portfolio accounted for by individual (consumer) loans.
LOANRE =	percent of loan portfolio accounted for by real estate loans.

We also create a variable, *PCTLOANS*, to represent the portion of a bank's assets represented by loans, and indicators for each Federal Reserve District.

Finally, we construct two indicator variables. *BANK* equals one if the firm is a bank, and equals zero if the firm is a matching firm. *NASDAQ* equals one if the firm is listed on NASDAQ, and zero if the firm is listed on the American Exchange (AMEX) or the New York Stock Exchange (NYSE). Our final sample of 243 banks contains 217 NASDAQ firms, 24 NYSE firms, and 2 AMEX firms. No sample bank switches exchanges during the sample period.

Table 1 presents variable descriptions and descriptive statistics for sample banks and matching firms. Panel A describes the construction of the opacity proxies. Panel B details construction of the bank asset characteristics variables, and Panel C defines our control variables. Panel D provides descriptive statistics for sample banks. Panel E provides the same statistics (for variables common to both) for matching firms.

Table 1 Variable definitions and descriptive statistics

Panel A. Returns informativeness proxies

BETARSQ =	coefficient of determination from yearly regression of weekly returns on the value-weighted CRSP excess market return.
SYNCHB =	$\log\left(\frac{BETARSQ}{1-BETARSQ}\right)$
BETAINDRSQ =	coefficient of determination from yearly regression of weekly returns on the value-weighted CRSP excess market returns and value-weighted excess 2-digit SIC code industry returns.
SYNCHBI =	$\log\left(\frac{BETAINDRSQ}{1-BETAINDRSQ}\right)$

Panel B. Bank asset portfolio characteristics

TRADE =	the fair value of assets held in trading accounts (includes government debt, CDs, commercial paper, and bankers acceptances).
OPAQUE =	the book value of bank premises and fixed assets, plus investments in unconsolidated subsidiaries, intangible assets, and "other assets."
PCTLOANS =	the percent of bank assets accounted for by loans.
HIGH_CB =	an indicator equal to one if the BHC's subsidiary commercial bank assets (summed from individual bank call reports) *exceed* the sample median proportion of total BHC assets.
LOANAG =	percent of loan portfolio accounted for by agricultural loans.
LOANCI =	percent of loan portfolio accounted for by commercial and industrial loans.
LOANDEP =	percent of loan portfolio accounted for by loans to depository institutions.
LOANIND =	percent of loan portfolio accounted for by individual (consumer) loans.
LOANRE =	percent of loan portfolio accounted for by real estate loans.

Panel C. Control variables

DIVERS =	revenue-based Herfindahl index of firm diversification using business segments reported in Compustat segment data, available from 1996.

HERF =	revenue-based Herfindahl index of 2-digit SIC industry-level concentration using Compustat annual data.
NIND =	the average number of firms used to calculate the weekly industry return index.
STDROA =	annual standard-deviation of quarterly return on assets (ROA) from Compustat.
RETCORR =	Spearman correlation between weekly market returns and value-weighted industry returns.
FUNDCORR =	the logarithmic transformation of the R^2 from a regression of the firm's quarterly return on assets (ROA) on a value-weighted index of ROA. FUNDCORR is calculated each year using the previous twelve quarterly observations.
REV =	number of analysts revising their forecast during the month divided by the number of analysts following the firm.
ΔINST =	the absolute change in the number of shares held by institutions, as a fraction of all shares outstanding.
MVE =	the market value of equity in thousands of dollars at the beginning of the year, calculated by multiplying share price by the number of shares outstanding from CRSP.
TRDSZE =	average number of shares per transaction during the calendar year (in thousands).
NEST =	number of analysts posting an earnings forecast for the firm's current fiscal year.
CSD =	cross-sectional standard deviation of analysts' forecasts, computed only for firms with more than one analyst.
FE =	median absolute EPS forecast error, divided by share's price at the start of the fiscal year, and multiplied by 10,000 (to measure forecast error in basis points).
SHRTURN =	annual share volume divided by shares outstanding (from CRSP) multiplied by 1000.
log(.) =	the log of *MVE*, *NIND*, *MB*, and *TRDSZE* or the log of one plus *REV*, *ΔINST*, *INST*, *SHRTURN*, *NEST*, *CSD*, *FE*, and *HERF*.
DIVERSmissing =	an indicator equal to one if a missing value of *DIVERS* is set to zero, and equal to zero otherwise.
log(ΔINST)missing =	an indicator equal to one if a missing value of *log(ΔINST)* is set to zero, and equal to zero otherwise.
log(NEST)missing =	an indicator equal to one if a missing value of *log(NEST)* is set to zero, and equal to zero otherwise.
log(CSD)missing =	an indicator equal to one if a missing value of *log(CSD)* is set to zero, and equal to zero otherwise.
log(FE)missing =	an indicator equal to one if a missing value of *log(FE)* is set to zero, and equal to zero otherwise.
NASDAQ =	an indicator equal to one if the firm is traded on NASDAQ, zero otherwise.
WKRETVAR =	the variance of weekly firm stock returns.
WKRETKURT =	the kurtosis of weekly firm stock returns.

Panel D. Descriptive statistics: Banks

	Mean	Std. Dev.	5th Ptcl.	25th Pctl.	Median	75th Pctl.	95th Pctl.	*n*
Opacity proxies								
BETARSQ	0.108	0.122	0.006	0.026	0.068	0.143	0.365	1186
SYNCHB	-2.751	1.468	-5.196	-3.610	-2.620	-1.790	-0.553	1186
BETAINDRSQ	0.172	0.145	0.023	0.069	0.131	0.230	0.468	1186
SYNCHBI	-1.913	1.111	-3.733	-2.601	-1.892	-1.210	-0.130	1186
Firm characteristics								
DIVERS	0.409	0.112	0.302	0.323	0.387	0.458	0.577	5
HERF	0.025	0.004	0.023	0.024	0.026	0.026	0.029	1186
STDROA	0.001	0.001	0.000	0.000	0.000	0.001	0.002	1127
INST	17.554	16.046	0.520	4.950	13.730	25.550	50.820	1009
ΔINST	3.695	5.594	0.090	0.710	1.920	4.420	13.130	929
MVE	562609.4	1846717.8	20797.5	52500.0	120298.9	396264.1	2291599.0	1186
FUNDCORR	-2.804	2.329	-7.256	-3.851	-2.414	-1.225	-0.111	1109
NIND	699.877	86.172	551.725	671.275	700.360	746.769	789.308	1186
RETCORR	0.744	0.133	0.498	0.648	0.785	0.856	0.882	1186
TRDSZE	9.587	7.790	3.417	5.564	8.063	11.883	20.061	1186
SHRTURN	4.427	4.721	0.829	1.820	3.113	5.487	12.375	1186
LEVERAGE	0.911	0.025	0.871	0.901	0.914	0.927	0.941	1141
WKRETVAR	0.002	0.002	0.000	0.001	0.001	0.002	0.004	1182
WKRETKURT	2.204	3.158	-0.370	0.380	1.278	2.879	7.614	1182
IBES analyst coverage								
NEST	3.880	4.096	1.000	1.000	2.000	4.750	13.000	800
REV	0.286	0.238	0.000	0.100	0.250	0.417	0.750	800
CSD	0.032	0.042	0.005	0.013	0.023	0.038	0.090	571
FE	0.006	0.014	0.000	0.001	0.002	0.006	0.024	797
Asset portfolio characteristics								
TRADE	0.018	0.109	0.000	0.000	0.000	0.000	0.078	1055
OPAQUE	0.435	0.299	0.135	0.236	0.357	0.544	0.969	1055
PCTLOANS	0.647	0.109	0.458	0.589	0.662	0.722	0.810	1055
HIGH_CB	0.698	0.460	0.000	0.000	1.000	1.000	1.000	1055
LOANAG	0.012	0.026	0.000	0.000	0.001	0.012	0.071	1055
LOANCI	0.183	0.116	0.041	0.109	0.165	0.230	0.415	1055
LOANDEP	0.001	0.008	0.000	0.000	0.000	0.000	0.004	1055
LOANIND	0.109	0.089	0.012	0.036	0.089	0.162	0.289	1055
LOANRE	0.662	0.164	0.388	0.563	0.676	0.778	0.902	1055

Panel E. Descriptive statistics: Matches

	Mean	Std. Dev.	5th Ptcl.	25th Pctl.	Median	75th Pctl.	95th Pctl.	*n*
Opacity proxies								
BETARSQ	0.113	0.108	0.007	0.035	0.077	0.157	0.349	1186
SYNCHB	-2.594	1.356	-4.908	-3.332	-2.478	-1.679	-0.625	1186
BETAINDRSQ	0.182	0.146	0.031	0.077	0.140	0.247	0.471	1186
SYNCHBI	-1.799	1.069	-3.447	-2.483	-1.815	-1.114	-0.131	1183
Firm characteristics								
DIVERS	0.811	0.330	0.302	0.553	1.000	1.000	1.000	565
HERF	0.071	0.077	0.021	0.037	0.044	0.073	0.227	1185
STDROA	0.028	0.101	0.001	0.005	0.010	0.021	0.099	1137
INST	38.724	26.067	1.610	16.840	34.685	60.180	84.360	934
ΔINST	9.476	12.039	0.210	1.860	4.815	12.630	33.760	852
MVE	521295.7	1521851.0	20814.8	51744.0	122111.5	395714.7	2042705.0	1186
FUNDCORR	-2.700	2.234	-6.768	-3.746	-2.379	-1.108	0.195	1120
NIND	291.925	253.398	20.627	81.808	196.808	444.314	806.620	1186
RETCORR	0.656	0.213	0.216	0.567	0.722	0.808	0.872	1186
TRDSZE	11.212	9.182	3.653	5.710	8.923	14.333	25.313	1186
SHRTURN	21.176	34.091	1.527	4.320	11.803	26.855	66.553	1186
LEVERAGE	0.422	0.212	0.122	0.239	0.399	0.592	0.794	1084
WKRETVAR	0.009	0.012	0.001	0.002	0.005	0.011	0.030	1178
WKRETKURT	2.459	3.751	-0.346	0.423	1.368	2.924	9.217	1178
IBES analyst coverage								
NEST	5.130	5.009	1.000	2.000	3.333	6.500	15.250	806
REV	0.431	0.273	0.000	0.229	0.417	0.625	0.917	806
CSD	0.073	0.123	0.003	0.018	0.038	0.080	0.253	677
FE	0.016	0.034	0.000	0.002	0.006	0.018	0.061	801

Large differences exist between banks and matches in firm characteristics. Although the lower value of *DIVERS* for banks (mean *DIVERS* = 0.409) makes banks appear to be more diversified than their matching firms (mean *DIVERS* = 0.811), one must be careful to note that the Compustat segment data reports only five firm-year observations for banks, as opposed to 565 firm-year observations for matching firms. If we assume that firms with no segment information in Compustat are not diversified at all (*DIVERS* = 1), then banking firms have a mean *DIVERS* of 0.998 versus their industrial matches mean *DIVERS* of 0.910, indicating that banks are less diversified than matching firms.

The banking industry is also less concentrated (mean *HERF* = 0.025) versus matching firm industries (mean *HERF* = 0.071), consistent with historical regulatory restrictions, such as branching limitations, on the concentration of banking. Institutions own and trade smaller portions of banking firms (mean *INST* = 17.554, mean *ΔINST* = 3.695) than of their industrial counterparts (mean *INST* = 38.724, mean *ΔINST* = 9.476). Consistent with the findings of Flannery, Kwan and Nimalendran (2004), bank stocks are less liquid (mean *SHRTURN* = 4.427) than matching industrial firms (mean *SHRTURN* = 21.176).

Large differences also exist between banks and matches in analyst statistics. More analysts follow matching firms (mean *NEST* = 5.130) than banks (mean *NEST* = 3.880), but analysts produce better estimates of bank earnings (mean *REV* = 0.286, mean *CSD* = 0.032, mean *FE* = 0.006) than of matching firm earnings (mean *REV* = 0.431, mean *CSD* = 0.073, mean *FE* = 0.016). In the model of Kirschenheiter and

Melumad (2002), managers smooth earnings until firm-specific news is sufficiently bad, when they under-report earnings by the maximum amount in what has come to be known as a “big bath.” Presumably, earnings management is easier to achieve in opaque firms. If banks are more opaque, perhaps their earnings are “smoother” and therefore easier to predict, leading to the analyst statistics we observe and the observations of Flannery et al. (2004) regarding NASDAQ banks.

We begin with univariate tests of the statistical significance of differences in opacity measure values between banks and matching firms. Assuming a normal distribution of these measures (which holds more strictly for the logarithmic transformations of the R^2 measures), we perform Student’s *t*-test for the comparison of two population means, with the null hypothesis that the means of these measures are equal for banks and matching firms. Additionally, we perform the Mann-Whitney-Wilcoxon *z*-test for differences in medians, with the null hypothesis that the medians of these measures are equal for banks and matching firms.

Next, we perform multivariate analysis to examine differences in opacity measures between banks and matching firms. Following Piotroski and Roulstone (2004), we perform Fama and MacBeth (1973) regressions to determine the relation between our opacity proxies and the independent variables. The resulting coefficients are the average coefficients from ten annual estimations. We calculate *t*-statistics based on standard errors derived from the empirical distribution of the annual coefficient estimates following Fama and MacBeth (1973).

We use control variables suggested by Flannery et al. (2004) and Piotroski and Roulstone (2004), and also control for differences between Federal Reserve Districts by creating indicator variables for districts one through ten (to avoid over-specifying the model). Controlling for geographic differences is important because smaller banks, although perhaps diversified over several industries and types of loans, tend to be geographically undiversified, which might affect our results if the opacity of loans varies by locale.

We also perform Fama and MacBeth (1973) regressions to determine the relation between our firm-specific opacity proxy, *SYNCHBI*, and bank asset composition. The resulting coefficients are the average coefficients from ten annual estimations. We calculate *t*-statistics based on standard errors derived from the empirical distribution of the annual coefficient estimates following Fama and MacBeth (1973).

Our information regarding bank assets comes from the FR Y-9C bank holding company reports. We use proxies for proportions of different types of assets (*TRADE* and *OPAQUE*) developed by Flannery et al. (2004). We also use the percent of assets represented by loans (*PCTLOANS*), and the percent of the loan portfolio represented by agricultural (*LOANAG*), commercial and industrial (*LOANCI*), depository institution (*LOANDEP*), consumer (*LOANIND*), and real estate (*LOANRE*) loans. Panel E of Table 1 provides descriptive statistics for these variables. The average bank holding company in our sample holds 64.7 percent of its assets in the form of loans. The average sample bank holding company's loan portfolio is composed of 1.2 percent agricultural loans, 18.3 percent commercial and industrial loans, 0.1 percent loans to depository institutions, 10.9 percent consumer loans, and 66.2 percent real estate loans. The remaining 3.3 percent is composed of loans to foreign governments and "other" loans.

5. Results

5.1 Univariate Tests

Table 2 presents the results of our univariate examination. We test whether the various opacity proxies are significantly different between banks and matches by examining whether the differences in means and medians (banks – matches) are significantly different from zero. Ceteris paribus, if banks are more opaque than matching firms, positive and significant differences should exist. All statistically significant differences recorded in Table 2 are negative, in direct opposition to any hypothesis of bank asset opacity. However, banks are fundamentally different from matching firms along many dimensions previously shown to be related to R^2, so we withhold judgment on the opacity of bank assets pending the results of multivariate tests.

Table 2 Univariate tests: Comparing means and medians of matching parameters and opacity proxies for banks and matches

We calculate *t*-statistics for the null hypothesis of no difference in means between banks and matches. We calculate *z*-statistics using the Mann-Whitney-Wilcoxon test for the null hypothesis of no difference in medians between banks and matches. We indicate significant results (five percent alpha, two-tails) using bold.

		mean				median			
	n	Bank	match	difference	*t*-statistic	bank	match	difference	*z*-statistic
Market Equity	1186	562609.4	521295.7	41313.8	0.59	120298.9	122111.5	-1812.6	0.07
Share Price	1186	21.315	21.107	0.207	0.44	19.250	18.750	0.500	0.64
BETARSQ	1186	0.108	0.113	-0.005	-1.14	0.068	0.077	**-0.010**	**-3.12**
SYNCHB	1186	-2.751	-2.594	**-0.157**	**-2.71**	-2.620	-2.478	**-0.143**	**-3.12**
BETAINDRSQ	1186	0.172	0.182	-0.010	-1.75	0.131	0.140	**-0.009**	**-2.56**
SYNCHBI	1186	-1.913	-1.799	**-0.115**	**-2.56**	-1.892	-1.815	**-0.077**	**-2.46**

5.2 Multivariate Analysis

Table 3 presents the results of multivariate tests of the difference between banks and matching firms in *SYNCHB*, the log transformation of R^2 from the market model regression. We perform Fama and MacBeth (1973) regressions of *SYNCHB* on the *BANK* indicator, the *NASDAQ* indicator, and two sets of control variables suggested by Piotroski and Roulstone (2004) and Flannery et al. (2004). Models 1 through 5 use only the former set of controls, while models 6 through 10 use both sets. All models control for firm size through inclusion of the natural log of the market-value of equity, *log(MVE)*. Flannery et al. (2004) assert that this is the appropriate control for size (as opposed to assets) given that "equity traders experience valuation uncertainty in proportion to their equity claim." All models also control for leverage, given the large difference in leverage between banks and matching firms.

Table 3 Regressions of SYNCHB on *BANK* indicator, NASDAQ indicator, and controls.

This table presents average coefficients from ten annual estimations each model following Fama and MacBeth (1973). We calculate t-statistics (in parentheses) using the standard errors derived from the empirical distribution of the ten annual coefficient estimates. P&R Controls consist of *DIVERS*, *log(HERF)*, *STDROA*, *log(REV)*, and *log(ΔINST)*. FK&N Controls consist of *log(TRDSZE)*, *log(CSD)*, *log(FE)*, and *log(SHRTURN)*. We indicate significant results (five percent alpha, two-tails) using bold.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BANK		**0.329**		**0.341**	**0.568**		**0.441**		**0.447**	**0.748**
		(2.17)		**(2.19)**	**(2.48)**		**(2.98)**		**(3.04)**	**(3.14)**
NASDAQ			0.029	0.002	0.158			0.037	0.004	0.204
			(0.23)	(0.01)	(1.22)			(0.33)	(0.04)	(1.42)
NASDAQBANK					-0.282					-0.366
					(-1.27)					(-1.49)
log(MVE)	**0.324**	**0.322**	**0.320**	**0.315**	**0.314**	**0.248**	**0.238**	**0.249**	**0.235**	**0.225**
	(9.34)	**(9.52)**	**(9.67)**	**(9.76)**	**(9.62)**	**(7.01)**	**(6.85)**	**(8.35)**	**(8.25)**	**(8.10)**
LEVERAGE	-0.005	-0.418	-0.009	-0.447	-0.425	**0.314**	-0.219	**0.300**	-0.249	-0.240
	(-0.03)	(-1.80)	(-0.05)	(-1.93)	(-1.87)	**(2.49)**	(-1.04)	**(2.37)**	(-1.21)	(-1.17)
WKRETVAR	**42.803**	**44.219**	**42.431**	**43.91**	**42.523**	**17.246**	**17.298**	**17.123**	**17.147**	**16.800**
	(4.59)	**(4.93)**	**(4.18)**	**(4.58)**	**(4.51)**	**(2.12)**	**(2.21)**	**(1.95)**	**(2.07)**	**(1.99)**
WKRETKURT	**-0.060**	**-0.059**	**-0.059**	**-0.058**	**-0.058**	**-0.049**	**-0.048**	**-0.048**	**-0.047**	**-0.047**
	(-4.16)	**(-4.04)**	**(-4.01)**	**(-3.88)**	**(-3.69)**	**(-3.75)**	**(-3.66)**	**(-3.64)**	**(-3.55)**	**(-3.33)**
P&R Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FK&N Controls	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Average Adj. R^2	0.194	0.199	0.196	0.201	0.203	0.225	0.231	0.225	0.230	0.234
Average *n*	215	215	215	215	215	215	215	215	215	215

The coefficient on the size control is positive and significant in all models, consistent with the findings of Roll (1988). Larger firms experience higher R^2 in asset pricing model regressions. The coefficient on leverage is significant in two of ten regressions, but is never significant in any regression containing the *BANK* indicator. The coefficient on the *NASDAQ* indicator does not achieve significance in the any of the models. However, the *BANK* indicator coefficient is positive and significant in all specifications, consistent with greater R^2 among banks. This result is supportive of **H1**, that banks are more opaque than matched firms in other industries. The coefficients on the *NASDAQ* indicator and the *NASDAQBANK* interaction are not significantly different from zero in any of the models, which supports **H2**.

The transformed R^2 used in the Table 3 regressions (*SYNCHB*) represents the proportion of return volatility that can be accounted for using market returns. The unexplained variation contains both industry-specific information and firm-specific information, so we cannot conclusively state from these results that bank returns contain less firm-specific information than matching firm returns, which would indicate greater opacity among banks. Matching firms might load more heavily on industry returns, resulting in less firm-specific information in matching firm returns than in bank returns. To address this problem, we run identical regressions using *SYNCHBI* as the dependent variable. Table 4 presents the results of these regressions.

Table 4 Regressions of SYNCHBI on *BANK* indicator, NASDAQ indicator, and controls.

This table presents average coefficients from ten annual estimations each model following Fama and MacBeth (1973). We calculate t-statistics (in parentheses) using the standard errors derived from the empirical distribution of the ten annual coefficient estimates. P&R Controls consist of *DIVERS*, *log(HERF)*, *STDROA*, *log(REV)*, *log(ΔINST)*, *FUNDCORR*, and *log(NIND)*. FK&N Controls consist of *log(TRDSZE)*, *log(CSD)*, *log(FE)*, and *log(SHRTURN)*. We indicate significant results (five percent alpha, two-tails) using bold.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BANK		0.243		0.256	**0.577**		0.301		**0.313**	**0.715**
		(1.68)		(1.81)	**(3.93)**		(1.84)		**(1.97)**	**(4.12)**
NASDAQ			-0.016	-0.033	0.153			-0.032	-0.051	0.181
			(-0.17)	(-0.34)	(1.29)			(-0.35)	(-0.55)	(1.49)
NASDAQBANK					**-0.359**					**-0.454**
					(-2.21)					**(-2.83)**
log(MVE)	**0.305**	**0.306**	**0.297**	**0.293**	**0.292**	**0.227**	**0.219**	**0.222**	**0.212**	**0.204**
	(12.85)	**(12.17)**	**(12.00)**	**(11.53)**	**(11.25)**	**(7.23)**	**(6.64)**	**(8.26)**	**(7.60)**	**(7.46)**
LEVERAGE	0.192	-0.110	0.193	-0.131	-0.109	**0.404**	0.049	**0.403**	0.027	0.034
	(1.46)	(-0.60)	(1.47)	(-0.72)	(-0.59)	**(3.98)**	(0.29)	**(4.01)**	(0.17)	(0.20)
WKRETVAR	**33.911**	**35.063**	**34.177**	**35.368**	**34.554**	**15.130**	**15.164**	**15.604**	**15.609**	**15.525**
	(7.36)	**(7.65)**	**(7.03)**	**(7.51)**	**(7.85)**	**(2.41)**	**(2.57)**	**(2.56)**	**(2.70)**	**(2.59)**
WKRETKURT	**-0.043**	**-0.044**	**-0.044**	**-0.044**	**-0.045**	**-0.036**	**-0.036**	**-0.036**	**-0.037**	**-0.037**
	(-4.25)	**(-4.33)**	**(-4.15)**	**(-4.24)**	**(-4.47)**	**(-3.47)**	**(-3.56)**	**(-3.43)**	**(-3.53)**	**(-3.70)**
P&R Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FK&N Controls	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Average Adj. R^2	0.249	0.255	0.253	0.259	0.261	0.295	0.304	0.299	0.308	0.309
Average *n*	215	215	215	215	215	215	215	215	215	215

In models 1 through 4, we find no statistically significant coefficients on any of the indicator variables of interest. However, model 5 produces a different result, with a positive and significant coefficient on *BANK* and a negative and significant coefficient on the interaction term. The coefficient on *BANK* is larger in magnitude than the coefficient on the interaction term, consistent with NASDAQ banks being less opaque than non-NASDAQ banks, but more opaque than matching firms. Once again, the coefficient on the size proxy is positive and significant in every model, and the coefficient on leverage only attains significance in models where the *BANK* indicator is absent. Similar to the set of models with only the Piotroski and Roulstone (2004) controls, the final model has a positive and significant coefficient on *BANK* and a negative and significant coefficient on the interaction term. The coefficient on *BANK* is larger in magnitude than the coefficient on the interaction term, consistent with NASDAQ banks being less opaque than non-NASDAQ banks, but more opaque than matching firms, consistent with **H2**. *SYNCHBI* is higher among banks than matching firms, consistent with bank returns varying more with market and industry returns than matching firm returns. This result is consistent with bank returns containing less firm-specific information than matching firm returns, leading to a conclusion of greater opacity among banks.

5.3 The Opacity of Specific Bank Assets

In this section, we decompose bank opacity to determine which types of assets are responsible for bank opacity. Table 5 presents results from regressions of *SYNCHBI* on the percent of the bank's assets held as loans, the *TRADE, OPAQUE*, and *HIGH_CB* variables suggested by Flannery et al. (2004), our proxy for bank size, and the loan portfolio characteristic variables suggested by Beatty, Ke and Petroni (2002). Additional control variables include the Federal Reserve District indicators, and controls suggested by Piotroski and Roulstone (2004) and Flannery et al. (2004).

Table 5 Regressions of SYNCHBI on asset characteristics and controls.

This table presents average coefficients from ten annual estimations each model following Fama and MacBeth (1973). We calculate t-statistics (in parentheses) using the standard errors derived from the empirical distribution of the ten annual coefficient estimates. P&R Controls consist of *DIVERS*, *log(HERF)*, *STDROA*, *log(REV)*, *log(ΔINST)*, *FUNDCORR*, and *log(NIND)*. FK&N Controls consist of *log(TRDSZE)*, *log(CSD)*, *log(FE)*, and *log(SHRTURN)*. We indicate significant results (ten percent alpha, two-tails) using bold.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PCTLOANS	0.019	0.348	0.329	0.286	-0.189	1.593	0.570	0.542
	(0.12)	(0.90)	(0.85)	(0.71)	(-0.94)	(0.74)	(0.71)	(0.66)
TRADE	0.209	-0.307	-0.531	-0.698	-0.189	0.051	-0.239	-0.510
	(0.79)	(-0.83)	(-1.38)	(-1.26)	(-0.94)	(0.05)	(-0.21)	(-0.42)
OPAQUE	0.373	0.440	0.440	0.442	0.398	-0.118	-0.105	-0.118
	(1.60)	(0.74)	(0.74)	(0.75)	(1.39)	(-1.02)	(-0.90)	(-0.99)
HIGH_CB	0.012	**-0.126**	**-0.116**	-0.075	0.006	0.024	0.035	0.068
	(0.20)	**(-2.38)**	**(-2.16)**	(-1.06)	(0.09)	(0.15)	(0.21)	(0.40)
NASDAQ			**-0.163**	-0.074			-0.126	0.015
			(-2.06)	(-0.66)			(-1.33)	(0.10)
log(MVE)	**0.365**	**0.447**	**0.443**	**0.445**	**0.404**	0.087	0.075	0.076
	(9.87)	**(2.67)**	**(2.55)**	**(2.57)**	**(14.09)**	(0.36)	(0.31)	(0.31)
WKRETVAR	49.373	141.310	140.931	123.848	39.723	-103.528	-108.95	-112.75
	(1.46)	(1.00)	(0.99)	(0.81)	(0.93)	(-0.94)	(-0.98)	(-0.89)
WKRETKURT	**-0.027**	-0.007	-0.009	-0.012	**-0.025**	**-0.040**	**0.042**	**-0.038**
	(-1.91)	(-0.35)	(-0.42)	(-0.56)	**(-1.66)**	**(-1.84)**	**(-1.89)**	**(-1.73)**
LOANAG					**-2.964**	**-9.237**	**-9.35**	**-10.996**
					(-1.66)	**(-1.73)**	**(-1.75)**	**(-2.07)**
LOANCI					-0.427	-3.780	-3.917	-4.150
					(-0.36)	(-1.18)	(-1.23)	(-1.27)
LOANDEP					-8.292	-9.428	-9.657	-6.948
					(-1.62)	(-1.43)	(-1.48)	(-1.22)
LOANIND					-1.252	**-4.186**	**-4.336**	**-4.610**
					(-0.96)	**(-1.67)**	**(-1.74)**	**(-1.82)**
LOANRE					-0.175	-3.070	-3.214	-3.565
					(-0.17)	(-1.29)	(-1.36)	(-1.54)
FRD Controls	No	No	No	Yes	No	No	No	Yes
Other Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Average Adj. R^2	0.248	0.329	0.325	0.335	0.291	0.378	0.375	0.380
Average *n*	105	98	98	94	105	98	98	94

The coefficient on *HIGH_CB* is negative and significant in models 2 and 3, but loses significance once we include the Federal Reserve District indicators. In all specifications containing the loan portfolio characteristics variables, *LOANAG* has a negative and significant coefficient. In all specifications containing the loan portfolio characteristics variables and control variables, *LOANIND* has a negative and significant coefficient, albeit with a 10% level of significance. Our evidence is consistent with greater opacity among banks with lower proportions of agricultural and consumer loans in their portfolios.[3] Using coefficients from model 8 of Panel A, a one standard deviation decrease in *LOANAG* relates to an increase in *SYNCHBI* of 25.73 percent of a standard deviation, ceteris paribus. Similarly, a one standard deviation decrease in *LOANIND* relates to an increase in *SYNCHBI* of 36.93 percent of a standard deviation, ceteris paribus. This evidence supports **H3**, which states that the opacity of banks depends on the composition of their assets.

6. Conclusions

Jin and Myers (2006) and Veldkamp (2006) develop models to explain the positive relation between R^2 and firm opacity. Other studies (i.e., Durnev et al. (2003), Piotroski and Roulstone (2004), and Haggard et al. (2008)) verify this relation empirically. In this study, we use the relation between R^2 and firm opacity to provide evidence consistent with banks being more opaque (less transparent) than matching industrial firms. This conclusion is robust to inclusion of industry returns in the asset pricing model. We find that, while NASDAQ banks might be less opaque than banks traded on NYSE or AMEX, they are not less opaque than matching industrial firms, in contrast to the conclusion of Flannery et al. (2004).

Our results are robust to consideration of the different cash flow risks faced by banks and industrial firms. Following Jin and Myers (2006), we include the volatility and kurtosis of firm returns as proxies for firm-to-firm differences in cash flow risk. Doing so strengthens our results. We also present evidence consistent with agricultural loans and consumer loans being more transparent than other types of loans made by banks. Assets previously identified as affecting bank opacity tend to lose statistical significance after the inclusion of appropriate control variables and loan portfolio characteristics.

[3] Large banks generally have smaller percentages of agricultural and consumer loans. Their opaqueness is likely attributable to much larger off-balance-sheet activities. In turn, their higher degree of opaqueness might explain why the recent financial crisis had a greater impact on very large banks.

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