Rationality in Financial Markets: Evidence from Bank Loan Financing Arrangements and Security Analysts' Earnings Forecasts

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Abstract

In this paper I examine whether banks' rationally utilize security analysts' earnings forecasts to determine loan interest rates. I define rationality as correctly accounting for the precision of and bias in analysts' earnings forecasts. I derive conditions that should be satisfied if banks rationally utilize analysts' earnings forecasts and empirically test whether these conditions are satisfied with data on the terms of bank loans and analysts' earnings forecasts. My results support the assertion that banks rationally account for the deficiencies in analysts' earnings forecasts. Economically, the results imply that on average a one standard deviation increase in analysts' earnings forecasts unaccompanied by an increase in the forecasts' bias reduces bank loan borrowing costs by 6 percent.

1 Introduction

It is crucial from both an academic and regulatory standpoint to understand the extent to which investors in capital markets rationally utilize financial market information to make informed investment decisions. If large investors in capital markets fail to recognize the deficiencies in financial market information, investment funds will not be efficiently allocated to society's most productive uses. In this paper, I examine whether interest rates charged in the corporate loan market reflect banks' rational use of (security) analysts' earnings forecasts.[1] I base

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[1] Although the importance of bank loan financing for large corporations has diminished relative to the importance of the commercial paper market, recent reseach still suggests that

this study on the substantial economics and finance literature that argues for the replacement of traditional rational expectations assumptions with behavioral assumptions to improve upon explanations of financial market phenomenon.[2] I focus on two potential behavioral deviations from a rational expectations model concerning the use of analysts' earnings forecasts for bank loan interest rate determination: 1) banks' overconfidence regarding the precision of analysts' earnings forecasts; and 2) the failure of banks' to correctly account for the bias in analysts' earnings forecasts. I define overconfidence regarding the precision of analysts' earnings forecasts as banks' naively overoptimistic belief in the precision of the analysts' earnings forecast. I define banks' failure to account for the bias in analysts' earnings forecast as the naivety and/or cognitive failure of banks in accounting for the bias in analysts' earnings forecasts.[3,4]

A large literature supports the use of behavioral assumptions to describe analysts' influence for the cost of debt and equity financing. Research by Rajan and Savares (1997) argues that analysts' are often overoptimistic prior to initial public equity offerings (IPO's) leading to inflated security prices due to investors that do not appropriately account for the positive bias in analysts' long term growth projections. Other research by Dechow, Hutton, and Sloan (1999), Bradshaw, Richardson, and Sloan (2006), and Michaely and Womack (1999) suggests that analysts generate overoptimistic earnings forecasts and recommendations intended to generate investment banking business for the underwriting division of their investment banks and/or inflate the value of security issues. These authors maintain that analysts' have incentives to provide exaggerated earnings forecasts due to investors' failure to fully account for the positive bias in analysts' earnings forecasts prior to security issues.

Recently, regulators have also taken the view that there were serious deficiencies in analysts' earnings forecasts included in their research reports and that such forecasts could be used to affect the views of some investors. The settlement required that investment banks disclose that the bank "does and seeks to do business with companies covered in its research reports," disclose that "each firm publish on its website" information regarding each analysts' past performance, and spend $80 million in order to educate investors on how to correctly interpret financial market information in order to make informed

bank loan financing is an important liquidity backup to commercial paper. For a discussion of these issues see Strahan and Gatev (2003) and Saidenberg and Strahan (1999).

[2]For reviews of these literatures see Baker, Ruback, and Wurgler (2006), Daniel, Hirshleifer, and Teoh (2003), Barberis and Thaler (2003).

[3]Typically, in the asset pricing literature overconfidence is related to investors' overconfidence in their own abilities (see Daniel, Hirshleifer, and Teoh (2003), and Barberis and Thaler (2003)) such as self-attribution bias where investors attribute their past success to their own abilities or hindsight bias where investors believe that they "knew it all along." The difference between the typical definition of overconfidence in the behavioral finance literature and the definition used in this study is that I define overconfidence as the banks' naive overoptimism regarding the accuracy of public earnings forecasts in contrast to overoptimism regarding informativeness of the banks' own private information.

[4]For studies examining investors inability to fully account for analysts' forecast bias see Dechow, Hutton, and Sloan (1999), Bradshaw, Richardson and Sloan (2006), Bradshaw, Skinner, and Sloan (2003), and Michaely and Womack (1999).

investment decisions.[5]

In this paper I make three contributions. The main contribution is providing evidence regarding banks' rational use of analysts' earnings forecasts to determine loan interest rates. First, I derive specific conditions that should be satisfied if banks rationally account for precision of and bias in analysts' earnings forecasts. Then, I empirically test whether these conditions hold using data on the terms of bank loans and analysts' earnings forecasts. The results suggest that banks correctly account for the precision of and bias in analysts' earnings forecasts in order to make informed loan pricing decisions.

The second contribution is providing evidence that analysts influence a precisely measured ex-ante cost of corporate financing while thoroughly controlling for the non-price terms of the financing arrangement and borrowers' observable credit risks. Typically, studies have used ex-post equity or debt returns which have been shown to be a poor predictor of the cost of equity and debt capital to provide evidence regarding analysts' influence on the cost of capital due to the lack of an easily observable ex-ante cost of capital.[6,7] I am able to avoid the use of ex-post security returns using data from bank loan financing arrangements which provides a unique measurement of an ex-ante cost of capital.

The third contribution is that I examine the association between analysts' earnings forecasts and bank loan interest rates utilizing a generalized method of moments (GMM) estimator based on Arellano and Bover (1995) and Blundell and Bond (1998) in order to provide consistent and efficient estimates, while controlling for the simultaneous determination of analysts' earnings forecasts and bank loan interest rates. Without accounting for the simultaneous determination of analysts' earnings forecasts and the cost of bank loan financing, one cannot be confident that the results reflect the exogenous influence of analysts' earnings forecasts on bank loan interest rates.

2 A Simple Model-Deriving the Rationality Conditions

This section describes a debt contract between a bank and a large publicly traded firm. The model consists of three economic entities. The three entities are a large publicly traded firm, a bank, and security analysts. The decisions of the firm and the analysts are exogenously given while the main decision maker is the bank. The model is assumed to be a two period model. In the first period the firm has access to an investment opportunity of size I, where the size of the

[5]Some of the main charges against the investment banks stated analysts' "issued research reports that were not based on principles of fair dealing and good faith and did not provide a sound basis for evaluating facts, contained exaggerated or unwarranted claims about the covered companies, and/or contained opinions for which there were no reasonable bases."

[6]For a discussion of the poor performance of ex-post security returns as a predictor of the cost of capital see Fama and French (1997).

[7]For examples of this literature see, Bradshaw, Richardson and Sloan (2006), Bradshaw, Skinner, and Sloan (2003), Dechow, Hutton, and Sloan (1999), Doukas, Kim, and Pantzalis (2004), Mansi, Maxwell, and Miller (2006), and Michaely and Womack (1999).

project is fixed. It is assumed that the project returns an amount θI, where, θ is the earnings per dollar of assets and is normally distributed with mean, μ_θ, and variance, σ_θ^2. However, the firm has insufficient wealth, W, to finance the project and must borrow an amount, $B = W - I$, at a gross interest rate, R. In the second period, the returns to the project are realized and the firm either repays the principle of the loan plus the interest, or defaults leaving the bank to confiscate the returns to the project.

2.1 The Banks' Information Set

Security analysts are assumed to be the only economic entity to exogenously observe the firms future earnings realization with noise. I assume that analysts observe and send out a signal regarding the earnings state variable, θ, given by

$$S^a = \theta + \eta \tag{1}$$

where η is the error term and is normally distributed with mean, μ_η, and variance, σ_η^2. The signal is the models equivalent of a consensus earnings per share forecast.[8] Therefore, it is interpreted as one analyst sending a single signal to financial markets.

Given the unconditional distribution of the earnings state, θ, denoted by $g\left(\mu_\theta, \sigma_\theta^2\right)$, the bank forms a posterior belief regarding future earnings per dollar of assets which is the distribution of future earnings conditional on the analysts signal. The conditional distribution is given by

$$g\left(\mu_\theta, \sigma_\theta^2 | S^a\right) = g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right) \tag{2}$$

where the conditional mean, $\hat{\theta}$, and conditional variance, $\hat{\sigma}_\theta^2$, is given by the following two equations

$$\hat{\theta} = \mu_\theta + \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_\eta^2}\left(S^a - \mu_\theta - \mu_\eta\right) \tag{3}$$

$$\hat{\sigma}_\theta^2 = \frac{\sigma_\theta^2 \sigma_\eta^2}{\sigma_\theta^2 + \sigma_\eta^2} \tag{4}$$

I note that the conditional mean in equation (3) has the following two properties

$$\lim_{\sigma_\eta^2 \to \infty} \hat{\theta} = \mu_\theta \tag{5}$$

$$\lim_{\sigma_\eta^2 \to 0} \hat{\theta} = S^a \tag{6}$$

[8] A more realistic interpretation is that security analysts observe numerous private and public signals regarding firms' future profitability and then update their prior beliefs and provide their posterior beliefs to financial markets. For an example, see Lim (2000). However, the security analysts' posterior beliefs can still be interpreted as a noisy signal with a given error term.

Interpretation of the limits is that if the analysts signal becomes infinitely noisy then the bank's conditional distribution will be a function solely of the prior mean of the earnings state. On the opposite extreme, the second property in equation (6) is consistent with a perfect information model where analysts correctly observe the earnings state without noise. The main intuition behind the conditional mean is that the weight given to the difference between analysts signal and the expected signal in the banks conditional mean is a function of the signals' precision.

In addition, I note that equation (4) implies that $\hat{\sigma}_\theta^2 < \sigma_\theta^2$, if $\sigma_\theta^2 > 0$ and $\sigma_\eta^2 < \infty$. This property can be interpreted as an additional signal reducing uncertainty as long as any uncertainty exists ex-ante regarding the firms' future earnings state and the variance of analysts' forecast errors has a finite limit.

Two deviations from a fully rational model influence the mean and variance of the banks' posterior distribution of the earnings state. The first deviation from rationality is investors inability to correctly account for the bias in analysts' earnings forecasts. For example, investors might erroneously believe that consensus analyst earnings forecast is much closer to being an unbiased observation of the firms earnings than the forecast is in reality. This is described by a conditional mean of the form

$$\hat{\theta} = \mu_\theta + \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_\eta^2}\left(S^a - \mu_\theta - \kappa\mu_\eta\right) \text{ where } \kappa < 1 \tag{7}$$

The second behavioral bias is the banks' overconfidence regarding the precision of the analysts' earnings forecast which formulated in the conditional mean and variance as

$$\hat{\theta} = \mu_\theta + \frac{\sigma_\theta^2}{\sigma_\theta^2 + \phi\sigma_\eta^2}\left(S^a - \mu_\theta - \mu_\eta\right) \text{ where } \phi < 1 \tag{8}$$

$$\hat{\sigma}_\theta^2 = \frac{\phi\sigma_\theta^2\sigma_\eta^2}{\sigma_\theta^2 + \phi\sigma_\eta^2} \tag{9}$$

For the remainder of the paper I incorporate both behavioral biases in the banks decision making process.

2.2 The Debt Contract

I assume that the bank finances corporate loans with bank deposits at a cost, ρ, and operates in a perfectly competitive loan market.[9] It is assumed that

[9] The assumption of a perfectly competative banking sector is used to ensure that the equilibrium interest rate, R^*, depends solely on the information set of the bank. In this setup, if $\hat{\sigma}_\theta^2 = 0$ then the equilibrium interest rate is, $R^* = (1+\rho)$. In addition, it can be shown that $\frac{\partial R^*}{\partial \hat{\sigma}_\theta^2} = \frac{\int_{-\infty}^{\frac{BR}{I}} -\frac{\left(\theta - \hat{\theta}\right)^2}{\hat{\sigma}_\theta^3}(I\theta - BR)g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right)d\theta}{\frac{\partial \pi}{\partial R^*}} > 0$. Therefore, firms' with no ex-ante uncertianty pay the lowest interest rate, and any factor that increases uncertianty leads to an increase in the equilibrium interest rate.

the bank charges a gross interest rate, R^*, to maximize profits where a zero profit condition entails setting the expected return on loans equal to the cost of deposits. The expected return on loans for the bank consists of two separate components. The first component is the full debt repayment, which is the principle and interest on the loan given by, BR. The second component is the expected losses due to the borrowers default when $\theta < \frac{BR}{I} = \tilde{\theta}$. In this case the bank loses an amount $I\theta - BR$, as $I\theta < BR$. The bank chooses an optimal interest rate, R^*, to solve the following problem

$$R^* \in \arg\max_R \pi = BR + \int_{-\infty}^{\frac{BR}{I}} (I\theta - BR)\, g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right) d\theta - (1+\rho)\, B^{10} \tag{10}$$

The solution to the problem in equation (10) is the first order condition for the interest rate, R^*, given by

$$\frac{\partial \pi}{\partial R} = 1 - \int_{-\infty}^{\frac{BR}{I}} g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right) d\theta = 0 \tag{11}$$

where the equilibrium interest rate, R^*, satisfies a zero profit condition given by

$$\pi = BR + \int_{-\infty}^{\frac{BR}{I}} (I\theta - BR)\, g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right) d\theta - (1+\rho)\, B = 0 \tag{12}$$

A simple argument shows that a unique equilibrium exists. First, note that if $\hat{\sigma}_\theta^2 > 0$, and the bank charges an interest rate equal to the risk free rate, ρ, that the banks profits are negative and equal to, $\int_{\infty}^{\frac{B\rho}{I}} (I\theta - B(1+\rho))\, g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right) d\theta < 0$. Therefore, since profits are less than zero when the interest rate is equal to the cost of deposits, and the first order condition for the interest rate in equation (11) is greater than zero for all R, there exists a unique equilibrium interest rate, R^* for which equation (12) is satisfied.

2.3 Comparative Statics

Given the assumption of a perfectly competitive loan market, equation (12) is sufficient to derive all comparative static results regarding the bank loan interest rate. There are a total of three comparative static results regarding the bank loan interest rates and analysts' earnings forecasts obtained from implicit differentiation of equation (12) given by $\frac{\partial R^*}{\partial S^a}$, $\frac{\partial R^*}{\partial \mu_\eta}$, and $\frac{\partial R^*}{\partial \sigma_\eta^2}$.

The first result concerns the marginal impact of the analysts earnings forecast on the bank loan interest rate, $\frac{\partial R^*}{\partial S^a}$, given by

[10] I assume that bank solves $R^* \in \arg\max_R \pi = BR\left(1 - \int_{\infty}^{\frac{BR}{I}} g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right) d\theta\right) - (1+\rho)\, B$ subject to $BR\left(1 - \int_{\infty}^{\frac{BR}{I}} g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right) d\theta\right) = (1+\rho)\, B$ when $\int_{\infty}^{\frac{BR}{I}} I\theta g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right) d\theta < 0$ given that $BR\left(1 - \int_{\infty}^{\frac{BR}{I}} g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right) d\theta\right) > BR + \int_{-\infty}^{\frac{BR}{I}} (I\theta - BR)\, g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right) d\theta$ if $\int_{\infty}^{\frac{BR}{I}} I\theta g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right) d\theta < 0$. All of the comparative static results continue to hold and are available upon request.

$$\frac{\partial R^*}{\partial S^a} = -\frac{\sigma_\theta^2}{\sigma_\theta^2 + \phi\sigma_\eta^2}\left[\frac{\int_{-\infty}^{\frac{BR^*}{I}} (I\theta - BR^*)\frac{(\theta-\hat{\theta})}{\hat{\sigma}_\theta^2} g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right) d\theta}{\frac{\partial \pi}{\partial R^*}}\right] < 0^{11} \tag{13}$$

In equation (13) analysts' earnings forecasts lower the equilibrium loan interest rate, R^*, through the term in the numerator. This term represents a marginal increase in bank profits due to a decrease in expected losses due to default. Expected losses due to default decrease because an increase in the analysts' signal increases the mean of the banks' posterior distribution of the earnings state. I also note that the magnitude of this effect depends directly on the signal to noise ratio utilized by the bank in forming the conditional mean which implies that the earnings forecast can have a larger effect than in a rational expectations model if the parameter governing the banks overconfidence in the precision of the signal satisfies $\phi < 1$.

The second comparative static is the impact of forecast error mean on the bank loan interest rate given by

$$\frac{\partial R^*}{\partial \mu_\eta} = \frac{\kappa\sigma_\theta^2}{\sigma_\theta^2 + \phi\sigma_\eta^2}\left[\frac{\int_{-\infty}^{\frac{BR^*}{I}} (I\theta - BR^*)\frac{(\theta-\hat{\theta})}{\hat{\sigma}_\theta^2} g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right) d\theta}{\frac{\partial \pi}{\partial R^*}}\right] > 0^{12} \tag{14}$$

Intuition is that an increase in the mean analysts' forecast error influences the bank loan interest rate by marginally increasing the expected losses due to default. An increase in the forecast error mean increases the banks' expected losses due to default by lowering the mean of the banks' posterior distribution of the earnings state. An important interpretation of equation (14) is that holding all else constant, including the analysts' earnings forecast, an increase in the mean forecast error increases the banks' expected losses due to default due to a reduction in the portion of the forecast that is considered an innovation above and beyond the firms expected earnings state.

The third comparative static result entails the impact of the variance of the forecast error on the bank loan interest rate and is given by

$$\frac{\partial R^*}{\partial \sigma_\eta^2} = \frac{\frac{1}{2}\int_{-\infty}^{\frac{BR^*}{I}} \left(\frac{\partial\left(\frac{\theta-\hat{\theta}}{\hat{\sigma}}\right)^2}{\partial \hat{\sigma}_\theta^2} - \frac{1}{\hat{\sigma}_\theta^2}\frac{\partial \hat{\sigma}_\theta^2}{\partial \sigma_\eta^2}\right)(I\theta - BR^*)\, g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right) d\theta}{\frac{\partial \pi}{\partial R^*}} \tag{15}$$

Equation (15) is positive (negative) if a decrease (increase) in forecast precision increases (decreases) the expected losses due to default. The result is ambiguous because the sign of $\frac{\partial\left(\frac{\theta-\hat{\theta}}{\hat{\sigma}}\right)^2}{\partial \hat{\sigma}_\theta^2}$ is inconclusive. The derivative is given by

[11] See Appendix A for signing the derivative.

[12] The arguments for the sign of the derivative are the same as those in equation (13).

$$\frac{\partial\left(\frac{\theta-\hat{\theta}}{\hat{\sigma}}\right)^2}{\partial\hat{\sigma}_\theta^2}=\left(-\frac{\left(\theta-\hat{\theta}\right)}{\partial\sigma_\eta^2}\frac{\partial\hat{\theta}}{\partial\sigma_\eta^2}-\frac{\left(\theta-\hat{\theta}\right)^2}{\hat{\sigma}_\theta^3}\frac{\partial\hat{\sigma}_\theta^2}{\partial\sigma_\eta^2}\right) \tag{16}$$

The first term in equation (16) is the marginal change in the the conditional mean due to an increase in the signal to noise ratio which is positive (negative) depending on whether or not the earnings forecast is greater than (less than) the expected earnings forecast. Intuition is that uncertainty helps firms' receiving poor forecasts because it is more likely that poor projections are based on noise rather than true fundamentals whereas strong earnings forecasts work to reduce the cost of bank loan financing only when the earnings forecasts are perceived by the bank as being more informative. The second term is the increase in overall uncertainty due to an increase in the variance of the conditional distribution which unambiguously increases the equilibrium interest rate, R^*.

2.4 The Conditions for Rationality

This section concludes by describing two conditions that are satisfied if bank loan interest rate determination described by the problem in equations (10) and (12) is consistent with a fully rational model. The first condition involves summing the comparative static derivatives given by equations (13) and (14) is given by

$$\frac{\partial R^*}{\partial S^a}+\frac{\partial R^*}{\partial\mu_\eta}=0 \text{ for } \kappa=1 \tag{17}$$

Equation (17) states that if banks correctly account for the expected bias in the earnings forecast then a marginal decrease in the equilibrium interest rate due to an increase in the earnings forecast plus the marginal increase in the equilibrium interest rate due to an increase in the expected forecast error should sum to zero. An important interpretation is that if the analysts intentionally raise the earnings forecast above the expected value of the earnings state on average, the decrease in the equilibrium interest rate due to the inflated earnings forecast should be offset by an increase in the bank loan interest rate that accounts for the increase in the mean forecast error if the bank rationally sets $\kappa=1$. This implies that the forecast bias does not have any influence on the equilibrium interest rate if $\kappa=1$.

The second test of the banks rationality entails solving for, ϕ, the parameter which governs the extent to which the bank is overconfident regarding the precision of analysts' earnings forecasts. To solve for , ϕ, the comparative static derivative describing the marginal impact of an increase in the mean earnings state, μ_θ, on the equilibrium loan interest rate is also needed. The derivative is given by

$$\frac{\partial R^*}{\partial \mu_\theta} = -\left(1 - \frac{\sigma_\theta^2}{\sigma_\theta^2 + \phi\sigma_\eta^2}\right)\left[\frac{\int_{-\infty}^{\frac{BR^*}{I}} (I\theta - BR^*) \frac{(\theta-\hat{\theta})}{\hat{\sigma}_\theta^2} g\left(\hat{\theta}, \hat{\sigma}_\theta^2\right) d\theta}{\frac{\partial \pi}{\partial R^*}}\right] < 0^{13} \quad (18)$$

Combining the comparative static derivatives from equations (18) and (13), ϕ, can be solved for as

$$\phi = \frac{\sigma_\theta^2 \frac{\partial R^*}{\partial \mu_\theta}}{\sigma_\eta^2 \frac{\partial R^*}{\partial S^a}} \quad (19)$$

Given values or estimates of the derivatives $\frac{\partial R^*}{\partial S^a}$ and $\frac{\partial R^*}{\partial \mu_\theta}$ the value of, ϕ, can be calculated. A simple hypothesis test as to whether an estimate of ϕ is equal to 1 can detect whether the bank loan interest rate determination is consistent with a model where banks correctly account for the precision of analysts' earnings forecasts.

3 Data and Empirical Methodology

This section presents the empirical exercise to test the comparative static predictions regarding the influence of analysts' earnings forecasts on equilibrium bank loan interest rates. In addition, the validity of the conditions that should be satisfied if banks rationally account for both the positive bias and/or lack of precision in analysts' earnings forecasts are tested. This section concludes with a discussion of the results and a discussion of the possible criticism that analysts' earnings forecasts may proxy for the banks private information.

3.1 Data

Data is gathered from three sources. Data on bank loans is gathered from the Loan Pricing Corporation's DEALSCAN database, which is a database containing information regarding the terms of loan contracts between banks and large publicly traded firms, firm level accounting data is gathered from COMPUSTAT which is database of the financial statement filings of all publicly traded firms in the S&P 500, and data on securities analysts' earnings forecasts is gathered from the Institutional Brokers Estimate System (I/B/E/S) which is a database of earnings forecasts and stock recommendations made by analysts.

3.1.1 Loan Data-DEALSCAN

DEALSCAN is a database containing details of loan contracts between large publicly traded firms and banks, where the data is typically gathered from SEC

[13] The argument for the sign of the derivative is the same as in equation (13).

filings, large loan syndicates, or the Loan Pricing Corporations' own reporters.[14] The database typically contains deals for the largest publicly traded corporations in the United States and around the world, but contains relatively little data regarding deals between banks and small and medium sized firms.

The DEALSCAN database is organized by "deal" and "facility" where a deal is a loan contract between the borrower and lender and a specific borrowing arrangement is known as a facility. Typically, a deal consists of a multiple facilities where the most common combination is a term loan combined with a revolving line of credit. There are numerous types of facilities in the DEALSCAN database. Table 1 lists the facilities and their frequency in the merged DEALSCAN, COMPUSTAT, I/B/E/S database used for the estimations. Table 1 shows that the revolving line of credit is the most common facility followed by various term loans.

The data of interest from the DEALSCAN database consists of the price and non-price terms of the loan contract. The main variable of interest is the price of the loan contract which is the All-In-Drawn Spread. The All-in-Drawn Spread is the interest rate the firm pays on a term loan or the withdrawn portion of a line of credit. In the previous section the All-In-Drawn spread proxies for the equilibrium bank loan interest rate, R^*. Also note that in the DEALSCAN database, the All-In-Drawn Spread is expressed as the number of basis point markup over the London-Interbank Offered Rate (LIBOR).

The other variables of interest are the non-price loan terms of the deal such as the maturity length of the facility, the principle amount of the facility, and a variable indicating whether or not the facility is collateralized. The maturity length of the facility is the number of days from the start date of the facility to the final maturity date of the facility and has no counterpart in the theoretical model. The principle amount of the facility is the size of the facility in dollars and proxies for the size of the borrowing arrangement from the previous section. The secured/unsecured status of the facility is a variable indicating whether or not the firm was required to pledge assets as collateral for the facility but provides no specific information regarding the terms of the collateralization. This variable has no direct counterpart in the theoretical model because the previous section assumed that the bank confiscated output in the default state.

The final variables used in the empirical estimations include simple transformations of the original data provided in the DEALSCAN database. The All-In-Drawn Spread is converted from a basis point spread to an interest rate spread. For example 6.25% is included as 6.25. The amount of the facility is included as the log of the principle amount of the facility in dollars. The maturity of the facility is utilized as the log of the maturity in days. The secured/unsecured indicator is represented as a dummy variable equal to one if the facility is secured and zero if the facility is unsecured or the secured/unsecured status is missing.[15]

[14] For an excellent description of the data also see Strahan (1999).

[15] I also include a variable indicating whether or not the secured variable is missing. The inclusion of this variable has no significant impact on the results.

One complication with the DEALSCAN database is that the database possibly consists of many deals for a single firm and may include multiple deals per year or include deals that do not occur in consecutive fiscal years. As a result, the database is not conducive to estimating panel data models. Therefore, in order to estimate the parameters of the empirical specifications described in the following sections, the database must be converted to a panel format with a single firm observation per year. The data set is collapsed to include one firm observation per year where the All-In-Drawn Spread is converted to a size weighted average to arrive at an average interest rate for all of the firms' yearly borrowings, borrowing amounts are converted to a sum of all of the firms borrowings for the fiscal year, and the maturity length of the borrowing arrangement is also presented as a size weighted average of the maturities of all facilities acquired throughout the fiscal year.

3.1.2 Firms' Financial Data-COMPUSTAT

Firms' financial data comes from Standard and Poor's widely used COMPUSTAT database. A number of variables are constructed to proxy for the variables in the theoretical model and other standard observable risk proxies that banks may use to price loan contracts.

The proxies for firms observable credit risk characteristics come directly from the theoretical model and other studies examining credit risk and bank loan interest rates.[16] The proxies created to reflect firms' credit risk are the log of total assets, the firms' debt to asset ratio, and a variable indicating whether or not a firm is eligible for bank investment.

The log of total assets is intended to proxy for the size of the firms investment opportunities from the simple model in addition to any past investment opportunities not explicitly modeled in the previous sections. The simple model's interpretation of how capital reduces credit risk is that larger investments relative to the debt burden, BR^*, lowers the default threshold, $\frac{BR^*}{I}$, for the return per dollar of capital that the firm needs to exceed in order to fully repay the loan, thereby reducing expected losses due to default. Practically, this measure proxies for how firms' assets reduce credit risk. First, larger firms are likely have more collateralizable assets and second large firms have likely existed many years due to more than good luck. The log of total assets is calculated by the log of COMPUSTAT item6.

The dummy variable indicating whether or not the firm is eligible for bank investment is constructed from COMPUSTAT item 280. This variable is Standard and Poor's long term domestic issuer credit rating. The COMPUSTAT data manual indicates that this variable represents "a current opinion of an issuers overall creditworthiness" taking into account not only the issuer's capacity to repay, but also their "willingness to repay." The data manual states that a credit rating of BBB or above indicates that a firm is regarded as "eligible for bank investment." Therefore, the dummy variable is constructed as equal to 1 if

[16] Previous research includes but is not limited to Strahan (1999), Gande, Puri, Saunders, and Walter (1997) and Carey, Post, and Sharpe (1998).

the borrower has a credit rating of BBB or greater and zero if the credit rating is missing or below BBB. This variable is expected to be the main competitor in explaining the variation in bank loan interest rates with securities analysts' earning forecasts as it is a widely used signal of creditworthiness in debt markets whereas securities analysts' earnings forecasts are tailored toward signaling in equity markets.

The firms debt to asset ratio is intended to be a proxy for the past debt stock which is absent from the model. An increase in repayment obligations to other creditors increases the likelihood of default as more parties have a claim to a fixed amount of revenues. The debt to asset ratio is constructed as the sum of long term debt and debt in current liabilities divided by lagged total assets which is computed as COMPUSTAT ((item9+item34)/item6).

3.1.3 Securities Analysts Forecast Data-I/B/E/S

Securities analysts' earnings forecasts provided by I/B/E/S contain data on each securities analysts earnings per-share forecasts for the current fiscal year and for each subsequent fiscal year for up to five fiscal years. In addition, the securities analysts provide a long term earnings growth forecasts to I/B/E/S intended to capture the expected earnings growth rate for the next 5 fiscal years. The I/B/E/S database defines a analyst as any individual that makes an earnings per share forecast for an investment bank or securities research firm. Since the I/B/E/S database is not available for commercial use, securities analysts provide earnings forecasts to the I/B/E/S database in exchange for the earnings per share forecasts of other analysts.

The variables utilized from the I/B/E/S database are the current and one year ahead fiscal year earnings per share forecast, the long term growth forecast, and actual earnings per share. The variables calculated from the I/B/E/S database are the present discounted value of forecasted earnings, the standard deviation of earnings forecast errors, the standard deviation of actual earnings per share, the mean forecast error, and the mean of past earnings per share. The earnings per share forecasts utilized in the empirical exercise are the consensus (mean) forecasts from the first four months of firms' fiscal year. This in order to ensure that the forecasts are the securities analysts' mean observation of firms' earnings potential rather than securities analysts learning from each other or learning from the later quarterly outcomes of the firms earnings throughout the fiscal year.

The main proxy for, S^a, in the simple model is Tobin's "Real Q" calculated based on the method of Bond and Cummins (1999) where the authors develop a proxy for Tobin's Q based on a direct calculation the present discounted value of forecasted earnings per dollar of assets. The main data required from the I/B/E/S to calculate Real Q is the earnings per share forecast for time t and $t+1$ and the long term earnings growth forecast. To calculate total forecasted earnings, the earnings per-share forecast is multiplied by the number of shares outstanding during the fiscal year from the center for research in prices (CRSP) database. Likewise, actual earnings is calculated in the same manner by multiplying actual earnings per share from the I/B/E/S data base by the number of shares outstanding from CRSP in the most recently available fiscal year.

To calculate Tobin's "Real Q", Bond and Cummins (1999) propose the following formula

$$
\begin{aligned}
RQ_{i,t} &= \frac{V_{i,t}}{K_{i,t-1}} = \\
& \frac{FC_{i,t} + \beta FC_{i,t+1} + \sum_{j=2}^{4} \beta^{j} \left(MFC_{i,t}\right)\left(1+GR_{i,t}\right)^{j-1}}{K_{i,t-1}} \\
& + \frac{\beta^{4}\left(MFC_{i,t}\right)\left(1+GR_{i,t}\right)^{3}}{(r-g)\,K_{i,t-1}}
\end{aligned}
\tag{20}
$$

In the above formula a firm is represented by $i = 1....N$ and time is a fiscal year represented by $t = 1....T$. In equation $RQ_{i,t}$ is the present discounted value of analysts earnings forecasts, MFC is the mean total earnings forecasted for time periods t and $t+1, GR_{i,t}$ is the long term earnings growth forecast directly taken from I/B/E/S for firm i at time t, K is the level of total assets from COMPUSTAT item6 for firm i at time t, r is the average nominal interest rate over the sample period which is about 15% and g is the average growth rate of the economy over the period which is about 6 percent. In all computations the discount factor, β, is set to .90.

One problem with utilizing the present discounted value of expected future earnings as a proxy for, θ, is that there exists no tractable measures of the mean forecast error or forecast error standard deviation without basing calculations on numerous questionable assumptions. Therefore, in order to test the restrictions regarding the rational use of analysts' earnings forecasts for bank loan interest rate determination I utilize a measure based on the time t earnings forecast which is directly comparable to my measures of the forecast error mean and forecast error standard deviation.

The standard deviation of the securities analysts earnings forecast error is computed as the standard deviation of the earnings per dollar of assets forecast error. The error is calculated as the mean earnings per share forecast for the current fiscal year minus the actual earnings per share from the current fiscal year multiplied by shares outstanding from CRSP divided by lagged total assets which is COMPUSTAT item6. The standard deviation of the forecast error is calculated as the standard deviation of a rolling three year window from time $t-1$ to time $t-3$. Three years is chosen to provide a time frame long enough to estimate the standard deviation of the forecast error but still have current enough observations so that forecast errors at time $t-3$ still realistically have weight in the banks belief. The standard deviation of actual earnings per share is also calculated on a three year rolling window to facilitate comparison with the forecast error standard deviation. The past standard deviation of the forecast error and past earnings are utilized as a proxy for the current standard deviation of the forecast error and actual earnings based on the assumption that outcomes in the recent past are the best predictor of the future.

The final forecast variable is the mean of past forecast errors. This variable is intended to proxy for the lenders prior belief regarding the mean of the forecast error from the model denoted as μ_η. The mean forecast error is calculated as the average of the one year forecast errors from time $t-1$ to time $t-3$. The mean forecast error is calculated as the consensus earnings per share forecast from the current fiscal year minus actual earnings per share multiplied by shares outstanding from CRSP divided by lagged total assets from COMPUSTAT item6.

The final variable calculated from the I/B/E/S database is the mean of past actual earnings and is intended to proxy for the banks prior belief regarding the mean of firms earnings from the model denoted as μ_θ. Prior actual earnings is calculated as actual earnings per share multiplied by shares outstanding from CRSP divided by lagged total assets which is COMPUSTAT item6. The mean of past earnings is also calculated on a 3 year rolling window.

3.1.4 Summary Statistics

Table 3 provides summary statistics for the data sample utilized for the estimations. The summary statistics provide some assurance that the data generally support the assumptions of the theoretical model. The proxy for μ_η in the model which is given by the mean of past forecast errors has a mean value of .009 which is significantly different from zero at the 1% level. The mean forecast error can be economically interpreted as analysts overestimating the average firms earnings by 40.5 million dollars. In addition, I also plot an estimate of the distribution of the mean of past forecast errors in Figure 1 which is plotted alongside a generic normal distribution. This graph implies that mean of past forecast errors approximately follows a normal distribution with the majority of probability mass located in the positive region indicating that analysts earnings forecasts have a positive bias with little variation.

It is also important to have an idea regarding whether the mean of past earnings and the mean of past forecast errors reasonably proxy for the mean current fiscal year earnings forecast. Inspection of Table 3 indicates that summing the sample average of the mean of past forecast errors and the mean of past earnings sums to .049 which is reasonably close to the mean current fiscal year forecast of .054. This provides assurance that the proxies for the mean of the forecast errors and earnings reflect the components of the expected earnings forecast. In addition, density estimates for the mean of past forecast errors, the mean of past earnings, and analysts' current fiscal year earnings forecasts are included in Figure 2 which suggest that all three variables are approximately normally distributed and that the earnings forecast reasonably appears to be a normal distribution where the forecast distribution is related to distributions of the mean past forecast errors and the mean of past earnings.

Table 3 also shows that standard deviation of the analysts' earnings forecast error has a mean value of .015 which is statistically significant at the 1% level which economically amounts to a standard deviation of 67.5 million dollars for the average firm in the sample. In order to have a benchmark to compare the standard deviation of the forecast error against, the mean volatility of the forecast error can be compared to the mean volatility of actual earnings per dollar of assets which is .024. In addition, the summary statistics include two other variables which are the estimate of the signal to noise ratio in the conditional mean in equation (3) and the conditional variance in equation (4) computed using the standard deviation of earnings per dollar of assets and the standard deviation of the analysts' past forecast errors. The mean value of the signal to noise ratio estimate is .616 and the mean value of the conditional standard deviation is .012. The mean signal to noise ratio implies that 61.6% of analysts' earnings forecasts are explained by variation in the actual earnings ability of the firm, and the mean conditional standard deviation implies that the analysts' earnings forecast reduces uncertainty regarding the firms' return per dollar of assets by 51%.

The summary statistics are also worthwhile in determining the importance of bank loan financing for large publicly traded firms. Simply comparing the mean loan principle amount to the mean total assets of the firm implies that the mean bank loan amounts to 11% of the mean firms' total assets. Also, for the mean firm paying the mean All-In-Drawn Spread for a loan with a 3 year maturity amounts to roughly 20 million dollars in interest expenses which is roughly 4% of the average firms total earnings over 3 years which is an economically significant amount.

Overall, basic analysis of the data provides assurance that the restrictions of the simple model in section 2 reasonably coincide with the data available for the empirical exercise.

A final note is that 35% of loans are indicated as being secured and 21% of firms have investment grade debt ratings implying that although firms are very large and creditworthy, few firms have loans with reduced risk due to collateralization or strong credit ratings which may suggest that the marginal value of other financial market information could be quite important.

3.2 Empirical Model

I estimate a standard linear econometric model to obtain estimates of all comparative static predictions simultaneously. The basic linear econometric model for the interest rate estimations is given by the following equation

$$INTR_{i,t} = \alpha_0 + \beta X + \gamma Z + \omega_i + \tau_t + \varepsilon_{i,t}{}^{17} \tag{21}$$

In equation (21) t denotes the time period for $t = 1.....T$ and i denotes each firm or firm $i = 1.....N$. $INTR_{i,t}$ is the dependent variable which is the All-In-Drawn spread which is explained by a series of endogenous explanatory variables in the matrices X and Z. The explanatory variables include those described in the previous data subsection. The matrix X includes all of the variables relating

[17] For the full econometric model see appendix B.

to analysts' earnings forecasts which incudes the earnings forecast $(RQ_{i,t})$, the mean of the past forecast errors $(MFE_{i,t-1})$, the standard deviation of past forecast errors $(SDFE_{i,t-1})$, and an interaction term between the the earnings forecast and the mean of past forecast errors $(RQ_{i,t} * MFE_{i,t-1})$, and the interaction term between the earnings forecast and the standard deviation of past forecast errors $(RQ_{i,t} * SDFE_{i,t-1})$. The interaction terms are included to control for any nonlinear effects that the mean and variance of the forecast error have directly on the marginal effect of the earnings forecast. The vector β is a (1×5) coefficient vector where the first three coefficients correspond to the comparative static derivatives in equations (13)-(15). The matrix Z includes the remaining control variables derived from the simple model and previous research regarding the determinants of bank loan financing costs. These variables are the log of the size of loan $(LNS_{i,t})$, the log of the maturity of the loan $(MAT_{i,t})$, the secured/unsecured status of the loan $(SEC_{i,t})$, the indicator for whether or not the firm has an investment grade debt rating $(DRAT_{i,t-1})$, the log of the total assets $(AST_{i,t-1})$, the debt to asset ratio$(LEV_{i,t-1})$, the standard deviation of actual earnings $(SDE_{i,t-1})$, and the mean of past earnings $(MPE_{i,t-1})$. The vector γ is a (1×8) vector of coefficient estimates. All additional control variables are dated at time $t-1$ in order to ensure the that the controls reflect the state of the firm prior to commencement of the financing arrangement thereby reflecting the banks information set when determining the All-In-Drawn spread. The model also contains three disturbance terms which are a firm specific error term ω_i, a time specific error τ_t, and a white noise error term distributed normally with mean 0 and variance σ_{ε}^2. I control for year specific errors by utilizing year dummy variables.

Estimation of the parameters of equation 20 is complicated by two problems. The first problem is the possible correlation between the firm specific error ω_i and the explanatory variables in the X and Z matrices. The second problem is the correlation of the explanatory variables in the X and Z matrices dated at time s with the error term $\varepsilon_{i,t}$ at time $s = t$. In order to obtain consistent and efficient estimates of the parameters in equation (21) I utilize a general method of moments estimator (GMM) suggested by Arellano and Bover (1995) and Blundell and Bond (1998).[18,19] This estimator utilizes a standard difference

[18] A simple difference estimtor is not utilized for the estimations for 2 reasons. The first reason is that I lose a significant number of obserations when differencing the data due to the gaps between observations within each firm. Second, the difference estimator which uses lagged levels as instruments often performs poorly for persistent variables where the differences are close to innovations.

[19] A standard GMM difference estimator is based on the following moment conditions

$E\left[(\Delta\varepsilon_{i,t})\, X_{i,t-q}\right] = 0$ for $q \geq 2$

However, the difference estimator performs poorly when the variables in the estimations are highly persistent. However, if the following condition holds

$E\left[\omega_i \Delta X_{i,t-q}\right] = c - c = 0$ for all q

Then a model in levels based on the following moment conditions

$E\left[(\omega_i + \varepsilon_{i,t})\, \Delta X_{i,t-q}\right] = 0$ for $q \geq 1$

can be added to the moment conditions in differences to improve upon the efficiency of the difference estimator. The estimator combining both the equations in levels and differences is the GMM system estimator.

(GMM) estimator where variables in levels dated $t - s$ for $s \geq 2$ are utilized as instruments for endogenous variables and augments the difference estimator with a model in levels where variables in deferences dated $t - p$ for $p \geq 1$ are utilized as instruments for endogenous variables. The identifying assumptions of this estimator is that the correlation between the explanatory variables in the X and Z matrices have a constant correlation with the firm specific error term ω_i, that there is no second order serial correlation in the error term $\varepsilon_{i,t}$, and that initial values of the endogenous variables are predetermined.

3.3 Estimation Results

The first results concern the impact of analysts' earnings forecasts on the All-In-Drawn spread which is the result most comparable with the previous literature focusing on analysts impact on the cost of corporate debt and equity financing. Table 4 includes the result for Tobin's "Real Q" and Table 5 includes the result for the time t or current fiscal year earnings forecast. From Table 4, the results from interest rate model in equation (21) imply that a one standard deviation increase in "Real Q" leads to a roughly .11 decrease in the All-In-Drawn spread which amounts to roughly 8 percent of the mean All-In-Drawn spread. In order to obtain a greater understanding as to what this interest rate reduction means to firms it is useful to calculate the impact of the interest rate reduction on total interest payments for a representative firm. For example, assuming that interest is continuously compounded, for a firm taking a loan out with the average maturity length of 3.2 years and an average principle amount of 515 million dollars, increasing a firm's present discounted value of expected future earnings from the by one standard deviation leads to a 1.8 million dollar decrease in total interest payments.[20] In Table 5 the results for the current fiscal years earnings forecast implies that a one standard deviation increase in the current fiscal year earnings forecast leads to a decrease in the All-In-Drawn spread of .08 percent which amounts to roughly 6 percent of total bank loan financing costs, or a 1.3 million dollar decrease in interest payments for a firm taking out a loan with the average principle, maturity length, and continuously compounded interest payments. Encouragingly, the marginal effects of both forecast measures imply economically similar impacts. One possible explanation for the smaller economic impact of "Real Q" may be measurement error.[21]

Despite knowing that analysts earnings forecasts have significant explanatory power for bank loan interest rates, this does not imply that these forecasts improve the allocation of capital or that banks use of analysts' earnings forecasts is rational. If analysts raised their average forecast above the expected value of firms' earnings in order to inflate expectations of firms' future earnings, then the allocation of capital will be inefficiently allocated to firms with stronger earnings forecasts if banks to not account for the positive bias in the earnings

[20] In order to understand the calculations define the future repayment to the bank as FV, the size of the loan as P, the interest rate as r, and maturity as m. Interest payments are calculated as $FV - B = Be^{rm} - FV$.

[21] For an discussion of measurement error in "Real Q" see Bond and Cummins (2001).

forecasts. Therefore, in order to have an idea regarding the extent to which analysts' earnings forecasts improve the allocation of capital, it is necessary to try to understand how banks account for the expected bias in analysts' earnings forecasts. The results from Tables 4 and 5 indicate that a one standard deviation increase in the mean of past forecast errors increases the All-In-Drawn spread by roughly .132 points as the parameter estimates are fairly constant across both sets of results implying a fairly stable relationship between past forecast errors and the All-In-Drawn spread. This result highlights that although banks lower the All-In-Drawn spread for firms with stronger earnings forecasts, for firms that receive the same earnings forecasts, banks expect the earnings forecasts of firms with greater past forecast error biases to contain less information regarding firms expected future earnings.

Again, despite having estimates that indicate mean of analysts' past earnings forecast errors influences the All-In-Drawn Spread it still can not be inferred whether the evidence suggests that banks rationally account for the bias in the earnings forecasts from the parameter estimates alone. In order to infer whether banks use of analysts' earnings forecasts is consistent with a rational expectations model, the condition in equation (17) must be satisfied. Equation (17) states that sum of the marginal effect of an increase in analysts' earnings forecasts on the All-In-Drawn spread and the marginal effect of an increase in the expected forecast error on the All-In-Drawn spread must be equal to zero. The extent to which the sum deviates from zero determines the extent to which the bank fails to fully account for the bias in analysts' earnings forecasts. The empirical counterpart to equation (17) is

$$\beta_1 + \beta_2 = 0 \tag{22}$$

Table 5 indicates that the sum of the two coefficients is equal to .48 where a Wald test fails to reject the null hypothesis that $\beta_1 + \beta_2 = 0$. In addition, taking the ratio of the two coefficients implies a value of κ equal to 1.31. This result indicates that bank loan interest rate determination is consistent with a model where the bank accounts for the positive bias in analysts' forecasts.

The second test regarding banks' rational use of analysts' earnings forecasts entails testing whether an empirical estimate of, ϕ, given by $\hat{\phi}$, satisfies, $\hat{\phi} = 1$. An estimate of $\hat{\phi}$ can be constructed as

$$\hat{\phi} = \frac{\sigma_\theta^2 \gamma_8}{\sigma_\eta^2 \beta_1} = .927 \tag{23}$$

A Wald test that fails to reject the null hypothesis that $\hat{\phi} = 1$ when treating the sample averages of σ_θ^2 and σ_η^2 as the theoretical counterparts to the simple model presented earlier.[22]

[22]For this Wald test it is assumed that $\frac{\sigma_\theta^2}{\sigma_\eta^2}$ is constant. Due to the large sample size the mean value of $\frac{\sigma_\theta^2}{\sigma_\eta^2}$ is precisely measured and can be treated as constant. In addition, given that the variance of actual earnings and the forecast error are not normally distributed, the usual application of the "delta method" is not applicable.

However, perhaps a more accurate interpretation of the results in relation to the model is that the firm solves a static problem every year using a different value of σ_θ^2 and a different value of σ_η^2. Therefore, it may be informative to have an idea about the distribution of $\hat{\phi}$ when the parameter is calculated on a yearly basis for each borrower. In addition, it is important to know the frequency with which a hypothesis test rejects the null hypothesis that $\hat{\phi} = 1$ for each borrower-year. Figures 4 and 5 show the distribution of $\hat{\phi}$ and the p-values for the Wald test with a null hypothesis that $\hat{\phi} = 1$. Clearly, from Figure 4 the distribution of $\hat{\phi}$ is skewed to the right and from Figure 5 a majority of the mass of the p-values falls blow .90 indicating that Wald test more often than not fails to reject the null hypothesis that $\hat{\phi} = 1$.[23] Another perspective is offered in Table 6 which shows that there is significant variation in the estimate of, $\hat{\phi}$, above and below a value of 1, which is consistent with a rational behavior. It is important to note that rational behavior does not imply that the bank correctly accounts for the forecast precision all of the time, but rather does so on average. This is consistent with results where the bank both over and under accounts the precision of the forecast with equal likelihood.[24] The results show that overall, that loan interest rate determination is consistent with a model where the bank correctly accounts for the precision of analysts' earnings forecasts on average.

The final results concerning analysts' earnings forecasts include the effects of the past forecast error standard deviation and the interaction terms of the past forecast error mean and standard deviation with the earnings forecast on the All-In-Drawn Spread. The comparative static derivative from equation (15) provides no distinct prediction regarding the sign of the coefficient β_3, therefore I let the data determine the dominant effect. Results from Table 5 indicate that the past forecast error standard deviation has a significant and positive effect on the bank loan interest rate. Relating the estimated sign of the coefficient to the discussion of the derivative in equation (16) implies that the effect of lowering the weight on weak forecasts does not dominate the influence of the of the past forecast error standard deviation on the All-In-Drawn Spread. Rather, the lower weight placed on strong earnings forecasts and the increase in overall uncertainty appears to dominate the influence the forecast error standard deviation for the All-In-Drawn Spread.

The results from the interaction terms provide no significant sign for the influence of the mean forecast error or standard deviation of the forecast error on the marginal impact of the earnings forecast. It appears that the main effects of the earnings forecast, the mean of past forecast errors, and the standard deviation of past forecast errors are primarily independent.

Before concluding this section I briefly summarize the remaining important results to ensure that the overall estimation results are consistent with traditional thinking regarding the cost of bank loan financing. Table 5 indicates that

[23]In order to provide a meaningful description of the distribution of the estimate of $\hat{\phi}$ the bottom and top 5% of observations were dropped. Including the bottom and top 5% induces a large skew to the right in the distribution.

[24]A simlar argument was used by Fama (1998) to argue that long run abnormal returns were not necessarily evidence of stock market inefficiency.

receiving an investment grade debt rating has a significant and negative impact on the All-In-Drawn spread. The coefficient estimates indicate that acquiring an investment grade debt rating lowers the All-In-Drawn Spread by about .50 which would be roughly 35% of the mean All-In-Drawn Spread. This result is reasonable given that credit ratings are intended to signify greater creditworthiness.

A series of other results concern the observable risk characteristics of the firm which includes the impact of firms' size on the All-In-Drawn Spread which is negative and significant as expected. Large firms have a greater amount of collateralizable assets and have likely become large due to strong performance implying greater creditworthiness. In addition, the mean and variance of firms fundamental earnings have reasonably expected signs. Greater past earnings performance reduces the banks expected losses due to default. Greater uncertainty regarding firms earnings potential increases the All-In-Drawn spread and is likely due to an increase in banks' expected losses due to default. The debt to asset ratio has a significant and positive influence on the All-In-Drawn Spread which is consistent with thinking that an increase in debt obligations or an increase in claims to a fixed amount of revenues increases the banks expected losses due to default.

The final results all concern the impact of the non-price terms of the loan contract on the All-In-Drawn Spread which include whether or not the loan is collateralized, the maturity length of the loan, and the principle amount of the loan. Standard thinking might imply that firms with collateralized loans should face lower financing costs being that creditors have can still recover some of their losses in the event of the borrowing firms default. In addition, standard thinking might imply that loans with greater maturity and size should create more default risk for the bank causing an increase in the All-In-Drawn spread charged to borrowers. However, for all three non-price loan contract terms the opposite unexpected effects emerge from the results.

3.4 Do Analysts' Earnings Forecasts Proxy For Banks' Private Information?

One potential criticism of the estimation results is that analysts' earnings forecasts may proxy for the banks private information. This section shows that under certain plausible assumptions about the relationship between banks' private information and analysts' earnings forecasts, the test of overidentifying restrictions should be rejected if analysts' earnings forecasts proxy for the banks private information.

Assume that in the context of the theoretical model that the bank receives a private signal regarding the firms future earnings per dollar of assets is given by

$$S^b = \theta + \tau \tag{24}$$

where the error term, τ, is normally distributed with mean, $\mu_\tau = 0$, and variance, σ_τ^2. In addition, assume that the analysts' earnings forecast (the signal from the model),S^a, can be rewritten as a noisy signal $\tilde{S}^a$ denoted as

$$\tilde{S}^a = S^b + \upsilon \tag{25}$$

where the error term, υ, is distributed normally with mean, $\mu_\upsilon > 0$, and variance, σ_υ^2.

Relating equation (25) to the empirical model of equation (21), assume that banks have an unbiased private signal, $RQ_{i,t}^b$. In relation to the analysts' forecast, $RQ_{i,t}$, the analysts' consensus earnings forecast could be rewritten

$$RQ_{i,t} = RQ_{i,t}^b + \upsilon_{i,t} \tag{26}$$

where the error term is distributed normally with mean μ_υ, and variance σ_υ^2. Intuitively, equation (26) could be interpreted as the bank receiving an unbiased signal possibly due to an independent internal assessment of the borrowers future earnings ability, and analysts providing a signal which is equivalent to the banks private signal plus an error term.

If the bank ignored analysts' earnings forecasts and instead based their decision on their own internal assessment, then the empirical results from the previous section would have been generated with the following moment conditions for the level and difference equations respectively

$$\begin{aligned} & E\left[(\omega_i + \varepsilon_{i,t} + \beta_1 \upsilon_{i,t})\left(\Delta RQ_{i,t-s}^b + \Delta\upsilon_{i,t-s}\right)\right] \\ = \; & E\left[\omega_i + \varepsilon_{i,t} + \beta_1 \upsilon_{i,t}\right] E\left[\Delta RQ_{i,t-s}^b + \Delta\upsilon_{i,t-s}\right] \qquad \text{for } S \in [2,3] \\ & + COV\left[\omega_i + \varepsilon_{i,t} + \beta_1 \upsilon_{i,t},\, \Delta RQ_{i,t-s}^b + \Delta\upsilon_{i,t-s}\right] \end{aligned} \tag{27}$$

$$\begin{aligned} & E\left[(\Delta\varepsilon_{i,t} + \beta_1 \Delta\upsilon_{i,t})\left(RQ_{i,t-z}^b + \upsilon_{i,t-z}\right)\right] \\ = \; & E\left[\Delta\varepsilon_{i,t} + \beta_1 \Delta\upsilon_{i,t}\right] E\left[RQ_{i,t-z}^b + \upsilon_{i,t-z}\right] \qquad \text{for } z = 1 \\ & + COV\left[\Delta\varepsilon_{i,t} + \beta_1 \Delta\upsilon_{i,t},\, RQ_{i,t-z}^b + \upsilon_{i,t-z}\right] \end{aligned} \tag{28}$$

If it is assumed that the difference between analysts' earnings forecast and the banks internal signal, $\upsilon_{i,-}$, is correlated across fiscal years, then no moments would be able to identify the parameters of the model. In this case, the test of overidentifying restrictions should have power to reject the validity of the empirical specification. Upon examining the test of overidentifying restrictions, the p-vaules of 0.259 and 0.262 from tables 4 and 5 suggest that there is no serially correlated term $\upsilon_{i,-}$.[25]

Although, no data describing banks private information is available for this paper, given reasonable arguments regarding the structure of the deviations between the banks private information and analysts' forecasts over time, one can be more confident that the results from tables 4 and 5 reflect the exogenous influence of analysts' forecasts for bank loan interest rate determination.

[25] For a similar result see Bond and Cummins (2001).

4 Conclusion

This paper provides evidence regarding the rational use of information in financial markets. Specifically, I examine whether banks correctly account for the precision of and bias in analysts' earnings forecasts to determine loan interest rates. I derive conditions that should be satisfied if banks rationally account for the deficiencies in analysts' earnings forecasts when determining loan interest rates, and empirically test whether these conditions hold using data on the terms of bank loans and analysts' earnings forecasts. My results support the assertion that banks, a crucial source of liquidity for corporations, rationally account for the precision of and bias in analysts' earnings forecasts when determining loan interest rates. Further research is needed to assess the extent to which different types of investors are rational in their use of financial market information.

5 Appendix

5.1 Appendix A

The sign of the derivative in equation (13) depends on the sign of the term $\int_{-\infty}^{\frac{BR}{I}} (I\theta - BR) \frac{(\theta-\hat{\theta})}{\hat{\sigma}_{\theta}^{2}} g\left(\hat{\theta}, \hat{\sigma}_{\theta}^{2}\right) d\theta$. Expanding the integral I obtain

$$\int_{-\infty}^{\frac{BR}{I}} I\theta \frac{\theta - \hat{\theta}}{\hat{\sigma}_{\theta}} g\left(\hat{\theta}, \hat{\sigma}_{\theta}^{2}\right) d\theta - \int_{-\infty}^{\frac{BR}{I}} \frac{BR}{\hat{\sigma}_{\theta}} \left(\frac{\theta - \hat{\theta}}{\hat{\sigma}_{\theta}}\right) g\left(\hat{\theta}, \hat{\sigma}_{\theta}^{2}\right) d\theta \tag{29}$$

The sign of the second term in equation (29) is seen to be negative by substituting $z = -\frac{1}{2}\left(\frac{\theta-\hat{\theta}}{\hat{\sigma}_{\theta}}\right)^{2}$ and rewriting the integral as $-\frac{BR}{\hat{\sigma}_{\theta}} \int_{-\infty}^{\frac{BR}{I}} g(z)\, dz < 0$. The first term, $\int_{-\infty}^{\frac{BR}{I}} I\left(\theta^{2} - \hat{\theta}\theta\right) g\left(\hat{\theta}, \hat{\sigma}_{\theta}^{2}\right)$, is positive for the following argument. Since $\int_{-\infty}^{\frac{BR}{I}} \left(\theta - \hat{\theta}\right)^{2} g\left(\hat{\theta}, \hat{\sigma}_{\theta}^{2}\right) d\theta > 0$ this implies $\int_{-\infty}^{\frac{BR}{I}} \left(\theta^{2} - 2\hat{\theta}\theta - \hat{\theta}^{2}\right) g\left(\hat{\theta}, \hat{\sigma}_{\theta}^{2}\right) d\theta > 0$. Given that $\int_{-\infty}^{\frac{BR}{I}} \left(\theta^{2} - \hat{\theta}\theta\right) g\left(\hat{\theta}, \hat{\sigma}_{\theta}^{2}\right) > \int_{-\infty}^{\frac{BR}{I}} \left(\theta^{2} - 2\hat{\theta}\theta\right) g\left(\hat{\theta}, \hat{\sigma}_{\theta}^{2}\right) d\theta$ when $\int_{-\infty}^{\frac{BR}{I}} \theta g\left(\hat{\theta}, \hat{\sigma}_{\theta}^{2}\right) > 0$ the first term is seen to be positive.[26]

[26] See the footnote to equation (10).

5.2 Appendix B

The full econometric model from equation (21) in section 3.2.1is given by

$$
\begin{aligned}
INTR_{i,t} \quad = \quad & \alpha_0 + \beta_1 RQ_{i,t} + \beta_2 MFE_{i,t-1} + \beta_3 SDFE_{i,t-1} + \beta_4 RQ_{i,t} * MFE_{i,t-1} + \\
& \beta_5 RQ_{i,t} * SDFE_{i,t-1} + \gamma_1 LNS_{i,t} + \gamma_2 MAT_{i,t} + \gamma_3 SEC_{i,t} + \gamma_4 DRAT_{i,t-1} \\
& + \gamma_5 AST_{i,t-1} + \gamma_6 LEV_{i,t-1} + \gamma_7 SDE_{i,t-1} + \gamma_8 MPE_{i,t-1} + \omega_i + \tau_t + \varepsilon_{i,t}
\end{aligned} \tag{30}
$$

6 References

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Table 1 Frequency Facility Types

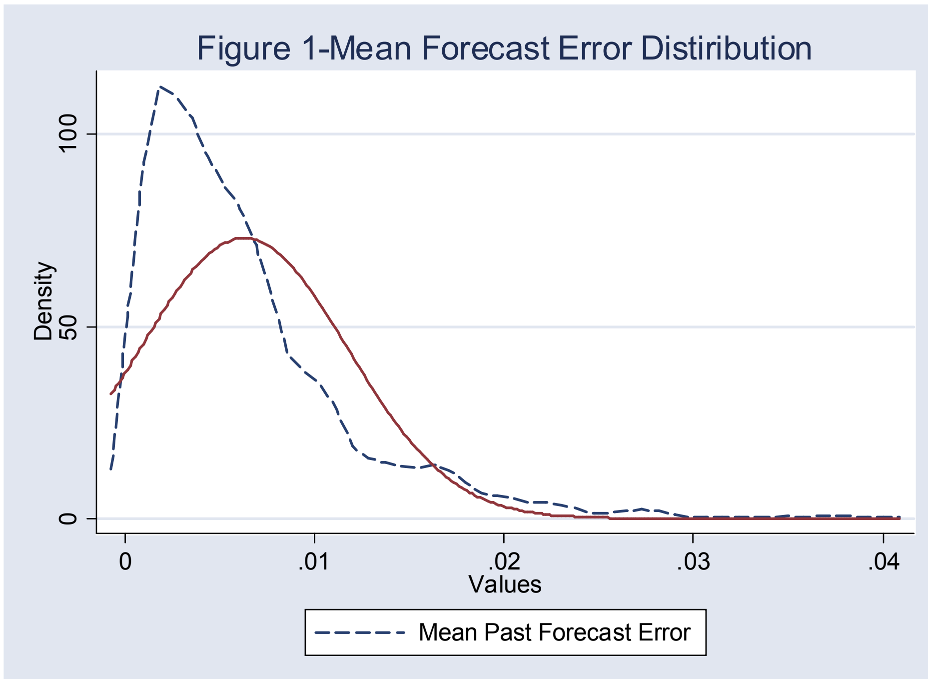
	Frequency	Percentage
364-Day Facility	1,969	18.15
Acquisition Facility	24	0.22
Bankers Acceptance	1	0.01
Bridge Loan	179	1.65
Delay Draw Term Loan	70	0.65
Demand Loan	17	0.16
Floating Rate Bond	1	0.01
Guidance Line (Uncommitted)	6	0.06
Lease	11	0.1
Limited Line	94	0.87
Multi-Option Facility	14	0.13
Note	25	0.23
Other Loan	37	0.34
Revolving Line of Credit $<$ 1 Year	321	2.96
Revolving Line of Credit $>$ 1 Year	5,637	51.96
Revolving Term Loan	305	2.81
Synthetic Lease	93	0.86
Term Loan	1,207	11.13
Term Loan A	227	2.09
Term Loan B	502	4.63
Term Loan C	76	0.7
Term Loan D	21	0.19
Term Loan E	5	0.05
Term Loan F	2	0.02
Term Loan G	1	0.01
Term Loan H	1	0.01
Trade Letter of Credit	2	0.02
Total	10,848	100

Table 2 Frequency Loan Purpose

	Frequency	Percentage
Acquisition Line	475	4.38
Commercial Paper Backup	1,474	13.59
Capital Expenditures	34	0.31
Collateralized Debt Obligation	1	0.01
Corporate Purposes	2,949	27.18
Debt Repayments	2,331	21.49
Debtor in Possesion	8	0.07
ESOP	10	0.09
Equipment Purchases	41	0.38
Exit Financing	1	0.01
IPO Related Financing	3	0.03
LBO/MBO	79	0.73
Lease Finance	3	0.03
Mortgage Warehouse	3	0.03
Other	69	0.64
Project Finance	55	0.51
Purchase Hardware	2	0.02
Real Estate	20	0.18
Rec. Prog.	6	0.06
Recapitalization	72	0.66
Securities Purchase	11	0.1
Spinoff	28	0.26
Stock buyback	94	0.87
Takeover	1,248	11.5
TelcomBuildout	6	0.06
Trade finance	7	0.06
Working Capital	1,818	16.76
Total	10,848	100

Table 3 Summary Statistics

	Mean	Standard Deviation	N
Current Fiscal Year Earnings Forecast	0.054	0.083	6826
Long Term Earnings Forecast	1.038	1.194	5777
Mean Past Forecast Errors	0.009	0.057	6826
Standard Deviation of Past Forecast Errors	0.015	0.032	6826
All-In-Drawn Spread	1.450	1.097	6826
Principle Amount of Loan (Millions)	515.000	732.000	6826
Maturity Length of Loan (Days)	1168.337	722.420	6826
Total Assets(Millions)	4499.413	16644.030	6826
Stdev. Past Earnings	0.024	0.054	6826
Mean of Past Earnings	0.039	0.110	6826
Debt to Asset Ratio	0.362	1.105	6826
Signal to Noise Ratio	0.616	0.286	5634
Conditional Stdev.	0.012	0.023	5634
Percentage with Secured Loan	0.3524728		6826
Percentage with Investment Grade Debt Rating	0.2146206		6826



The non-dashed line represents a comparative normal density

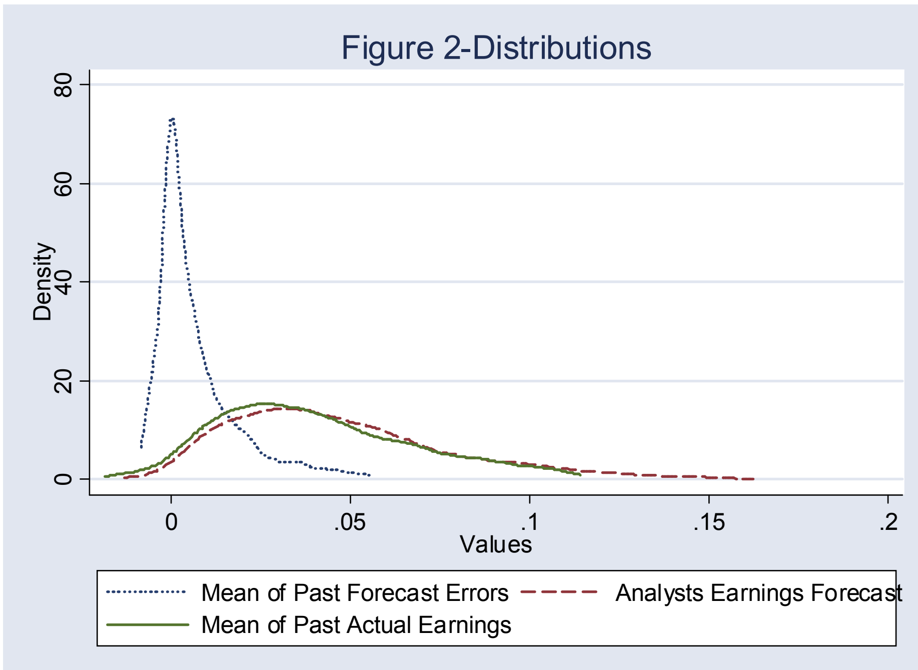
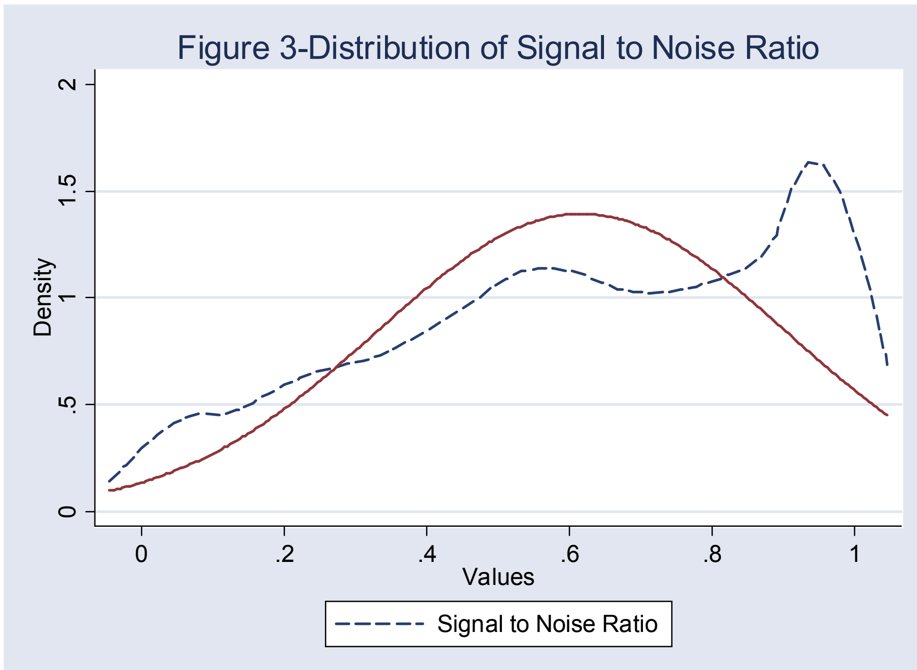


Figure 2-Distributions
Density
80
60
40
20
0
0
.05
.1
.15
.2
Values
Mean of Past Forecast Errors
Analysts Earnings Forecast
Mean of Past Actual Earnings



The non-dashed line represents a comparative normal density

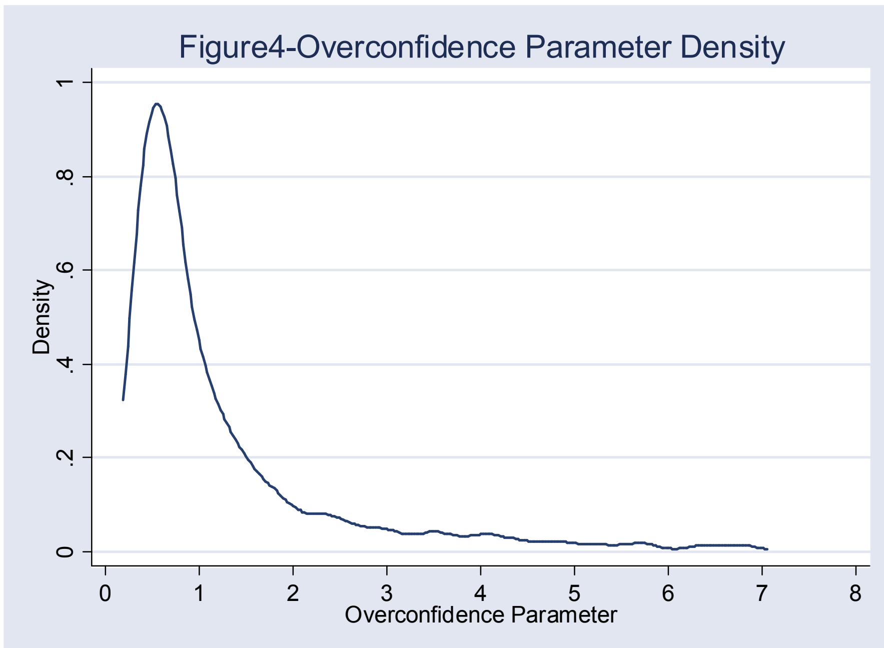


Figure4-Overconfidence Parameter Density
Density
0
.2
.4
.6
.8
1
0
1
2
3
4
5
6
7
8
Overconfidence Parameter

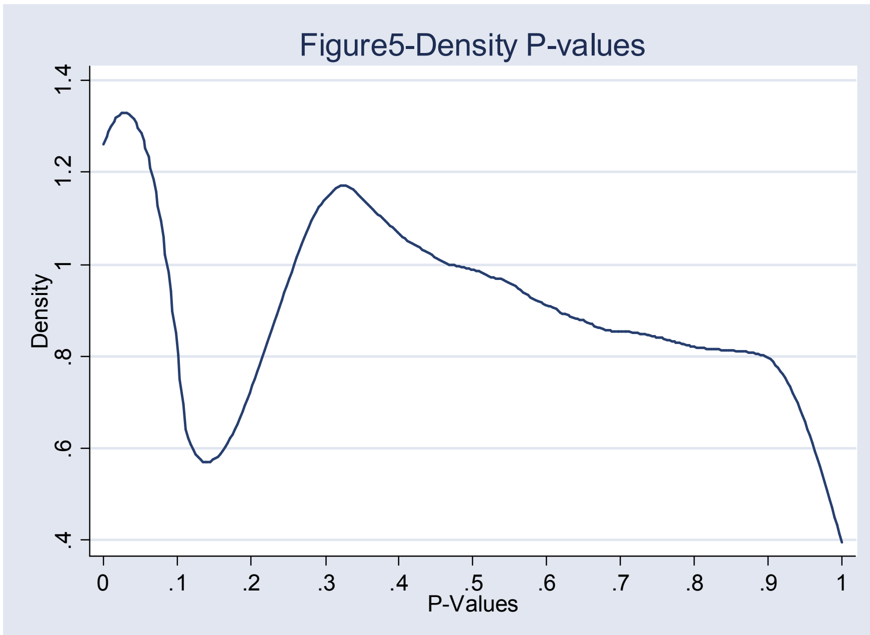


Figure5-Density P-values
Density
1.4
1.2
1
.8
.6
.4
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
P-Values

Table 4 (GMM) System Estimator Results for Interest Rate Model with Long Term Earnings Forecast

Long Term Earnings Forecast	-0.0895***
	(0.0371)
Mean of Past Forecast Errors	2.4477***
	(1.0637)
Stdev of Past Forecast Errors	.0086
	(1.1722)
(Mean of Past Forecast Errors)*	-1.0312
(Long Term Earnings Forecast)	(0.7575)
(Stdev of Past Forecast Errors)*	-0.9172
(Long Term Earnings Forecast)	(0.9293)
Secured/Unsecured Dummy	0.9447***
	(0.0944)
log(Principle Amount of Loan)	-0.0877***
	(0.0410)
Log(Maturity Length of Loan in Days)	-0.0458
	(0.0512)
Investment Grade Debt Rating Dummy	-0.4904***
	(0.0826)
Log(Total Assets)	-0.1114***
	(0.0436)
Stdev of Past Earnings	3.0317***
	(0.6991)
Mean of Past Earnings	-1.8310***
	(0.4975)
Debt-to Asset Ratio	0.1585***
	(0.0795)
Number of Firms	1890
Number of Observations	5777
P-Value Hansen Test of Overidentifying Restrictions	0.259
Test of Second Order Serial Correlation P-Value	0.271

All estimations include year dummy variables

Instruments are dated t-1 in the level equations and t-2 and t-3 in the difference equations.

Standard errors are in parenthases and ***,**,* denote significance at the 1%,5%, and 10% level respectively

Table 5 (GMM) System Estimator Results for Interest Rate Model with Current Fiscal Year Earnings Forecast

Current Fiscal Year Earnings Forecast	-1.5724***
	(0.6718)
Mean of Past Forecast Errors	2.0572***
	(1.0700)
Stdev of Past Forecast Errors	3.1131***
	(1.3111)
(Mean of Past Forecast Errors)*	-8.9480
(Current Fiscal Year Earnings Forecast)	(11.5413)
(Stdev of Past Forecast Errors)*	8.8789
(Current Fiscal Year Earnings Forecast)	(15.0632)
Secured/Unsecured Dummy	0.8917***
	(0.0891)
log(Principle Amount of Loan)	-0.0688*
	(0.0387)
Log(Maturity Length of Loan in Days)	-0.0694
	(0.0490)
Investment Grade Debt Rating Dummy	-0.5335***
	(0.0846)
Log(Total Assets)	-0.1264***
	(0.1987)
Stdev of Past Earnings	2.1540
	(0.83161)
Mean of Past Earnings	-.9170***
	(0.4544)
Debt-to Asset Ratio	0.2640***
	(0.0766)
Number of Firms	2233
Number of Observations	6826
P-Value Hansen Test of Overidentifying Restrictions	0.262
Test of Second Order Serial Correlation P-Value	0.404

All estimations include year dummy variables

Instruments are dated t-1 in the level equations and t-2 and t-3 in the difference equations.

Standard errors are in parenthases and ***,**,* denote significance at the 1%,5%, and 10% level respectively

Table 6
Qunitiles of the Overconfidence Parameter and
Hypothesis Test P-Values

Overconfidence Parameter			
Quintile	Mean	Min	Max
1	0.2655	0.0014	0.4208
2	0.5375	0.4217	0.6495
3	0.7863	0.6500	0.9705
4	1.3451	0.9710	1.9300
5	9.0700	1.9310	1302.9510
Overall Mean		3.1	
P-Values			
Quintile	Mean	Min	Max
1	0.0176	0	0.0929
2	0.2400	0.0941	0.3395
3	0.4299	0.3360	0.5254
4	0.6380	0.5258	0.7533
5	0.8749	0.7537	0.9997