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Information Disclosures, Default Risk, and Bank Value

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Abstract

This paper investigates the causal effects of voluntary information disclosures on a bank's expected default probability, enterprise risk, and value. I measure disclosure via a self-constructed index for the largest 80 U.S. bank holding companies for the period 1998–2011. I provide evidence that a bank's management responds to a plausibly exogenous deterioration in the supply of public information by increasing its voluntary disclosure, which in turn improves investors' assessment of the bank risk and value. This evidence suggests that disclosure may alleviate informational frictions and lead to a more efficient allocation of risk and return.

Keywords: Disclosure, default probability, firm value, risk management, asymmetric information, corporate governance

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1 Introduction

Investors' limited information on the risks held by financial intermediaries is generally understood to amplify both phases of the 2008 credit cycle. Opacity in banks contributed to a general mispricing of risk, as investors badly misunderstood the risks inherent in structured products. Reliable, timely, and granular information disclosure can help in alleviating these problems. Hence, the current banking reform proposals and reports of regulatory authorities have focused on transparency through greater disclosure.[1] The objective of this paper is to investigate the causal relationships among disclosure, bank risk, and bank value, which are of key importance to investors, banks, and regulators.

This paper makes two important contributions. First, I provide the first evidence that bank managers can impact investors' assessment of credit risk and bank value by varying the information they disclose. In contrast to majority of the literature, I examine the disclosure–risk–value relationship by employing a sample of financial institutions rather than corporations and study the causal effects of disclosure by employing an instrumental variable approach. Two, in order to measure voluntary disclosure, I propose a template that is constructed by using publicly available data and focusing on the risk profile of a bank. Despite data limitations, the validating experiments suggest the adequacy of the template in measuring disclosure.

I show that a bank's management responds to a deterioration in the supply of public information by increasing its voluntary disclosure, which in turn improves the investors' assessment of bank risk and the bank value. The first result provides empirical evidence for one of the central assumptions in theoretical models of disclosure: managers seek to shape their informational environment through disclosure. The second result further shows that managerial actions can impact investors' assessment of bank risk and ultimately the value of their shares.

Why does disclosure matter? Given the balance sheet risk, if sufficient transparency and monitoring by investors impose incentives on banks to hold less risky positions, then banks that disclose more information should choose less risky activities. In other words, investors or debt holders may exercise a direct market discipline, allowing a reduction

[1] Basel II, Pillar 3 recognizes disclosure as a way to impose strong incentives on banks to perform less risky activities. The December 2009 and 2011 Financial Stability Reports of the Bank of England underline enhanced disclosure as a tool to mitigate informational frictions especially in stress times. In 2012, the Enhanced Disclosure Task Force (EDTF) is established by the Financial Stability Board to respond to the demands of investors of better access to risk information of banks. EDTF lists sufficient disclosure as the first step in rebuilding investors' confidence in the banking industry.

in bank's risk.[2] Even if banks do not choose to perform less risky activities, rational investors can interpret the absence of disclosure as a negative signal about the firm's value, since a less informed party presumes that withheld information is less favorable information (Grossman and Miller, 1980; Grossman, 1981; Milgrom, 1981; Verrecchia, 2001). Putting it differently, higher disclosure reduces the information asymmetries among bank management, depositors, and regulators. This in turn may affect investors' assessment of the riskiness of the bank or reduce the heterogeneity of beliefs about its true value (Lambert et al., 2007).

Motivated by the aforementioned theoretical papers, I first hypothesize that banks with a higher level of disclosure benefit from lower expected default probabilities in the following year, where the latter is estimated through option prices. Next, I examine whether enhanced disclosure is associated with other bank enterprise risks: aggregate, downside, systematic, and idiosyncratic risks. Finally, I test whether disclosure is value relevant, i.e. whether disclosure is associated with bank value and performance.

The empirical proxy for disclosure is a self-constructed voluntary disclosure index, based on the summary measures proposed in December 2009 and 2011 Financial Stability Reports of the Bank of England.[3] The index gauges the level of disclosure provided on four main categories: liquidity risk profiles of the companies, risk positions of key group affiliates and sub-groups, intra-annual information, and finally exposures between financial institutions and exposures to hidden risks. I hand-collect data to construct the disclosure index. Data collection and validation requires some effort. Hence, the sample is restricted to the publicly open largest 80 U.S. bank holding companies (BHCs) in terms of asset value as of December 2007 for the period 1998–2011. This accounts for the 75 percent of the total assets of the U.S. banking system. I select the sample based on 2007 to include the actually defaulted (delisted) BHCs during the 2008-crises.

My focus on bank holding companies is motivated by four: first, they file periodic reports to the Securities and Exchange Commission, from which one is able to obtain 10–K and proxy statements. Second, U.S. BHCs are regulated by the Federal Reserve and the

[2]Nier and Baumann (2006) show that banks that disclose more information on their risk profile are subject to stronger degree of market discipline and choose to hold higher capital buffers to reduce their probability of default. Tadesse (2006); Fonseca and Gonzalez (2010) show better disclosures have positive effects on market discipline; lead to lower financing costs and lower risk profile.

[3]The index is available upon request from the author. I sincerely thank Christian Castro from the Bank of Spain, Rhiannon Sowerbutts, and Peter Zimmerman from the Bank of England for insightful comments and suggestions for the creation of the disclosure template. A variation of this template is employed by Sowerbutts et al. (2013) to quantify and compare the disclosure practices in UK, EU, USA, Canada, and Australia over time in the 2013 Bank of England Quarterly Bulletin.

FDIC. Hence, they are subject to uniform requirements, which are important to identify voluntary disclosures. Third, a typical BHC has a complex structure. It is comprised of several independent subsidiaries and involved in a wide range of financial activities. This complexity may enhance the importance of granular financial disclosure for investors to identify correctly the risk taking behavior. Finally, with a very few exceptions (e.g., Nier and Baumann, 2006) the literature on disclosure focuses on non-financial corporations and there is little evidence on banking sector.

Examining the effects of disclosure requires it being exogenous after controlling for bank holding company characteristics, year, and bank fixed effects. However, the changes in disclosure are not random. A bank exposed to higher risk may choose to disclose more information to reduce the uncertainty and change investors' assessment of its risk or value. Otherwise, some unobserved time-invariant bank characteristics may jointly affect the implied default probability, BHC value, and disclosure. To overcome this possible self-selection bias, I first employ an instrumental-variable approach and second the Arellano and Bond (1991) dynamic panel GMM estimation approach.

I instrument a BHC's level of disclosure with two proxies, both derived from analysts' forecasts. A high level of analyst coverage creates a better information environment for firms and leads to a smaller degree of information asymmetry (Healy and Palepu, 2001; Yu, 2008; He and Tian, 2013). Hence, first, I use the total number of analysts providing earning forecasts in a given year as an instrument. However, analysts could choose to cover bigger firms or firms with a better information environment (Bushman et al., 2005). Alternatively, the value added for an analyst to cover an opaque firm could be higher. Hence, second, I instrument a BHC's level of disclosure with expected coverage, which is first introduced by Yu (2008). Expected coverage is driven by the change of the size of brokerage houses. Since the size of a brokerage house, i.e., the number of analysts that a house employs, depends on its own revenue and loss dynamics, and business decisions, rather than the bank it covers, it is expected to be exogenous.[4]

Results confirm the hypotheses; a higher level of disclosure is associated with lower levels of market implied default probability, other enterprise risks (aggregate, downside, systematic, and idiosyncratic risks), and higher bank value. The documented associa-

[4]For example in June 2007, Prudential Financial Inc. announced that they have decided to reduce their equity research group since the revenue generated by the group was substantially smaller than other businesses that the parent company Prudential Financial provided. This business decision deteriorates the information environment of the banks that the group was covering. The number of analysts working for Prudential Financial and providing coverage for my sample banks drops from 45 to 12 in a year. See He and Tian (2013) for similar real-world examples that illustrate this point.

tions are economically significant: a one standard deviation increase in the current level of disclosure is associated with an 18 percent decrease in the next year's probability of default and increases the firm value by 22 percent. All of the specifications include year and bank fixed effects to capture any time-invariant heterogeneity across BHCs. The results are robust to the inclusion of various bank characteristics, the alternative measures of disclosure, and alternative econometric models.

This paper is related to the literature that investigates the consequences of corporate disclosure on capital markets. Leuz and Verrecchia (2000) document a positive association between the disclosure and higher stock liquidity and a negative relationship between the firm's cost of capital and disclosure. Jiao (2011), Foerster et al. (2013), and Balakrishnan et al. (2014) show that disclosure has a sizable and beneficial effect on firm value. Botosan (1997), Botosan and Plumlee (2002), and Barth et al. (2013) document supporting evidence of the negative relationship between transparency and cost of capital. Bushee and Noe (2000) and Kothari et al. (2009) document a negative and significant association of disclosure with stock return volatility. I contribute to this literature by conducting the analysis on bank holding companies, rather than corporate firms and examining the link among the voluntary disclosures, various bank enterprise risks, bank value, and performance. Moreover, the listed papers assume that the disclosure choice is exogenous, with few exceptions (for example Balakrishnan et al., 2014; Foerster et al., 2013). I address the endogeneity issue by adopting an instrumental variable approach.

My paper also contributes to a number of self-constructed disclosure indexes in the current literature. In one of the earliest studies, Botosan (1997) produces a cross-sectional ranking of disclosure levels by using the annual reports of 122 firms in 1990. Francis et al. (2008) further develop Botosan (1997)'s disclosure index for a sample of 677 firms in 2001. Lang and Lundholm (2000) measure the disclosure level by the score associated with main four groups of announcements around seasoned equity offerings identified in the Dow Jones News Retrieval and then Lexis/Nexis news databases. Nier and Baumann (2006)'s disclosure index records whether the particular category is disclosed in BankScope database or not. Finally, in a recent study, Cheung et al. (2010) create a transparency index based on the OECD Principles of Corporate Governance for 100 major Chinese listed companies for the period 2004–2007.

I contribute to this literature by considering several dimensions of voluntary disclosure. In contrast to the index of Botosan (1997) and Francis et al. (2008), for instance, my disclosure index mainly focuses on the disclosure of the riskiness, rather than the profitability of an institution. Similar to the study of Nier and Baumann (2006), I look at the maturity and type of funding. On the other hand, instead of focusing on the risk factors that turn out to be compulsory due to current Basel regulations, for example credit risk, my index focuses on risk factors that threaten the financial system recently, like liquidity or spillover risk. Finally, in addition to the aforementioned disclosure templates, I consider disclosures on the structure of the banking group, to test whether investors place value on information about intra-group exposures.

This paper is organized as follows: next section develops the hypotheses tested in this paper and frames them in the theoretical literature. Section 3 describes the sample and data sources. Moreover, the construction of the disclosure index, validation of the metric, and details for the estimation of the option implied probability of default are provided. In Section 4, empirical methodologies along with a preliminary analysis is introduced. Section 5 presents the results and discussions. Finally, additional robustness checks are reported. Section 6 concludes.

2 Hypothesis Development

The seminal findings of Grossman and Miller (1980); Grossman (1981); Milgrom (1981) note that rational buyers' beliefs about the asset worth are not fixed. Market participants interpret the absence of information as a negative signal about the asset value or quality. Consequently, the buyer discounts the asset's value until the point at which it is in the seller's best interest to reveal the information, however unfavorable it may be (Verrecchia, 2001).

Extending this adverse-selection problem into the area of financial reporting is straightforward. While banks are subject to a considerable amount of mandatory financial reporting through regular reports, managers may still hold additional information, whose disclosure is not required. The information quality in turn affects the degree of uncertainty over the firm's value and the degree of adverse selection between the managers and investors. Thus higher information disclosures may affect market participants' assessment of the riskiness of the firm or firm value.

Motivated by the aforementioned theoretical studies, I hypothesize that higher information disclosures lower the expected default risk of a bank. Although the actual default probability is a function of the fundamentals, the expected default risk provides market participants' forward looking views about an institution's riskiness, which can be altered through the increased information.

Hypothesis 1 *By disclosing more information, managers can impact investors' assessment of the riskiness of a bank. Banks with higher level of disclosure in the current year benefit from lower expected default probabilities in the following year.*

I test Hypothesis 1 under the alternative that disclosure does not have any real impact on investors' assessment of the default probabilities of banks. This may be because of the failure of market discipline, a market mechanism in which investors have sufficient information to assess and they monitor risk taking behavior of banks (Crockett, 2002). Although increased transparency is a necessary condition for investors to reach informed judgments, it is not sufficient. Investors only price the risks which they actually bear. If market participants are insured then their incentives to monitor and punish the risky institutions are reduced.

Second, I test the impact of increased disclosure on other enterprise risks. Increased information can affect bank risk through various channels. First, I use the standard deviation of a bank's weekly equity returns as a proxy for aggregate risk. The effect of disclosure on volatility is ambiguous. On one hand, disclosure moves the stock prices and increases volatility (e.g., Ross, 1989; Leuz and Verrecchia, 2000). On the other hand, market microstructure theory suggests that in a market where some investors have access to better information, disclosure diminishes the advantage to be better-informed by reducing the information asymmetries. To the extent that this is true, enhanced disclosure reduces the price impact of a trade initiated by informed agents (Diamond and Verrecchia, 1991).

Third, as a proxy for downside risk, I consider implied volatility calculated from the option prices written on the banks stock, which gives the investors a forward looking view on the firm's volatility. Ederington and Lee (1996) model the impact of information releases on implied volatility and conjecture that following a scheduled announcement, implied volatility decreases in the long run as uncertainty is resolved.

Finally, I consider the systematic and idiosyncratic risks of a bank. The former is the beta of the firm estimated from the CAPM model, whereas the latter is calculated as the standard deviation of the weekly residuals of the CAPM model[5]. In their theoretical

[5]I conduct an analysis using Fama-French three factor model instead of CAPM. The results are qualitatively similar hence, not reported.

models, Barry and Brown (1985); Lambert et al. (2007) study the effects of information quality and show that it affects investors' assessment of both the idiosyncratic and systematic risk of a firm.

Hypothesis 2 *Higher disclosure is associated with lower enterprise risks.*

A natural question arises as to whether disclosure is value enhancing. If disclosure is associated with reduction in risk through increased information quality, as hypothesized in 1 and 2, then one expects a bank to benefit from higher disclosure. Finance theory suggests that disclosure can raise firm value by lowering its cost of capital on external financing (Diamond and Verrecchia, 1991; Easley and O'Hara, 2004) or by lowering investors' information acquisition costs. High levels of disclosure are also more likely to increase the stock liquidity by attracting investors, who are more confident that the stock is trading at "fair" prices (Kim and Verrecchia, 1991, 1994), which in turn has a sizable and beneficial effect on firm value.

The predictions for the risk adjusted performance are more ambiguous. On one hand, higher disclosure may allow the bank to reduce its assessed risk. If the reduced risk is mainly as a result of the systematic risk, then in this case increased disclosure should encourage investors to demand lower returns. Hence, the association of disclosure with *risk-adjusted performance* depends both the magnitudes of the reduced risk and reduced return. Alternatively, since there is an information asymmetry between managers and investors, there is a gap between the managers' and investors' valuation of a firm's stock price. As Verrecchia (1983), Dye (1985), Healy and Palepu (1993) hypothesize, credible disclosures reduce this misvaluation and the bank with a higher level of disclosure can benefit from a significant improvement in expected stock returns, hence, an improvement in risk adjusted performance, following the disclosure. Thus, whether enhanced disclosure is positively or negatively associated with stock risk-adjusted performance is an interesting empirical question.

Hypothesis 3 *Disclosure is value relevant. It is positively associated with bank value and operating performance and significantly associated with risk-adjusted performance.*

3 Data and Empirical Proxies

In Section 3.1, I introduce the sample and data sources. Section 3.2 describes in detail the disclosure index, the evidence supporting its reliability, and the descriptive analysis conducted on the index. Section 3.3 introduces the methodology and empirical implementation of the option implied default probabilities and provides the preliminary analysis.

3.1 Sample selection and data sources

The sample includes the 80 largest publicly traded U.S. bank holding companies (BHCs) in terms of asset value as of December 2007 for the period 1998–2011. The sample does not contain some financial institutions that were not a BHC, but became a BHC after 2008, such as Goldman Sachs, Metlife, and American Express.

Several sources are used to construct the data set. The information related to the disclosure index is hand-collected from the bank holding companies' 10–K statements, proxy statements as well as the annual reports from the SEC–Edgar system. Moreover, I use the SEC–Edgar system to extract the dates when the 10–K reports of a given BHC is available to public (released at the web page). Table B.1 in the Appendix lists the sample BHCs with the corresponding identifiers.

In order to estimate the option implied default probability (IPoD) for a BHC for a given date, I use the OptionMetrics Standardized Options dataset. All of the information regarding the call options; bid and ask prices, trading volumes, open interests, and the corresponding strike prices are obtained from the OptionMetrics dataset. From the sample, a day is eliminated if the trading volume is 0 for all of the options traded. Moreover, I consider only the options with time to expiry greater than 6 months. After these filtrations, the sample reduces to 75 BHCs.

I obtain data on daily stock returns, market capitalization, and bid and ask prices of the equity for each BHC from CRSP. Market returns and the risk free rates are from Kenneth French's online data library. FR Y-9C reports from the Federal Reserve Bank of Chicago are used for the end of the year consolidated financial statement data.

Finally, I use data from the Thompson-Reuters I/B/E/S summary, detail, and actual estimates databases in order to measure the exogenous variation in informational environment of a BHC. For a given day, the databases include the identifiers for the bank, the analyst who provides coverage, and the brokerage house that the analyst is working for, as well as the actual and forecasted earnings-per-share values, forecast date, and announcement date.

3.2 Measuring disclosure

December 2009 and 2011 Financial Stability Reports of the Bank of England provide possible areas for improved disclosure and summary measures to assess the quantitative information provided by a financial institution. I further work on this assessment and propose an index of voluntary disclosures. The index consists of 14 sub-indices of voluntary disclosures, forming four main categories: liquidity risk profiles of the companies, risk positions of key group affiliates and sub-groups, period averages, highs and lows, and exposures between financial institutions and exposures to the hidden risks. For all of the sub-indices, I assign a score of 1 if a given bank holding company (BHC) includes the corresponding information in its 10–K, annual, or proxy reports for a given year. Table 1 presents the disclosure template used in the analysis.

[Table 1 approximately here]

The first set of variables, liquidity risk, attempts to capture whether a given institution discloses information related to its liquidity position. I first collect information on the decomposition of funding sources by maturity and currency. Institutions reliant on short-term or foreign currency based funding sources are argued as being particularly vulnerable to stresses in financial markets (Fahlenbrach et al., 2012). Hence, I search whether a given BHC includes its liabilities breakdown by term structure and whether it is decomposed into different non-local currencies. Second, I focus on the liquidity risk profile of a bank's balance sheet and its holdings of liquid assets, i.e., liquidity resilience. I specifically search for the liquidity ratios and level or ratio of high-quality unencumbered assets.

Information on group structure is the second main category. Disclosing information on the profitability of key group affiliates is compulsory for the U.S. BHCs. However, particularly in the case of large and complex financial groups, detailed information on the riskiness and balance sheets of subsidiaries is non-negligible. In addition, instead of group subsidiaries, I search the same information regarding the main group segments such as the derivatives desk, card services, and insurance services. A failure of one segment of a large institution not only increases the risk exposures of an individual bank, but can also trigger a broader systemic failure (Ellul and Yerramilli, 2013).

The third key area I include in my index is the publication of intra-annual information. End-of-year figures can be unrepresentative of banks' behavior either due to intra-period volatility in banks' business activity or window dressing at the period end. Hence, reporting period averages and highs/lows to present a window on the risks that institutions run during reporting periods is helpful (Bank of England, 2009). I look for the detailed quarterly information and high and lows of balance sheet items and risk ratios.

The final group is information on the network or spillover risk. First, I look for information on the exposure of assets and liabilities of a given BHC to different types of financial institutions. In his annual conference on Bank Structure and Competition in May 2008, Ben Bernanke underlined the banks' substantial exposures to subprime risk and off-balance sheet vehicles. Similarly, the Senior Supervisors Group (2008) mention the importance of enhanced public disclosures to possibly reduce the uncertainty regarding exposures to off-balance sheet items that the market considers to be high-risk following the crises. Hence, I also check whether the detailed breakdown of the off-balance sheet items and maximum loss exposure to special-purpose vehicles (or variable interest entities) are present in a given report.

In order to avoid the subjective judgments regarding the relative importance of disclosure on sub-indices, following Tetlock (2007); Ellul and Yerramilli (2013), I employ principal component analysis (PCA) to reach the aggregated disclosure score, DSCORE. DSCORE is obtained as the eigenvector in the decomposition of the correlation matrix of the four main groups with the highest eigenvalue. For each bank b, and at a given year t, it is defined as:

$$\mathrm{DSCORE}_{b,t} = \mathrm{PCA}\left(\mathrm{LIQ}_{b,t}, \mathrm{GRP\_STR}_{b,t}, \mathrm{INTRA}_{b,t}, \mathrm{SPIL}_{b,t}\right), \tag{1}$$

where $\mathrm{LIQ}_{b,t}$ is the disclosure score on liquidity risk calculated as the first principal component of liquidity related sub-indices (L^1, L^2, L^3, and L^4 listed in Table 1). The disclosure scores on group structure (GRP_STR), intra-annual information (INTRA), and finally spillover risk (SPIL) are calculated analogously. The four main groups are positively correlated with each other and with the aggregated score, DSCORE.

3.2.1 Assessing the validity of the disclosure index

To quantify a disclosure level is not a straightforward task. Investors can capture information not only through the annual reports or 10–K statements but as well through the reports of financial analysts, rating agencies, intra-annual disclosures of the companies, news channel, or regulatory reports. For instance, the National Information Center collects and publishes (call reports) data about banks for which the Federal Reserve is the supervisor. Finally, investors may value the quality of a disclosure, not only the quantitative disclosures. Although I acknowledge all above, in order to reach a metric, I focus only on the information provided via publicly available 10–K, annual or proxy reports. I implicitly assume that searching for disclosure on multiple sources requires some additional costly effort. Moreover, I check whether a given characteristic of the bank is disclosed, rather than attempt to measure how well it is disclosed. Keeping these possible limitations in mind, I conduct a correlation analysis between DSCORE and various variables identified in prior research to be associated with disclosure level. This may provide some insights into the reliability of the self-constructed index: if my disclosure index indeed measures the disclosure level, it should be significantly correlated with these variables.

The positive link between the size of the firm and disclosure is documented by many (Botosan and Plumlee, 2002; Francis et al., 2008, among others). Various studies show that firms with higher disclosures benefit from improved liquidity and they face a reduced cost of capital (See Healy and Palepu (2001) for a literature review). Hence, I examine the relationship between disclosure, firm size, liquidity, and finally cost of capital.

The firm size is measured as the natural logarithm of the market value of a given BHC at the end of each year. I employ three different proxies to measure liquidity: the bid-ask spread (SPR), Amihud (2002) illiquidity measure (AMD), and stock turnover (TRN). SPR is the annual average of the difference between the weekly closing ask and bid prices. AMD is the absolute value of the weekly returns scaled by turnover and price, averaged annually. Finally TRN is the ratio of trading volume to the number of shares outstanding, averaged across a year. Following Sironi (2003) I proxy the cost of capital (COSTCAP) as the average of the primary market spread to the benchmark security at the time of the subordinated debt issue. I obtain the subordinated debt issue data from Bloomberg and Dealogic databases. COSTCAP is the average spread on the subordinated debt issued by a bank following the disclosure in a given year.

Results presented in Table 2 show that the aggregated disclosure score, calculated as in (1), is significantly and negatively correlated with cost of capital, positively correlated with the size of the firm and liquidity. Within the liquidity measures, the highest correlation is with the Amihud (2002) illiquidity measure. Higher disclosure is associated with a lower price impact, i.e. higher liquidity, on average. Finally, note that the small sample size on the analysis on cost of capital is due to missing data points on the subordinated debt spreads.

[Table 2 approximately here]

3.2.2 Descriptive analysis– disclosure index

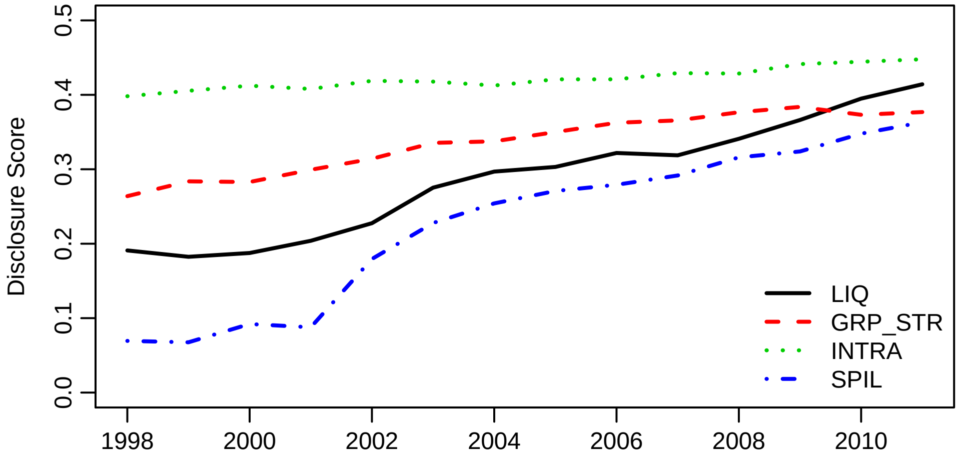
Table 3 presents the descriptive statistics on the sub–indices of the disclosure index. The majority of the U.S. bank holding companies disclose the average balance sheet items and the risk ratios of the main subsidiaries throughout the whole sample period. Hence, the average score is very close to the maximum attainable one for a given category. On the other hand, only a single bank discloses information on the currency breakdown of funding sources, risk ratios of sectors or sub-units, and detailed information on the exposure to special-purpose vehicles in all years. The average scores attained are far lower than 1 for almost all of the sub-indices.

[Table 3 approximately here]

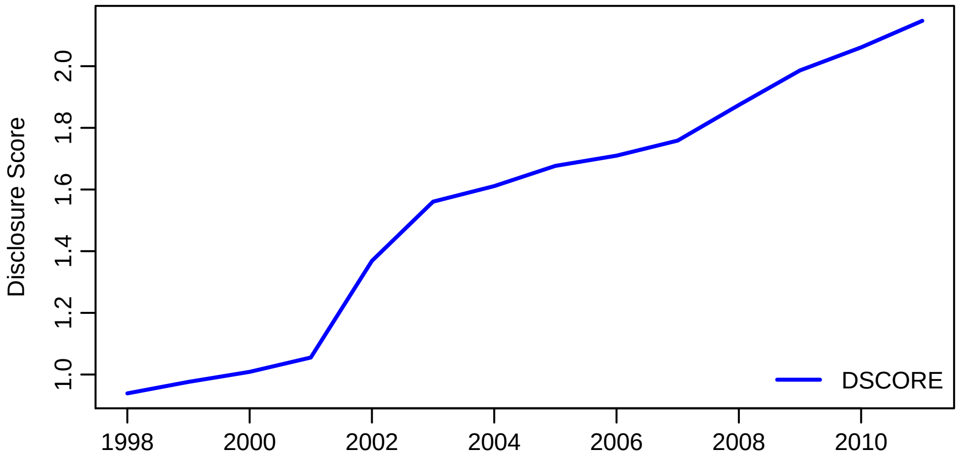
Figure 1 Panels A and B plot the main categories and composite disclosure index (DSCORE), respectively, averaged across the BHCs. There is an increasing trend for the disclosure scores throughout the period in the study, with a particular improvement in the liquidity risk and the spillover and hidden risks (information on off-balance sheet items or exposure to special-purpose entities). The average highest score, 0.448, is on the disclosures related to intra–annual information, whereas the scores related to the spillover risk are the lowest among the four main categories. Another area where progress has been slow over the period is the provision of the balance sheet and the risk positions of the main group affiliates and segments (GRP_STR). The (unreported) results reveal that disclosure varies across the BHCs in the sample in a given year. The minimum standard deviation is around 0.149, whereas it increases up to 0.332 in 2011 for the score on spillover risk.

3.3 Measuring expected probability of default

The default probability of an institution depends on the unobservable factors such as the value of the company or the firm volatility that needs to be translated from publicly observable data. Several studies use different proxies to estimate the default probability.



(a) Panel A: Disclosure Score–sub-indices



(b) Panel B: Aggregated Disclosure Score

Figure 1: Panel A plots the disclosure scores assigned to each of the sub-indices of disclosure throughout the sample period, averaged across the bank holding companies. Disclosure score on liquidity (LIQ), for example, is obtained as average of the scores on the liquidity-related sub-indices: L^1, L^2, L^3, and L^4 for each bank in a given year. GRP_STR stands for the disclosure on group structure, INTRA for intra-annual information, and finally, SPIL for spillover risk. For all of the categories, the minimum attainable score is 0, whereas the maximum attainable score is 1. Panel B presents the cross-sectional average of the aggregate disclosure score (DSCORE) obtained as the first principal component of the four sub-indices.

Nier and Baumann (2006) proxy the default risk by the book leverage, Anginer and Yildizhan (2010) use corporate credit spreads. Using the maximum entropy principle, Jeong (2010) proposes a methodology to estimate the default probability of a firm using binary option prices. An appealing methodology is proposed by Capuano (2008). The idea is to use the Merton (1974) framework to extract implied probabilities of default from equity option prices. This is quite a flexible framework; the default barrier and the probability distribution of the firm value is endogenously estimated. Though, one can argue two possible drawbacks of the methodology. First, since in case of a default, there is neither stock, nor options trading, we do not have any information regarding the default state. One can only estimate parameters of *entering* to the default state. Second, it estimates the expected level of default in a risk neutral world rather than the actual probability measure. However, as options are forward-looking instruments, using option prices brings us the advantage of extracting information on market participants' expectations. This paper employs Capuano (2008)'s implied probability of default (IPoD) model to measure an institution's expected default probability.[6]

3.3.1 The methodology

Merton (1974)'s structural framework suggests that a company goes bankrupt if its value of assets, V, is lower than the face value of its debt, D. If the default value and the distribution of assets are known, then one can estimate the probability of default as follows:

$$PoD(D) = \int_0^D f(V_T)dV_T, \tag{2}$$

where $f(V)$ is the probability density function of the value of the assets V. Hence, to calculate the probability of default, one needs to estimate the default barrier D as well as infer the $f(V_T)$. Capuano (2008) employs the principle of minimum cross-entropy, which makes it possible to recover the probability distribution of a random variable by minimizing the relative distance between the prior and posterior density functions using the option prices (Cover and Thomas, 2006). The density functions can be estimated

[6] One possible alternative is to use CDS spreads of the institutions. However, the available CDS data does not span the panel sample used in this study.

through the available option contracts since the payoff of a call option written on a stock can be written as:

$$C_T^K = \max(E_T - K; 0) = \max(V_T - D - K; 0), \tag{3}$$

where K is the corresponding strike price and E is the equity. The second equality holds since equity holders receive either 0 in case of a default or the residual amount in case of no-default. Once $f^*(V_T)$ and D^* are obtained through numerical optimization, the IPoD is calculated through (2). Recently, Vilsmeier (2011) suggests a technical modification to Capuano's (2008) framework which increases the robustness and feasibility of the numerical optimization. This paper follows Vilsmeier (2011)'s methodology to estimate the IPoD.[7] The steps required for the estimation of IPoD are outlined in Appendix A. For further details, see Capuano (2008) and Vilsmeier (2011).

At least two option contracts written on the same stock with the same expiry date are needed to solve the problem. The first one is used to shape the density function $f^*(V, D)$, whereas the second one is needed to estimate the threshold level D^*. I apply the framework only to the call options since put options relate by the put-call parity. Moreover, I consider only the options with time to expiry more than 6 months due to instability of the results for options with shorter time-to-maturity. Trading and expiry dates, strike prices corresponding to each option, underlying stock price, the risk-free rate, and the closing bid and ask prices are required to estimate IPoD. Option prices are the average of bid and ask prices. Finally, in order to capture the liquidity differences, I weight the option contracts by using the open interest of each option.[8]

3.3.2 Descriptive analysis–IPoD

Figure 2 plots the estimated IPoD values in a log-linear scale throughout the sample period for the whole sample, for defaulted BHCs only, and finally for non–defaulted ones. The results reveal relatively low market based default probabilities for the 2003–2006 period, where the average expected default rate is 0.18. On the other hand, there is a significant increase in 2007 with a peak in 2009. From 2006 to 2009, the average value

[7] I sincerely thank Johannes Vilsmeier for sharing his codes to estimate the probability of default.

[8] Capuano (2008) uses the trading volume as the weight, whereas Vilsmeier (2011) uses the open interests. I estimate the IPoD using both trading volume and open interests and the results are qualitatively similar. However, the IPoD estimated through open interests are more stable. Hence, I report only the results, where open interest is used to weight the liquidity of an option.

of implied default probability increases from 0.15 percent to over 10 percent. Moreover, the mean of IPoD for the defaulted companies is higher from the non-defaulted ones for the 2006–2009 period.

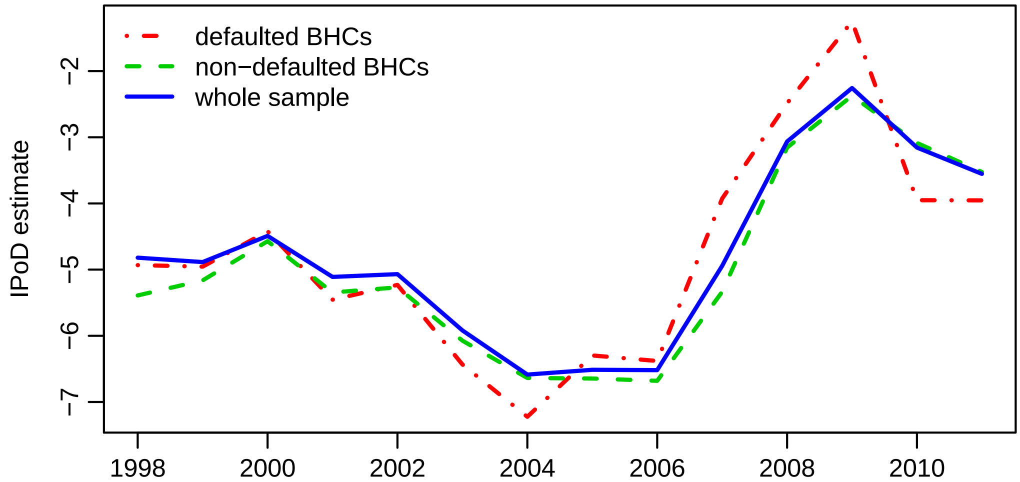


Figure 2: The figure plots the market implied probability of default (IPoD) estimates throughout the sample period, averaged across the bank holding companies (BHCs) in a log-linear scale. A BHC is identified as defaulted if it is delisted in a given year.

One expects that the market's assessment of the riskiness of a stock increases with the market–wide uncertainty. Hence, in order to validate the IPoD estimates, I proxy the overall uncertainty in the stock market with the Chicago Board Options Exchange Market Volatility Index (VIX). As expected, the Spearman correlation coefficient between the VIX index and IPoD is 0.2566 and significant at the 1 percent level.

4 Empirical Methodology and Preliminary Analysis

This section introduces the empirical methodologies employed to test Hypotheses 1, 2, and 3. Section 4.1 outlines the panel regressions estimated via ordinary least square regressions and introduces the control variables. Section 4.2 presents a preliminary analysis conducted on key variables. In Section 4.3, I give the details of the instrumental variables employed and introduce two-stage least squares regressions and Arellano and Bond (1991) dynamic panel GMM estimation approach.

4.1 Ordinary least squares regressions

The following panel regression is employed to test the relationship between disclosure and market expected default risk:

$$\log \text{IPoD}_{b,t+1} \quad = \quad \gamma \text{DSCORE}_{b,t} + \kappa * X_{b,t} + \nu_t + \eta_b + \varepsilon_{b,t}. \tag{4}$$

Subscript b denotes the bank holding company (BHC) and t denotes the year. Year and BHC fixed effects are included in the regression to capture any time-invariant unobserved BHC characteristics. The dependent variable, $\log \text{IPoD}_{b,t+1}$, is the natural logarithm of the average implied probability of default for bank b between two annual 10–K statements disclosure dates.[9] For example, if a bank's 2008 10–K report became public on the SEC–Edgar database on the 26$^{\text{th}}$ of February 2009, $\text{IPoD}_{b,t+1}$ is calculated as the natural logarithm of the average IPoD estimates from 27$^{\text{th}}$ of February 2009 until 16$^{\text{th}}$ of February 2010, which is the disclosure date of 10–K statement for the year 2009.

The main independent variable, $\text{DSCORE}_{b,t}$, is the aggregated disclosure score of bank b at year t, calculated as in (1). In line with Hypothesis 1, the coefficient of interest, γ_1, is expected to be negative; investors assess high disclosed banks as less likely to default.

The first control variable is the size of a given bank holding company (SIZE), measured as the natural logarithm of the year-end total market capitalization. I then control for the volatility of the firm value, proxied as the standard deviation of weekly equity returns in a given year. Finally, I include other bank holding company financial characteristics. Nier and Baumann (2006) proxy the (inverse) default probability with individual banks' capital buffers and document a positive relationship between disclosure and the capital buffer. In a cross-country analysis, Beltratti and Stulz (2012) show that large banks with more capital perform significantly better during the crises. Hence, I define capital buffer, CAPBUF, as a bank's equity capital divided by its total liabilities. To capture other accounting risks, I consider non-performing loans, return on equity ratio, and finally deposits in log terms. The definitions of the variables are presented in detail in Appendix B.

[9]Given the high skewness/kurtosis of the distribution, I use the logarithm of the IPoD estimates instead of the levels in the analysis (see for instance Laeven and Levine, 2009). For brevity, "IPoD" refers to the natural logarithm of IPoD in the rest of the paper.

4.2 Preliminary analysis

Table 4 Panel A presents the summary statistics of key variables. Disclosure score has an annual mean of 1.58. Its value ranges from 0.06 to 7.69 with a standard deviation of 1.40. The minimum annual IPoD value is -11.87 (corresponding to a 0 probability of default), and it increases up to -0.76 (equivalently, a 47 percent of implied default probability). The mean market value of common equity (SIZE) is $2.91 billion. Capital buffer and the return on equity have significant variations across bank holding companies.

[Table 4 approximately here]

The figures of Panel B reveal that the correlation between disclosure and implied default probability is negative as expected, however the relationship is not statistically significant. Size is negatively related to IPoD and positively related to disclosure, both being highly significant. In other words, investors assess bigger banks as less likely to default and bigger banks disclosure more. There is a strong statistical relationship between the size of a BHC and BHC characteristics: bigger banks hold higher capital buffers, have better operating performance, have a lower ratio of non-performing loans, and have a higher level of deposits. Volatility is significantly and positively correlated with IPoD, suggesting that higher market risk increases the investors' expectations of default probability. Within the accounting variables, the ratio of non-performing assets are significantly related to both disclosure and IPoD.

Finally, I identify a bank as a high-disclosed (low-disclosed) one if its disclosure score is higher (lower) than the median disclosure score in a given year. In order to understand the differences in characteristics between high-disclosed and low-disclosed bank holding companies, I then employ a univariate mean comparison test between these two samples. The results presented in Table 4 Panel C show that a BHC that discloses more information on its risk profile than its peers has significantly lower average market implied default probability in the following year. Not surprisingly, BHCs with higher levels of disclosure are larger in size. Larger BHCs are more likely to be complex in structure and involved in riskier non-banking activities. Thus they have higher incentives to mitigate informational frictions by disclosing more information. Finally, high-disclosed BHCs have higher levels of deposits and better operating performance measured by ROE compared with their low-disclosed pairs. Obviously, the analysis does not answer whether higher disclosure leads to an increase in those variables, or higher values of the aforementioned accounting characteristics encourage the management to disclose more information.

4.3 Instrumental-Variables regressions

The underlying assumption of regression model (4) is that disclosure, DSCORE, is exogenous after controlling for market risk, bank holding company characteristics, year, and bank fixed effects. However, causality may run in both directions–from management's decision on disclosure level to default probability and vice versa. For instance, a bank holding company exposed to higher risk may choose to disclose more information to reduce the uncertainty and change investors' assessment of its risk. Otherwise, some unobserved time-invariant bank characteristics may jointly affect the default probability and disclosure. In these cases, the regressors will be correlated with the error term, which produces biased coefficients. I attempt to correct this self-selection bias by first employing an instrumental-variable (IV) approach and second by the Arellano and Bond (1991) dynamic panel GMM estimation approach.

To examine the causal effects of disclosure on the market implied default probabilities, one needs a source of exogenous variation in information asymmetry. One can safely assume that the forecasts provided by the analysts who actively cover a stock provide valuable information to investors assessing the performance or the riskiness of a company. In this case, an increased number of estimates is associated with lower information asymmetry.

I first employed the analyst coverage as an instrument for disclosure. Analyst coverage ($\text{COVER}_{b,t}$) is calculated as the number of analysts providing earnings-per-share (EPS) estimates for the end of year t for bank b. However COVER may not necessarily be exogenous. Bigger stocks may benefit from higher analyst coverage, or banks with greater uncertainty or less disclosure may attract more coverage. Hence, second, I employ expected coverage first introduced by Yu (2008) as an instrument. Expected coverage ($\text{EXPCOVER}_{b,t}$) depends on the size of the brokerage house, which is less likely to be affected by the risk of banks or banks' managers actions that the brokerage house covers. It rather depends on the changes of brokerage houses' own revenue, profits, and business decisions. In other words, the coverage driven by the change of broker size is a plausibly exogenous variation (Yu, 2008; He and Tian, 2013). It is defined as follows:

$$\begin{aligned}\text{EXPCOVER}_{b,t,j} &= \frac{\text{BROKERSIZE}_{t,j}}{\text{BROKERSIZE}_{t-1,j}}\text{COVER}_{b,t-1,j} \\ \text{EXPCOVER}_{b,t} &= \sum_{j=1}^{N}\text{EXPCOVER}_{b,t,j} \qquad (5)\end{aligned}$$

where $\text{EXPCOVER}_{b,t,j}$ is the expected coverage for bank b from brokerage house j in a given year t. $\text{BROKERSIZE}_{t,j}$ and $\text{BROKERSIZE}_{t-1,j}$ are the total number of analysts employed by brokerage house j in years t and $t-1$, respectively. Finally N is the total number of brokerage houses. The following 2SLS regressions are estimated:

$$\begin{aligned}\text{DSCORE}_{b,t} &= \beta\text{IV}_{b,t} + \kappa * X_{b,t} + \nu_t + \eta_b + \varepsilon_{b,t} \qquad (6) \\ \log\text{IPoD}_{b,t+1} &= \theta\widehat{\text{DSCORE}}_{b,t} + \lambda * X_{b,t} + \alpha_t + \mu_b + \xi_{b,t}.\end{aligned}$$

where IV is the chosen instrument, either COVER or EXPCOVER. Subscript b denotes the BHC and t denotes the year.

Finally, I take into account that a bank holding company's past level of market implied default risk can affect both the current level of default risk and the decision on disclosure. In other words, IPoD and DSCORE can be *dynamically endogenous*. To adjust for this possible dynamic relationship, I employ the Arellano and Bond (1991) dynamic panel GMM estimator, which enables us to use the lags of the endogenous variables to provide instruments for identifying the relationship between disclosure and IPoD.

5 Results

5.1 Effects of disclosure on expected default risk

In this section, I test Hypothesis 1 that the previous level of disclosure is associated with lower levels of current market implied default probability. I start the analysis by employing the OLS regressions. Estimated coefficients of (4) are presented in Table 5 Columns I and II. The coefficient on DSCORE is negative and statistically significant at the 5 percent level, confirming the hypothesis: higher disclosure is associated with lower market expected default risk. The documented association is highly economically significant: one standard deviation increase in disclosure is associated with a 18 percent decrease in expected default risk in the following year, when controlled with the BHC characteristics. This suggests that high disclosed banks are assessed as less likely to default.

[Table 5 approximately here]

Table 5 Columns III–VI present the results of the two-stage least squares (2SLS) regressions in (6). The relevance condition requires that a valid instrument must strongly correlate with the endogenous variable, in my case, disclosure. The first stage results suggest that a BHC indeed increases its voluntary disclosure when the information environment deteriorates, measured by analyst coverage or expected coverage. Second stage regression results conclude that the increased disclosure has a beneficial effect on market expected default probability, irrespective of the chosen instrument for disclosure.

Finally, Column V reports the Arellano and Bond (1991) dynamic panel GMM estimation results, which uses the two lags of the endogenous variables as instruments. The coefficient on DSCORE continues to be negative and significant and the joint validity of the instruments cannot be rejected with a p–value of over 0.26, confirming the conclusion.

I note that both 2SLS and GMM results point to biases in OLS estimates. When the causality of the relationship is taken into account, the economic relationship between disclosure and the default probability is stronger. This suggests that the OLS estimates are likely to be substantially downward biased. This is in line with the findings of Balakrishnan et al. (2014), which considers the causal relationship between the voluntary disclosure and liquidity.

Besides DSCORE, in all of the specifications, size is significantly and negatively associated with the expected default risk. Bigger bank holding companies are assessed as less likely to default, which could be a result of implicit too-big-to-fail guarantees or other benefits of size such as diversification across products and geography. Finally, the bank holding company accounting characteristics have expected signs. Higher non-performing loans indicate higher expected losses and associated with higher expected default risk. Higher profitability may signal greater efficiency and lower default risk. However, a higher value might also indicate higher risk-taking activities. The results suggest that above-sample-average ROE is assessed as increased risk. Similarly, higher deposits could be argued as a stable source of funding, and hence, reducing the risk or could be a signal of an increased maturity gap of funding as typically deposits have short term maturity. We find the evidence supporting the latter that deposits are positively associated with next period's default risk.

5.2 Effects of disclosure on other enterprise risks

Besides the expected default risk, I test the effects of disclosure on aggregate, downsize, systematic, and idiosyncratic risk. First, I use the standard deviation of a bank's weekly equity returns as a proxy for aggregate risk (AGGRISK) (Nier and Baumann, 2006). Second, I measure downside risk (DOWNRISK) as the mean of implied volatility estimates from the option prices written on the bank's stock (Cremers and Weinbaum, 2010; Xing et al., 2010). Third, I measure the systematic risk (SYSRISK) by the beta of the firm, estimated from the CAPM model, and finally, I include the idiosyncratic risk (IDIORISK) calculated as the standard deviation of the weekly residuals of the CAPM model. Similar to the calculation of IPoD, I use the natural logarithm of the risk estimates instead of the levels.

In Table 6, I present the 2SLS and GMM regression results where EXPCOVER is used as an instrument for disclosure. The results indicate that the estimated coefficient on disclosure is negative, significant, and robust to the alternative specifications and empirical methodologies for aggregate, downside, and idiosyncratic risk. On the other hand, although significant under OLS regressions (not reported), the relationship between disclosure and systematic risk is no longer significant under the GMM regressions. Finally, if COVER is used as an instrument, the results are qualitatively similar and quantitatively stronger.

My findings support the theoretical works of Ederington and Lee (1996); Lambert et al. (2007); Diamond and Verrecchia (1991); higher disclosure is associated with lower aggregate and implied volatility, beta and idiosyncratic risk. These findings are in line with the existing empirical literature that provides evidence on corporate firms (see for example, Bushee and Noe, 2000; Kothari et al., 2009; Rogers et al., 2009; Foerster et al., 2013). In addition to this literature, I provide new evidence that the relationship holds for the banking sector. The results therefore suggest that the level of information is an important determinant of both diversifiable risk and nondiversifiable risks. Increased disclosure may be perceived as an increased transparency by investors, which in turn affects the agents' perceptions regarding the riskiness of the given bank holding company.

5.3 Effects of disclosure on bank value and performance

If disclosure leads to a more efficient allocation of risk, as presented in the previous sections, then one may expect the information presented in the annual reports to be value relevant. In order to test Hypothesis 3, I estimate the 2SLS regressions presented in (6) along with the panel GMM estimator by using bank value, operating performance, and the Sharpe ratio as dependent variables. Similar to the calculation of IPOD, I calculate the value of the dependent variable as the average value for bank b between the two 10–K report disclosure dates corresponding to year t. The bank value (FV) is measured as the ratio of the bank market equity to its book value. Operating performance is proxied by return on assets (ROA), which is the ratio of income to book asset value. Finally the Sharpe ratio is used as a risk-adjusted performance measure and calculated as the ratio of the annual of excess stock returns (excess from the market return) as well as the standard deviation of weekly excess returns.

The results presented in Table 7 confirm the hypothesis that disclosure is value relevant; reduced assessed risk leads to increased firm value and operating performance. This could be a result of voluntary disclosure reducing a firm's cost of capital as documented in various studies (see for instance, Botosan, 1997; Leuz and Verrecchia, 2000; Botosan and Plumlee, 2002; Barth et al., 2013) or increasing liquidity, which in turn improves the bank value (Balakrishnan et al., 2014).

[Insert Table 7 approximately here]

The association of previous year's disclosure level with the current year's risk-adjusted performance is found to be positive and statistically significant at the 5 percent level, confirming the theoretical predictions of Verrecchia (1983) and Dye (1985). This implies that investors value and learn from credible disclosures. In other words, disclosure helps to reduce the asymmetric information between investors and managers and the banks with higher level of disclosure can outperform their peers following an enhanced disclosure.

5.4 Additional robustness checks

I perform four sets of additional robustness tests to confirm the validity of the results. First, I examine whether the documented relationship between disclosure and the annual implied default probability (IPoD) holds for other time intervals. By using expected coverage (EXPCOVER) as instrument, I re-estimate the baseline 2SLS regressions (6) with dependent variables equal to the log of bimonthly, three-months, and semi-annual averages of IPoD estimates following the disclosure date. Second, I assess the sensitivity of the results to model specification by using the logit-transformed market implied default probability instead of a log-transformation.

Third, one can argue that the results could be driven by the crisis period. In the end, it is likely that in good times, investors may not price the disclosed accounting information or certain risks, but that may become significant only in a crisis-period. Hence, I exclude the data for 2008 and 2009 from the sample and re-run (6). Finally, I change the definition of the instrumental variable. For a given year t, I proxy disclosure with ΔCOVER_t and $\Delta\text{EXPCOVER}_t$ defined as the average increase in coverage and expected coverage over the period $t-2$ to t, respectively.

Table 8 presents the results. Results confirm the robustness of the documented relationship between market implied default probability and disclosure. Columns II to IV show that irrespective of the horizon, disclosure is negatively and significantly associated with the next period IPoD. The economic significance of the association is highest for the three-months ahead and lowest for the annual. It is compulsory for a bank holding company to file quarterly 10–Q reports to the SEC. Although those reports are not as comprehensive as the annual 10–K statements, they still provide a continuing view of a company's financial position. Hence, it is likely that the informativeness of an annual report decreases with releases of 10–Q statements, i.e., after three months of the release of an annual report. Results are robust to the model specification, sample period, and changes in the definition of instruments.

[Table 8 approximately here]

6 Conclusion

Increased uncertainty is argued as one of the main reasons for the breakdown of trading and the associated withdrawal of liquidity in many markets during the global financial crisis. In periods of stress, there is a flight to quality and safe-haven. Hence, investors with imperfect information about the quality of assets reduce their holdings, while holders of "safe" assets are unwilling to sell, leading to a collapse of market functioning. The evidence presented in this paper suggests that disclosure may help to mitigate some of these informational frictions.

In particular, I show that increased disclosure affects the investors' beliefs on the riskiness of a bank and is followed by increased firm value. Hence, one can argue that the communication processes increase transparency and eliminate disparities between what investors understand and what management intends to deliver. Managers can actively influence their bank's value by altering the voluntary information disclosures. The results are robust to the inclusion of a number of other bank characteristics and adjustments for possible endogeneity. The economic effects of disclosure estimated in the 2SLS models are about three times greater than the ones estimated through OLS, suggesting that the OLS estimates are likely to be substantially downward biased due to endogeneity.

This paper provides possible policy implications. High disclosure is a necessary condition for market discipline and it seems to provide incentives for investors to reward the high disclosed banks. This is mutually beneficial for the bank, as reduced risk is translated into higher bank values, possibly through reduced cost of capital as documented in the literature. The constructed index shows that there are especially two areas in which banks fail to provide sufficient information, suggesting that more granular quantitative disclosures could be beneficial. The first area is disclosures on liquidity risk, especially on the information on unencumbered funding and liquid asset holdings, whereas the second one is disclosures on credit exposures to other financial institutions and to the special-purpose entities.

Appendix A. IPoD: Summary of the estimation methodology

Merton (1974)'s structural framework suggests that a company has two sources of financing of his assets (V): debt (D) and equity (E). The company goes to bankrupt if its value of assets is lower than the face value of its debt. The default probability can be written as:

$$PoD(D) = \int_0^D f(V_T) dV_T \tag{1}$$

where $f(V)$ is the probability density function of the value of the assets and D is the default barrier.

Option implied probability of default (IPoD) requires to determine D and the probability that V_T ends up below D through option prices. To do so, Capuano (2008) employs the concept of minimum cross entropy (Cover and Thomas, 2006). The cross-entropy can be interpreted as a measure of relative distance between the prior and the posterior density functions, or the degree of uncertainty around $f(V)$. The problem to be solved turns out to be:

$$\min_D \left\{ \min_{f(V_T)} \int_0^\infty f(V_T) \log \frac{f(V_T)}{f_0(V_T)} dV_T \right\} \tag{2}$$

where $f_0(V)$ is the prior probability density function of the value of asset V and $f(V_T) \log \frac{f(V_T)}{f_0(V_T)}$ is the cross-entropy (or relative entropy) between $f(V)$ and $f_0(V)$. The minimization problem (2) is subject to the following constraints:

1. **Option pricing constraint**—The current price of an option is the discounted future cash flows under risk neutral measure:

   $$C_0^{K_i} = e^{-rT} \int_{V_T = D + K_i}^\infty (V_T - D - K_i) f(V_T) dV_T \tag{3}$$

   where K_i is the strike price of option i. Note that the current stock price S_0 is included as an option with $K = 0$.

2. **Additivity constraint**—The probability density function must sum up to 1:

   $$1 = \int_{V_T = 0}^\infty f(V_T) dV_T \tag{4}$$

Hence, the Lagrangian adds up to:

$$
\begin{aligned}
L = & \int_0^\infty f(V_T)\log\frac{f(V_T)}{f_0(V_T)}dV_T + \lambda_0\left[1-\int_{V_T=0}^\infty f(V_T)dV_T\right] \\
& + \sum_{i=1}^N \lambda_i\left[C_0^{K_i} - e^{-rT}\int_{V_T=D+K_i}^\infty (V_T - D - K_i)f(V_T)dV_T\right]
\end{aligned}
\tag{5}
$$

where N is the number of options available, $\lambda_0, ..., \lambda_N$ are the corresponding Lagrange multipliers. The first step is to determine the optimal values of λs through the first order conditions. For a given value of D:

$$
\begin{aligned}
\frac{\partial L(f(V,\lambda),\lambda)}{\partial\lambda} &= e^{-rT}\int_{V_T=0}^\infty \mathbb{1}_{V_T>D+K_i}(V_T - D - K_i)f(V_T)dV_T - C_0^{K_i} \\
&= 0, \qquad i = 1,..,N.
\end{aligned}
$$

I started by assuming that the prior probability density function $f_0(V_T)$ is uniform. The first order conditions describe how to optimally modify the prior and construct a posterior density $f(V_T)$ that is able to satisfy the price constraints observed in the market. The optimization problem should be solved numerically via a multivariate algorithm, such as the Newton–Paphson algorithm. However, the majority of my optimization trails failed due to the non-singularity of the Jacobian matrix resulting from the first Taylor approximation, which is a problem noted by Vilsmeier (2011). The author suggests a technical modification to the Capuano (2008)'s framework to solve this issue. Following Alhassid et al. (1978), he uses a robust and computationally efficient algorithm to calculate the optimal set of λs. This paper follows Vilsmeier (2011)'s methodology to estimate the optimal λs.

Once the optimal λs are obtained, one can get $f^*(V_T, D)$. Given $f^*(V_T, D)$, the default barrier D^* is calculated trough another numerical optimization of:

$$
\lim_{\Delta\to 0}\frac{L\left(f^*(V_T, D+\Delta)\right) - L\left(f^*(V_T, D)\right)}{D+\Delta} = 0. \tag{6}
$$

Finally the IPoD is estimated through (1) once $f^*(V_T)$ and D^* are given.

Appendix B. Variable Descriptions and BHC Sample

- **DSCORE**: Total disclosure score. It is calculated as the first principal component of the four main groups: liquidity risk, group structure, intra-annual information and spillover risk.

- **IPoD**: Option implied probability of default. It is extracted from equity option prices using the methodology proposed by Capuano (2008) and introduced in Section 3.3 and detailed in Appendix A.

Risk Measures:

- **AGGRISK**: Aggregate risk, calculated as the standard deviation of a bank's weekly equity returns.

- **DOWNRISK**: Downside risk. It is average implied volatility estimated from options written on a bank's stock.

- **SYSRISK**: Systematic risk, estimated as the beta of a bank from regressions of bank weekly equity returns on the weekly returns of CRSP value-weighted index.

- **IDIORISK**: Idiosyncratic risk, calculated as the standard deviation of the weekly residuals of the CAPM model.

Performance Measures:

- **FV**: Firm value, calculated as the ratio of the bank market equity to its book equity (BHCK3210).

- **ROA**: Return on assets, calculated as the ratio of the income before extraordinary items (BHCK4300) to total book assets (BHCK2170).

- **SHARPE**: The Sharpe ratio is calculated as the ratio of the annual stock returns in excess of the market return (between two annual report dates) divided by the standard deviation of weekly excess returns. Market return is calculated as the value-weight return of all CRSP firms listed on the NYSE, AMEX, or NASDAQ.

Bank holding company characteristics:

- **SIZE**: Natural logarithm of the BHC's total market value at the end of the year.

- **VOLA**: Volatility calculated as the standard deviation of weekly equity returns.
- **CAPBUF**: Capital buffer of a BHC at the end of the year. Calculated as the bank's equity capital as a proportion of its total liabilities (BHCK3210/BHCK2948).
- **NPL**: The non-performing loans ratio. It is calculated as the ratio of the sum of loans past due 90 days or more (BHCK5525) and non-accrual loans (BHCK5526) to total assets (BHCK2170).
- **ROE**: Return on equity, calculated as the ratio of the income before extraordinary items (BHCK4300) to total book equity (BHCK3210).
- **DEPO**: The natural logarithm of total deposits (BHDM6631+BHDM6636+BHFN6631+BHFN6636).

Instrumental variables:

- **BROKERSIZE**: The total number of analysts employed by a given brokerage house in a year t.
- **COVER**: Coverage is the number of analysts providing EPS estimates for the end of year t for bank b. I/B/E/S detail estimates file is used.
- **EXPCOVER**: Expected coverage is the sum of expected analyst coverage from all brokers covering bank b in year t, where the expected coverage from brokerage house j is the product of the analyst coverage from broker j for bank b in year $t-1$ multiplied by the ratio of broker j's size (total number of analysts employed by the broker) in year t divided by broker j's size in year t-1. I/B/E/S detail estimates file is used.

Table B.1: List of Bank Holding Companies
This table lists the sample of bank holding companies (BHCs) included in the analysis with the corresponding identifiers.

NAME	**2007 TA ($bn)**	**STATE**	**RSSID**	**PERMNO**	**SAMPLE**
ASSOCIATED BANC CORP	21.59	WI	1199563	15318	1998–2011
BANCORPSOUTH	13.20	MS	1097614	85789	1998–2011
BANK OF AMER CORP	1720.69	NC	1073757	58827/ 59408	1998–2011
BANK OF HI CORP	10.47	HI	1025309	16548	1998–2011
BANK OF NY MELLON CORP	197.84	NY	3587146	49656	2002–2011
BB&T CORP	132.62	NC	1074156	71563	1998–2011
BOK FC	20.90	OK	1883693	76892	1998–2011
BOSTON PRIVATE FNCL HOLD	6.83	MA	1248078	80223	1998–2011
CAPITAL ONE FC	150.59	VA	2277860	81055	1998–2011
CATHAY GEN BC	10.40	CA	1843080	76504	1998–2011
CENTRAL PACIFIC FC	5.68	HI	1022764	11628	1998–2011
CITIGROUP	2187.63	NY	1951350	70519	1998–2011
CITIZENS REPUBLIC BC	13.52	MI	1205688	86685	1998–2011
CITY NAT CORP	15.89	CA	1027518	23916	1998–2011
COLONIAL BANCGROUP	25.97	AL	1080465	24628	1998–2008
COMERICA	62.76	TX	1199844	25081	1998–2011
COMMERCE BC LLC	49.37	NJ	1117679	86845	1998–2007
COMMERCE BSHRS	16.21	MO	1049341	25129	1998–2011
CORUS BSHRS	8.93	IL	1200393	67046	1998–2008
CULLEN/FROST BKR	13.65	TX	1102367	27888	1998–2011
CVB FC	6.29	CA	1029222	20395	1998–2011
EAST W BC	11.85	CA	2734233	86719	1998–2011
FIFTH THIRD BC	110.96	OH	1070345	34746	1998–2011
FIRST BC	17.19	PR	2744894	11018	1998–2011
FIRST CITIZENS BSHRS	16.23	NC	1075612	10777	1998–2011
FIRST COMMONWEALTH FNCL	5.89	PA	1071306	77643	1998–2011
FIRST HORIZON NAT CORP	37.02	TN	1094640	36397	1998–2011
FIRST MIDWEST BC	8.10	IL	1208184	35917	1998–2011
FIRSTMERIT CORP	10.41	OH	1070804	35167	1998–2011
FNB CORP	6.09	PA	3005332	10629	1998–2011
FRANKLIN RESOURCES	9.63	CA	1246216	37584	1998–2011
FULTON FNCL CORP	15.92	PA	1117129	88197	1998–2011
HANCOCK HC	6.10	MS	1086533	76684	1998–2011
HUNTINGTON BSHRS	54.63	OH	1068191	42906	1998–2011
INTERNATIONAL BSHRS CORP	11.17	TX	1104231	85875	1998–2011
IRWIN FC	6.17	IN	1199732	89237	1998–2008
JPMORGAN CHASE & CO	1562.15	NY	1039502	47896	2000–2011
KEYCORP	99.57	OH	1068025	64995	1998–2011
M&T BK CORP	64.88	NY	1037003	35554	1998–2011

Table B.1: List of BHCs in the sample (cont.)

NAME	2007 TA ($bn)	STATE	RSSID	PERMNO	SAMPLE
MB FNCL	7.83	IL	1090987	81541	1998–2011
NATIONAL CITY CORP	150.38	OH	1069125	56232	1998–2007
NATIONAL PENN BSHRS	5.82	PA	1117026	56611	1998–2011
NEW YORK CMNTY BC	30.60	NY	2132932	79859	1998–2011
NEWALLIANCE BANCSHARES	8.23	CT	3214095	90132	2003–2011
NORTHERN TR CORP	67.61	IL	1199611	58246	1998–2011
OLD NAT BC	7.85	IN	1098303	12068	1998–2011
PACIFIC CAP BC	7.39	CA	1029884	83551	1998–2011
PARK NAT CORP	6.50	OH	1142336	76266	1998–2011
PNC FNCL SVC GROUP	138.98	PA	1069778	60442	1998–2011
POPULAR	44.41	PR	1129382	16505	1998–2011
PROSPERITY BSHRS	6.38	TX	1109599	86432	1998–2011
PROVIDENT BSHRS CORP	6.47	MD	1247633	11823	1998–2008
PROVIDENT FNCL SVC	6.36	NJ	3133637	89653	2002–2011
REGIONS FC	141.04	AL	3242838	35044	2004–2011
SANTANDER BC	9.15	PR	2847115	86398	2000–2009
SOUTH FNCL GROUP	13.87	SC	1141599	10825	1998–2009
STATE STREET CORP	142.94	MA	1111435	72726	1998–2011
STERLING FC	12.15	WA	3152245	11056	1998–2011
SUNTRUST BK	179.57	GA	1131787	68144	1998–2011
SUSQUEHANNA BSHRS	13.08	PA	1117156	73809	1998–2011
SVB FNCL GRP	6.45	CA	1031449	11786	1998–2011
SYNOVUS FC	33.02	GA	1078846	20053	1998–2011
TCF FC	16.07	MN	2389941	10375	1998–2011
TRUSTMARK CORP	8.97	MS	1079562	35263	1998–2011
U S BC	237.62	MN	1119794	66157	1998–2011
UCBH HOLD	11.80	CA	2694814	86437	1998–2008
UMB FC	9.34	MO	1049828	78829	1998–2011
UMPQUA HC	8.35	OR	2747644	86004	1999–2011
UNIONBANCAL CORP	55.73	CA	1378434	20694	1998–2011
UNITED BSHRS	7.99	WV	1076217	11369	1998–2011
UNITED CMNTY BK	8.21	GA	1249347	89323	1998–2011
VALLEY NAT BC	12.75	NJ	1048773	80072	1998–2011
W HOLD CO	17.93	PR	2801546	93105	1999–2008
WACHOVIA CORP	782.90	NC	1073551	36469	1998–2007
WEBSTER FNCL CORP	17.21	CT	1145476	10932	1998–2011
WELLS FARGO & CO	575.44	CA	1120754	38703	1998–2011
WHITNEY HC	11.03	LA	1079740	77053	1998–2011
WILMINGTON TR CORP	11.62	DE	1888193	83030	1998–2011
WINTRUST FC	9.37	IL	2260406	84636	1998–2011
ZIONS BC	52.95	UT	1027004	84129	1998–2011

References

Alhassid, Y., N. Agmon and R. D. Levine, "An upper bound for the entropy and its applications to the maximal entropy problem," *Chemical Physics Letters* 653 (1978), 22–26.

Amihud, Y., "Illiquidity and stock returns: cross-section and time-series effects," *Journal of Financial Markets* 5 (2002), 31–56.

Anginer, D. and C. Yildizhan, "Is there a Distress Risk Anomaly? Corporate Bond Spread as a Proxy for Default Risk," (January 2010), World Bank Policy Research Working Paper, 5319.

Arellano, M. and S. Bond, "Some tests of specification for panel data: Monte carlo evidence and an application to employment equations.," *Review of Economic Studies* 58 (1991), 277–297.

Balakrishnan, K., B. Billings, M., T. Kelly, B. and A. Ljungqvist, "Shaping liquidity: On the causal effects of voluntary disclosure," *Journal of Finance* 69 (2014), 2237–2278.

Bank of England, "Financial Stability Report," (2009), December.

———, "Financial Stability Report," (2011), December.

Barry, C., B. and S. Brown, J., "Differential Information and Security Market Equilibrium," *Journal of Financial and Quantitative Analysis* 20 (1985), 407–422.

Barth, M., Y. Konchitchki and W. Landsman, "Cost of capital and earnings transparency," *Journal of Accounting and Economics* 55 (2013), 206–224.

Beltratti, A. and M. Stulz, R., "The Credit Crisis Around the Globe: Why Did Some Banks Perform Better?," *Journal of Financial Economics* 105 (2012), 1–17.

Botosan, C., A., "Disclosure Level and the Cost of Equity Capital," *The Accounting Review* 72 (1997), 323–349.

Botosan, C., A. and A. Plumlee, M., "A Re-Examination of Disclosure Level and the Expected Cost of Equity Capital," *Journal of Accounting Research* 40 (2002), 21–40.

Bushee, J., B. and F. Noe, C., "Corporate Disclosure Practices, Institutional Investors, and Stock Return Volatility," *Journal of Accounting Research* 38 (2000), 171–202.

Bushman, R., J. Piotroski and A. Smith, "Insider trading restrictions and analysts incentives to follow firms," *Journal of Finance* 60 (2005), 33–66.

CAPUANO, C., "The Option-iPoD. The Probability of Default Implied by Option Prices Based on Entropy," Technical Report, IMF, WP/08/194, 2008.

CHEUNG, Y., P. JIANG AND W. TAN, "A transparency Disclosure Index measuring disclosures: Chinese listed companies," *Journal of Accounting Public Policy* 29 (2010), 259–280.

COVER, T. AND J. THOMAS, *Elements of Information Theory* (Wiley, New York, 2006).

CREMERS, M. AND D. WEINBAUM, "Deviations from put-call parity and stock return predictability," *Journal of Financial and Quantitative Analysis* 45 (2010), 335–367.

CROCKETT, A., "Market discipline and Financial stability," *Journal of Banking and Finance* 26 (2002), 977–987.

DIAMOND, D. AND R. VERRECCHIA, "Disclosure, liquidity, and the cost of capital," *Journal of Finance* 66 (1991), 1325–1355.

DYE, R., "Disclosure of Nonproprietary Information," *Journal of Accounting Research* 23 (1985), 123–145.

EASLEY, D. AND M. O'HARA, "Information and the Cost of Capital," *Journal of Finance* 59 (2004), 1553–1583.

EDERINGTON, H., L. AND J. H. LEE, "The creation and resolution of market uncertainty: the impact of information releases on implied volatility," *Journal of Financial and Quantitative Analysis* 31 (1996), 513–539.

ELLUL, A. AND V. YERRAMILLI, "Stronger Risk Controls, Lower Risk: Evidence from U.S. Bank Holding Companies," *Journal of Finance* 68 (2013), 1157–1803.

ENHANCED DISCLOSURE TASK FORCE, T., "Enhancing the Risk Disclosures of Banks," Technical Report, The Bank of England, 2012.

FAHLENBRACH, R., R. PRILMEIER AND M. STULZ, R., "This time is the same: Using bank performance in 1998 to explain bank performance during the recent financial crisis," *Journal of Finance* 67 (2012), 2139–2185.

FOERSTER, R., G. SAPP AND Y. SHI, "The Effect of Voluntary Disclosure on Firm Risk and Firm Value: Evidence from Management Earnings Forecasts," (2013), working Paper.

FONSECA, R., A. AND F. GONZALEZ, "How bank capital buffers vary across countries: The influence of cost of deposits, market power and bank regulation," *Journal of Banking and Finance* 34 (2010), 892–902.

FRANCIS, J., D. NANDA AND P. OLSSON, "Voluntary Disclosure, Earnings Quality, and Cost of Capital," *Journal of Accounting Research* 46 (2008), 53–99.

GROSSMAN, J., S., "The Informational Role of Warranties and Private Disclosure about Product Quality," *Journal of Law and Economics* 24 (1981), 461–483.

GROSSMAN, S. J. AND O. D. MILLER, "Disclosure Laws and Takeover Bids," *Journal of Finance* 35 (1980), 323–334.

HE, J. AND X. TIAN, "The dark side of analyst coverage: The case of innovation," *Journal of Financial Economics* 109 (2013), 856–878.

HEALY, P. AND K. PALEPU, "Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature," *Journal of Accounting and Economics* 31 (2001), 405–440.

JEONG, G., M., "The Probability of Default Implied by Binary Option Prices," *International Journal of Contemporary Mathematical Sciences* 5, no 5 (2010), 201–207.

JIAO, Y., "Corporate Disclosure, Market Valuation, and Firm Performance," *Financial Management* Fall (2011), 467–676.

KIM, O. AND E. VERRECCHIA, R., "Market reaction to anticipated announcements," *Journal of Financial Economics* 30 (1991), 273–309.

———, "Market liquidity and volume around earnings announcements," *Journal of Accounting and Economics* 17 (1994), 41–67.

KOTHARI, P., S., X. LI AND E. SHORT, J., "The Effect of Disclosures by Management, Analysts, and Business Press on Cost of Capital, Return Volatility, and Analyst Forecasts: A Study Using Content Analysis," *The Accounting Review* 84 (2009), 1639–1670.

LAEVEN, L. AND R. D. LEVINE, "Bank governance, regulation and risk taking," *Journal of Financial Economics* 93 (2009), 259–275.

LAMBERT, R., C. LEUZ AND R. VERRECCHIA, "Accounting information, disclosure, and the cost of capital," *Journal of Accounting Research* 45 (2007), 385–420.

LANG, M. AND R. LUNDHOLM, "Voluntary Disclosure and Equity Offerings: Reducing Information Asymmetry or Hyping the Stock?," *Contemporary Accounting Research* 17 (2000), 623–662.

LEUZ, C. AND R. VERRECCHIA, "The Economic Consequences of Increased Disclosure," *Journal of Accounting Research* 38 (2000), 91–124.

MERTON, R., "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance* 29 (1974), 449–470.

MILGROM, R., P., "Good News and Bad News: Representation Theorems and Applications," *The Bell Journal of Economics* 12 (1981), 380–391.

NIER, W., E. AND U. BAUMANN, "Market discipline, disclosure and moral hazard in banking," *Journal of Financial Intermediation* 15 (2006), 332–361.

ROGERS, L., J., J. SKINNER, D. AND A. VAN BUSKIRK, "Earnings guidance and market uncertainty," *Journal of Accounting and Economics* 48 (2009), 90–109.

ROSS, S. A., "Information and Volatility: The No–Arbitrage Martingale Approach to Timing and Resolution Irrelevancy," *Journal of Finance* 1 (1989), 1–17.

SENIOR SUPERVISORS GROUP, "Leading-Practice Disclosures for Selected Exposures," (2008).

SIRONI, A., "Testing for Market Discipline in the European Banking Industry: Evidence from Subordinated Debt Issues," *Journal Money Credit and Banking* 35 (2003), 332–361.

SOWERBUTTS, R., P. ZIMMERMAN AND I. ZER, "Banks' Disclosure and Financial Stability," Technical Report, The Bank of England, 2013, The Bank of England Quarterly Bulletin Q4.

TADESSE, S., "The economic value of regulated disclosure: Evidence from the banking sector," *Journal of Accounting and Public Policy* 25 (2006), 32–70.

TETLOCK, P. C., "Giving content to investor sentiment: The role of media in the stock market," *Journal of Finance* 62 (2007), 1139–1168.

VERRECCHIA, E., R., "Essays on disclosure," *Journal of Accounting and Economics* 32 (2001), 97–180.

VERRECCHIA, R., "Discretionary Disclosure," *Journal of Accounting and Economics* 5 (1983), 179–194.

VILSMEIER, J., "Updating the Option Implied Probability of Default Methodology," (October 2011), bGPE Discussion Paper, No. 107.

XING, Y., X. ZHANG AND R. ZHAO, "What does individual option volatility smirk tell us about future equity returns?," *Journal of Financial and Quantitative Analysis* 45 (2010), 641–662.

Yu, F., "Analyst coverage and earnings management," *Journal of Financial Economics* 88 (2008), 245–271.

Table 1: Disclosure Index–the Template

Table lists the sub–indices of the disclosure index used in the analysis. For all of the 14 sub-indices, a score of 1 is assigned if disclosure is present in the corresponding 10–K, annual or proxy report of a given company and a given year. Otherwise, a score of 0 is assigned.

I. Liquidity Risk

Decomposition of funding sources:

L^1: Liabilities breakdown by term structure: minimum should distinguish between short–term and long–term borrowing

L^2: Liabilities breakdown by currency: minimum should decompose into two currencies

Liquidity resilience:

L^3: Liquidity ratios: any kind of quantitative liquidity ratio that helps investors assess ability to withstand funding stress

L^4: Level or ratios of high–quality unencumbered assets

II. Group Structure

G^1: Balance sheet information of main group subsidiaries, branches or affiliates

G^2: Balance sheet information of sectors, sub–units or segments

G^3: Risk ratios of main group subsidiaries, branches or affiliates (e.g. capital, liquidity, loan loss reserves)

G^4: Risk ratios of sectors, sub–units or segments (e.g. capital, liquidity, loan loss reserves).

III. Intra-annual Information

I^1: Detailed average figures of balance sheet items between reporting dates

I^2: Quarterly information for balance sheet items

I^3: Risk ratios on quarterly basis

IV. Spillover Risk

S^1: Credit exposures to banks or financial institutions

S^2: Detailed breakdown of off-balance sheet items

S^3: Exposures to off-balance sheet entities (SPEs)

Table 2: Verification of the Disclosure Index–Correlation Analysis
Table presents the Spearman correlation coefficients among disclosure and firm size, liquidity measures, and cost of capital. $\mathrm{DSCORE}_{b,t}$ is the aggregated disclosure score of the bank b at year t, calculated as in Equation (1). $\mathrm{SIZE}_{b,t}$ is the natural logarithm of the market value of a given BHC at the end of year t. The bid-ask spread (SPR), Amihud (2002) illiquidity measure (AMD), and stock turnover (TRN). SPR is the annual average of the difference between the weekly closing ask and bid prices. AMD is the absolute value of the weekly returns scaled by turnover and price, averaged annually. Finally TRN is the ratio of trading volume to the number of shares outstanding, averaged across a year. $\mathrm{COSTCAP}_{b,t}$ is the cost of capital, calculated as the average of the primary market spread to the benchmark security at the time of the subordinated debt issue. The number of observations and the $p-$values corresponding the null hypothesis that disclosure and the given variable is independent are presented as well.

		$\mathrm{SIZE}_{b,t}$	$\mathrm{SPR}_{b,t}$	$\mathrm{AMD}_{b,t}$	$\mathrm{TRN}_{b,t}$	$\mathrm{COSTCAP}_{b,t}$
$\mathrm{DISC}_{b,t}$	Spearman ρ	0.4863	-0.3439	-0.5161	0.2547	-0.2292
	$p-$value	0.0000	0.0000	0.0000	0.0000	0.0129
	Obs.	984	978	986	986	117

Table 3: Descriptive Statistics-Disclosure Sub–indices
Table presents the descriptive statistics on the sub–indices of the disclosure index. Panel includes the largest 80 U.S. BHCs spanning the period 1998–2011. The first column gives the number of the banks that disclose the particular information in all of the years, whereas the second column reports the number of the banks that never discloses the particular category throughout the whole period. The last two columns report the sample average and standard deviation of each disclosure category, respectively. For all of the categories, the minimum attainable score is 0, whereas the maximum attainable score is 1.

	disclosing in all periods	disclosing in no periods	average	stdev
L^1: term breakdown	29	0	0.665	0.472
L^2: currency breakdown	1	1	0.059	0.235
L^3: liquidity ratio	13	0	0.290	0.454
L^4: unencumbered assets	2	4	0.131	0.338
G^1: B/S info of subsidiaries	4	2	0.130	0.337
G^2: B/S info of sectors/sub-units	9	0	0.222	0.416
G^3: risk ratios of subsidiaries	64	1	0.932	0.252
G^4: risk ratios of sectors/sub-units	1	0	0.059	0.237
I^1: average B/S figures	78	0	0.986	0.118
I^2: quarterly B/S figures	12	0	0.201	0.401
I^3: risk ratios on quarterly basis	3	1	0.077	0.267
S^1: credit exposure to financial inst.	4	1	0.154	0.361
S^2: off-balance sheet items	14	3	0.346	0.476
S^3: exposure to SPEs	1	1	0.178	0.382

Table 4: Descriptive Analysis–Key Variables

Table presents the descriptive analysis for the key variables used throughout the paper. Panels A and B report the summary statistics and the pair-wise correlations. Panel C presents a univariate comparison analysis for banks with high versus low level of disclosure. A bank is identified as high-disclosed (low-disclosed) if its disclosure score is higher (lower) than the median score in a given year. The superscript * (**) denotes the 10 percent (5 percent) level one-sided statistical significance for the null hypothesis that both samples have the same mean for a given characteristics. $\text{IPoD}_{b,t+1}$ is the natural logarithm of the average implied probability of default estimates, calculated between two annual report disclosure dates. DSCORE is the aggregated disclosure score defined in (1). All of the variables are introduced in Section 4.1 and as well defined in Appendix B. The sample contains the largest 80 U.S. bank holding companies for a period of 1998 to 2011.

PANEL A: Summary statistics

	$\text{IPOD}_{b,t+1}$	$\text{DSCORE}_{b,t}$	$\text{SIZE}_{b,t}$	$\text{VOLA}_{b,t}$	$\text{CAPBUF}_{b,t}$	$\text{NPL}_{b,t}$	$\text{ROE}_{b,t}$	$\text{DEPO}_{b,t}$
mean	-5.281	1.580	14.885	5.180	0.132	0.011	0.088	16.364
median	-5.073	1.137	14.513	4.090	0.102	0.005	0.121	15.969
min	-11.870	0.058	10.384	1.492	0.017	0.000	-3.800	12.618
max	-0.758	7.686	19.428	36.096	3.766	0.243	0.266	20.844
std. dev.	2.052	1.405	1.609	3.776	0.262	0.016	0.230	1.494
Obs.	651	996	1001	1012	966	896	966	966

PANEL B: Pair-wise correlations among key variables

	$\text{IPOD}_{b,t+1}$	$\text{DSCORE}_{b,t}$	$\text{SIZE}_{b,t}$	$\text{VOLA}_{b,t}$	$\text{CAPBUF}_{b,t}$	$\text{NPL}_{b,t}$	$\text{ROE}_{b,t}$	$\text{DEPO}_{b,t}$
$\text{DSCORE}_{b,t}$	-0.036	1						
$\text{SIZE}_{b,t}$	-0.248**	0.540**	1					
$\text{VOLA}_{b,t}$	0.543**	0.048	-0.186**	1				
$\text{CAPBUF}_{b,t}$	0.014	-0.048	0.118**	0.02	1			
$\text{NPL}_{b,t}$	0.410**	0.093**	-0.182**	0.593**	-0.061*	1		
$\text{ROE}_{b,t}$	-0.306**	0.006	0.281**	-0.529**	0.044	-0.553**	1	
$\text{DEPO}_{b,t}$	-0.063	0.625**	0.864**	0.071**	-0.203**	0.122**	0.019	1

PANEL C: Comparison of high and low disclosed banks

	$\text{IPOD}_{b,t+1}$	$\text{SIZE}_{b,t}$	$\text{VOLA}_{b,t}$	$\text{CAPBUF}_{b,t}$	$\text{NPL}_{b,t}$	$\text{ROE}_{b,t}$	$\text{DEPO}_{b,t}$
High Disclosed	-5.406	15.574	4.951	0.105	0.011	0.103	17.112
Low Disclosed	-5.035	14.174	5.109	0.161	0.010	0.072	15.619
Difference	-0.371	1.399	-0.158	-0.056	0.000	0.031	1.493
$p-$value	0.037	0.000	0.249	0.001	0.584	0.022	0.000

Table 5: Effects of Voluntary Disclosure on IPoD

Table provides the results of panel regressions that examine the impact of disclosure on a bank holding company's risk. The panel includes the largest 80 U.S. BHCs and spans the time period 1998–2011. The dependent variable $\text{IPoD}_{b,t+1}$, is the natural logarithm of the average IPoD for bank b between the two annual report disclosure dates. Columns I and II present the results for (4), where the coefficients are estimated through OLS. For columns III through VI, the regressions are estimated using the 2SLS estimator, as introduced in (6). In columns III and IV, I use COVER as an instrument for disclosure, which is the number of analysts providing EPS estimates for the end of year t for bank b. On the other hand, in Columns V and VI, I use expected coverage, EXPCOVER, as an instrument. EXPCOVER is calculated as in (5). Finally, Column VII reports the estimated coefficients of the Arellano and Bond (1991) dynamic panel GMM estimator, hence, the two lagged values of endogenous variables are used as instruments. DSCORE is the aggregated disclosure score and VOLA is the realized volatility calculated as the standard deviation of weekly equity returns. SIZE is measured as the natural logarithm of the year-end total market capitalization. CAPBUF is the ratio of bank's equity capital to total liabilities, NPL is the non-performing loans ratio, ROE is the return on equity, and finally DEPO is the natural logarithm of the total deposits. The standard errors that are robust and clustered at BHC level are reported in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level (two-sided), respectively. The sample size, the Kleibergen–Paap Rank Wald F statistic for the weak-identification test, the Hansen test statistics for over-identifying restrictions with the corresponding $p-$values are also reported.

	OLS		$\text{IV}_{b,t}$=$\text{COVER}_{b,t}$		$\text{IV}_{b,t}$=$\text{EXPCOVER}_{b,t}$		GMM
			1st stage	2nd stage	1st stage	2nd stage	
	I	II	III	IV	V	VI	VII
Instrumented level of disclosure:							
$\text{DSCORE}_{b,t}$	-0.136**	-0.160**		-1.186***		-0.597**	-1.266***
	(0.0653)	(0.0679)		(0.418)		(0.252)	(0.381)
$\text{IV}_{b,t}$			-0.0372***		-0.0324***		
			(0.010)		(0.007)		
$\text{SIZE}_{b,t}$		-0.525***	-0.304***	-0.848***	-0.351***	-0.662***	-3.829***
		(0.200)	(0.108)	(0.241)	(0.105)	(0.184)	(1.011)
$\text{VOLA}_{b,t}$		0.0766**	-0.0167	0.0638**	-0.0188	0.0712***	0.0391
		(0.030)	(0.019)	(0.031)	(0.019)	(0.026)	(0.030)
$\text{CAPBUF}_{b,t}$		-0.737	-0.0573	-0.823	-0.0312	-0.774	-1.570***
		(1.517)	(0.105)	(0.525)	(0.110)	(0.501)	(0.251)
$\text{NPL}_{b,t}$		26.65***	0.949	25.64***	0.670	26.22***	-28.66*
		(7.603)	(3.998)	(7.445)	(3.835)	(6.465)	(15.49)
$\text{ROE}_{b,t}$		0.633	0.358**	0.969***	0.317*	0.776***	6.771**
		(0.800)	(0.167)	(0.277)	(0.165)	(0.228)	(2.901)
$\text{DEPO}_{b,t}$		0.548*	0.302*	0.739**	0.336**	0.629**	5.549***
		(0.289)	(0.161)	(0.306)	(0.157)	(0.268)	(1.139)
Obs.	649	596	596	596	596	596	514
adjR^2	0.718	0.769	0.378	0.662	0.395	0.755	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Kleibergen-Paap F stat.			15.674		24.156		
Hansen χ^2							66.76
Hansen $p-$ value							0.256

Table 6: Effects of Voluntary Disclosure on Other Enterprise Risks

Table provides the results of the second stage instrumental variable (IV) and dynamic panel GMM regressions that examine the impact of disclosure on a bank holding company's (BHC) enterprise risks. The dependent variable corresponding to each specification is listed at the column header. AGGRISK is the aggregate risk, calculated as the natural logarithm of the standard deviation of weekly stock returns, DOWNRISK is the downside risk, measured as the natural logarithm of option implied volatility written on bank's stock. SYSRISK captures the systematic risk and calculated as the estimated beta of the bank from the CAPM model, log-transformed, and finally IDIORISK is the idiosyncratic risk calculated as the natural logarithm of the standard deviation of the weekly residuals of the CAPM model. I use expected coverage, EXPCOVER, as an instrument calculated as in (5). The Arellano and Bond (1991) dynamic panel GMM estimator uses the two lagged values of endogenous variables as instruments. The sample includes the largest 80 U.S. BHCs and spans the time period 1998–2011. All of the control variables are introduced in Table 5. The standard errors that are robust and clustered at BHC level are reported in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level (two-sided), respectively. The sample size, the Kleibergen–Paap Rank Wald F statistic for the weak-identification test, the Hansen test statistics for over-identifying restrictions with the corresponding $p-$values are also reported.

	$\text{AGGRISK}_{b,t+1}$		$\text{DOWNRISK}_{b,t+1}$		$\text{SYSRISK}_{b,t+1}$		$\text{IDIORISK}_{b,t+1}$	
	2nd stage IV	GMM	2nd stage IV	GMM	2nd stage IV	GMM	2nd stage IV	GMM
	I	II	III	IV	V	VI	VII	VIII
Instrumented level of disclosure:								
$\text{DSCORE}_{b,t}$	-0.173***	-0.308**	-0.133***	-0.180**	-0.336***	-0.126	-0.117**	-0.261*
	(0.0549)	(0.143)	(0.0433)	(0.0837)	(0.0880)	(0.0997)	(0.0578)	(0.134)
$\text{SIZE}_{b,t}$	-0.252***	-1.643***	-0.168***	-1.010***	-0.232***	0.0819	-0.280***	-1.826***
	(0.045)	(0.315)	(0.033)	(0.276)	(0.066)	(0.218)	(0.045)	(0.358)
$\text{VOLA}_{b,t}$	0.00983	0.00279	0.0132***	0.0126	0.0105	0.0141	0.00957	0.0153
	(0.00705)	(0.0111)	(0.00504)	(0.00896)	(0.00867)	(0.00911)	(0.00738)	(0.0124)
$\text{CAPBUF}_{b,t}$	-0.159	-0.653***	-0.0651	-0.318***	-0.139	-0.292**	-0.256	-0.744***
	(0.210)	(0.109)	(0.108)	(0.0596)	(0.146)	(0.114)	(0.213)	(0.0964)
$\text{NPL}_{b,t}$	3.230**	-28.35***	3.925***	-12.87***	2.203	-14.50***	4.100***	-42.71***
	(1.362)	(5.671)	(1.103)	(3.490)	(2.135)	(5.213)	(1.462)	(7.044)
$\text{ROE}_{b,t}$	0.0324	2.436**	0.210***	1.850**	0.290***	-1.340*	-0.0580	2.732**
	(0.0660)	(1.155)	(0.0414)	(0.873)	(0.0713)	(0.781)	(0.0773)	(1.330)
$\text{DEPO}_{b,t}$	0.217***	2.240***	0.162***	1.262***	0.293***	1.245***	0.212***	2.286***
	(0.0544)	(0.351)	(0.0461)	(0.296)	(0.0965)	(0.228)	(0.0576)	(0.406)
Obs.	804	724	597	514	794	713	796	716
Adj. R^2	0.850		0.853		0.566		0.828	
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	Yes	No	Yes	No	Yes	No	Yes	No
Kleibergen-Paap F stat.	28.874		24.268		27.908		28.724	
Hansen χ^2		72.77		69.4		70.54		72.66
Hansen $p-$ value		0.125		0.19		0.166		0.126

Table 7: Effects of Voluntary Disclosure on Bank Value and Performance

Table provides the results of the second stage instrumental variable and dynamic panel GMM regressions that examine the impact of disclosure on a bank holding company's (BHC) performance and firm value. The dependent variable corresponding to each specification is listed at the column header. $\text{FV}_{b,t+1}$, $\text{ROA}_{b,t+1}$, and $\text{SHARPE}_{b,t+1}$, are the average firm value, return on assets (x100) and Sharpe ratio for bank b between two annual 10–K report disclosure dates. Firm value is calculated as market to book ratio and Sharpe ratio calculated as the ratio of the annual stock return in excess of market return divided by the standard deviations of excess returns. All of the control and instrumental variables (COVER and EXPCOVER) are introduced in Table 5. For the first two columns corresponding to each dependent variable, the regressions are estimated using the two-staged least squares (2SLS) estimator and the employed instrument is listed at the column header. Columns III, VI, and IX report the estimated coefficients of the Arellano and Bond (1991) dynamic panel GMM estimator, where the two lagged values of endogenous variables are used as an instrument. The sample includes the largest 80 U.S. BHCs and spans the time period 1998–2011. The standard errors that are robust and clustered at BHC level are reported in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level (two-sided), respectively. The sample size, the Kleibergen–Paap Rank Wald F statistic for the weak-identification test, the Hansen test statistics for over-identifying restrictions with the corresponding $p-$values are also reported.

	$\text{FV}_{b,t+1}$			$\text{ROA}_{b,t+1}$			$\text{SHARPE}_{b,t+1}$		
	COVER	EXPCOVER	GMM	COVER	EXPCOVER	GMM	COVER	EXPCOVER	GMM
	I	II	III	IV	V	VI	VII	VIII	IX
Instrumented level of disclosure:									
$\text{DSCORE}_{b,t}$	0.592**	0.199**	0.153	1.124***	0.346*	0.436**	4.351**	2.057*	4.668**
	(0.230)	(0.0993)	(0.110)	(0.419)	(0.187)	(0.200)	(2.028)	(1.156)	(1.983)
$\text{SIZE}_{b,t}$	0.911***	0.752***	1.244***	1.096***	0.885***	1.102***	-3.196***	-4.125***	-8.749***
	(0.139)	(0.0909)	(0.211)	(0.204)	(0.175)	(0.297)	(1.238)	(1.046)	(2.533)
$\text{VOLA}_{b,t}$	0.0240	0.0123	0.00973	0.0607**	0.0360	-0.0702**	0.0476	-0.0205	0.497***
	(0.0170)	(0.0114)	(0.00746)	(0.0304)	(0.0233)	(0.0299)	(0.157)	(0.137)	(0.127)
$\text{CAPBUF}_{b,t}$	0.0852	0.0862	1.081***	1.258**	1.237**	0.142	-3.302	-3.295	-9.362***
	(0.230)	(0.216)	(0.181)	(0.596)	(0.600)	(0.232)	(2.417)	(2.459)	(2.387)
$\text{NPL}_{b,t}$	3.915	3.974	3.350	-12.96	-15.47*	43.21***	-106.0***	-105.7***	-126.1**
	(3.511)	(2.785)	(4.007)	(8.699)	(8.064)	(11.50)	(31.66)	(29.67)	(59.34)
$\text{ROE}_{b,t}$	-0.818***	-0.632***	-2.242***				1.346	2.431*	14.08
	(0.169)	(0.0973)	(0.774)				(1.563)	(1.454)	(9.074)
$\text{DEPO}_{b,t}$	-0.793***	-0.699***	-2.291***	-1.077***	-0.975***	-2.811***	0.183	0.731	-8.124***
	(0.134)	(0.104)	(0.248)	(0.223)	(0.198)	(0.327)	(1.323)	(1.249)	(2.594)
Obs.	804	804	724	814	814	736	803	803	723
Adj. R^2	0.468	0.678		0.238	0.447		0.536	0.593	
Year FEs	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F stat.	15.424	28.874		14.009	28.051		15.377	28.864	
Hansen χ^2			69.49			62.49			72.45
Hansen $p-$ value			0.188			0.111			0.130

Table 8: Robustness Analysis

Table presents the results for the robustness analysis. The panel includes the largest 80 U.S. BHCs and spans the time period 1998–2011. Column I repeats the estimated coefficients for the baseline 2SLS regression (6), where the dependent variable is the logarithm of the annual average of IPoD estimates. In columns II, III, and IV, the dependent variables are the bimonthly, three-months, and semi-annually averages of log-transformed IPoD following the announcement of an annual report. Column V reports the estimated coefficients when logit transformation is used instead of a log-transformation. Column VI reports the estimated coefficients when years corresponding to the global recession (2008 and 2009) are excluded from the sample. Columns I through VI use EXPCOVER as an instrument for disclosure. Finally, in columns VII and VIII disclosure is proxied by ΔEXPCOVER$_t$ and ΔCOVER$_t$ defined as the average increase in expected coverage and coverage over the period $t-2$ to t, respectively. The definitions of variables are presented in Table 5. In all of the specifications year and bank fixed effects are included and the explanatory variables are standardized. The standard errors reported in parentheses are robust and clustered at a BHC level. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level (two-sided), respectively. For each of the specification, the sample size and the adjusted R^2s are also reported.

	IPoD$_{b,t+1}$	IPoD$_{b,t+2M}$	IPoD$_{b,t+3M}$	IPoD$_{b,t+6M}$	logitIPoD$_{b,t+1}$	IPoD$_{b,t+1}$	IPoD$_{b,t+1}$	IPoD$_{b,t+1}$
	I	II	III	IV	V	VI	VII	VIII
Instrumented level of disclosure:								
DSCORE$_{b,t}$	-0.597**	-0.779**	-0.828**	-0.721**	-0.607**	-0.697**	-0.297*	-0.639***
	(0.252)	(0.333)	(0.332)	(0.288)	(0.256)	(0.295)	(0.169)	(0.242)
SIZE$_{b,t}$	-0.662***	-1.018***	-0.999***	-0.866***	-0.720***	-0.681***	-0.568***	-0.676***
	(0.184)	(0.287)	(0.253)	(0.207)	(0.191)	(0.261)	(0.167)	(0.185)
VOLA$_{b,t}$	0.0712***	0.147***	0.137***	0.108***	0.0704**	0.0922	0.0749***	0.0706***
	(0.0264)	(0.0387)	(0.0381)	(0.0285)	(0.0277)	(0.0591)	(0.0259)	(0.0268)
CAPBUF$_{b,t}$	-0.774	-0.700	-0.872	-0.989**	-0.762	0.632	-0.749	-0.777
	(0.501)	(0.733)	(0.644)	(0.499)	(0.521)	(1.334)	(0.492)	(0.502)
NPL$_{b,t}$	26.22***	1.640	5.444	7.393	27.17***	24.61**	26.51***	26.18***
	(6.465)	(9.409)	(7.612)	(5.885)	(6.693)	(10.90)	(6.246)	(6.511)
ROE$_{b,t}$	0.776***	0.275	0.991***	0.952***	0.850***	0.724***	0.678***	0.790***
	(0.228)	(0.901)	(0.323)	(0.261)	(0.243)	(0.258)	(0.223)	(0.226)
DEPO$_{b,t}$	0.629**	0.747**	0.681*	0.538*	0.684**	0.756**	0.573**	0.637**
	(0.268)	(0.364)	(0.357)	(0.300)	(0.273)	(0.334)	(0.260)	(0.270)
Obs.	596	551	568	578	596	467	596	596
adjR^2	0.755	0.708	0.693	0.709	0.755	0.720	0.773	0.751
Year & Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes