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Bank Opaqueness in Europe

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To Mum, Dad, Assel and Danara

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Aidyn Bibolov*

Abstract

This paper examines the opaqueness of banking assets in Europe. I measure the opaqueness by the earnings forecasts errors for banks versus non-banking companies in 18 countries in Europe.

When banks are compared with the whole sample of non-banking companies, they show no particular opaqueness. However, for the samples matched by size and stock price, opaqueness proxies are higher for banks. Asset composition and financial performance variables explain a significant portion of opaqueness proxies for banks. Countries with better banking regulation enjoy lower bank opaqueness. Implications for regulatory policy are discussed.

JEL Classification Numbers: G15, G21, G28

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1. Introduction

It is hard to underestimate the role that banks play in the modern economy. However, how much do we know about banks? Are they very different from other companies? If so, what makes them different, and what are the implications of these differences?

This paper is on the subject of bank opaqueness. Opaqueness can take two forms. In one form, it can signify shortage of information from the company. Information may not available or it can be limited to the insiders. In another form, the information is available, but it is hard to understand. Due to its complexity, the general public still cannot judge about company's prospects. Thus, opaqueness leads to inferior decisions by investors.

The question of bank opaqueness has significant implications particularly for the regulatory policies. Deposit insurance, capital requirements, and other restrictions are imposed on banks to protect the economy against falling into crisis should one bank become insolvent. Outsiders view banks as "black boxes" which are hard to understand. The implied opaqueness of banking industry is one of the main reasons for its strict regulation by authorities in many countries.

Nevertheless, the question of bank opaqueness has received limited attention in the literature. I found very few studies directly on the subject. Moreover, evidence on bank opaqueness has been inconclusive. While two papers by Morgan (2002) and Iannotta (2006) state that banking is an opaque industry, the other by Flannery, Kwan and Nimalendran (2004) suggests that there is noting particular opaque in them.

This paper continues the discussion by looking at the European markets. Similar to Flannery et al. (2004), relative opaqueness of banking assets is measured by the earnings

forecasts errors for banking versus non-banking companies in 18 countries in Europe. Larger errors would mean that banking earnings are harder to value and that banks are more opaque. Test of asset opaqueness and effect of banking regulations on bank opacity are performed.

Earnings forecast errors are lower for banks when they are compared against all non-banking companies. When banks are matched by similar-sized companies, forecast error and standard deviation of forecasts are higher for them. Banks are particularly opaque in countries that did not adopt the single Euro currency at the time of observation. Asset composition and other variables explain a significant portion of opaqueness proxies for banks. European countries with better regulation and bank governance principles have lower forecast errors and standard deviation of EPS forecasts for their banks.

The paper proceeds as follows. In Section 2, I analyse the relevant literature. In Section 3, I describe the model and the data used for the empirical analysis. Tests results are presented in Section 4. Conclusion and final remarks close in Section 5.

2. Survey of relevant literature

My literature review consists of four parts. In the first part, I consider the general literature on banking theory; next, I deal with the literature on comparison of bank opaqueness with non-banking companies. After that, papers on banks' assets structure effect on opaqueness are reviewed, followed by papers on analysts' earnings forecast errors.

2.1. Sources of bank opaqueness

The main function of banks is financial intermediation. In an otherwise perfect world, there would be no use of banks, as investors would carry out all transactions themselves. Since in reality there are frictions, such as for example informational asymmetry (Campbell and Kracaw, 1980), banks play an important role in the market. As Diamond and Dybvig (1986) show, banks provide valuable liability and liquidity services. They accumulate large number of deposits from small investors and transform these deposits into debt obligations of governmental agencies and private companies. By providing credit to them, banks take the role of monitors that otherwise would be too costly for providers of funds to perform (Berlin and Loeys, 1988). By doing so, banks take risks associated with loans and obtain private information from borrowers. By accumulating a portfolio of loans, banks have access to information that may not be available to outside investors and therefore themselves become opaque. That is how informational asymmetry between borrowers and lenders causes informational asymmetry between investors and banks.

Two main arguments usually cited in favour of regulation are systemic risk and small depositor protection (Santos, 2000). First, banks can become victims of the simultaneous withdrawals of funds by depositors. Since a bank works as a liquidity provider it may not be able to fulfil all their demands in time and may become insolvent, even if it is financially sound. The collapse of one bank can provoke a chain reaction among other banks, sending the whole economy into crisis. Thus, lack of information or its misinterpretation can potentially cause bank runs and other inadequate actions by investors.

On another hand, small depositors may not have enough resources to monitor the financial standing of banks. It may be economically inefficient for them to monitor their funds. Hence,

there is a need for another monitor, like the governments' bodies and agencies as in many countries worldwide. This "monitor of monitors" will oversee financial soundness of banks for small investors. Regulation of the banking industry aims to mitigate negative consequences of a perceived opaqueness.

The support for additional measures in regulation of the banking industry has been growing in the last years. For example, the Basel Committee on Banking Supervision in its consultative paper (2001) calls for an increased market discipline and transparency in banking. Increased and higher quality of information, in the Committee's opinion, shall "promote safety and soundness in banks and financial systems".[1]

Nevertheless, although opaqueness of banking assets is frequently cited as one of the main arguments behind regulation in banking, the empirical evidence on the matter had been limited. There are only few articles on this topic.

2.2. Comparison of opaqueness of banks and non-banking companies

The direct test of bank opaqueness compares opaqueness variables for banking sector versus non-banking industries. Few papers had addressed this before. While Flannery, Kwan and Nimalendran (2004) use equity-based measures of opaqueness, Morgan (2002) and Iannotta (2006) employ debt obligations as a proxy. Thus, this part of the review will continue according to measures used in research.

[1] Basel Committee on Banking Supervision Working Paper (2001), p.1

2.2.1. Equity-based opaqueness proxy

Flannery et al. (2004) test bank opaqueness hypothesis using two main proxies: microstructure variables and earnings forecast errors. From the microstructure theory point of view, if banks were more opaque, then investors would trade their stocks less frequently. Market makers in turn would quote higher spreads to minimize losses from trades by informed traders. In order to test for that, the authors compare a sample of 320 U.S. banks[2] and a matched sample of non-banking companies traded in the NYSE, AMEX and NASDAQ exchanges in 1990-1997. As microstructure variables Flannery et al. use bid-ask spread, trading activity and return volatility of stocks. For these variables, NYSE banks show very similar characteristics to that of their non-bank counterparties. On the other hand, banks traded on NASDAQ have lower bid-ask spreads and trading activity. In order to check if the asset composition of banks affects proxies for opaqueness, the authors run regressions of microstructure variables on banks' assets, capital and income variables. They find that asset composition significantly affects the cost of trading bank stock; however, the explanatory effect of asset structure is comparable to the traditional market microstructure variables.

Another proxy for bank opaqueness comes from earnings per share estimates. The authors employ analysts' forecast errors, standard deviation of analysts' forecasts, number of forecast revisions and number of analysts following a company as proxies for opaqueness. Comparison with non-banking companies shows that NASDAQ banks differ from their control sample. They have lower forecast errors and lower percentage of analysts' revisions than non-banks. That is NASDAQ banks seem to be less opaque than their control companies. In contrast, NYSE banks do not differ significantly from non-banking companies. The authors run similar regressions of earnings opaqueness proxies on assets of banks as for

[2] Actually, they study issuance of debt by BHC - bank holding companies. However, for the purposes of this article, I make no distinction between banks and BHC, using the generic term "banks" for all of them.

microstructure variables. Asset variables add significantly to the explanatory power of regressions for forecast error and standard deviation of analysts' forecasts. Substitution from transparent assets into loans and real estate assets significantly increases earnings forecast errors. Higher profit, higher leverage and a larger proportion of non-interest income tend to reduce earnings forecast errors.

Two major findings come from Flannery et al. (2004). First, banks are not particularly opaque. If anything, banks are even easier to understand than non-banking companies. Secondly, asset composition matters. Certain assets and financial variables explain variation in opaqueness proxies for banks.

2.2.2. Debt-based proxy for opaqueness

Morgan (2002) takes a different approach to analyse opacity. His proxy for bank opaqueness is a disagreement between Standard and Poor's and Moody's ratings on new bonds issued in the U.S. between 1983 and 1993. According to his hypothesis, if banks are more opaque than non-banks then split ratings should be more common for banks. He uses the following probability model to test his hypothesis:

Probability of disagreement=F (issuer type, average rating, face value, maturity, year) + e

The proxy for opaqueness, the probability of disagreement, is measured as probability of the split ratings between Standard and Poor's and Moody's rating agencies. Morgan finds that these agencies tend to disagree more often on bond ratings for banks and insurance companies than for other industries. The author uses asset structure variables and bond characteristics to examine their effect on the split rating. He finds that loans, trading assets and cash increase

probability of disagreement, while banks' fixed assets, real estate and capital tend to mitigate it. The effect of asset structure on disagreement is stronger for lower capitalized banks. Morgan concludes that banks belong to the opaque industry and that this opaqueness is inherently related to the nature of their asset structure.

Iannotta (2006) follows the approach of Morgan and uses disagreement between the two major rating agencies as a proxy for opaqueness in Europe. He runs similar regression for bonds issued by companies from 14 European countries in 1993-2003. Iannotta finds that banks do not generate the highest number of disagreements among industries per se, but after controlling for risk, predicted probability of a split rating is higher for banks. Disagreement is positively correlated with loans, investments in securities, size of bank, and its capital. Subordinated debt issues generate more splits than senior debt. Overall, the author concludes that banks are among the most opaque industries in Europe with some degree of opaqueness inherent in their assets. A summary of articles on the direct test of bank opaqueness is presented in Table 1.

TABLE 1 ABOUT HERE

2.3. Balance sheet composition test of bank opaqueness

We can judge bank opaqueness in another dimension. The difference of banks' financial positions is reflected in publicly available information: balance sheets, credit ratings, financial ratios and other indicators. If investors can differentiate between banks based on these indicators, it will signify that banks are not relatively hard for investors to understand and so they are not particularly opaque. This test is essentially the test of market discipline for which a vast amount of publications appeared in recent years. More precisely, this will be market

monitoring test of market discipline as defined by Bliss and Flannery (2002) – test how effectively investors can incorporate information of financial positions of banks into prices of stocks and bonds. Accordingly, the review of bank opaqueness as tested in the market monitoring literature will be divided according to the measures used to access investors' reaction to changes in bank standing.

2.3.1. Bond spreads

The spread of bonds issued by banks is the most popular measure for the market monitoring test. Flannery and Sorescu (1996) analyse the spread for 422 subordinated debt issued by 83 banks in the U.S. in 1983-1991. They hypothesize that spread will be increasing in the risk of bank as measured by accounting variables. In order to separate the effect of "too big to fail" (TBTF) government guarantees to save major banks, they divide their sample in three periods according to the policy run by the Federal Reserve in the U.S. with respect to troubled banks. Flannery et al. find that investors do differentiate between risk profiles of banks and that asset variables influence spreads. Most prominently, the relation between risk and spread shows up in the last sub-period 1989-1991 when the U.S. government stepped back from TBTF guarantees.

Jagtiani, Kaufman and Lemieux (2002) measure spread dependency on accounting measures of risk for banks. They use a sample of 268 debt issues on the secondary market throughout 1992-1997 in the U.S. The authors find that the spread depends on bank risk that is reflected in accounting variables, credit ratings from S&P and Moody's and CAMEL and BOPEC regulatory ratings in the U.S.

Morgan and Stiroh (2001) take a sample of U.S. banks that issued bonds in 1993-1998. They analyse if investors can price risks of banks by charging higher spreads on bonds at the issuance. The authors find that banks that move from relatively less risky loans to more risky ones pay higher spread at issuance. Morgan et al. find that the evidence of market monitoring is stronger on individual bank level.

Sironi (2003) analyses spread on subordinated debt issues by European banks in 1991-2000. He tests whether spreads on new issues reflect risk profiles of banks after controlling for the various issue and issuer characteristics. The author finds that spreads depend on the financial positions of banks, particularly after the gradual removal of TBTF guarantees in Europe in the 1990's. Sironi also finds that accounting measures of risk perform much better when interacted with country dummies.

Krishnan, Ritchken and Thomson (2005) do not find evidence of what they call "strong market monitoring discipline". They analyse if changes in credit spreads are due to changes in risk variables based on a sample of bond transactions for 185 banks during 1994-1999. The authors document relationship between levels of risk variables and spreads. However, they do not find evidence in support that changes in bank risk variables are related to changes in credit risk spreads. Therefore, Krishnan et al. conclude that there is no strong market discipline in bond prices.

2.3.2. Equity returns

Several papers have explored the market monitoring issue using equity market prices for banks. Billett, Garfinkel and O'Neal (1998) analyse stock price reaction to the announcement of bank downgrades by Moody's rating agency. They find that negative abnormal equity

returns are lower for banks that rely more on insured deposits. That is, equity investors penalize less banks that have more capital in protected funds. This finding implies that investors are able to differentiate between risk profiles of banks.

Gropp, Vesala and Vulpes (2006) derive distance-to-default estimates from equity prices and use them to predict deterioration in banks financial position in EU since 1991. They find that their estimator is capable of predicting banking problems six to eighteen months in advance. Spreads on subordinated bonds can predict downgrades only close to the critical time. The authors conclude that the market is able to incorporate information about banks' financial condition both in equity and debt prices.

2.3.3. Capital and risk relation

Flannery and Rangan (2004) analyse U.S. banks capital ratios in 1986-2001 and document that capital was increasing from 1986. In their quest for reasons for capital build-up, they find that a major motive behind it must have been increased risk of bank portfolios as measured by the volatility of banks equity and accounting variables. Overall, investors are able not only to understand risk profiles of banks, but also to influence their behaviour. This is evidence of market monitoring as well as of market influence as defined by Bliss et al. (2002).

Similarly, Nier and Baumann (2006) test whether bank capital responds to changes in risk. They construct large cross-country sample for 32 countries, which includes banks in the U.S., Japan, EU and emerging markets. The authors find evidence of market discipline; however, it is stronger for banks that do not receive support from the state in the form of TBTF guarantees. Banks respond to increased risks by growing reliance on their capital, which is consistent with the market influence hypothesis.

2.3.4. Regulatory rating prediction

Evanoff and Wall (2001) test whether various capital ratios and subordinated debt spreads are able to predict BOPEC and CAMEL regulatory ratings for banks in the U.S. They take bonds issued by U.S. banks and track them during the 1985-1999 period. The authors find mixed evidence in favour of market monitoring hypothesis. Capital ratios and spreads can help in predicting supervisory ratings, but they do not provide information to differentiate between high-rated and low-rated banks.

Krainer and Lopez (2004) analyse if a mix of balance sheet and equity market variables can correctly predict BOPEC regulatory U.S. ratings for banks. The authors find that these variables can predict changes in ratings up to four quarters in advance. Therefore, they conclude that investors can use publicly available data to infer financial position of banks.

A summary of articles for the balance sheet composition tests of bank opaqueness is provided in Table 2.

TABLE 2 ABOUT HERE

2.4 Analysts' earnings forecasts literature

There is a wide spectrum of studies on the topic of analysts' forecasts. I will mention some comparatively recent selected papers related to the subject of this study.

Capstaff, Paudyal and Rees (1995) analyse analysts' earnings forecasts in the UK for 1315 companies in 1987-1990. They find a positive bias in forecasts. Analysts tend to overestimate

companies' earnings. The authors also find that forecasts are better at the shorter time horizons. Capstaff et al. suggest that financial analysts in the UK do not take into consideration all available information at the time of forecast. The authors also document some evidence that the size of a company mitigates the error.

In their next paper (Capstaff et al., 1998), the authors analyse earnings forecasts in Germany from 1987 to 1995. Mean forecast error is larger than in the UK, which the authors attribute to the less informative nature of financial disclosure. However, the optimistic bias in Germany is significantly lower, which is explained by less pressure on analysts in Germany to issue favourable forecasts. Thus, differences in the financial structures of the two countries affect accuracy of earnings forecasts.

In their summary paper, Capstaff et al. (2001) compare analysts' forecasts in nine European countries in 1987-1994. In accordance with previous findings for the UK and Germany, the authors document optimistic bias in analysts' forecasts and decreasing accuracy of forecasts with time. They also find that forecast errors vary among sample countries.

Dreman and Berry (1995) document analysts' errors properties in the U.S. for 1974-90. They find that average absolute forecast errors are about 40%. Dreman et al. also define the "acceptable" range forecast error as 10% within actual EPS and find that most of the estimations done by analysts fall outside of this acceptable range. Based on these findings, the authors argue that analysts' errors are too high to be relied upon by the investment community. Since findings persist over the sample period, they also note that forecast errors have behavioural explanations.

Brown (1997) performs a similar analysis for analysts' errors in the 1985-1996 period. While the author confirms the evidence of large forecast errors and an optimistic bias in forecasts, he argues that both errors decrease over time. Brown also reports that errors are smaller for firms with larger market capitalization, absolute value of earnings forecasts and number of analysts following a company. He also finds that depository institutions have more observations within 10% "acceptable" error region, as specified in Dreman et al. paper, but he does not explicitly compare banking companies against other industries.

Basu, Hwang and Jan (1998) analyse the effect of different accounting rules on the earnings forecasts in ten countries in 1987-1994. They find an optimistic bias in analysts' forecasts for nine countries of the sample. Basu et al. document that higher degree of alignment between tax and financial accounting, wider use of accruals and more choice in accounting methods decrease forecast errors.

Beckers, Steliaros and Thomson (2004) analyse analysts' forecasts for ten European countries. Similarly to previous studies, they use forecast error and forecast bias measures to analyse accuracy of forecasts. The authors attempt to specify particular characteristics of companies that have effect on those errors. Beckers et al. find that forecast errors increase with a dispersion in analysts' forecasts and with stock volatility. The number of analysts providing forecasts for a company is negatively related to the error, but market capitalization has no effect. The authors also find differences in forecasts accuracy by countries and sectors. Results of the paper are probably driven by selection of companies in the sample as Beckers et al. include only companies with market capitalization over one billion dollars followed by at least seven analysts during the 10-year period in 1983-1992. This eliminates all small companies from the sample, which explains the finding that size does not affect errors, as all companies in the sample are relatively large by market capitalization.

Fan, So and Yeh (2006) analyse the accuracy of the earnings forecasts in the insurance industry. They compare errors for a sample of 244 insurance companies in the U.S. in 1989-1998. Fan et al. find that prior to 1993 forecast error for insurance companies is larger than for other industries, but after 1993, the situation reverses. They attribute this fact to the improved reporting by insurance companies. The authors further find that error decreases with the firm's size and number of analysts following company. The error increases with the level of disagreement between analysts.

A summary of articles on analysts' forecasts is presented in Table 3.

TABLE 3 ABOUT HERE

2.5. Summary of the literature review

While there is certain evidence that investors differentiate among banks based on their financial characteristics through equity and debt cost, the question as to whether banks are more opaque than other industries remains open. Contrary to Flannery et al. (2004) who do not find the banking industry to be particularly opaque, Morgan (2002) concludes his paper with the following remark: "…banks maybe the black holes at the centre of the financial universe, powerful and influential, but are to some degree, unfathomable".[3]

I explore opaqueness of banks in the European context. Similar to Flannery et al. (2004), I use earnings forecast errors as a proxy for company opaqueness. This allows an analysis for each country as well as a cross-country comparison for Europe.

[3] Morgan (2002), p. 888.

The main contribution of this paper comes from its analysis of European as opposed to the U.S. data for the analysis. European banks are different from their U.S. counterparts - they are more protected by the governments, thus increasing their potential opaqueness (see, for example, Sironi, 2003, 446-447); financial markets in Europe and the U.S. differ as well. Overall, banks in Europe play more important role in providing funds to the industry.[4] Cross-country analysis of European countries can help to identify how various settings in which banks operate influence bank opaqueness. As Barth et al. (2004) note in their paper, "the increasing globalization of banking and finance mandate a broad, cross-country perspective on banking issues. Indeed, cross-country comparisons can add insight into basic issues in banking that may not emerge, or are only partially discernible, from single-country analyses"[5]. Comparison of regulations in various countries in the sample can reveal what are particular characteristics of "good regulation" that tend to mitigate opaqueness of banking assets.

The paper benefits from the use of recent data with good analysts' coverage of companies in the sample. It also benefits from the availability of cross-country data on banking regulation.

[4] For example, see Allen and Gale (2001).
[5] Barth, Caprio and Nolle (2004), p. 46-47.

3. Methodology and Data Description

3.1. Banks versus non-banking companies comparison

I designate earnings forecasts from the IBES database as a proxy for the degree of firm's opaqueness. This database provides forecasts for the earnings of over 18,000 companies in major world markets. I concentrate on earnings forecasts for 18 European countries[6] and collect data for all public companies traded on local stock exchanges for which earnings estimates were available at IBES database for 1990-2004. The initial sample consisted of 4,036 companies, of which 199 were banks. To be included in the final sample, each company needed to have earnings forecast with actual positive earnings available for at least one year. The final sample consists of 3,504 companies, of which 171 are banks.

Each company's industry was identified according to the WorldScope General Industry Classification codes, field 06010 (please see Appendix 1 for details). Banks are in the code 4: "Bank/Savings & Loan". Balance sheet data and other financial variables for companies were taken from the WorldScope database. Breakdown of companies by the industry according to the WorldScope classification is provided in Table 4. The vast majority of companies are in the industrial sector – almost 80%, followed by other financial sector companies with 7.42% and banks with 4.88%.

TABLE 4 ABOUT HERE

[6] Eighteen countries in the sample are: the UK, Poland, Belgium, Denmark, France, Germany, Italy, the Netherlands, Norway, Sweden, Switzerland, Austria, Greece, Hungary, Portugal, Spain, Finland and Czech Republic

From the IBES database, I collected information on mean, median, highest and lowest earnings estimates, standard deviation of analysts' forecasts, number of annual estimates, and actual annual earnings per share. I use the following proxies for opaqueness:

- FE - earnings forecast error, computed as the absolute value of the difference between mean forecast estimate and actual annual earnings for companies in the sample;
- SD - standard deviation of earnings forecasts for each company-year (calculated only when two or more estimates are available):

For standardization purposes, I divide these opaqueness proxies by the actual EPS value for that year. This is a typical standardization that is used in analysts' forecasts research.[7] The formulas for FE and SD opaqueness proxies are as follows:

$$FE = \frac{|Forecast\ \ EPS - Actual\ EPS|}{Actual\ EPS}$$

$$SD = \frac{\text{Standard Deviation}\ \ of\ \ forecasts}{Actual\ EPS}$$

- HL – dummy variable that equals to zero if the actual EPS data falls between highest and lowest earnings forecasts for each company and unity otherwise. This variable shows if analysts are able at least to forecast the range of the actual EPS correctly:

$$HL = \{\ 0\ if\ \ Low \le Actual\ \ EPS \le High, 1\ \text{otherwise}\ \ \}$$

A value of this variable equal to unity indicates greater opaqueness, that is analysts not being able to forecast even the range of the actual EPS correctly.

[7] For example, 6 out of 8 studies on analysts' forecasts reviewed in this work used actual EPS values for standardization.

The first two of the opaqueness proxies, forecast error – FE, and standard deviation – SD, are used in Flannery et al. (2004) as well.[8] The third proxy, range forecast variable HL, is adopted from the analysts' forecasts literature. A summary of opaqueness proxies used in this paper is presented in Table 5.

TABLE 5 ABOUT HERE

My hypothesis is that opaque companies are more difficult for analysts to evaluate. These companies will have a higher earnings forecast error and standard deviation of forecasts and a higher proportion of HL variables equal to unity.

Flannery et al. (2004) also use the number of analysts as an opacity measure. They explain this from the market microstructure theory as more intensive following by analysts reduces adverse selection costs and hence opacity of the stock. In this case, this variable will be not so much a proxy, but rather a cause of the opacity; therefore, it should be treated as opacity measure with caution. For example, Brown (1997) and Basu et al. (1998) use the number of analysts as an explanatory variable for forecasting error. I use data on number of estimates of earnings for each company in the sample as a NES variable for comparison purposes when I compare banks versus non-banking companies. I explicitly use it as an explanatory variable in opaqueness proxies' regressions for banks.

A summary of companies included in the sample by country of origin is reported in Table 6. I cut off 5% extreme values for opaqueness proxies FE and SD to avoid distortion from outliers. Companies around Europe vary by their characteristics and by opaqueness proxies' values. The majority of banks come from Italy, Denmark, and the UK. Together these

[8] Flannery et al. use stock price as a denominator for FE and SD proxies. More on these proxies in the Tests section.

countries provide 69 out of 171, or 40%, of all sample banks. In turn, the UK, France and Germany provide more than 50% of the companies in the sample. For observations, 30% of non-banking companies come from the UK, followed by France and Germany, while for banks, Italy is a clear leader with 16% of observations, followed by Denmark and the UK. Each bank has 8.3 observations, while a non-banking company has 7.7 annual observations on average. Practically all developed countries in Europe with relatively large stock markets (including the UK, France, Germany, Italy, the Netherlands, and Switzerland) have larger companies on average as measured by market capitalization.

The average forecast error, FE, for the sample is 34.1%, though errors for Norway (60%) and Sweden (50%) are particularly high. Average standard deviation of forecasts, SD, is 14.2% with highest values in the Czech Republic and Greece and lowest deviations in the UK and the Netherlands. The average value for HL range proxy for all countries is 68%, which means that analysts made accurate predictions within the range of actual EPS only in one of three cases. As most of the values for this variable are in the range of 60-70%, the job of financial analysts seems to be tough. Analysts perform relatively better in Switzerland and Spain where forecasts ranges include actual EPS value in more than 50% of the cases. In Norway, the UK, and Sweden analysts perform worse and predict the range correctly in less than 25% or one-fourth of the cases. Another extreme case is Belgium, where the proportion of HL variables equal to zero for banks is 85% (not reported in the table), which means you can consider the EPS forecasts for Belgium banks with far more confidence than anywhere else.

The Netherlands, Spain, and Germany are leaders in the average number of forecasts with more than 10 forecasts on average. In contrast, a company in Greece receives about four forecasts during the year with the sample average around eight EPS forecasts.

I also compute signed forecast error to analyse some properties of errors distribution. This variable is extensively called "earnings surprises" or "forecast biases" in analysts' forecasting literature. I compute it as:

FES = (mean EPS estimate-actual EPS) / actual EPS

A positive sign of this variable would indicate an optimistic bias in analysts' forecasts while a negative sign would show a pessimistic bias in expectations. Signed forecast errors (or optimistic bias) are positive for 17 out of 18 countries in the sample. This confirms the findings of pervious papers on analysts' forecasts - analysts systematically tend to overestimate actual EPS for companies. [9]

TABLE 6 ABOUT HERE

A more detailed summary and histograms of signed forecast errors for banks and non-banking companies is presented in Table 7. I cut off 5% of extreme values on the left and right in order to avoid distortion from outliers. The distribution of signed forecasts errors for companies is presented in Figure 1.

TABLE 7 ABOUT HERE

FIGURE 1 ABOUT HERE

The means for both types of companies are positive (0.07 and 0.34), indicating that on average analysts tend to have an optimistic bias towards earnings, which is consistent with the

[9] See, for example, the review in Brown (1993), also the ones in Capstaff et al. (1995, 1998, 2001)

literature on analysts' forecasts. The mean for banks is closer to zero; skewness and kurtosis are also smaller for banks. However, both distributions have fat tails with excess kurtosis and positive skewness. Kolmogorov-Smirnov test rejects normality assumption for both distributions at 1% level.

3.2. Asset structure effect on bank opaqueness

If banks are inherently opaque, then their asset composition shall provide indication of opacity. The assets that are harder to value should result in higher degree of opaqueness as measured by designated proxies. In order to test the influence of the asset composition on earnings forecast accuracy variables, I run the following fixed-effect pooled regression for two opaqueness proxies for banks:

$$Y_i = a_i + \sum_k b_k BS_{ki} + \sum_j l_j PL_{ji} + e_i ,$$

where

Y_i – measure of bank opaqueness for bank i (forecast error - FE - or standard deviation of forecasts - SD);

BS_{ki} – balance sheet asset variable for asset k and bank i;

PL_{ji} – control variable j for bank i;

For the range forecast HL proxy, I run the binary logistic regression in the following form:

$$HL = f\,(assets,\ control\ variables)$$

I use the following exhaustive classification of bank assets for regressions:

- Cash and due from banks (I will call this category simply cash);
- Total investments;

- Net loans;
- Reserves for loan losses (this is contra account for total loans; sum of net loans and reserves for loan losses is equal to total loans account on the balance sheet);
- Investments in unconsolidated subsidiaries;
- Fixed assets - property, plant and equipment and real estate assets;
- Other assets.

I expect that an increase in more opaque assets will an increase in the opaqueness proxy variables. For example, investments in securities increase trading risks of banks; therefore I expect them to have a positive coefficient. More loans provided by banks increase informational asymmetry between banks and outsiders, and I expect opacity proxies to increase in loans. An increase in reserves for loan losses signifies deterioration in loans quality and therefore shall have an increasing effect on analysts' errors as well.

Investors and analysts may pay more attention to the larger banks. Therefore, I include market capitalization and number of annual EPS estimates as control variables. More attention from analysts is expected to decrease forecast errors. As earnings valuation depends on non-interest income too, I include commission and fees amount to account for that effect. [10] I expect it to have a mitigating impact on my opaqueness proxies as well.

I include the following control variables in the regressions:

- Natural logarithm of market capitalization for each bank;
- Number of EPS estimates for each bank;
- Commission and fees – income from maintaining clients' accounts in the bank.

[10] I also run regressions with inclusion of other explanatory variables, for example, leverage and net income, as in Flannery et al. (2004). While results remain qualitatively similar, none of these variables is statistically significant.

For HL proxy, I add two more control variables:

- Earnings volatility for each bank;
- EPS forecast volatility for each bank.

Both volatilities variables are expected to increase earnings forecast errors.

In order to standardize the explanatory variables, I divide all of them by total assets value for each bank in the current year.[11] I collect asset structure, financial variables, and earnings forecasts information for banks from the WorldScope and IBES databases for the 1990-2004 period.

3.3. Effect of banking structure and regulations on bank opaqueness

Analysis of banks in cross-country settings can help in identifying particular characteristics of the banking sector that influence opaqueness. The bank regulation and supervision database developed by the World Bank Group has a wealth of information on many countries in the world, including 17 out of 18 countries in the sample.[12] In connection with this database, I use data from Barth, Caprio and Levine, 2001 (BCL, 2001), Barth, Caprio and Levine, 2004 (BCL, 2004) and Barth, Caprio and Nolle (BCN, 2004). The authors collect information on the state of banking systems and regulation in 55 countries around the world. For each variable, I devise a dummy that divides the countries in my sample in two parts based on a chosen point. The summary of selected variables for banking structure and regulation for countries in the sample and appropriate dummy variables created is presented in Table 8. Data for US banks is shown for comparative purposes below the sample averages.

[11] In order to make figures across all countries and years comparable, the monetary values were converted in Euro equivalents.

[12] Out of 18 European countries in the sample, there is no data for Norway; data for Austria and Hungary is available for a limited number of variables.

TABLE 8 ABOUT HERE

3.3.1. Bank importance

Barth et al. measure bank importance as the ratio of the sum of all banking assets in the country to its GDP. The higher the ratio, the greater the importance of the banking sector in the economy. This ratio varies significantly for the sample countries. For five of them – Switzerland, the Netherlands, Germany, Belgium and the UK – it is higher than 300%, while for some others, like Poland and Finland, it is less than 100%. If we take into account countries with the same income level, this ratio can indicate whether country's economy is prevalently bank-based or market-based. For example, if we take the U.S. – clearly a market-based system, the share of banks in GDP is 66% - well below 209%, the average among European countries in the sample. The dummy for this category equals to unity (low to medium importance) if bank assets to GDP ratio for country is less than 200%. For countries where ratio is more than 200%, dummy is equal to two (high importance).

In countries where banks play more important role in the economy, bank opaqueness is expected to be lower as investors will be paying more attention to banks and demand better disclosure from them. Therefore, I expect negative relationship between bank importance and opaqueness proxies values.

3.3.2. Bank concentration

The degree of banking concentration as measured by the share of the three largest banks' assets for each country also varies among European countries. In Finland, the Netherlands and Denmark top three banks hold more than 70% of total assets, while in the UK and Germany

this ratio is less than 20%. Overall, concentration in European banking is much higher than in the US – 52% versus 22%.

Banking concentration can have various effects on the bank opaqueness, as Barth et al. note in their 2004 paper[13]. On one hand, it may be easier for interested parties to monitor few large banks. As analysts will be paying more attention to them, forecast errors will be smaller. On the other hand, these few large banks may be more difficult to understand and so forecasting errors will be larger for them. The dummy for this category equals to 1 (low concentration) if there are less than 50% of all banking assets in top 3 banks for each country; otherwise dummy equals to two (high concentration).

3.3.3. Government ownership

In Germany and Poland governments own more than 40% of the banking assets. This is in sharp contrast with the UK, Belgium, Denmark, Sweden and Spain where governments do not have any stake in banks at all. In the US, the government does not own banks as compared to a 12.6% average for the European sample. Banks are divided in low government ownership group (less than 10% of total assets owned by government entities) and high degree (more than 10%).

Government is rarely considered as an effective assets owner in economic literature. Increased moral hazard and pressure to use other than risk-reward combination criteria under government ownership makes banks more prone to credit problems and leads to poorer

[13] BCN, 2004, p. 12.

profitability.[14] Therefore, I expect a positive relationship between government ownership and bank opaqueness.

3.3.4. Moral hazard from deposit insurance

The authors measure the ratio of funds covered by deposit insurance agency to the country's GDP per capita level. This ratio equals one for the majority of the sample countries. The big exceptions are France and Italy, where the ratio equals 3 and 6 respectively. US banks are as always different from their European counterparts and for them this ratio equals to 3 which is twice higher than for the sample average.

Deposit insurance is meant to save financial system from bank runs. By decreasing the "first come-first serve" nature of depository institutions, this insurance shall promote banking stability. However, the increased reliance on the insurance from the investors' side may result in a less responsible behaviour by the banks which will engage in riskier activities. Thus, greater deposit insurance/GDP per capita ratio can lead to the higher degree of moral hazard by banks, which I measure by moral hazard dummy that equals to unity (low degree) for countries with ratio equal or less than one, and two otherwise (high degree of moral hazard).

3.3.6. Corporate Governance in banks

The recent scandals with major multinationals fixing numbers in accounting statements, turned the attention of economists to the corporate governance as one of the major issues in the health of the economy. Barth et al. compute a governance index based on the information on the effectiveness of bank audits, transparency of bank accounting statements and external

[14] See, for example, La Porta et al. (2002) and BCN (2004).

monitoring by creditors. A higher index indicates better corporate governance in the country. Most of the countries score near the sample average of 10, although Italy, France and the Czech Republic have a lower index (7 to 8) and Switzerland has better than average corporate governance in place (index equal to 12). The US scored a little better than the European average with index equal to 11.

The better corporate governance in banks shall ensure better quality information for investors. Therefore, I expect that better government principles and more transparency in banking operations will decrease bank opaqueness and analysts' forecast errors. Dummy for corporate governance equals to one (low level of governance) for countries with BCN index lower than 10 and two for all other countries (high level).

The summary of dummy variables chosen with their description and expected effect on bank opaqueness is provided in Table 9.

TABLE 9 ABOUT HERE

3.4. Data limitations

There are certain limitations in data for this research that may affect the analysis. First, the number of banks for which there is a good coverage by analysts is limited. This decreases the number of observations for comparisons between banking and non-banking companies and for the analysis of asset and banking structure and regulation effect on bank opaqueness.

Another limitation is that I have the number of EPS estimates for each company, but I do not have data for each individual analyst. This limits the study of such issues as the effect of

herding behaviour by analysts on opaqueness proxies. Similarly, the absence of data for each individual forecast precludes from using other opaqueness proxies, such as the mean of absolute differences for each observation (the use of means for forecast error estimation can average all errors and mitigate potential errors by different forecasts).

Data for banking structure and regulation comes from the World Bank surveys for 1998-2000, thus representing point of time values for countries. Although many variables, particularly for bank regulation, are stable for countries, this can underestimate effect of changes in variables. Finally, data availability for banks differs throughout the sample period. This makes it hard to run balanced regression for opaqueness proxies. Nevertheless, test results are consistent in many variations, which puts assurance in stability results robustness with the use of better data as well.

4. Test results

4.1. Comparison of opaqueness for banks versus non-banking companies

A summary of actual EPS and forecast variables for all observations is reported in Table 10. Banks have lower actual and forecast EPS estimates, standard deviations of forecasts, highest and lowest EPS forecasts and stock price both in mean and median values. Banks are much larger in terms of market capitalization and total assets values. They receive more annual EPS estimates as compared to non-banking companies too.

TABLE 10 ABOUT HERE

4.1.1. Opaqueness variables comparison

If banks were more opaque than non-banking companies, then it would be more difficult for analysts to predict accurately their earnings. A comparison of opaqueness variables for banks and non-banking companies is provided in Table 11. When comparing means for the opaqueness variables, I use a 95% cut point independently for banking and non-banking observations for forecast error FE and standard deviation SD variables in order to reduce influence of outliers.

TABLE 11 ABOUT HERE

All opaqueness proxies are significantly lower for banks in mean values. EPS forecast error FE is 27% versus 35% for non-banking companies, standard deviation of EPS forecasts SD is 13% against 14% for non-banking companies. Analysts are able to forecast the range of actual EPS in 10% more cases for banks (41% of correct forecast ranges versus 31% for non-banking companies). On average, banks receive almost two more forecasts than non-banking companies.

For median values, the evidence is mixed. Median EPS forecast error for banks is 16.1%, which is significantly smaller than the 19% median error for non-banking companies. However, standard deviation of forecasts for banks is larger now in median value – 9.6% versus 8.7% for non-banking companies and this difference is statistically significant. Banks still receive more earnings estimates in median values – six versus five. Median values for HL proxy equal to unity simply mean that most of the time forecasters are off the actual EPS range both for banks and non-banking companies (which we already observe from the fact

that means for both groups are greater than 0.5). Overall, banks do not seem to be more opaque than non-banking companies.

4.1.2. Multivariate tests of bank opaqueness

Univariate test settings do not account for other potentially important companies characteristics. For example, EPS forecasts may be more accurate for larger firms, with more attention from analysts, a phenomenon documented in previous studies. The number of EPS estimates may also represent a mitigating factor for forecast errors. Forecast errors may increase in earnings and forecasts volatilities for companies. In order to control for the effect of those variables, I run the following multivariate regression for forecast error FE and standard deviation SD opaqueness proxies:

$$Y_i = a_0 + d_k Bank\ ID_k + c_i \ln MV_i + s_i NES_i + f_k EPS\_vol_k + w_k FOR\_vol_k + g_{\tilde{n}} D_c + n_y D_y + e_i$$

where

Y_i – opaqueness proxy for observation *i*, consequently FE or SD variables;

Bank ID_k- dummy variable that equals 1 if company *k* is a bank and 0 otherwise;

ln MV_i – natural logarithm of market capitalization for company observation *i*;

NES_i – number of annual EPS estimates for company observation *i*;

EPS_vol_k – annual EPS volatility for company *k*;

FOR_vol_k – annual volatility of EPS forecasts for company *k*;

D_c and D_y– dummies for country *c* and year *y* respectively.

For the range forecast HL proxy, I run the binary logistic regression with the same control variables:

$$HL_i = f\,(Bank\ ID_k,\ ln\ MV_i,\ NES_i,\ EPS\_vol_k,\ FOR\_vol_k,\ Country,\ Year)$$

where

HL_i – value of HL opaqueness proxy for observation i;

and other variables are as described above.

Bank ID dummy is designated in accordance with the WorldScope general industry classification codes (Appendix 1) in the following way:

Bank ID=1 for industry code 4 - Bank/Savings & Loan;

Bank ID=0 companies under codes 1 and 3 - Industrial and Transportation.

I compute annual volatility of earnings and EPS forecasts for each company for 1989-2004. These variables are constant for each company over its observations.

The sign and significance of the coefficient for the Bank ID dummy in these multivariate tests will indicate degree of bank opaqueness. The positive significant sign of the coefficient for the Bank ID dummy would indicate than banks are opaque (as opaqueness proxies would be higher for them). If banks are not opaque, then this coefficient is expected to be insignificant or to have a significant negative sign.

I run four regressions for each opaqueness measure:

(0) - a regression with year and country dummies only;

(1) - a regression with year and country dummies, natural logarithm of market capitalization and number of EPS estimates;

(2) - a regression with year and country dummies, natural logarithm of market capitalization, number of EPS estimates and Bank ID dummy variable;

(3) - a full regression with all explanatory variables including earnings and EPS forecasts variables.

Comparison between these regressions for FE and SD proxies will show if adding new variables significantly increases the explanatory power as measured by F-test of increases in the adjusted R-square values. Results of the regressions for FE and SD opaqueness proxies are presented in Table 12.

TABLE 12 ABOUT HERE

To save space, I show the results of the three last regressions only without reporting coefficients for year and country dummies. F-test that all coefficients are jointly equal to zero is rejected for all regressions for the FE proxy. Adding new variables increases the power of regressions in all versions as measured by the adjusted R-squares and these increases are significant at the 1% level. The adjusted R-square grows from 3.8% for regression with year and country dummies to 5.9% when market capitalization and number of estimates are included. For regression with Bank ID dummy, R-square increases to 6.0% and it further grows to 6.4% when earnings and forecast volatilities for companies are included.

Individually, market capitalization and number of estimates remain strongly significant in all regressions. The size effect of market capitalization is well pronounced which is reasonable as larger companies attract more attention from analysts and as a result have better earnings forecasts. The market size effect had been documented in practically all previous studies on analysts' forecasts (for example, Capstaff et al. 1995, 1998, 2001, Beckers et al. 2004, Fan et al. 2006). Both size and number of annual EPS estimates for each company have decreasing

effect on forecast error FE. Each 1% increase in market capitalization decreases error on 2.3%, whereas each additional EPS forecast decreases FE proxy by 0.3%.

Most importantly, the coefficient for the Bank ID variable has a significant negative sign in both regressions at the 1% level. The fact that the company under consideration is a bank decreases the forecast error on average by 4.7%. An increase in forecast volatility has a small, but significantly positive effect on forecast error FE ar the 1% level. That is companies with higher forecast volatility have higher forecast errors. The coefficent for earnings volatility is significant, but practically equals to zero.

Results of the regressions for standard deviation of forecasts SD proxy are less pronounced, but qualitatively similar to FE proxy regressions. While the coefficient for the Bank ID dummy is not significant, although close to 10% level of significance, it has a negative sign, signifying that banks have lower standard deviation of forecasts. Market capitalization remains strongly significant as in previous regressions. A 1% increase in capitalization decreases the SD proxy by 1.4%. The coefficient for the number of annual estimates practically equals to zero and is not significant in any of the regressions this time. The coefficient for forecasts volatilities has a small, but statistically significant positive value, as it did for the FE proxy. The earnings volatility coefficient equals to zero and is not significant. F-test that coefficients in regressions are jointly equal to zero is rejected for all of the models. F-tests for adjusted R-square increases show significance of adding new variables at 1% level for all regressions except for regression when Bank ID dummy is added. This again suggests that banks are at least no more opaque that their non-banking counterparties, as the Bank ID dummy remains very nearly insignificant with the negative sign. Results of the multivariate regressions for HL opaqueness proxy in Table 13 confirm regressions results for FE and SD proxies.

TABLE 13 ABOUT HERE

The market capitalization and number of estimates variables remain strongly significant with negative signs in all regressions except the last where market capitalization is insignificant. An increase in market capitalization by 1% increases the chance that analysts will be able to predict range of forecast correctly by 2%. Each additional EPS estimate increases the correct forecast chance by 7%. Forecasts volatility decreases this chance by 1.7%. The coefficient for the Bank ID dummy variable is not significant in any regression, so there is no particular difference between banks and non-banking companies for HL proxy.

Overall, results of the multivariate test replicate univariate test results. Judging by the FE opaqueness proxy, banks are significantly *less* opaque as forecast error is lower for them both in mean and median values.

As banks are larger in market capitalization and have more attention from analysts' side, another check of opaqueness requires comparison of similar-sized banks and non-banking companies.

4.1.3. Alternative opaqueness proxies' comparison

In order to compare alternative opaqueness proxies, I use the following sample selection procedure: for each bank, I take the control company for the same year and country with the closest value of market capitalization.[15] If the stock price for the control company is within 25% of the price for banking stock, then I select it as my control non-banking company;

[15] As control non-banking companies, I take firms in industrial and transportation sectors according to the WorldScope classification.

otherwise, I take the next closest non-banking company by market capitalization and perform the check.[16] This procedure yields to 1407 banking and non-banking companies pairs.

Following Flannery et al. (2004), I compute two of the opaqueness proxies, forecast error (FEP) and standard deviation (SDP) according to the following formulas:

$$FEP = \frac{|Forecast\ EPS - Actual\ EPS|}{Stock\ \mathrm{Pr}ice}$$

$$SDP = \frac{\text{Standard Deviation}\ \ of\ \ forecasts}{Stock\ \mathrm{Pr}ice}$$

The formula for HL opaqueness proxy remains the same.

Since I use comparison by the country and year of observation, companies in two samples shall be comparable in size and average stock price. Table 14 data for two samples suggests that they are indeed comparable. Mean and median values for market capitalization and stock prices are close for both groups. Non-parametric tests reject significance of the differences for them both in mean and median values.

TABLE 14 ABOUT HERE

In Table 15, I present results of a comparison of the opaqueness proxies between stratified samples. For the very first time in all tests, banks have larger values of forecast error FEP and standard deviation of forecasts SDP both in mean and median values. Although differences are not large, all of them are significant for two opaqueness proxies on 1 to 10% levels. Now

[16] I follow Flannery et al. (2004) method for selecting companies for my samples.

it is non-banking companies that receive significantly more EPS estimates both in mean and median values. The HL range forecast variable is the same for both samples.

TABLE 15 ABOUT HERE

For stratified samples comparison it is banks now that have higher opaqueness proxies. The difference with the results of prior tests of bank opaqueness can be due to the fact that in previous samples, banks were larger and received more attention from the analysts' side. In stratified samples, market capitalization is not a factor anymore and it seems that banks are harder to evaluate by analysts than non-banking companies. In order to further test for bank opaqueness, I run multivariate regressions for FEP and SDP opaqueness proxies using stratified samples in the same way as for FE and SD proxies. Results of the regressions are presented in Table 16.

TABLE 16 ABOUT HERE

As in the previous regressions, I report results of the last three models only, without coefficients for year and country dummies. While market capitalization continues to be a mitigating factor for both proxies, the coefficient for the Bank ID dummy is significant for the SDP proxy only. It enters significantly regressions for standard deviation of forecasts increasing the adjusted R-square from 14.3% to 15% with a positive sign. Thus, the fact that a company is a bank increases this opaqueness proxy. However, the coefficient for the dummy is not significant for the forecast error FEP. No other coefficient is significant in regressions, earnings and forecasts volatility do not increase the adjusted R-square significantly. Note that the R-squares significantly grow as compared to multivariate regressions for FE and SD proxies reported in Table 12 – from 6%-10% to 10-15% for FEP and SDP proxies. Banks are

opaque in Europe in stratified samples regressions, particularly for standard deviation SDP proxy.

European integration can have an impact on better transparency of companies in the Eurozone. Countries that adopted the single currency may enjoy more attention from the analysts side that will decrease opaqueness of banking companies traded on local stock exchanges. In order to check for this effect, I run separate multivariate regressions for FEP and SDP proxies dividing all observations in stratified samples by membership in Eurozone:

- Group 1 comprises of all observations for countries where Euro was adopted as a currency. This group includes observations for 11 countries in the sample that adopted Euro from 1999 (Belgium, Germany, Greece, Spain, France, Ireland, Italy, Luxembourg, the Netherlands, Austria, Portugal and Finland) and Greece for observations from 2001;
- Group 2 consists of all other observations. That is it includes all observations for countries that do not use Euro as a currency and Eurozone countries prior to 1999 (prior to 2001 for Greece).

I run three different regressions for each opaqueness proxy:

(0) - a regression with year and country dummies only;

(1) - a regression with year and country dummies, natural logarithm of market capitalization, number of EPS estimates and earnings and forecast volatilities;

(2) - a regression with variables from (1) and a Bank ID dummy.

Results of the separate regressions for two groups of observations are reported in Table 17. To save space, results of the regressions for year and country dummies are not reported.

TABLE 17 ABOUT HERE

Regression results are different for countries within and outside of Eurozone. For countries outside of the Eurozone, the coefficient for the Bank ID dummy is significantly positive at the 1% level for both opaqueness proxies and adding it significantly increases the adjusted R-square. The only other significant variable in the regressions for non-Eurozone countries is market capitalization that significantly reduces both forecast error and standard deviation of forecasts.

For the Eurozone countries, the regressions coefficient for the Bank ID dummy is not significant and even changes its sign for the FEP variable. Adding the Bank ID dummy does not significantly increase adjusted R-square for both regressions. The only significant variable for the Eurozone countries regressions is forecast volatility which is positive for both proxies, but differs from zero only for FEP variable.

Results support the hypothesis that banks in the Eurozone are less opaque than their counterparties outside of it. For countries outside of the Eurozone, banks have larger forecast error and standard deviation of EPS forecasts. For Eurozone members, banks do not differ from their non-banking counterparts.

4.2. Asset structure test of bank opaqueness

4.2.1. Assets structure of banks

What is the asset structure of European banks in the sample? Preliminary examination of data for assets of banks uncovered that some of the observations had values for property, plant and

equipment larger than for total assets. There were 51 such observations primarily for six banks from different countries. These observations were eliminated from the sample. After analysing reserves for loan losses category, I found that, for many cases when data for this category were missing, information was available for total loans and net loans categories. Since reserves for loan losses are just the difference between total loans and net loans variables, I re-construct observations for missing reserves data where possible; this increases number of valid observations for reserves for loan losses from 872 to 1,128. The summary of balance sheet and income statement variables is presented in Table 18.

TABLE 18 ABOUT HERE

From the table, we can see that loans represent the largest category for the sample of European banks – two thirds of the assets. Next are investments in securities, fixed assets, and cash. Although banks in the majority of countries exhibit similar asset structure, there are particularities for some of them. Banks in Belgium hold one fourth of the assets in cash, but give out just one third of assets in loans, far less than the sample average. Banks in Greece and Hungary tend to have significant amounts of cash as well, while in Sweden cash is less than 1% of assets. Leaders in investments are the Netherlands and Belgium, while Norway invests just 8.6% of assets in securities. As a compensation for that, Norwegian banks are the largest per asset lenders in the sample giving out 87% of assets in loans. In the Czech Republic loans are also above 80% of assets, but this is partially due to the high reserves for loan losses in this country – 4.7% - four times more than the sample average. Banks in Austria, Finland and Germany are financed largely by debt – leverage in those countries is larger than 50% in these countries; while Eastern European banks in Poland, Hungary and Czech Republic borrow far less than the sample average. In terms of return on assets, the most profitable banks in Europe are in Belgium, while Greece, Hungary and the Netherlands lead

on return on equity indicator. The least profitable banks in the sample are in Austria, Czech Republic and Germany. The largest banks by total assets are in France, Germany and the UK, but by market capitalization, UK banks are indisputable leaders. The smallest banks in Europe are in Finland, Hungary and Poland.

Table 18 shows that banks in Europe are different. Now let us look at the development of assets and liabilities structure of banks throughout the sample period as presented in the Table 19 and Figure 2.

TABLE 19 ABOUT HERE

FIGURE 2 ABOUT HERE

A visual analysis of variables by years reveals several pronounced trends in asset development. Banks significantly reduced their holdings of cash – from more than 12% of total assets in 1990 to about 2% in 2004. Loans grew from 62% to 70%. Investments also expanded from less than 17% to 21.7% in the same period; however, this increase was not monotonic. Another clear trend is the growth of banks in both total assets and market capitalization terms. Average total assets value grew from 25 million Euro equivalents in 1990 to more than 100 million in the new century. Market capitalization also changed the scale – from 1 million Euro to figures in 10 millions later in the sample. While there seem to be no clear trend for leverage value, banks on average became more profitable throughout the period.

4.2.2. Opaqueness variables regressions

If there are banking assets that are inherently opaque, then proxies for opaqueness shall increase in these assets. I run separate regression for each proxy to find opaque assets. Significant coefficients in regressions will indicate particular variables effect on analysts' forecast errors.

I run several regressions for the FE and SD opaqueness proxies:

(0) - a regression that includes only fixed effects;

(1) - a regression with fixed effects and control variables: natural logarithm of market capitalization, number of EPS estimates for banks and commission and fees amount;

(2) - a full regression with inclusion of all previous and asset composition variables.[17]

The comparison between adjusted R-square values for these regressions will show if adding new explanatory variables increases the power of the regression. Table 20 summarizes test results. I omit the first regression with fixed effects and their coefficients from other regressions to save space.

TABLE 20 ABOUT HERE

Asset structure and control variables have a stronger effect on forecast error (FE) than on dispersion measure (SD) variable. For forecast error, adding control variables increases the adjusted R-square from 33.8% to 36.4%, and adding asset variables further increases it to 36.9%. All these increases are significant at the 1% level (F-test for significance). One percent increase in market capitalization decreases error by 6.4% while each additional EPS estimate

[17] I also run separate regression for banks within and outside of the Eurozone. Results are very similar to the general regression.

decreases it by 0.3%. Commission and fees on clients' accounts also decrease the error. Since commission is a relatively stable source of revenues for a bank, the negative effect on the error is as expected - more predictability, less mistakes.

For asset variables omitted category is Cash and due from banks; therefore, coefficients on assets show how substitution from cash into those assets affects opaqueness proxies. An increase in investments in securities is positively correlated with the earnings forecast error. The transfer of funds from cash into volatile securities increases uncertainty of earnings. Each one perecnt transfer of total assets from Cash into Investments increases forecast error FE by 0.34%. A more pronounced effect on the error is for the Other assets category. As these assets are opaque, even by their name, it is not surprising that they have significant impact on the error at 5% level. Here one percent transfer from Cash into Other assets increases error by almost 0.7%. The hypothesis that all coefficients of the regression are jointly equal to zero is rejected at 1% level.

For the standard deviation SD variable, results are similar but less pronounced than for the forecast error. F-test of the significance of the adjusted R-squares for the regression with fixed effects is strongly significant at 1% level. However, test for the increase in adjusted R-square in regressions from adding asset structure is not significant. All coefficients have the same signs as for FE proxy, with market capitalization and number of EPS estmates being significant. The only significant assets is Other assets category which increases standard deviation proxy, just as it did for forecast error. F-test of the signifciance of coefficients rejects hypothesis that they jointly equal to zero at 1% level for all regressions.

Now let us analyse the results of the regression for the range forecast HL proxy. I run three regressions for this opaqueness proxy:

(1) – a regression with market capitalization, number of estimates and commission and fees account only;

(2) – a regression with control variables as in (1) and asset categories variables;

(3) – a full regression with all explanatory variables including earnings and forecasts volatilities.

The results of the binary logistic regression are presented in Table 21.

TABLE 21 ABOUT HERE

The assets and control variables have a significant effect on the range HL opaqueness proxy. Market capitalization, as in the previous regressions for FE and SD proxies, reduces opaqueness of banking earnings, but it becomes significant at 10% level only in the second and third models of regressions when additional variables are added. Each 1% increase in capitalization increases the chance of the correct range of forecasts approximately by 10%. More pronounced is the effect for the number of EPS estimates: each additional estimate increases the chance of the correct range forecast by around 3.5% and this effect is significant at 1% level in all regressions. This is reasonable, as with more forecasts, chances of the correct range increase.

Assets enter significantly in the regression confirming the fact that there are particularly opaque categories among them. An increase in reserves for loan losses indicates deterioration in asset quality and less certainty in banks earnings. Therefore, the negative effect of an increase in reserves on the correctness of forecast range is as expected. In the same way, an increase in Other assets significantly increases opaqueness for HL proxy, as it did for FE and SD proxies. Both effects are significant at 5% level.

At the 5% level of significance earnings and forecast volatilities increase the chance of the wrong range forecast as well. These results conform to previous findings that both variables increase opaqueness of banks for analysts. Commission and fees variable is significant only in the first model of regression

Empirical results of assets structure confirm the findings in previous papers by Flannery et al., Morgan and Iannotta that there are assets that are harder to understand for investors. Other assets category appears to be the most opaque among all assets as it increases all opaqueness proxies used. Investments in securities increase forecast error. Although loans themselves do not have significant coefficients, reserves for loan losses increase the proportion of out of the range forecasts. Banks that are larger and that attract more attention from the analysts' side, get better quality forecasts overall. Forecast error and standard deviation for them are smaller and EPS forecast range is significantly more precise. Earnings volatility is positively related to the opaqueness of banks' earnings.

4.2.3. Test of banking structure and regulations on bank opaqueness

Banking structure and regulation can influence bank opaqueness. Comparative statistics on bank opaqueness proxies based on the dummies developed form the World Bank database is presented in Table 22.

TABLE 22 ABOUT HERE

For two of the opaqueness proxies – forecast error FE and standard deviation of forecasts SD – differences between values of opaqueness proxies are significant for all banking structure and regulation groups. Countries with higher degree of bank importance have lower forecast

error and standard deviation of forecasts. This is as expected as analysts in countries where banks play a more important role, will pay more attention to them. Bank concentration has an increasing effect on the two variables. It seems that less competition leads to an increased difficulty of analysts' work. Government ownership increases these opaqueness proxies as well. Such effect is consistent with previous studies on the contradictory role of government as the owner. Moral hazard resulting from overreliance on deposit insurance increases opaqueness proxies. Both FE and SD variables are higher for countries with higher coverage ratio for deposits. Finally, countries with better corporate governance have significantly lower FE and SD values.

Differences for HL range proxy are significant only for two variables with somehow puzzling results. HL proxy is significantly lower for higher degrees of bank concentration and government ownership in banks which contradicts results for two other proxies. As discussed before, higher degree of concentration can help analysts as well, as they have to analyse less banks and pay more attention to the remaining ones. In the same way, government ownership can result in more stable earnings. As HL proxy measures the fact that at least one forecast is correct, the lower values of this proxy could mean that for some analysts, more concentration and larger proportion of government ownership make earnings of banks more predictable.

Comparison shows that two of opaqueness proxies – forecast error FE and standard deviation SD - differ depending on the state of banking structure and regulation, and the difference is as expected from the theory. In order to see if this effect is not due to the difference in market capitalization or other variables that affected proxies in prior tests, I run the following regressions for FE and SD opaqueness proxies:

$$Y_i = a_0 + c_i \ln MV_i + s_i NES_i + d_i CF_i + \sum_k b_k BS_{ki} + f_k EPS\_vol_k + w_k FOR\_vol_k + REG_k + e_i$$

where

Y_i – opaqueness proxy for observation i, consequently FE or SD variables;

$\ln MV_i$ – natural logarithm of market capitalization for bank observation *i*;

NES_i – number of annual EPS estimates for bank observation *i*;

CF_i - Commission and Fees on clients' accounts;

BS_{ki} – balance sheet asset variable for asset *k* and bank *i*;

EPS_vol_k – annual volatility of EPS for bank *k*;

FOR_vol_k – annual volatility of EPS forecasts for bank *k*;

REG_k - bank structure and regulation variable: BIP, CON, GOV, RES, MOH or CG.

I add explanatory variables in steps in order to see if the R-square increases are significant. Therefore, I run four regressions for each opaqueness measure:

(1) - a regression with natural logarithm of market capitalization, number of EPS estimates and commission and fees on clients' accounts;

(2) - a regression with inclusion of variables from (1) and asset variables;

(3) - a regression with variables from (2) and earnings and forecast volatilities data;

(4) - a full regression with all explanatory variables included.

Results of the regressions for forecast error FE and standard deviation SD are presented in Table 23.

TABLE 23 ABOUT HERE

Regression results support previous comparison of opaqueness proxies. For brevity, I report only results for the last regression for each variable. For the forecast error FE, only one banking regulation variable enters the regressions significantly. Higher moral hazard by investors and banks resulting from high deposits coverage ratio increases forecast error. Adjusted R-square grows significantly when moral hazard dummy is added in regression.

Market capitalization and commission and fees mitigate the error, while movements of assets from cash into securities, reserves for loan losses and other assets increase it. Earnings volatility continues to increase forecast error as in previous regressions. Forecasts volatility decreases error in some cases which is hard to explain. Overall, F-test rejects zero hypotheses that all coefficients are jointly equal to zero for all regressions.

Banking structure and regulation variables play even a more important role for the standard deviation of forecasts SD. These variables are significant in all regressions and significantly increase adjusted R-square. Increased bank importance and better corporate governance decrease standard deviation, while higher concentration, larger government ownership and higher degree of moral hazard tend to increase it. Market capitalization, number of estimates and commission and fees decrease SD proxy. The major difference with the previous regressions comes from the sign of the coefficient for net loans. For four out of six banking structure and regulation variables regressions it decreases the standard deviation of forecasts. One of the reasons for such results can be herding behaviour of analysts. The SD proxy measures the disagreement between analysts on EPS estimate, but it does not measure forecast relation to the actual EPS. Analysts may have incentives not to deviate from others in order to decrease risks of the incorrect forecast. Therefore, an increase in loans may signal more complexities in earnings valuation, and analysts may follow each other's forecast, thus decreasing standard deviation of forecasts. In order to analyse this issue further, we will need to have better data on each analyst' EPS forecast.

5. Conclusion

This paper provides results that have importance in three dimensions. First, opaqueness for banking and non-banking companies is compared in the European setting. Second, tests of the banking assets structure effect on the opaqueness are performed. Finally, the issue of whether there are particular characteristics of banking structure and regulation that influence bank opaqueness is empirically investigated.

The opaqueness of banking assets is measured by earnings forecast errors, standard deviation of analysts' forecasts and by the EPS range variable. Empirical results suggest that when banks are compared with the whole sample of non-banking companies, they have lower opaqueness proxies in mean values. Multivariate regressions support the result. Banks, however, are more opaque when they are compared to the sample of non-banking companies matched by the market capitalization. They have larger earnings forecast errors and standard deviation of EPS forecasts. Multivariate regressions support this difference only for standard deviation proxy. In countries that did not adopt Euro at the time of observation, banks continue to show increased opaqueness as compared to non-banking companies. However, for countries-members of the Eurozone, banks do not show particular opaqueness. This means that countries that created European Monetary Union enjoy better transparency in the banking field than other countries in Europe, as analysts are able to predict banking earnings at least as good as for non-banking companies.

Asset composition variables explain a significant portion of the opaqueness proxies for banks. Substitution from cash into more opaque assets such as investments in securities and other assets categories increases forecast errors. An increase in reserves for loan losses decreases

the chance of obtaining correct EPS forecast range. Market capitalization, number of EPS estimates and commission and fees amount decrease uncertainty of earnings.

Banking structure and regulation have an impact on bank opaqueness. Countries with higher bank importance and better bank corporate governance have lower forecast error and standard deviation of EPS forecasts. Larger concentration of banking assets, larger governmental share of assets, and higher degree of moral hazard resulting from deposit insurance result in higher forecast errors and standard deviations of forecasts.

Overall, the results presented in this paper have relevant policy implications. Banks can be an opaque industry by the inherent nature of their assets. This opaqueness can be decreased by the proper regulation and efficient structure of the banking system. Better corporate governance and improved access by investors to data can lower the potential opaqueness of banks and thus improve resource allocation in the economy.

Future research can aim to solve the question of bank opaqueness by using cross-country comparison of banks around the world and by refining opaqueness proxies. An interesting direction for further analysis is represented by the impact of the Euro introduction on the transparency of companies in the Eurozone.

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Tables and figures

Table 1
SUMMARY OF ARTICLES ON COMPARISON OF OPAQUENESS OF BANKS AND NON-BANKING COMPANIES

Authors	Opaqueness Proxy	Conclusion
Flannery, Kwan, Nimalendran (2004)	i) Microstructure variables - bid-ask spread, trading activity and return volatility - for a sample of U.S. traded companies in 1990-1997	Banks in the U.S. are not particularly different in their opaqueness from non-banking companies. Asset composition has an effect on opacity proxies; however, it has equal explanatory power as microstructure variables. For earnings forecast errors, asset composition matters the most for mean forecast error and standard deviation of forecasts.
	ii) EPS forecast data: mean forecast error, standard deviation of forecasts, number of forecast revisions and number of analysts following the company	
Morgan (2002)	Probability of disagreement between S&P and Moody's for bond issues in the U.S. in 1983-1993	Banks in the U.S. represent particularly opaque industry. Probability of the disagreement between rating agencies on banking issues is higher. The opacity of banks is inherent in their asset composition.
Iannotta (2006)	Probability of disagreement between S&P and Moody's on bonds issued in 14 European countries in 1993-2003	Banking is one of the most opaque industries in Europe. After controlling for risk, split rating probability is higher for banks. Asset composition affects disagreement between agencies.

Table 2
SUMMARY OF ARTICLES ON THE BALANCE SHEET COMPOSITION TEST OF BANK OPAQUENESS

Authors	Dependent Variable	Evidence of understanding of bank financial position by investors
Billett, Garfinkel and O'Neal (1998)	Abnormal returns for Moody's downgrade announcements for U.S. banks in 1990-1995	Yes, negative returns are lower for banks that rely more on insured deposits.
Evanoff and Wall (2001)	CAMEL and BOPEC regulatory ratings for U.S. banks issued in 1983-1991	Mixed evidence. Capital ratios and spreads help to predict supervisory ratings.
Flannery and Rangan (2004)	Bank capital ratio for largest U.S. banks in 1986-2001	Yes, capital ratio had been increasing in response to increased risk of banks' portfolios.
Flannery and Sorescu (1996)	Spread for subordinated issues for U.S. banks in 1983-1991	Yes, spread is positively related to risk as measured by accounting variables, particularly after removal of TBTF guarantees.
Gropp, Vesala and Vulpes (2006)	Bonds downgrading to junk status by Fitch IBCA individual bank strength rating of EU banks issues since 1991	Yes-distance to default can predict downgrades up to 18 months in advance. Spreads for subordinated issues are effective only close to downgrade event.
Jagtiani, Kaufman and Lemieux (2002)	Spread for subordinated issues on secondary markets for U.S. banks in 1992-1997	Yes, spread depends on bank's risk as measured by accounting variables, and credit and regulatory ratings.
Krainer and Lopez (2004)	BOPEC regulatory ratings for U.S. banks for 1990-1999	Yes, balance sheet and equity market variables can predict BOPEC rating up to four quarters in advance.
Krishnan, Ritchken and Thomson (2005)	Spread for transactions for banks bonds in the U.S. in 1994-1999	Partial evidence. Level of risk is reflected in spreads, but change in risk is not reflected in changes in spreads.
Morgan and Stiroh (2001)	Spread at issuance for bank bonds in 1993-1998 in the U.S.	Yes, spread increases as bank increases proportion of risky loans in portfolio.
Nier and Baumann (2006)	Bank capital ratio for banks from 32 countries in 1993-2000	Yes, as risk increases, banks rely more on their capital.
Sironi (2003)	Spread at issuance for European subordinated debt issues in 1991-2000	Yes, spread depends on the financial profile of a bank.

Table 3
SUMMARY OF ARTICLES ON ANALYSTS' EARNINGS FORECASTS

Authors	Dependent variable	Relevant conclusions	Sample
Basu, Hwang, Jan (1998)	Forecast error standardized by stock price	A greater alignment between tax and financial accounting, accrual basis accounting and more choice in accounting methods are negatively correlated with errors.	1987-94, 10 countries
Beckers, Steliaros, Thomson (2004)	Forecast error standardized by actual EPS	Error increases with forecast dispersion and stock volatility and decreases with number of analysts following the company.	1983-92, 10 European countries
Brown (1997)	Forecast error standardized by actual and forecast EPS	Forecast errors and optimistic bias decrease over the time. Size, forecast EPS value and numbers of analysts mitigate errors.	1985-96, the U.S.
Capstaff, Paudyal, Rees (1995)	Forecast error standardized by actual EPS	Analysts have an optimistic bias; forecasts are more accurate closer to the announcement day.	1987-93, the UK
Capstaff, Paudyal, Rees (1998)	Forecast error standardized by actual EPS	Optimistic bias in forecasts; analysts are more precise at a short time horizons. Mean error in Germany is higher than in the UK, but optimistic bias is smaller.	1987-95, Germany
Capstaff, Paudyal, Rees (2001)	Forecast error standardized by actual EPS	Optimistic bias in forecasts; analysts are more precise at a short time horizons. Mean errors vary by country.	1987-94, 9 European countries
Dreman, Berry (1995)	Forecast error standardized by actual and forecast EPS; other measures	Analysts' forecasts errors are too large to be relied upon by investment community. Optimistic bias in forecasts.	1974-90, the U.S.
Fan, So, Yeh (2006)	Forecast error standardized by forecast EPS	Forecast error is larger for insurance companies prior to 1993 and is smaller thereafter. Error decreases for insurance companies in size of the company and number of analysts and increases with disagreement between analysts.	1989-98, the U.S.

Table 4
COMPANIES IN THE SAMPLE BY INDUSTRY

Summary of companies in the sample according to the WorldScope industry classification. Data for all companies included in the sample for 1990-2004.

Industry Code	Number of companies	% of total
Industrial	2782	79.39%
Utility	129	3.68%
Transportation	89	2.54%
Banks	171	4.88%
Insurance	73	2.08%
Other Financial	260	7.42%
Total	3504	100.00%

Table 5
OPAQUENESS PROXIES DESCRIPTION

Opaqueness proxy	Definition	Formula	Relation to Opaqueness
Forecast Error, FE	The absolute value of the difference between mean forecast estimate and actual annual earnings for companies in the sample.	$FE = \frac{\lvert Forecast\ EPS - Actual\ EPS \rvert}{Actual\ EPS}$	The higher FE, the more opaque company is.
Standard Deviation of forecasts, SD	Standard deviation of earnings forecasts for each company-year (calculated only when two or more estimates are available).	$SD = \frac{\text{Standard Deviation } of\ \ forecasts}{Actual\ \ EPS}$	The higher SD, the more opaque company is.
Range Forecast, HL	Equals to zero if the actual EPS data falls between highest and lowest earnings forecasts and unity otherwise. This variable shows if analysts are able at least to forecast the range of the actual EPS correctly.	HL={0, if Low EPS forecast < <Actual EPS < High EPS forecast, and 1 otherwise}	The higher proportion of HL variables equal to unity indicates higher degree of opaqueness.

Table 6
SUMMARY OF COMPANIES IN THE SAMPLE BY THE COUNTRY OF ORIGIN

Summary of companies in the sample by their countries of origin.

FE - a standardized earnings forecast error, computed as the absolute value of the difference between mean forecast estimate and actual annual earnings for companies in the sample standardized by the actual EPS value.
SD - standard deviation of earnings forecasts for each company-year (calculated only when two or more estimates are available) standardized by the actual EPS value.
HL - a proportion of forecasts when analysts did not define the range of the actual EPS correctly (it is based on the dummy variable that equals to zero if the actual EPS data falls between highest and lowest earnings forecasts and unity otherwise). The higher value of this variable indicates higher degree of opaqueness for the company.
NES - a number of annual EPS forecasts for a company.
FES - a signed forecast error or bias in analysts' forecasts computed as a difference between mean forecast estimate and actual EPS standardized by actual EPS value.

All values except number of companies and observations are averaged over the 1990-2004 period.
Market value and total assets figures are presented in thousands of Euro equivalents.
Outliers for forecast error FE and standard deviation SD were cut off at 95% level.

Country	Number of companies		Number of observations		Market Value, 000	Total Assets, 000	FE, %	SD, %	HL, %	NES	FES
	Non-banks	Banks	Non-banks	Banks							
UK	939	17	7800	158	2,025	5,625	30	9.2	78	5.94	2.29
Poland	47	12	190	58	382	1,610	43.1	21.7	69	5.58	1.64
Belgium	88	3	659	33	1,420	12,951	30.6	15.6	52	7.29	1.07
Denmark	112	22	970	172	492	2,613	43	19.7	76	5.15	0.76
France	467	12	3311	72	2,419	9,808	34.8	14.9	69	8.39	0.03
Germany	341	9	2537	62	2,678	13,494	36.7	14.9	69	11.58	-0.27
Italy	174	30	1230	230	2,282	13,181	37.3	18.8	57	8.81	0.53
Netherlands	134	5	1397	61	2,940	12,373	22.9	10.4	55	13.49	1.18
Norway	100	5	615	26	644	2,250	60.1	18.5	79	6.26	0.25
Sweden	210	5	1356	45	1,210	5,201	49.7	18.2	77	6.1	0.18
Switzerland	157	11	1606	129	2,697	12,984	27.2	15.4	48	8.25	0.67
Austria	52	5	427	44	477	3,395	23.1	14.6	53	5.11	0.13
Greece	205	11	1308	92	360	1,390	45.3	23.4	66	3.95	0.64
Hungary	25	2	143	15	541	1,056	37.8	19	58	8.18	5.76
Portugal	38	5	271	41	1,124	4,841	48.6	17.7	72	6.58	0.21
Spain	104	14	969	146	2,337	9,146	24.1	14.3	47	12.49	1.23
Finland	118	2	833	27	1,407	1,738	36.9	16.6	67	7.13	0.2
Czech Republic	22	1	106	9	585	2,399	47.9	23.5	70	5.71	16.21
Total	**3333**	**171**	**25728**	**1420**	**1,929**	**7,786**	**34.1**	**14.2**	**68**	**7.72**	**1.07**

Table 7
SUMMARY OF SIGNED EPS FORECAST ERRORS FOR BANKS AND NON-BANKING COMPANIES

Summary statistics for signed forecast error computed as:

FES = (mean EPS estimate-actual EPS)/actual EPS

KS test is Kolmogorov-Smirnov test for the normality of distribution. Kurtosis is excess kurtosis.

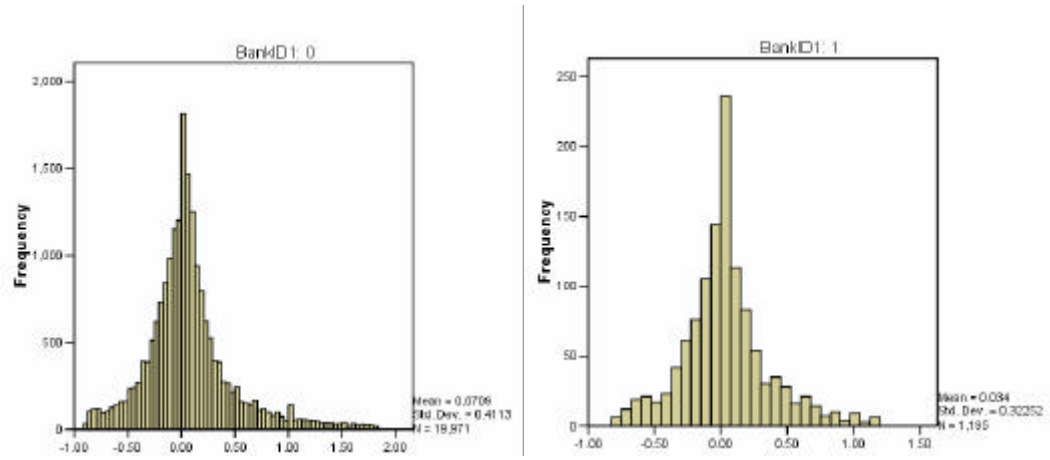
FES	Obs.	Mean	Median	Minimum	Maximum	Std. Deviation	Skewness	Kurtosis	KS test
Non-banks	19971	0.070	0.027	-0.89	1.82	0.4113	1.064	2.617	.000
Banks	1195	0.034	0.013	-0.8	1.17	0.3225	0.538	1.378	.000

FIGURE 1
DISTRIBUTIONS OF SIGNED EPS FORECAST ERRORS FOR BANKS AND NON-BANKING COMPANIES

Histogram of signed EPS forecast error (forecast bias) for banks and non-banking companies in the sample.

FES = (mean EPS estimate-actual EPS)/actual EPS

Y-axis shows number of observations, X-axis shows signed error. Data presented for the 1990-2004 period.



EPS forecasts for non-banking companies EPS forecasts for banks

Table 8
BANKING SYSTEM STRUCTURE AND REGULATION FOR COUNTRIES IN THE SAMPLE

Selected information from the World Bank survey database on banking structure and regulation for countries in the sample. Data for US banks is presented for comparison purposes. Data represents information primarily for 1999. Description and classifications of dummy variables in grey are provided in Table 5.

Country	Bank Assets/ GDP (%)	Bank Importance Dummy	% of Bank Assets in Top 3 Banks	Concentration Dummy	% of Bank Assets Government-Owned	Government Ownership Dummy	Coverage Ratio Limit/GDP per Capita	Moral Hazard Dummy	Corporate Governance Index	Corporate Governance Dummy
UK	311.1	**2**	16.2	**1**	0	**1**	1	**1**	11	**2**
Poland	54.5	**1**	39.7	**1**	43.7	**2**	0	**1**	9	**1**
Belgium	315.1	**2**	57.4	**2**	0	**1**	1	**1**	10	**2**
Denmark	121.4	**1**	73.6	**2**	0	**1**	1	**1**	11	**2**
France	146.8	**1**	42.4	**1**	8.7	**1**	3	**2**	8	**1**
Germany	313.3	**2**	17.7	**1**	42	**2**	1	**1**	10	**2**
Italy	150.5	**1**	37.1	**1**	17	**2**	6	**2**	7	**1**
Netherlands	357.6	**2**	79.0	**2**	5.9	**1**	1	**1**	10	**2**
Sweden	128.9	**1**	69.0	**2**	0	**1**	1	**1**	9	**1**
Switzerland	538.9	**2**	67.1	**2**	15	**2**	1	**1**	12	**2**
Greece	100.2	**1**	59.2	**2**	13	**2**	2	**2**	9	**1**
Portugal	238.3	**2**	34.2	**1**	20.8	**2**	1	**1**	11	**2**
Spain	155.8	**1**	44.0	**1**	0	**1**	1	**1**	10	**2**
Finland	75.3	**1**	97.2	**2**	21.9	**2**	1	**1**	12	**2**
Czech Republic	124.9	**1**	46.3	**1**	19	**2**	-	**-**	8	**1**
Austria		**-**	38*	**1**	4	**1**	-	**-**	-	**-**
Hungary		**-**	-	**-**	3	**1**	-	**-**	-	**-**
Average	**208.8**		**52.0**		**12.6**		**1.5**		**9.8**	
United States	65.9		21.5		0		3		11	

Source: Barth, Caprio and Nolle, 2004
* Data for Austria is from Barth, Caprio and Levine, 2001, and indicate percent of deposits in top five banks in the country.

Table 9
DESCRIPTION OF BANKING SYSTEM STRUCTURE AND REGULATION VARIABLES

Summary of banking structure and regulation variables based on the information from the World Bank and Barth, Caprio and Nolle, 2004.

##	Bank structure and regulation variable	Variable description	Potential effect on bank opaqueness
1	Bank Importance Category, BIP	Equals unity if Bank Assets/GDP ratio is less than 200% and two otherwise	Higher value results in lower opaqueness
2	Bank Concentration Category, CON	Equals unity if top 3 banks hold less than 50% of all banking assets and two otherwise	Can have an increasing as well as a decreasing effect on bank opaqueness
3	Government Ownership Category, GOV	Equals unity if government holds less than 10% of banking assets and two otherwise	Higher value results in higher opaqueness
4	Moral Hazard Category, MOH	Equals unity if deposit coverage/GDP per capita ratio is less or equal to 1 and two otherwise	Higher value results in higher opaqueness
5	Corporate Governance Category, CG	Equals unity if corporate governance index is less than 10 and two otherwise	Higher value results in lower opaqueness

Table 10
SUMMARY OF ACTUAL EPS AND FORECAST VARIABLES FOR ALL OBSERVATIONS

Data for observations for banks and non-banking companies for 1990-2004.
EPS - actual earnings per share.
Mean EPS - the average of EPS estimates by analysts.
High and Low - accordingly, the highest and lowest annual EPS forecasts by analysts.
St. Dev. EPS - standard deviation of analysts' forecasts.
Price - beginning of year stock price.
NES - number of annual EPS forecasts.
MV and TA - market capitalization and total assets values in thousands of Euro equivalents.

Variables	Non-banks				Banks			
	N	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.
EPS	22184	**9.41**	1.34	47.0	1420	**8.39**	1.00	22.3
Mean EPS	22184	**9.16**	1.42	174.0	1420	**8.02**	0.99	22.8
High	22180	**10.94**	1.72	112.7	1419	**8.96**	1.17	25.1
Low	22180	**7.09**	1.17	294.2	1419	**7.06**	0.80	20.7
St.dev EPS	17383	**2.02**	0.20	103.2	1156	**0.92**	0.11	3.9
Price	22182	**159.62**	25.89	1,030.9	1420	**125.09**	13.39	334.6
NES	22184	**7.59**	5.00	7.8	1420	**9.49**	6	9.2
MV, 000	22182	**1,470**	154	7,123	1420	**4,829**	803.14	12,345
TA, 000	21710	**2,142**	250	8,360	1383	**73,570**	10,757	151,998

Table 11
COMPARISON OF OPAQUENESS PROXIES FOR BANKING AND NON-BANKING COMPANIES IN EUROPE

Opaqueness proxy variables are:

FE - standardized earnings forecast error, computed as the absolute value of the difference between mean forecast estimate and actual annual earnings for companies in the sample standardized by the actual EPS value.
SD - standard deviation of earnings forecasts for each company-year (calculated only when two or more estimates are available) standardized by the actual EPS value.
HL- proportion of forecasts when analysts did not define the range of the actual EPS correctly (it is based on the dummy variable that equals to zero if the actual EPS data falls between highest and lowest earnings forecasts and unity otherwise). The higher value of this variable indicates higher degree of opaqueness for the company.
NES†- number of annual EPS forecasts for the company.

Mean values are averages for the 1990-2004 period. MW test is Mann-Whitney signed ranks non-parametric test. Median test is a non-parametric median test. Figures in MW Test and Median test columns show p-values for the comparison of means for banks and non-banking companies. *, ** and *** indicate significant differences between mean and medians for banks and non-banking companies respectively at 10%, 5% and 1% levels.

Opaqueness Proxy	Number of observations		Mean		MW Test	Median		Median Test
	Non-bank	Bank	Non-bank	Bank		Non-bank	Bank	
FE	18093	1261	0.35	0.27***	0.000	0.190	0.16***	0.000
SD	14865	1041	0.14	0.13*	0.056	0.086	0.096***	0.000
HL	22180	1419	0.69	0.59***	0.000	1	1	-
NES	22184	1420	7.59	9.49***	0.000	5	6***	0.000

† I do not explicitly use number of estimates NES variable as opaqueness proxy, but rather provide results for comparison purposes.

Table 12
MULTIVARIATE TEST OF BANK OPAQUENESS FOR EPS FORECAST ERROR AND STANDARD DEVIATION VARIABLES

Estimation of the regression:

$$Y_i = a_0 + d_k Bank\,ID_k + c_i \ln MV_i + s_i NES_i + f_k EPS\_vol_k + w_k FOR\_vol_k + g_{\tilde{n}} D_c + n_y D_y + e_i$$

where

Yi – opaqueness proxy for observation i, consequently FE or SD variables;
Bank ID_k - dummy variable that equals 1 if company k is a bank and 0 otherwise;
ln MV_i – natural logarithm of market capitalization for company observation i;
NES_i – number of annual EPS estimates for company observation i;
EPS_vol_k – annual EPS volatility for company k;
FOR_vol_k – annual volatility of EPS forecasts for company k;
D_c and D_y – dummies for country c and year y respectively.
Description of FE and SD opaqueness proxies is provided in Table 11.

Asterisks for adjusted R-square statistics represent F-test of increase in R-squares from adding new variables.
F-test – F statistic for the hypothesis that all explanatory variables in the regression are jointly zero.
T-statistics are in parentheses. *, ** and *** indicate significance respectively at 10%, 5% and 1% levels.

Explanatory variables	FE forecast error			SD forecast standard deviation		
	1	2	3	1	2	3
ln Market Value	-0.024***	-0.021***	-0.022***	-0.014***	-0.014****	-0.014***
	-(10.303)	-(9.148)	-(9.253)	-(14.782)	-(13.961)	-(13.98)
Number of Estimates	-0.003***	0.003***	-0.003***	0	0	0
	-(4.607)	-(5.080)	-(4.929)	-(0.253)	-(0.448)	-(0.409)
Bank ID		-0.047***	-0.046***		-0.007	-0.007
		-(3.835)	-(3.749)		-(1.476)	-(1.342)
Earnings Volatility			0***			0
			(4.234)			(1.109)
Forecasts Volatility			0.003***			0.001***
			(7.973)			(7.359)
Adjusted R^2, year and country dummies	0.038***			0.076***		
Adjusted R^2	0.059***	0.06***	0.064***	0.103***	0.103	0.106***
F-test	37.464***	36.821***	37.194***	55.772***	54.2***	52.904***
Number of observations	19062	19062	19062	15840	15840	15840

Table 13
MULTIVARIATE TEST OF BANK OPAQUENESS FOR HL RANGE INDICATOR PROXY

Estimation of the binary logistic regression:

$$HL_i = f\,(Bank\ ID_k,\ ln\ MV_i,\ NES_i,\ EPS\_vol_k,\ FOR\_vol_k,\ Country,\ Year)$$

where

HLi – value of HL opaqueness proxy for observation i;
Bank ID_k - dummy variable that equals 1 if company k is a bank and 0 otherwise;
ln MV_i – natural logarithm of market capitalization for company observation i;
NES_i – number of annual EPS estimates for company observation i;
EPS_vol_k – annual volatility of EPS for company k;
FOR_vol_k – annual volatility of EPS forecasts for each company k;
Country – dummy for country;
Year - dummy for year

Wald-test for coefficients are in parentheses.
*, ** and *** indicate significance respectively at 10%, 5% and 1% levels.

Explanatory variables	HL range indicator		
	1	2	3
ln Market Value	-0.021***	-0.018**	-0.017
	(3.167)	(2.164)	(1.948)
Number of Estimates	-0.072***	-0.072***	-0.072***
	(550.341)	(545.425)	(538.326)
Bank ID		-0.067	-0.053
		(1.086)	(0.690)
Earnings Volatility			0
			(0.365)
Forecasts Volatility			0.016***
			(31.404)
Nagelkerke R Square	0.154	0.154	0.157
Number of observations	22001	22001	22001

Table 14
COMPARISON OF CHARACTERISTICS FOR STRATIFIED SAMPLES OF BANKING AND NON-BANKING COMPANIES

Mean and median market capitalization and stock price data for banking and non-banking companies samples for 1990-2004. Market capitalization is expressed in thousands of Euro equivalents. MW test is a Mann-Whitney signed ranks non-parametric test. Median test is a non-parametric median test. Figures in MW Test and Median test columns show p-values for the mean and median comparison tests for banks and non-banking companies.
*, ** and *** indicate significant differences between mean and medians for banks and non-banking companies respectively at 10%, 5% and 1% levels.

Variable	Number of observations	Mean			Median		
		Non-banks	Banks	MW Test	Non-banks	Banks	Median Test
Market Value, 000	1407	4,195	4,778	0.437	752,750	797,990	0.763
Stock Price	1407	130.67	126.13	0.203	14.78	13.42	0.258

Table 15
COMPARISON OF ALTERNATIVE OPAQUENESS PROXIES FOR STRATIFIED SAMPLES OF BANKING AND NON-BANKING COMPANIES

Opaqueness proxy variables are:

FEP - standardized earnings forecast error, computed as the absolute value of the difference between mean forecast estimate and actual annual earnings for companies in the sample standardized by the share price of the company at the beginning of the year.
SDP - standard deviation of earnings forecast for each company-year (calculated only when two or more estimates are available) standardized by the share price of the company at the beginning of the year.
HL - proportion of forecasts when analysts did not define the range of the actual EPS correctly (it is based on the dummy variable that equals to zero if the actual EPS data falls between highest and lowest earnings forecasts and unity otherwise). The higher value of this variable indicates lower degree of opaqueness for the company.
NES† - number of annual EPS forecasts for the company.

Mean values are averages for the 1990-2004 period. MW test is Mann-Whitney signed ranks non-parametric test. Median test is a non-parametric median test. Figures in MW Test column show p-values for the comparison tests for banks and non-banking companies. *, ** and *** indicate significant differences between mean and medians for banks and non-banking companies respectively at 10%, 5% and 1% levels.

Opaqueness Proxies	Number of observations	Mean			Median		
		Non-bank	Bank	MW Test	Non-bank	Bank	Median Test
FEP	1250	0.0214	0.0224*	0.081	0.0112	0.0127**	0.034
SDP	994	0.0084	0.0097***	0	0.0057	0.0075***	0
HL	1407	0.59	0.59	0.818	1	1	-
NES	1407	12.31	9.46***	0	10	6***	0

† I do not explicitly use number of estimates NES variable as opaqueness proxy, but rather show results for comparison purposes

Table 16
MULTIVARIATE TEST OF BANK OPAQUENESS FOR ALTERNATIVE EPS FORECAST ERROR AND STANDARD DEVIATION VARIABLES

Estimation of the regression:

$$Y_i = a_0 + d_k Bank\,ID_k + c_i \ln MV_i + s_i NES_i + f_k EPS\_vol_k + w_k FOR\_vol_k + g_{\tilde{n}} D_c + n_y D_y + e_i$$

where

Yi – opaqueness proxy for observation i, consequently FE or SD variables;
Bank ID_k - dummy variable that equals 1 if company k is a bank and 0 otherwise;
ln MV_i – natural logarithm of market capitalization for company observation i;
NES_i – number of annual EPS estimates for company observation i;
EPS_vol_k – annual volatility of EPS for company k;
FOR_vol_k – annual volatility of EPS forecasts for each company k;
D_c and D_y – dummies for country c and year y respectively
Description of FE and SD opaqueness proxies is provided in Table 11

Asterisks for adjusted R-square statistics represent F-test of increase in R-squares from adding new variables;
F-test – F statistic for the hypothesis that all explanatory variables in the regression are jointly zero.
T-statistics are in parentheses. *, ** and *** indicate significance respectively at 10%, 5% and 1% levels.

Explanatory variables	FEP forecast error			SDP forecast standard deviation		
	1	2	3	1	2	3
ln Market Value	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-3.12)	(-3.252)	(-3.365)	(-4.545)	(-5.273)	(-5.323)
Number of Estimates	0*	0	0	0	0	0
	(-1.948)	(-1.615)	(-1.385)	(-0.286)	(0.77)	(0.885)
Bank ID		0.001	0.001		0.001***	0.001***
		(0.955)	(1.086)		(3.983)	(3.875)
Earnings Volatility			0			0
			(0.84)			(1.058)
Forecasts Volatility			0			0
			(1.605)			(0.263)
Adjusted R^2, year and country dummies	0.127***			0.126***		
Adjusted R^2	0.141***	0.141	0.142	0.143***	0.15***	0.149
F-test	13.233***	12.87***	12.258***	10.954***	11.18***	10.589***
Number of observations	2452	2452	2452	1966	1966	1966

Table 17
MULTIVARIATE TEST OF BANK OPAQUENESS FOR ALTERNATIVE OPAQUENESS PROXIES BASED ON THE EUROZONE MEMBERSHIP

Estimation of the regression:

$$Y_i = a_0 + d_k Bank\,ID_k + c_i \ln MV_i + s_i NES_i + f_k EPS\_vol_k + w_k FOR\_vol_k + g_{\tilde{n}} D_c + n_y D_y + e_i$$

where

Yi – opaqueness proxy for observation i, consequently FE or SD variables;
Bank ID_k - dummy variable that equals 1 if company k is a bank and 0 otherwise;
ln MV_i – natural logarithm of market capitalization for company observation i;
NES_i – number of annual EPS estimates for company observation i;
EPS_vol_k – annual volatility of EPS for company k;
FOR_vol_k – annual volatility of EPS forecasts for each company k;
D_c and D_y – dummies for country c and year y respectively
Description of FE and SD opaqueness proxies is provided in Table 11

Two groups are based on the division of the observations in the sample by Eurozone membership:
- Group 1 – 11 European countries which adopted Euro from 1999 (Belgium, Germany, Spain, France, Ireland, Italy, Luxembourg, the Netherlands, Austria, Portugal and Finland) and Greece from 2001;
- Group 2 – all other countries.

Asterisks for adjusted R-square statistics represent F-test of increase in R-squares from adding new variables;
F-test – F statistic for the hypothesis that all explanatory variables in the regression are jointly zero.
T-statistics are in parentheses. *, ** and *** indicate significance respectively at 10%, 5% and 1% levels.

Explanatory variables	FEP forecast error				SDP standard deviation			
	Non-Euro group		Euro Group		Non-Euro group		Euro Group	
	1	2	1	2	1	2	1	2
ln Market Value	-0.002***	-0.002***	-0.001	-0.001	-0.001***	-0.001***	0	0
	-(3.183)	-(3.537)	-(1.171)	-(0.838)	-(4.559)	-(5.429)	-(1.513)	-(1.527)
Number of Estimates	0	0	0*	0**	0	0**	0	0
	-(0.575)	-(0.011)	-(1.912)	-(2.196)	(0.795)	(1.979)	-(1.060)	-(0.945)
Earnings Volatility	0	0	0	0	0	0	0	0
	(1.014)	(0.840)	(0.396)	(0.451)	(1.447)	(0.971)	(1.002)	(0.990)
Forecasts Volatility	0	0	0.001***	0.001***	0	0	0***	0***
	(0.967)	(1.224)	(3.119)	(2.841)	-(0.866)	-(0.237)	(2.873)	(2.862)
Bank ID		**0.002****		**-0.002**		**0.002*****		**0**
		(2.002)		-(1.243)		(4.60)		(0.239)
Adjusted R^2, year and country dummies	0.131***		0.054***		0.146***		0.086***	
Adjusted R^2	0.143***	0.145**	0.085***	0.086	0.163***	0.175***	0.115***	0.113
F-test	9.563***	9.425***	4.387***	4.241***	9.126***	9.586***	4.673***	4.422***
Number of observations	1793	1793	658	658	1456	1456	509	509

Table 18
SUMMARY OF BALANCE SHEET AND INCOME STATEMENT VARIABLES FOR BANKS BY COUNTRY

Average values for 1990-2004 by country from the WorldScope database.
Balance sheet and income statement variables are standardized by their total assets values for each bank.
Figures for total assets and market capitalization are in thousands of Euro equivalents.

Country	Cash	Investments	Loans	Net Loans	Reserves for Loan Losses	Fixed Assets	Unconsolid. Subsidiaries	Other Assets	Total Assets, 000
UK	3.1%	20.7%	65.8%	64.0%	1.8%	4.6%	0.3%	10.2%	157,139
Poland	4.3%	22.2%	67.7%	65.6%	2.5%	10.2%	1.0%	3.7%	5,467
Belgium	25.9%	28.8%	38.9%	37.9%	0.2%	3.0%	3.3%	5.2%	127,061
Denmark	4.1%	20.3%	71.0%	70.5%	0.9%	4.0%	0.4%	2.6%	12,648
France	2.1%	24.3%	63.8%	63.0%	1.5%	5.2%	0.9%	8.5%	223,400
Germany	1.4%	22.2%	73.0%	72.3%	0.7%	1.1%	0.4%	2.9%	246,247
Italy	3.1%	21.2%	67.5%	66.0%	1.5%	7.9%	0.7%	7.1%	53,127
Netherlands	2.3%	31.4%	61.9%	63.5%	0.1%	6.7%	0.4%	2.5%	154,106
Norway	1.6%	8.6%	86.9%	85.7%	1.6%	6.4%	0.7%	2.6%	25,014
Sweden	0.9%	18.0%	71.7%	71.1%	0.6%	0.5%	0.2%	8.8%	103,690
Switzerland	5.1%	18.2%	69.9%	69.8%	0.1%	9.1%	1.1%	4.0%	116,359
Austria	6.3%	19.2%	70.8%	70.1%	0.8%	3.2%	1.0%	1.6%	18,847
Greece	12.0%	23.6%	58.6%	57.2%	1.4%	10.0%	0.8%	4.0%	17,158
Hungary	14.6%	16.6%	62.7%	61.0%	1.7%	0.2%	0.2%	3.5%	5,648
Portugal	4.1%	17.7%	70.4%	69.4%	1.0%	10.1%	1.2%	5.2%	26,203
Spain	2.0%	22.1%	71.2%	69.8%	1.4%	1.6%	1.1%	3.1%	49,222
Finland	4.8%	21.4%	67.9%	67.4%	0.5%	9.8%	0.2%	3.4%	6,062
Czech Rep.	6.0%	11.4%	81.5%	76.8%	4.7%	0.0%	0.6%	1.9%	12,953
Mean	**4.6%**	**21.1%**	**67.5%**	**66.5%**	**1.2%**	**5.7%**	**0.8%**	**5.2%**	**79,417**

Table 12 (continued)

Country	Commission & Fees	Total Debt	Net Income	Long-term debt	Provision for Loan Losses	Trading Assets	ROA	ROE	Market Value, 000
UK	3.6%	28.2%	1.8%	10.6%	0.5%	8.2%	3.06	19.23	15,788
Poland	1.9%	18.3%	1.2%	7.2%	0.7%	6.5%	1.73	12.49	852
Belgium	0.3%	48.1%	0.8%	6.9%	0.1%	7.8%	7.27	12.25	6,004
Denmark	1.0%	23.3%	0.9%	4.9%	0.9%	8.0%	1.35	11.01	699
France	1.1%	43.8%	0.5%	13.9%	0.4%	8.4%	0.84	11.65	7,819
Germany	0.4%	59.4%	0.1%	26.8%	0.3%	10.4%	0.64	5.33	6,164
Italy	2.1%	42.0%	0.7%	14.6%	0.4%	13.6%	1.18	8.71	4,103
Netherlands	1.3%	25.0%	0.7%	6.0%	0.1%	5.0%	1.25	21.17	7,310
Norway	0.9%	34.6%	0.8%	17.5%	0.2%	5.3%	1.18	13.62	1,628
Sweden	1.6%	47.4%	0.7%	16.4%	0.4%	8.4%	1.81	14.27	6,273
Switzerland	2.0%	27.0%	0.8%	12.3%	0.2%	8.6%	1.05	10.65	6,512
Austria	0.9%	52.1%	0.3%	35.3%	0.3%	3.6%	0.37	6.98	684
Greece	1.5%	19.3%	0.9%	5.5%	0.4%	5.3%	1.17	25.57	1,835
Hungary	2.1%	16.2%	1.4%	11.1%	0.5%	7.6%	2.59	26.66	892
Portugal	0.9%	27.0%	0.7%	11.6%	0.6%	3.1%	1.10	16.60	2,468
Spain	1.2%	29.1%	1.0%	4.5%	0.5%		1.30	15.60	5,336
Finland	0.6%	50.5%	0.6%	24.7%	0.3%	17.0%	0.78	10.88	165
Czech Rep.	1.3%	19.2%	0.1%	11.2%	2.0%	2.9%	0.40	-6.71	1,128
Mean	**1.6%**	**32.9%**	**0.9%**	**11.5%**	**0.5%**	**9.7%**	**1.57**	**13.60**	**5,277**

Table 19
SUMMARY OF BALANCE SHEET AND INCOME STATEMENT VARIABLES FOR BANKS BY YEAR

Average values across all countries for each year from the WorldScope database.
Balance sheet and income statement variables are standardized by their total assets values for each bank.
Figures for total assets and market capitalization are in thousands of Euro equivalents.

Year	Cash	Investments	Loans	Fixed Assets	Other Assets	Total Debt	ROA	ROE	Total Assets, 000	Market Value, 000
1990	12.1%	16.7%	62.4%	3.5%	3.6%	30.6%	1.36	9.95	25,155,864	1,196,547
1991	12.5%	17.7%	64.4%	2.7%	3.0%	29.3%	1.50	10.69	33,091,759	1,050,610
1992	7.6%	17.6%	69.0%	2.3%	3.4%	32.9%	0.89	6.19	40,195,430	1,104,254
1993	6.4%	20.3%	67.3%	5.3%	3.8%	33.7%	1.10	9.65	39,160,704	1,046,487
1994	5.1%	20.5%	68.9%	7.6%	3.8%	34.9%	1.20	11.95	40,643,952	1,606,406
1995	4.7%	21.9%	66.3%	9.0%	5.0%	32.2%	1.31	14.03	51,098,593	1,681,017
1996	4.9%	21.9%	66.1%	7.1%	4.9%	31.4%	1.36	14.50	53,238,036	2,102,225
1997	5.6%	21.9%	65.9%	7.4%	4.9%	29.3%	1.50	17.24	59,781,519	2,598,645
1998	5.1%	22.6%	65.7%	5.9%	4.8%	30.4%	1.58	16.64	67,217,552	4,665,695
1999	4.7%	22.6%	66.4%	6.6%	5.1%	33.7%	3.80	18.53	73,684,741	5,565,452
2000	3.1%	22.0%	67.4%	7.3%	6.3%	34.0%	1.58	17.67	94,178,880	7,903,124
2001	3.0%	21.2%	68.1%	4.6%	6.7%	34.3%	1.16	11.72	111,590,821	10,499,190
2002	2.2%	21.1%	69.5%	4.2%	6.4%	33.2%	1.18	8.52	115,645,410	9,919,790
2003	2.0%	21.3%	71.0%	3.7%	5.4%	34.5%	1.52	13.09	116,689,864	7,304,492
2004	2.1%	21.7%	69.5%	2.4%	6.4%	34.8%	1.58	15.16	138,814,097	9,209,565
Mean	4.6%	21.1%	67.5%	5.7%	5.2%	32.9%	1.57	13.60	79,416,595	5,277,352

Figure 2
DEVELOPMENT OF ASSETS AND LIABILITIES STRUCTURE VARIABLES FOR BANKS THROUGHOUT SAMPLE PERIOD

Assets and liabilities structure development for banks throughout 1990-2004.
Points on the lines represent averages across all countries in the sample for each year.

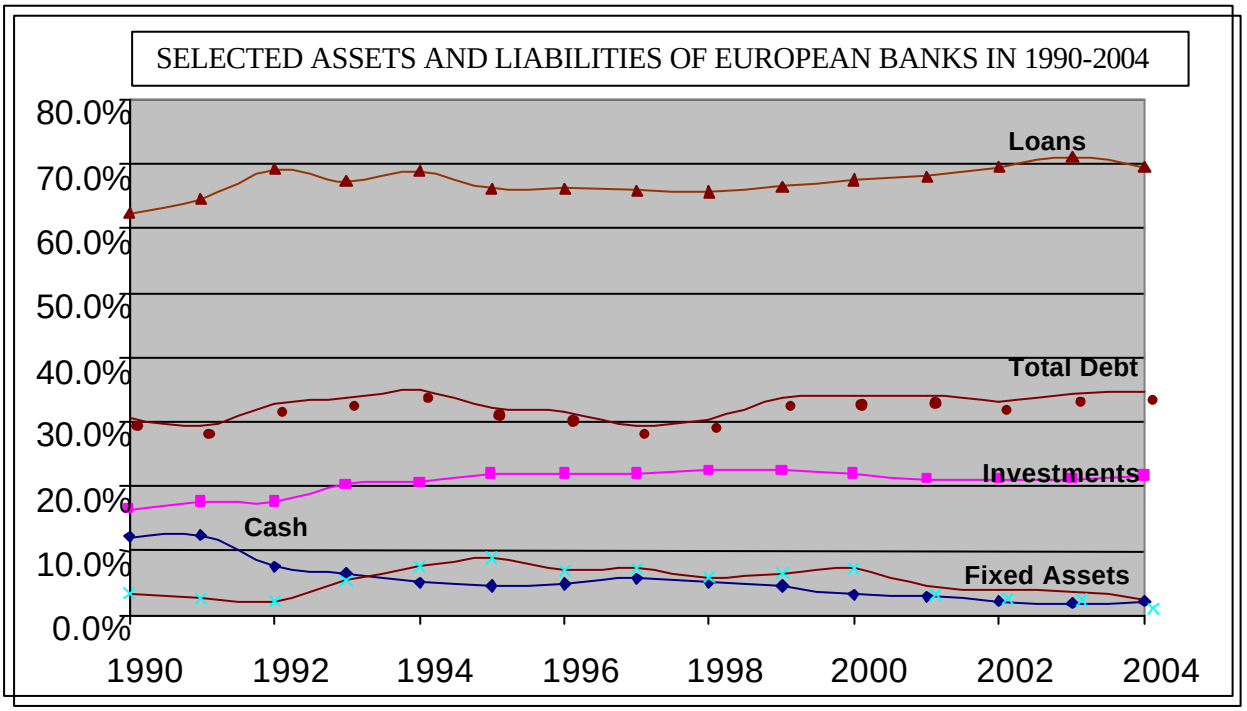


Table 20
BANKS ASSET COMPOSITION AND FINANCIAL CHARACTERISTICS EFFECT ON EARNINGS FORECAST ERRORS

Estimation of the regression:

$$Y_i = a_i + \sum_k b_k BS_{ki} + \sum_j l_j PL_{ji} + e_i$$

where

Yi – measure of bank opaqueness, consequently FE or SD variables;
BS_{ki} – balance sheet asset variable divided by total assets at the end of the year for asset *k* and bank *i*;
PL_{ji} – control variable *j* for bank *i*
FE - standardized earnings forecast error, computed as the absolute value of the difference between mean forecast estimate and actual annual earnings for companies in the sample standardized by the actual EPS value;
SD - standard deviation of earnings forecast for each company-year (calculated only when two or more estimates are available) standardized by the actual EPS value
Assets – Cash and due from banks, Investment in securities, Net loans, Reserves for net loans, Fixed assets – property, plant and equipment and real estate, Investments in unconsolidated subsidiaries and Other assets.
Control variables - Natural logarithm of market capitalization, Number of EPS estimates for each bank and Commission and fees on clients' accounts.
F-test – F statistic for the hypothesis that all explanatory variables in the regression are jointly zero.

Asterisks for adjusted R-square statistics represent F-test of increase in R-squares from adding new variables
T-statistics are in parentheses. *, ** and *** indicate significance respectively at 10%, 5% and 1% levels.

Explanatory variables	FE forecast error		SD Standard Dev.	
	1	2	1	2
ln Market Value	-0.056***	-0.064***	-0.009*	-0.012**
	(-5.268)	(-5.657)	(-1.919)	(-2.274)
Number of Estimates	-0.003**	-0.003**	-0.001*	-0.001*
	(-2.169)	(-2.106)	(-1.806)	(-1.881)
Commission & Fees	-1.356	-2.499*	-0.356	-0.593
	(-1.037)	(-1.741)	(-0.588)	(-0.889)
Investments		0.338*		0.141
		(1.755)		(1.55)
Net Loans		0.069		0.094
		(0.422)		(1.238)
Reserves for Loan Losses		0.809		0.031
		(1.013)		(0.076)
Fixed Assets		0.147		0.076
		(1.268)		(1.408)
Inv. in Unconsolid. Subsid.		2.244		0.621
		(1.169)		(0.711)
Other Assets		0.697**		0.22*
		(2.397)		(1.67)
Adjusted R^2, fixed effects	0.338***		0.202***	
Adjusted R^2	0.364***	0.369**	0.207*	0.207
F-test	4.765***	4.697***	2.716***	2.631***
Number of observations	948	948	793	793

Table 21
BANKS ASSET COMPOSITION AND FINANCIAL CHARACTERISTICS EFFECT ON HL RANGE OPAQUENESS PROXY

Estimation of the binary logistic regression:

HL = f (assets, control variables),

where
HL - dummy variable that equals to zero if the actual EPS data falls between highest and lowest earnings forecasts and unity otherwise
Assets - Cash and due from banks, Investment in securities, Net loans, Reserves for net loans, Fixed assets - property, plant and equipment and real estate, Investments in unconsolidated subsidiaries and Other assets.
Control variables - Natural logarithm of market capitalization, Number of EPS estimates for each bank, Commission and fees on clients' accounts, Earnings volatility and Forecasts volatility

Wald-test for coefficients are in parentheses.
*, ** and *** indicate significance respectively at 10%, 5% and 1% levels.

Explanatory variables	HL		
	1	2	3
ln Market Value	-.049	-.096*	-.108*
	(.990)	(2.982)	(3.327)
Number of Estimates	-.038***	-.038***	-.036***
	(15.139)	(14.678)	(12.752)
Commission & Fees	6.696*	5.046	2.322
	(3.224)	(1.408)	(.279)
Investments		.737	1.629
		(.424)	(1.802)
Net Loans		.261	1.045
		(.077)	(1.064)
Reserves for Loan Losses		13.077**	13.144**
		(5.125)	(5.147)
Fixed Assets		.167	.344
		(.078)	(.319)
Inv. in Unconsolid. Subsid.		-6.041	1.339
		(.529)	(.023)
Other Assets		3.184*	3.984**
		(3.404)	(4.960)
Earnings Volatility			.016**
			(6.271)
Forecasts Volatility			.076**
			(4.138)
Nagelkerke R Square	.062	.079	.095
Number of observations	831	831	831

Table 22
EFFECT OF THE BANKING STRUCTURE AND REGULATION VARIABLES ON BANK OPAQUENESS

Summary of opaqueness proxies for various banking structure and regulation variables for banks in the sample. Numbers represent means of opaqueness proxies FE, SD and HL for all valid observation in 1990-2004.

Description of dummy variables for banking structure and regulation is provided in Table 5.
Description of opaqueness proxies is provided in Table 7.

*, ** and *** indicate significant differences between mean values of opaqueness proxies for different groups of banks respectively at 10%, 5% and 1% levels.

Proxy	Bank Importance		Bank concentration		Government ownership		Moral hazard		Corporate governance	
	0	1	0	1	0	1	0	1	0	1
FE	0.28	0.248***	0.25	0.292***	0.26	0.275**	0.26	0.298**	0.29	0.261**
SD	0.15	0.116***	0.12	0.161***	0.1	0.166***	0.12	0.163***	0.16	0.119***
HL	0.48	0.46	0.5	0.43*	0.52	0.43***	0.49	0.44	0.45	0.49

Table 23
BANKING STRUCTURE AND REGULATION VARIABLES EFFECT ON EARNINGS FORECAST ERRORS

Estimation of the regression:

$$Y_i = a_0 + c_i \ln MV_i + s_i NES_i + d_i CF_i + \sum_k b_k BS_{ki} + f_k EPS\_vol_k + w_k FOR\_vol_k + REG_k + e_i$$

where

Yi –	opaqueness proxy for observation i, consequently FE or SD variables;
ln MV_i –	natural logarithm of market capitalization for bank observation i;
NES_i –	number of annual EPS estimates for bank observation i;
CF_i -	Commission and Fees on clients' accounts;
BS_{ki} –	balance sheet asset variable for asset k and bank i;
EPS_vol_k –	annual volatility of EPS for bank k;
FOR_vol_k –	annual volatility of EPS forecasts for bank k;
REG_k -	bank structure and regulation variable: BIP, CON, GOV, RES, MOH or CG.

F-test – F statistic for the hypothesis that all explanatory variables in the regression are jointly zero.
Asterisks for adjusted R-square statistics represent F-test of increase in R-squares from adding new variables
T-statistics are in parentheses. *, ** and *** indicate significance respectively at 10%, 5% and 1% levels.

Explanatory variables	FE forecast error				
	BIP	CON	GOV	MOH	CG
ln Market Value	-0.027***	-0.028***	-0.031***	-0.032***	-0.03***
	-(3.626)	-(3.778)	-(4.254)	-(4.151)	-(3.956)
Number of Estimates	-0.001	-0.001	0	-0.001	-0.001
	-(0.714)	-(0.506)	-(0.270)	-(0.390)	-(0.658)
Commission & Fees	-1.051*	-1.091*	-1.076*	-1.216**	-1.186**
	-(1.814)	-(1.925)	-(1.887)	-(2.116)	-(2.066)
Investments	0.399**	0.414***	0.378**	0.413***	0.406***
	(2.563)	(2.676)	(2.472)	(2.639)	(2.590)
Net Loans	0.129	0.139	0.107	0.143	0.129
	(1.008)	(1.091)	(0.867)	(1.114)	(1.003)
Reserves for Loan Losses	1.823***	2.317***	2.141***	1.993***	1.949***
	(2.615)	(3.371)	(3.233)	(2.887)	(2.816)
Fixed Assets	-0.076	-0.053	-0.088	-0.093	-0.084
	-(0.957)	-(0.683)	-(1.105)	-(1.167)	-(1.062)
Inv. in Unconsolid. Subsid.	-0.37	0.083	-0.322	-0.096	-0.043
	-(0.299)	(0.068)	-(0.273)	-(0.079)	-(0.036)
Other Assets	0.83***	0.919***	0.906***	0.83***	0.83***
	(3.584)	(3.954)	(3.942)	(3.577)	(3.574)
Earnings Volatility	0.003***	0.003***	0.003***	0.003***	0.003***
	(3.021)	(2.923)	(2.940)	(3.069)	(2.804)
Forecasts Volatility	-0.013***	-0.01**	-0.006	-0.01*	-0.011**
	-(2.679)	-(2.062)	-(1.255)	-(1.896)	-(2.216)
Structure and Regulation Variable	**-0.038**	**0.019**	**0.029**	**0.043***	**-0.022**
	-(1.486)	(0.885)	(1.405)	(1.714)	-(0.933)
Adjusted R^2	0.05	0.047	0.046	0.051*	0.048
F-test	4.846***	4.761***	4.739***	4.929***	4.728***
Number of observations	883	916	927	880	883

Table 23 (continued)
BANKING STRUCTURE AND REGULATION VARIABLES EFFECT ON EARNINGS FORECAST ERRORS

Banking structure and regulation variable – variables as defined in Table 9. The variable that enters regression is shown on the top of each column (for example, if top of column is "BIP", then Bank Importance variable enters regression).

BIP - Bank Importance Category
CON - Bank Concentration Category
GOV - Government Ownership Category
MOH - Moral Hazard Category
CG - Corporate Governance Category

Description of categories for banking structure and regulation is provided in Table 9.

Explanatory variables	SD standard deviation				
	BIP	CON	GOV	MOH	CG
ln Market Value	-0.005	-0.005	-0.007**	-0.007**	-0.007**
	-(1.567)	-(1.468)	-(2.254)	-(2.171)	-(2.027)
Number of Estimates	-0.001**	-0.001**	-0.001	-0.001*	-0.001
	-(2.218)	-(2.100)	-(1.512)	-(1.664)	-(1.620)
Commission & Fees	-0.588**	-0.641**	-0.843***	-0.68***	-0.665***
	-(2.435)	-(2.716)	-(3.694)	-(2.872)	-(2.821)
Investments	-0.072	-0.044	0.03	-0.052	-0.045
	-(1.007)	-(0.618)	(0.443)	-(0.732)	-(0.636)
Net Loans	-0.157**	-0.129**	-0.077	-0.134**	-0.126**
	-(2.519)	-(2.085)	-(1.341)	-(2.152)	-(2.033)
Reserves for Loan Losses	0.162	0.612*	0.257	0.088	-0.052
	(0.513)	(1.937)	(0.890)	(0.283)	-(0.165)
Fixed Assets	0.081**	0.088***	0.038	0.068**	0.073**
	(2.350)	(2.588)	(1.129)	(1.986)	(2.140)
Inv. in Unconsolid. Subsid.	0.267	0.76	0.85*	0.403	0.443
	(0.518)	(1.515)	(1.809)	(0.811)	(0.897)
Other Assets	-0.049	0.023	0.112	-0.054	-0.068
	-(0.499)	(0.229)	(1.197)	-(0.552)	-(0.697)
Earnings Volatility	-0.001*	-0.001**	0	-0.001*	0
	-(1.866)	-(2.389)	-(0.431)	-(1.835)	-(1.249)
Forecasts Volatility	-0.004*	-0.002	0.001	-0.003	-0.001
	-(1.807)	-(0.952)	(0.472)	-(1.163)	-(0.400)
Structure and Regulation	**-0.025****	**0.024****	**0.067*****	**0.04*****	**-0.046*****
	-(2.306)	(2.497)	(7.684)	(3.748)	-(4.614)
Adjusted R^2	0.07**	0.063**	0.123***	0.084***	0.089***
F-test	5.624***	5.333***	10.074***	6.608***	7.068***
Number of observations	742	768	777	738	742

Appendix 1

1. WORLDSCOPE GENERAL INDUSTRY CLASSIFICATION CODES

Industry Code	Industry Name
1	Industrial
2	Utility
3	Transportation
4	Bank/Savings & Loan
5	Insurance
6	Other Financial