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How does transparency affect bank financial performance?☆

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ABSTRACT

Theoretical studies suggest that increased transparency reduces a firm's cost of capital (Diamond & Verrecchia, 1991). Thus, more transparency should improve financial performance. We examine the relation between firm transparency and bank holding company (BHC) profit efficiency using the number of analysts following a BHC and the standard deviation of analysts' EPS forecasts to measure transparency. Our hypothesis is that more transparent BHCs are better managed, causing a positive relation between transparency and profit efficiency. The empirical results confirm that transparency has a positive effect on profit efficiency.

1. Introduction

Financial researchers have long been interested in the factors that explain differences in the financial performance of commercial banks. In this paper we test for the effect of transparency on bank holding company (BHC) performance using analyst following and the standard deviation of analyst earnings per share (EPS) forecasts to measure transparency. The *greater* the number of analysts, the more information is available for investors and, therefore, the *more* transparent the BHC. In addition, with greater transparency, there should be less dispersion in analysts' forecasts of EPS. Thus *larger* forecast dispersion is associated with *less* transparent BHCs. We hypothesize that more transparent BHCs (those with greater analyst following and lower forecast deviation) are more profit efficient than other BHCs. Our empirical results are consistent with the hypothesis.

Why does transparency matter? Diamond and Verrecchia (1991) construct a theoretical model which shows that reducing asymmetric information by revealing information to the public reduces a firm's cost of capital. Large investors are more likely to purchase the transparent firm's securities and these securities thus have increased liquidity. Baumann and Nier (2004) and Neir and Baumann (2006) apply this notion to the banking industry by constructing a bank disclosure index. They find that some publicly traded BHCs disclose much more information to investors than others and are thus more transparent. Neir and Baumann (2006) also find that more disclosure results in higher capital buffers. Hirtle (2007) extends this research and finds that more disclosure is associated with lower risk and higher risk-adjusted returns at BHCs.

The importance of transparency as an explanation for increased efficiency is also reflected in the results of two recent studies. Akhigbe and Stevenson (2010) find that increased efficiency is related to less use of multiple types of non-interest income. Reduced complexity creates a more transparent organization. Pasiouras, Sailesh, and Zopounidis (2009) find that restrictions on bank activities and increased use of market discipline increase profit efficiency. Fewer activities (assuming each are understood by investors) and more market information reflect increased transparency.

Our paper more directly addresses the effect transparency has on BHC profit efficiency, but to address this question we need proxies for transparency. Analyst following and the dispersion of analyst forecasts are widely used measures to show the level of information investors have regarding a firm. For instance, Jiang and Kim (2005) show that analyst following and institutional ownership are significantly negatively correlated with adverse selection costs and spreads (i.e. greater analyst following is associated with more transparency). Jiang and Kim conclude that non-US stocks face higher spreads and adverse selection costs related to lower analyst following and lower institutional shareholdings. In a related finding, Brennan and

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Subramanyam (1995) show that an increase in analyst following is associated with lower adverse selection components in the spread which reduces the importance of privately informed traders. Baker, Nofsinger, and Weaver (2002) use the number of analysts as a proxy for firm visibility based on work by Marcus and Wallace (1991) that shows analysts are an important information source for investors and Walther (1997) who shows that investors put more weight on analyst estimates as the number of analysts for the firm increases.

In relation to the dispersion of analyst forecasts, Flannery, Kwan, and Nimalendran (2004) show that BHC opacity is closely related to the dispersion of analyst expectations and analyst forecast deviations. Roulstone (2003) also finds that increased public information is related to lower dispersion of analysts' forecasts as well as a higher number of analysts, both of which increase liquidity.

Our empirical results show that transparency is an important determinant of profit efficiency. The measures of transparency we use are robust even after controlling for other factors that were found in previous studies to affect profit efficiency. These results hold across different samples including a sample of all publicly traded BHCs, a smaller sample of BHCs with reported forecast dispersion and for BHCs disaggregated by size.

This introduction is followed by Section 2 which describes the methodology and variables used in the empirical analysis. Section 3 describes the data, and Section 4 discusses the empirical results. Section 5 concludes.

2. Methodology, variable selection and expected relations

2.1. Frontier analysis

Profit efficiency is a sophisticated econometric financial performance measure found by comparing each BHC's efficiency in generating profits with the best achievable performance of all institutions in the sample, i.e., the BHCs on the best practice frontier. Following Akhigbe and McNulty (2003) and DeYoung and Hasan (1998), we use stochastic frontier analysis (SFA) on all BHCs to determine the efficient frontier.

We begin by obtaining data on all BHCs from the Federal Reserve Bank of Chicago's BHC database for 1996–2006, a total of eleven years of data. The data include balance sheet and income statement data that each BHC must report on form FRY-9C, which is similar to the call report for individual banks. We then identify publicly traded bank holding companies by hand-matching the BHCs in this dataset to information from Research Insight. To gather the data on the number of analysts and the standardized deviation of analyst forecasts we use the IBES database from Thomson Reuters.

We have a dataset of 3603 publicly traded BHCs. For this sample we create one frontier per year because this procedure provides a flexible estimation procedure allowing the regression coefficients to vary over time.[3] Within this larger sample is a smaller sample of 1562 BHCs for whom the standard deviation of analyst EPS forecasts is reported. We perform a separate SFA analysis for this group. Due to the size of this smaller subset, we must create a frontier using every two years of data except in the instance where we combine 2000, 2001 and 2002 because we have an odd number of years in the sample. Prior research has shown that creating frontiers over smaller intervals of time is a better procedure. For example, Avkiran (2007) finds that changes in interest rates distort the measurement of bank efficiency. By creating one frontier per year or one frontier for every two years we limit this effect.

The profit efficiency measure is estimated using PREROA as a measure of profitability. PREROA is earnings before taxes, extraordinary items and loan losses as a percent of total assets. While this measure is similar to return on assets, it focuses on operating performance by excluding the abovementioned items. We use the frontier equation to calculate the efficiency measure for the publicly traded BHCs. We then use this efficiency measure as a dependent variable in the regression analysis.

For the whole sample of publicly traded BHCs, we also calculate efficiency by disaggregating the sample by size. As Akhigbe and McNulty (2003) and DeYoung and Hasan (1998) point out, small banks differ from large banks in their production technologies and strategies. To take this into account, we examine three separate size classes – more than \$10 billion in total assets, between \$1 billion and \$10 billion and less than \$1 billion. This breakdown is very similar to that used by the FDIC (2011) in their *Quarterly Banking Profile*. Since the number of institutions in the large BHC sample does not allow enough degrees of freedom to perform the analysis for each year, we create a frontier for three separate time periods. Period 1 is 1996–2000, a time of growth in the US economy. Period 2 is 2001–2003, a time of relative economic decline. Period 3 is 2004–2006, when the US economy was growing again. Unfortunately, the sample of BHCs with data available for forecast deviation is not large enough to disaggregate by size to perform the SFA analysis.

There are two typical specifications used for the functional form, the translog and the Fourier-flexible form. The Fourier-flexible form enhances the translog by including Fourier trigonometric terms. McAllister and McManus (1993) and Mitchell and Onvural (1996) show that the Fourier-flexible form is a better approximation because of its flexibility; it also provides a global approximation. As in Akhigbe and McNulty (2003) and DeYoung and Hasan (1998), we use a hybrid version of the Fourier form with trigonometric versions of the output variables. The function is as follows:

$$\begin{aligned}
\ln(PREROA) = {}& \alpha + \sum_{i=1}^{4}\beta_i \ln(w_i) + \frac{1}{2}\sum_{i=1}^{4}\sum_{j=1}^{4}\beta_{ij}\ln(w_i)\ln\left(w_j\right) \\
&+ \sum_{k=1}^{3}\gamma_k \ln(y_k) + \frac{1}{2}\sum_{k=1}^{3}\sum_{m=1}^{3}\gamma_{km}\ln(y_k)\ln(y_m) + \sum_{r=1}^{5}\delta_r \ln(z_r) \\
&+ \frac{1}{2}\sum_{r=1}^{5}\sum_{s=1}^{5}\delta_{rs}\ln(z_r)\ln(z_r) + \sum_{i=1}^{4}\sum_{k=1}^{3}\eta_{ik}\ln(w_i)\ln(y_k) \\
&+ \sum_{i=1}^{4}\sum_{r=1}^{5}\rho_{ir}\ln(w_i)\ln(z_r) + \sum_{k=1}^{3}\sum_{r=1}^{5}\tau_{kr}\ln(y_k)\ln(z_r) \\
&+ \sum_{l=1}^{3}[\delta_l \cos X_i + \theta_l \sin X_l] \\
&+ \sum_{m=1}^{3}\sum_{n=1}^{3}[\delta_{mn}(\cos X_m + X_n) + \theta_{mn}(\sin X_m + X_n)] \\
&+ \sum_{o=1}^{3}\sum_{p=1}^{3}\sum_{q=1}^{3}\left[\delta_{opq}\left(\cos X_o + X_p + X_q\right) + \theta_{opq}\left(\sin X_o + X_p + X_q\right)\right] \\
&+ v + u
\end{aligned} \tag{1}$$

where $PREROA$ = earnings before extraordinary items, taxes and loan losses divided by total assets; w_1 = price of non-deposit related borrowing, w_2 = price of deposits, w_3 = price of labor, w_4 = price of property, plant and equipment, y_1 = loans, y_2 = non-interest income, y_3 = off-balance sheet items, z_1 = risk (assets 90 days past due and non-accrual status divided by total assets), z_2 = shareholder's equity, z_3 = average for risk in the state where the BHC is headquartered as measured by non-performing assets relative to total assets, z_4 = HHI and z_5 = total assets.[4] The X variables in the equation are transformations of the Y variables so that they fall in the interval $(0,2\pi)$.

In order to capture the operating environment, we include variables that reflect the inputs and outputs of the BHC and other BHC-specific

[3] Following the suggestion of Bauer et al. (1998), we use stochastic frontier analysis with all years combined. We also use a distribution-free analysis method to examine the consistency in the rankings of BHCs. As the results of both methods are comparable, we present only the SFA results.

[4] Off-balance sheet items include unused commitments, financial standby letters of credit, performance standby letters of credit, commercial letters of credit and securities lent. It does not include derivatives. The HHI is calculated using the FDIC's summary of deposits (branch office) data. The HHI is matched with each BHC based on the BHC's home office state and county.

characteristics that may affect performance. Off-balance sheet items, total loans and fee revenue are included to capture the major outputs of the BHC. We include these because several studies indicate that excluding off-balance sheet activities creates a downward bias in efficiency (see, e.g., Clark & Siems, 2002; Lieu, Yeh, & Chiu, 2005; Stiroh, 2000). Physical capital and human resource costs (the price of labor) measure the price of inputs in the bank production process. The cost of deposits and non-deposit borrowing also reflects the price of inputs. The level of non-accrual and past-due assets at the state level is included to measure the risk of a BHC's operating environment. The Hirschman–Herfindahl index (HHI) is the sum of the squared market shares of each bank; this is often used as a measure of competition. Total assets reflect the economies of scale in banks of larger size. Al-Sharkas, Hassan, and Lawrence (2008) find that, post-merger, banks have more allocative and technical efficiency than non-merged banks. While we do not have merger data, including size should pick up some of the benefits of larger scale. Finally, we include shareholders equity to measure a bank's insolvency and leverage risk, and adjust for a bank's risk aversion (Hughes, Lang, Mester, and Moon (1996a, 1996b, 1997).

The measure of profit efficiency, PROFEFF, is calculated as:

$$\text{PROFEFF} = (\text{Actual PREROA}/\text{Potential PREROA}) \text{ if PREROA} > 0,$$
$$\text{PROFEFF} = 0 \text{ if PREROA} < 0.$$

Potential PREROA is the actual PREROA plus inefficiency. For the most efficient banks PROFEFF will be near one, while for the least efficient it will be near zero.

Inefficiency is determined using stochastic frontier analysis (SFA) in LIMDEP 9.0. In SFA, the error term in Eq. (1) is assumed to be composed of two parts, u_i and v_i. In this method, v_i is assumed to be statistical noise that follows a normal distribution with a mean of zero. However, u_i, which measures inefficiency, is assumed to be half-normally distributed.

Inefficiency is computed using the method developed by Jondrow, Lovell, Materov, and Schmidt (1982) where[5]:

$$\hat{E} = [u|\varepsilon] = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi(z)}{1-\Phi(z)} - z\right], \varepsilon = v \pm u, z = \varepsilon\lambda/\sigma \quad (2)$$

where:

- u a one sided error term representing technical inefficiency;
- v a two-sided error term representing the statistical noise, $N(0,\sigma_v^2)$;
- ε error term representing $u + v$;
- σ standard deviation of u;
- λ the standard deviation of v;
- $\Phi(z)$ standard normal density function;
- $\Phi(z)$ cumulative distribution function.

Distributional assumptions besides half-normal are sometimes made for u_i. Bauer, Berger, Ferrier, and Humphrey (1998) note that, while individual firm efficiencies may vary, the benefit of using SFA is that the rankings are consistent whatever distributional assumptions are used. As we focus on comparing BHCs within a group, precise individual efficiencies are less important than accurate relative efficiencies.

2.2. Effect of transparency on performance — regression analysis

After we generate the profit efficiency measures, we use them as dependent variables. We estimate a regression using the profit efficiency measure for the whole sample, as well as separate regressions for the three size groups, and for the subsample with reported analyst EPS forecast deviation.

We expect variation in performance among public BHCs related to transparency. More transparent BHCs should be better managed. Using our estimates of profit efficiency, PROFEFF, we test this hypothesis with two measures of transparency, number of analysts and the standard deviation of analyst forecasts.

$$\begin{aligned}\text{PROFEFF} = \text{f}(&\text{Number of Analysts, Forecast Deviation, Return Volatility,}\\ &\text{Volume, RelNPA, AssetGr, FeeRev, DD, LGDD, } 1-\text{TL,}\\ &\text{LnAssets, Salary, Year/Period Dummies})\end{aligned} \quad (4)$$

where:

- PROFEFF our estimate of profit efficiency;
- Number of analysts number of analysts covering the BHCs common stock
- Forecast deviation the standard deviation from the mean of analyst EPS estimates expressed in U.S. dollars
- RetVol standard deviation of weekly returns for the BHC's stock for the previous year;
- LnVol log of trading volume of BHC stock in the previous year;
- RelNPA difference between the non-performing assets of the bank and the average non-performing assets for the state;
- AssetGr asset growth over the previous year;
- FeeRev total non-interest income divided by total revenue;
- DD demand deposits divided by total deposits;
- LGDD deposits over $100,000 divided by total deposits;
- 1-TL one minus total loans divided by total assets;
- LnAssets log of total assets;
- Salary total salary and benefits as a percentage of total assets;
- Year/period dummies 1 for the year/period of the observation, 0 otherwise. The first period/year is the default.

The primary independent variables of interest in the regression analysis are those related to transparency, i.e., number of analysts and standard deviation of analyst EPS forecasts. Our hypothesis is that larger analyst following and lower forecast deviation will be associated with more profit efficient BHCs.

Other independent variables are included to help explain the efficiency measures and develop the relation of profit efficiency to our two measures of transparency. Van Ness, Van Ness, and Warr (2001) find their estimates of asymmetric information and bid-ask spreads are negatively related to trading volume. Flannery et al. (2004) find volume is positively related to the amount of dispersion among analyst estimates while also being associated with narrower spreads. Since trading volume seems to indicate higher transparency with its negative relationship to spreads, but lower transparency with its positive relationship to analyst forecast dispersion, we include it in our analysis as a control variable (LnVol) and remain agnostic as to its expected sign.

The log of total assets (LnAssets) is included in the regression to allow for economies of scale.[6] If there are such economies, LnAssets should have a positive and significant relationship with profit efficiency. Non-performing assets to total assets relative to the state ratio of non-performing assets (RelNPA) are included as a measure of the relative quality of firm assets and risk exposure measured by the non-performing assets of the BHC relative to the same measure for the state in which the BHC is headquartered. RelNPA should have a negative relationship with profit efficiency, as it indicates

[5] A detailed description of the estimation technique also appears in Kumbhakar and Lovell (2003), pp. 74–80.

[6] There is some empirical evidence that size is not related to efficiency (e.g., Giradone, Molyneux, and Gardener (2004). Other research, such as Berger, Hancock, and Humphrey (1993), indicates that banks of different size do have measurable differences in efficiency. Since evidence points in both directions, we include size.

poor asset quality. We also include the return volatility (RetVol) of the BHC's stock as a measure of risk as measured by the market.

A higher ratio of demand deposits to total deposits (DD) is expected to improve profit efficiency since these deposits are a low-cost source of funds. The amount of large deposits (over $100,000) relative to total deposits (LGDD) is expected to have a negative coefficient because of the higher cost of these funds. If more uninsured funds at the bank create increased monitoring by these depositors, however, the result may be a positive and significant coefficient for LGDD.

Salary and benefits as a percentage of total assets (SALARY) is expected to have a negative coefficient because higher compensation per dollar of assets translates into higher costs relative to peers. One minus total loans (1 − TL) is included to capture the quiet life hypothesis as discussed in Akhigbe and McNulty (2003). Banks in less competitive markets may only choose loans with the highest reward-to-risk-ratio, and hence limit their lending. This could result in a less-than-optimal portfolio of loans. If bank behavior reflects this notion, we would expect the coefficient on 1-TL to be negative and significant. Asset growth from one year to the next (AssetGr) should have a negative sign. As BHCs grow faster, they may be less efficient, as rapid growth is a more difficult process to manage than slow, consistent growth, and is often associated with loan quality problems.

3. Descriptive statistics

Table 1 presents descriptive statistics for our full set of publicly traded BHCs for the period 1996 through 2006 and for the subset of BHCs with available forecast deviation for the same period. We started with 17,748 data points, each representing a single BHC in a single year. Some BHCs have missing data for some of the variables. This reduces the sample size to 17,163. Of this sample we identify 3,603 BHCs that are publicly traded and 1592 which have a reported EPS forecast deviation from IBES.

The first column of Table 1 shows the mean and standard deviation for each variable in the sample as a whole, while the median is shown in the second column. With a few notable exceptions, the means are close to the medians, especially for PREROA. The first exception is the Total Assets variable where the mean is substantially more than the median. This is a result of the very large number of small banks and the small number of large banks in the US.

Two other notable exceptions are the two transparency variables. In both cases the means are higher than the medians. For the number of analysts in the sample of all public BHCs, the median is one analyst and the mean is 3.09 analysts. In the sample with available forecast deviation the median is four with a mean of 6.77. The median and mean number of analysts are much lower in the sample of all public BHCs because, by definition, if there is none or one analyst for a BHC, it cannot have forecast deviation.[7] Also, where there was no reported number of analysts, we assumed there were zero analysts.

While it is fairly straightforward to assume zero analysts if no analysts are reported, we had to determine how to treat BHCs that had no reported EPS forecast deviation. For those BHCs, we set the EPS forecast deviation at zero. Thus, all of the BHCs with zero analysts and those with one analyst with one EPS estimate (i.e. no standard deviation of EPS forecast) have a standard deviation of zero.[8]

[7] In a few instances where the BHC has one analyst it is possible to have a forecast deviation reported because the analyst revises their estimate.

[8] This should actually bias the results against our hypothesis. If, as we and previous literature suggest, BHCs with low numbers of analysts (of which zero and one would qualify) are less transparent, by assigning them a forecast deviation of zero, we are actually giving them a forecast deviation that indicates high transparency. Thus, if our hypothesis is correct, these BHCs are being treated as highly transparent. This allows us to use all the data and it allows us to examine the sample by size. We also ran the regressions excluding the BHCs with no standard deviation of analyst forecast and the results are quantitatively similar.

Table 1
Descriptive statistics for all public BHCs and for public BHCs with available forecast deviation.

	All public BHCs		BHCs with forecast deviation data	
	Mean	Median	Mean	Median
PREROA	1.61% [0.67%]	1.61%	1.16% [0.43%]	1.17%
Number of analysts	3.09 [5.04]	1.00	6.77 [5.86]	4
Forecast deviation	0.0063 [0.0193]	0.0000	0.0146 [0.0271]	0.0100
Return volatility	62.88% [78.61%]	42.31%	57.98% [56.84%]	40.74%
Volume	38.02 [157.44]	2.06	67.38 [211.10]	9.23
RelNPA	−0.04% [0.43%]	−0.12%	−0.06% [0.36%]	−0.11%
Asset growth	15.74% [21.86%]	10.38%	15.39% [20.33%]	10.28%
Fee revenue	16.76% [10.38%]	14.40%	19.54% [11.52%]	16.81%
Demand deposits	13.63% [7.43%]	12.67%	13.21% [7.65%]	12.25%
Large deposits	15.08% [8.98%]	13.07%	15.20% [9.48%]	12.84%
1 − TL	36.30% [11.90%]	34.71%	36.58% [12.54%]	34.69%
Total assets	$14.31 [$72.98]	$1.2	$24.05 [$99.25]	$3.85
Salary	1.67% [0.62%]	1.59%	1.65% [0.64%]	1.55%
N	3603		1562	

Standard deviations are in brackets below the mean. PREROA is earnings before extraordinary items, taxes and loan losses/total assets. Number of analysts is the number of analysts following a BHC in a given year. Forecast deviation is the standardized forecast deviation of analyst forecasts for one year fiscal estimates. Return volatility is the standard deviation of the stock's weekly returns for the year. Volume is the log of the number of shares traded during the year (in millions). RelNPA is assets 90 days or more past-due or in non-accrual status/total assets for the BHC less the same measure for the state in which the BHC is headquartered. AssetGr is the change in assets between year t − 1 and year t/assets in year t − 1. FeeRev is non-interest income/total revenue. DD is demand deposits/total deposits. LGDD is time deposits in excess of $100,000/total deposits. 1 − TL is total assets less total loans/total assets. Salary is salary and benefit expense/total assets. Total assets are in billions of dollars.

Between the two columns, besides the mean and median of total assets being dramatically different, the total asset values indicate that the BHCs in the sample with available data on forecast deviation are much larger. Indeed, for the public BHC sample there are 542 large BHCs, 1492 medium BHCs and 1569 small BHCs. For the forecast deviation subset, there are 425 large BHCs, 931 medium BHCs and 206 small BHCs. Thus the analysis of the BHCs with available forecast deviation data is much more focused on large and medium BHCs. We will discuss this again later in our results section.

4. Empirical results for OLS regressions

4.1. Analysis of BHCs with available EPS forecast deviation

Table 2 provides regression results using the PROFEFF measures for the sample of 1562 publicly traded BHCs with available forecast deviation data. The first column regression includes both the number of analysts and forecast deviation, while column two contains only the number of analysts and column three contains only forecast deviation.

Our hypothesis that BHC transparency increases profit efficiency is based on the notion that more transparent publicly traded firms are better managed with a more reliable flow of information both within the firm and to investors.

Importantly, in all three columns, both transparency variables are significant with the expected sign. Forecast deviation is negative and significant, indicating that more transparent (i.e., lower forecast

Table 2
Analysis of profit efficiency for publicly traded BHCs — forecast deviation available.

	Num. of analyst and forecast deviation	Number of analyst only	Forecast Deviation Only
Intercept	0.97759***	1.05750***	0.94334***
	[15.26]	[16.51]	[15.36]
Number of analysts	0.00151*	0.00168**	
	[1.87]	[2.04]	
Forecast deviation	−0.62736***		−0.63215***
	[−7.11]		[−7.17]
Return volatility	−0.00011	−0.00419	−0.00109
	[−0.02]	[−0.89]	[−0.23]
Volume	−0.00480	−0.00276	−0.00265
	[−1.36]	[−0.77]	[−0.79]
RelNPA	−0.13263	−0.22636	−0.22038
	[−0.20]	[−0.34]	[−0.34]
AssetGr	−0.00520	−0.00891	−0.00550
	[−0.45]	[−0.75]	[−0.47]
FeeRev	0.05868	0.08005*	0.06183
	[1.36]	[1.83]	[1.43]
DD	0.00921	0.01074	0.00585
	[0.29]	[0.33]	[0.18]
LGDD	−0.01233	−0.02387	−0.01374
	[−0.47]	[−0.90]	[−0.52]
1 − TL	−0.03153	−0.04637**	−0.03865*
	[−1.46]	[−2.12]	[−1.81]
LnAssets	0.00164	−0.00383	0.00429
	[0.38]	[−0.88]	[1.04]
Salary	−0.78791	−1.20727*	−0.70427
	[−1.23]	[−1.86]	[−1.10]
Period 2	−0.03690***	−0.03310***	−0.03601***
	[−4.32]	[−3.82]	[−4.22]
Period 3	−0.06551***	−0.06117***	−0.06519***
	[−7.96]	[−7.34]	[−7.92]
Period 4	−0.09051***	−0.08938***	−0.09060***
	[−10.04]	[−9.77]	[−10.05]
Period 5	−0.07879***	−0.08138***	−0.07815***
	[−8.70]	[−8.86]	[−8.63]
N	1562	1562	1562
R^2	0.1325	0.0919	0.1187
F-Stat	13.25	10.43	13.88
F-Stat probability	<0.0001	<0.0001	<0.0001

Coefficients from the OLS regression are presented with t-statistics in brackets. Number of analysts is the number of analysts following a BHC in a given year. Forecast deviation is the standardized forecast deviation of analyst forecasts for one year fiscal estimates. Return volatility is the standard deviation of weekly returns for the year. Volume is the natural log of trading volume for the year. RelNPA is assets 90 days or more past-due or in non-accrual status/total assets for the BHC less the same measure for the state in which the BHC is headquartered. AssetGr is the change in assets between year t − 1 and year t/assets in year t − 1. FeeRev is non-interest income/revenue. DD is demand deposits/total deposits. LGDD is the dollar amount of time deposits over $100,000/total deposits. 1 - TL is assets less total loans/total assets. Salary is salary and benefit expense/total assets. LnAssets is the log of total assets. Period 1 is the default period and contains years 1996 and 1997. Period 2 is 1998 and 1999. Period 3 is 2000, 2001 and 2002. Period 4 is 2003 and 2004. Period 5 is 2005 and 2006.
* Indicates significance at the .10 level.
** Indicates significance at the .05 level.
*** Indicates significance at the .01 level.

deviation) BHCs are more profit efficient. Number of Analysts is positive and significant. Coverage by more analysts leads to more visibility (i.e., more information about the company is available to investors) and this dissemination of information leads to greater ability of investors to monitor the firm.[9]

Some of the control variables also show significance. 1 − TL is negative and significant in the number-of-analysts and forecast-deviation-only regressions. This suggests that BHCs with more liquidity (hence less loans) are less efficient. For the regressions with only the number of analysts, Salary is negative and significant and FeeRev is positive and significant. Thus, BHCs with lower salary costs and higher levels of fee revenue are more profit efficient.

[9] We also ran these same regressions for only BHCs with forecast deviation using the PROFEFF measures from the full 3603 sample of all publicly traded firms. The results are very similar since both Forecast Deviation and Number of Analysts show significance.

4.2. Analysis of all publicly traded BHCs

Table 3 provides regression results for the sample of 3603 publicly traded BHCs including both those institutions that have forecast deviation data available and those that do not. Like Table 2, the regression in the first column includes both the number of analysts and forecast

Table 3
Analysis of profit efficiency for publicly traded BHCs — both with and without forecast deviation data available.

	Num. of analysts and forecast deviation	Number of analysts only	Forecast deviation only
Intercept	0.89278***	0.90992***	0.87632***
	[19.29]	[19.66]	[19.09]
Number of analysts	0.00153***	0.00107*	
	[2.66]	[1.88]	
Forecast deviation	−0.48883***		−0.44209***
	[−4.73]		[−4.34]
Return volatility	−0.01422***	−0.01488***	−0.01480***
	[−5.38]	[−5.62]	[−5.62]
Volume	−0.01042***	−0.01028***	−0.00894***
	[−4.69]	[−4.62]	[−4.16]
RelNPA	−2.73535***	−2.75977***	−2.76475***
	[−6.12]	[−6.16]	[−6.18]
AssetGr	0.01030	0.00928	0.00870
	[1.17]	[1.05]	[0.99]
FeeRev	0.26012***	0.26904***	0.26497***
	[7.31]	[7.55]	[7.45]
DD	0.03414	0.03369	0.03329
	[1.25]	[1.23]	[1.22]
LGDD	0.02604	0.02124	0.02316
	[1.18]	[0.96]	[1.05]
1 − TL	−0.08760***	−0.09274***	−0.09054***
	[−5.05]	[−5.35]	[−5.23]
LnAssets	0.00730**	0.00617**	0.00868***
	[2.39]	[2.02]	[2.88]
Salary	−4.05643***	−4.17743***	−4.04801***
	[−7.98]	[−8.20]	[−7.95]
1997	−0.04512***	−0.04358***	−0.04516***
	[−5.13]	[−4.95]	[−5.13]
1998	−0.02979***	−0.02874***	−0.02916***
	[−3.37]	[−3.25]	[−3.30]
1999	−0.08977***	−0.08791***	−0.08891***
	[−10.23]	[−10.00]	[−10.13]
2000	−0.05452***	−0.05214***	−0.05367***
	[−6.08]	[−5.80]	[−5.98]
2001	−0.07785***	−0.07620***	−0.07695***
	[−8.81]	[−8.61]	[−8.71]
2002	−0.05813***	−0.05700***	−0.05735***
	[−6.51]	[−6.37]	[−6.42]
2003	−0.01197	−0.01124	−0.01159
	[−1.30]	[−1.22]	[−1.26]
2004	−0.05076***	−0.04981***	−0.05010***
	[−5.43]	[−*5.32]	[−5.36]
2005	−0.05684***	−0.05708***	−0.05579***
	[−6.06]	[−6.07]	[−5.95]
2006	−0.04827***	−0.04866***	−0.04764***
	[−4.88]	[−4.91]	[−4.82]
N	3603	3603	3603
R^2	0.1246	0.1191	0.1229
F-Stat	23.16	23.06	23.89
F-Stat probability	<0.0001	<0.0001	<0.0001

Coefficients from the OLS regression are presented with t-statistics in brackets. Number of Analysts is the number of analysts following a BHC in a given year. Forecast Deviation is the standardized forecast deviation of analyst forecasts for one year fiscal estimates. Return volatility is the standard deviation of weekly returns for the year. Volume is the natural log of trading volume for the year. RelNPA is assets 90 days or more past-due or in non-accrual status/total assets for the BHC less the same measure for the state in which the BHC is headquartered. AssetGr is the change in assets between year t − 1 and year t/assets in year t − 1. FeeRev is non-interest income/revenue. DD is demand deposits/total deposits. LGDD is the dollar amount of time deposits over $100,000/total deposits. 1 − TL is assets less total loans/total assets. Salary is salary and benefit expense/total assets. LnAssets is the log of total assets. 1996 is the default year.
* Indicates significance at the .10 level.
** Indicates significance at the .05 level.
*** Indicates significance at the .01 level.

deviation, while column two contains only the number of analysts and column three contains only forecast deviation. Since, as described in Section 3, we assume a forecast deviation of zero for BHCs with no available forecast deviation data for Table 3, column three utilizes the full sample of 3603 BHCs.

As noted previously in Section 3, the full sample contains a much larger contingent of small firms than in the sample of BHCs with available forecast deviation. Most of the small BHCs have no available data on number of analysts or forecast deviation. In addition, even the medium and large samples have a moderate number of BHCs lacking the analyst and forecast deviation data. These differences in the samples may be the reason that more of the control variables are significant in the regressions with the full set of 3603 BHCs.

First, as in Table 2, all three regressions in Table 3 show number of analysts and forecast deviation to be significant. The coefficients on number of analysts are positive indicating that increased analyst coverage, and thus increased transparency, are associated with greater profit efficiency. For Forecast Deviation, the coefficients are negative indicating that a greater variation in EPS forecasts by analysts, which indicates lower transparency, is associated with lower profit efficiency.

LnVol is both negative and significant. This result is consistent with the results of Van Ness et al. (2001) and Flannery et al. (2004) who show that higher trading volume is associated with lower information environments. The negative and significant coefficients on RetVol indicate that BHC stocks with higher volatility and higher risk are underperformers in terms of profit efficiency.

LnAssets is positive and significant reflecting economies of scale. Fee revenue bolsters financial performance, consistent with the results of many profit efficiency studies. Our measure of liquidity (1 − TL) and the salary variable are negative and significant.

4.3. Analysis of all publicly traded BHCs by size

For Table 4, the full sample of BHCs is divided into bank holding companies above $10 billion in total assets, between $10 billion and $1 billion, and less than $1 billion. We then determine PROFEFF for each BHC within its size category for the regressions in Table 4.

The result that both transparency variables are significant with the expected sign holds for medium-sized and small BHCs while only Forecast Deviation remains significant for large BHCs. For larger BHCs, the mean number of analysts is 11 (standard deviation of 7.77) with the median being 12. Perhaps since most large BHCs have a high number of analysts this measure does not draw a distinction between each BHC's transparency as strongly as in the other size classes.

5. Summary and conclusions

A comprehensive theoretical analysis by Diamond and Verrecchia (1991) demonstrates that transparency matters for a firm's cost of capital. Several empirical studies of BHCs [e.g., Neir and Baumann (2006)] confirm this result and find that transparency affects other measures of performance as well.

We ask if transparency affects profit efficiency using the number of analysts following a BHC's stock and the standardized deviation of analysts' forecasts to measure transparency. We hypothesize that more transparent BHCs would be better managed and thus more profit efficient. We find that increased transparency translates into better financial performance, as expected. High analyst following (high transparency) is positively related to profit efficiency while higher forecast deviation (lower transparency) is negatively related to financial performance, as expected. The measures of transparency we use are robust even after controlling for other factors that were found in previous studies to affect profit efficiency. These results hold across different samples including a sample of all publicly traded BHCs, a smaller sample of BHCs with reported forecast dispersion and for BHCs disaggregated by size.

Table 4
Analysis of profit efficiency by size for publicly traded BHCs — both with and without forecast deviation data available.

	TA > $10B	$10B > TA > $1B	TA < $1B
Intercept	1.15308***	0.85070***	0.52775***
	[10.98]	[10.00]	[4.50]
Number of analysts	0.00091	0.00224**	0.01273***
	[1.42]	[2.02]	[2.89]
Forecast deviation	−0.19058*	−1.14876***	−2.65999***
	[−1.76]	[−6.36]	[−3.67]
Return volatility	−0.02473***	−0.01556***	−0.00838**
	[−3.06]	[−3.57]	[−2.33]
Volume	−0.00076	−0.00480	−0.01666***
	[−0.13]	[−1.41]	[−4.39]
RelNPA	−2.59626*	0.87443	−3.78431***
	[−1.86]	[1.20]	[−5.93]
AssetGr	0.04487**	−0.00437	0.01037
	[2.52]	[−0.41]	[0.60]
FeeRev	0.28736***	0.10497**	0.39345***
	[4.48]	[2.07]	[6.35]
DD	0.01493	0.02049	0.07579
	[0.26]	[0.54]	[1.60]
LGDD	−0.20246***	0.05323**	0.00002
	[−3.25]	[1.98]	[0.00]
1 − TL	−0.11601***	−0.03256	−0.09337***
	[−3.11]	[−1.39]	[−2.99]
LnAssets	−0.00901	0.00296	0.02912***
	[−1.34]	[0.51]	[3.39]
Salary	−4.12918***	−1.21820*	−5.55104***
	[−3.84]	[−1.76]	[−6.58]
Period 2	0.01196*	0.02632***	0.00129
	[1.66]	[4.03]	[0.17]
Period 3	0.02167*	−0.00812	0.04184***
	[1.66]	[−1.16]	[4.36]
N	542	1492	1569
R^2	0.1694	0.0641	0.1467
F-Stat	7.68	7.23	19.08
F-Stat probability	<0.0001	<0.0001	<0.0001

Coefficients from the OLS regression are presented with t-statistics in brackets. Number of analysts is the number of analysts following a BHC in a given year. Forecast deviation is the standardized forecast deviation of analyst forecasts for one year fiscal estimates. Return volatility is the standard deviation of weekly returns for the year. Volume is the natural log of trading volume for the year. RelNPA is assets 90 days or more past-due or in non-accrual status/total assets for the BHC less the same measure for the state in which the BHC is headquartered. AssetGr is the change in assets between year t − 1 and year t/assets in year t − 1. FeeRev is non-interest income/revenue. DD is demand deposits/total deposits. LGDD is the dollar amount of time deposits over $100,000/total deposits. 1 − TL is assets less total loans/total assets. Salary is salary and benefit expense/total assets. LnAssets is the log of total assets. Period 1 which encompasses 1996–2000 is the default period. Period 2 covers 2001–2003 and Period 3 covers 2004–2006.

* Indicates significance at the .10 level.
** Indicates significance at the .05 level.
*** Indicates significance at the .01 level.

This result is consistent with the results of two other recent studies, although transparency is not their focus. Akhigbe and Stevenson (2010) find that increased efficiency is related to less use of multiple types of non-interest income. Reduced complexity creates a more transparent organization. Pasiouras et al. (2009) find that restrictions on bank activities and increased use of market discipline increase profit efficiency. Fewer activities and more market information should be related to increased transparency and, as our results suggest, greater profit efficiency.

References

Akhigbe, A., & McNulty, J. E. (2003). The profit efficiency of small U.S. commercial banks. *Journal of Banking and Finance*, *27*, 307–325.

Akhigbe, A., & Stevenson, B. (2010). Profit efficiency in U.S. BHCs: Effects of increasing non-traditional revenue sources. *The Quarterly Review of Economics and Finance*, *50*, 132–140.

Al-Sharkas, A., Hassan, M., & Lawrence, S. (2008). The impact of mergers and acquisitions on the efficiency of the US banking industry: Further evidence. *Journal of Business Finance & Accounting*, *35*, 50–70.

Avkiran, N. (2007). Removing the impact of environment with units-invariant efficient frontier analysis: An illustrative case study with intertemporal panel data. *Omega*, *37*, 535–544.

Baker, H. K., Nofsinger, J. R., & Weaver, D. G. (2002). International cross-listing and visibility. *The Journal of Financial and Quantitative Analysis*, *37*, 495–521.

Bauer, P. W., Berger, A. N., Ferrier, G. D., & Humphrey, D. B. (1998). Consistency conditions for regulatory analysis of financial institutions: A comparison of frontier efficiency methods. *Journal of Economics and Business*, *50*, 85–114.

Baumann, U., & Nier, E. (2004). Disclosure, volatility, and transparency: An empirical investigation into the value of bank disclosure. *Federal Reserve Bank of New York Policy Review*, 31–45.

Berger, A., Hancock, D., & Humphrey, D. (1993). Bank efficiency derived from the profit function. *Journal of Banking and Finance*, *17*, 317–347.

Brennan, M., & Subramanyam, A. (1995). Investment analysis and price formation in securities markets. *Journal of Financial Economics*, *38*, 361–381.

Clark, J. A., & Siems, T. F. (2002). X-Efficiency in banking: Looking beyond the balance sheet. *Journal of Money, Credit, and Banking*, *30*, 987–1,013.

DeYoung, R., & Hasan, I. (1998). The performance of de novo commercial banks: A profit efficiency approach. *Journal of Banking and Finance*, *22*, 565–587.

Diamond, D. W., & Verrecchia, R. E. (1991). Disclosure, liquidity and the cost of capital. *Journal of Finance*, *46*(4), 1325–1359.

Federal Deposit Insurance corporation (2011). *Quarterly Banking Profile*, various issues. Available at www.FDIC.gov.

Flannery, M. J., Kwan, S. H., & Nimalendran, M. (2004). Market evidence on the opaqueness of banking firms' assets. *Journal of Financial Economics*, *71*, 419–460.

Giradone, C., Molyneux, P., & Gardener, E. P. M. (2004). Analyzing the determinants of bank efficiency: The case of Italian banks. *Applied Economics*, *36*, 215–227.

Hirtle, B. (2007). Public disclosure, risk and performance at bank holding companies. *Federal Reserve Bank of New York Staff Reports*, *No. 293*.

Hughes, J. P., Lang, W., Mester, L. J., & Moon, C. (1996a). Efficient banking under interstate branching. *Journal of Money, Credit, and Banking*, *28*, 1045–1071.

Hughes, J. P., Lang, W., Mester, L. J., & Moon, C. (1996b). Safety in numbers? Geographic diversification and insolvency risk. *Federal Reserve Bank of Chicago, Proceedings of the Conference on Bank Structure and Competition* (pp. 202–218).

Hughes, J. P., Lang, W., Mester, L. J., & Moon, C. (1997). Recovering risky technologies using the almost ideal demand system: An application to U.S. banking. *Journal of Financial Services Research*, *18*, 5–27.

Jiang, C. X., & Kim, J. (2005). Trading costs of non-U.S. stocks on the New York Stock Exchange: The effect of institutional ownership, analyst following, and market regulation. *The Journal of Financial Research*, *3*, 439–459.

Jondrow, J., Lovell, C. A., Materov, I., & Schmidt, P. (1982). On the estimation of technical efficiency in the stochastic frontier production function model. *Journal of Econometrics*, *19*, 233–238.

Kumbhakar, S. C., & Lovell, C. A. K. (2003). *Stochastic frontier analysis.* The Press Syndicate of the University of Cambridge.

Lieu, P., Yeh, T., & Chiu, Y. (2005). Off-balance sheet activities and cost inefficiency in Taiwan's banks. *The Services Industry Journal*, *25*, 925–944.

Marcus, B., & Wallace, S. (1991). *Competing in the new capital markets: Investor relations strategies for the 1990s.* Harper Business.

McAllister, P. H., & McManus, D. (1993). Resolving the scale efficiency puzzle in banking. *Journal of Banking and Finance*, *17*, 389–405.

Mitchell, K., & Onvural, N. M. (1996). Economies of scale and scope at large commercial banks: Evidence from the Fourier flexible functional form. *Journal of Money, Credit, and Banking*, *28*, 178–199.

Neir, E., & Baumann, U. (2006). Market discipline, disclosure and moral hazard in banking. *Journal of Financial Intermediation*, *15*, 332–361.

Pasiouras, F., Sailesh, T., & Zopounidis, C. (2009). The impact of regulations on banks' cost and profit efficiency: Cross-country evidence. *International Review of Financial Analysis*, *18*, 294–302.

Roulstone, D. T. (2003). Analyst following and market liquidity. *Contemporary Accounting Research*, *20*, 551–578.

Stiroh, K. J. (2000). How did bank holding companies prosper in the 1990s? *Journal of Banking and Finance*, *24*, 1703–1745.

Van Ness, B. F., Van Ness, R. A., & Warr, R. S. (2001). How well do adverse selection components measure adverse selection? *Financial Management*, *30*, 77–98.

Walther, B. R. (1997). Investor sophistication and market earnings expectations. *Journal of Accounting Research*, *35*, 157–179.