Managers' earnings guidance forecasts and corporate innovation: Evidence from private loan facilities

Paul A. Griffin[a*], Hyun A. Hong[b], and Ji Woo Ryou[c]

Abstract In this study, we examine whether the quality of managers' earnings guidance forecasts plays a role in understanding how banks recognize corporate innovative efficiency. Based on a sample of private loan facilities to U.S. firms, we find that when innovatively efficient firms use private loan facilities, they borrow at lower cost and on better terms when their earnings guidance forecasts are less accurate. This phenomenon concentrates more on firms facing greater proprietary costs, such as small firms and firms with more competition from current rivals. A key implication is that firms with low-quality guidance forecasts are not necessarily firms with low innovative efficiency. These firms have incentives not to and apparently do not reveal their underlying (higher) efficiency. This finding supports the primary hypothesis of this paper – that entrepreneurs' choice of private loan facilities provides a cost-effective way to disclose high-quality forecasts to lenders but not to outsiders.

Keywords: Corporate innovation | Loan contracts | Patents | Loan spread | Managers' earnings guidance quality

JEL Classification: G12, G14, G21, M41

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[a] Graduate School of Management, University of California, Davis, California, USA 95616 e-mail: pagriffin@ucdavis.edu.

[b] Anderson Graduate School of Management, University of California, Riverside, California, USA 92521 e-mail: honghyuna@gmail.com.

[c] School of Accountancy, College of Business and Entrepreneurship, University of Texas Rio Grande Valley, Texas USA 78539 e-mail: jiwoo.ryou@utrgv.edu.

* Corresponding author. Graduate School of Management, University of California, Davis CA USA 95616. pagriffin@ucdavis.edu Tel. (530) 752-7372.

1 Introduction

For firms, long-run success and survival depend critically on managers' choices and implementation of successful innovation projects that use resources efficiently (Andrews and de Serres, 2012). Corporate finance theory predicts that when facing competition from established firms, small and young firms with high-quality innovative projects operate their projects in a confidential manner to ensure the profitability of the projects (e.g., Hall, 2002). Private financing arrangements help these firms operate their innovation projects in a confidential manner compared to public financing arrangements (Diamond, 1984, 1991; Yosha, 1995). This paper tests an implication of this prediction by examining whether the quality of managers' earnings guidance forecasts affects how banks recognize corporate innovative efficiency (hereafter, IE).

The use of private loan facilities to finance corporate innovation has grown considerably in recent years, in part, due to banks' greater use of patents and intangibles as collateral (Loumioti, 2014; Mann 2014). This is an interesting trend because it shifts control rights to creditors, who, in the event of unsuccessful outcomes that threaten default, would then have claims on the firm's assets, including patents and intangibles. This shift in control rights, however, could exacerbate lenders' adverse selection and moral hazard concerns, leading some to opine that the use of private loan facilities to fund risky innovation projects is unnecessarily costly; for example, due to credit rationing (Stiglitz and Weiss, 1981), uncertain collateral value (Kothari, Laguerre, and Leone, 2002), and information asymmetry (Holmstrom, 1989). In response, lenders may raise interest rates and incorporate stricter terms resulting in higher credit costs. Those same entrepreneurs, on the other hand, could alleviate the higher credit costs from information asymmetry by providing lenders with private or covered information about their firm's activities, including details of their research and development plans and patenting activities (Gorton and Khan, 2000; Winton, 2003). A private loan facility offers a protected way for borrowers to communicate this information, having the particular advantage that it does not impose significant proprietary costs on the firm that could occur with multi-party financings such as public debt or equity (Campbell, 1979; Bhattacharya and Chiesa, 1995; Yosha, 1995; Allen and Gale, 1999).

We address the issue of how management guidance forecast accuracy relates to firms' innovation decisions by testing whether the effects of innovative efficiency on the cost and terms of private loan facilities differ by managers' external forecasting ability in a manner consistent with corporate finance theory (Campbell 1979; Bhattacharya and Chiesa, 1995; Yosha, 1995; Allen and Gale, 1999). As previously noted, this theory states that the source of financing plays a critical role in determining innovators' choice to operate innovation projects in a transparent or confidential manner. Firms with internal financing can increase the value of their innovation by concealing innovation-related information from outsiders. In contrast, firms with external financing may need to increase transparency to raise sufficient capital while incurring the proprietary costs of the revelation of strategically sensitive information.

Our analysis of 777 firm-years over 1994–2006 yields the following findings. First, we document an empirical link between innovative efficiency and the cost of private loan facilities that depends on the quality of entrepreneurs' earnings guidance forecasts. Because private loan financing helps protect entrepreneurs' sensitive information from outsiders, this supports our key hypothesis – that the effects of innovative efficiency on the cost of private loan facilities favor borrowers with poor quality information. At first glance, this finding may seem counter-intuitive, as one would expect a lender to charge more for poor borrower information. Nonetheless, our results support this idea and comport with the corporate finance theory that entrepreneurs with high-quality internal information choose private loan facilities to fund their projects. In their view, a private disclosure of innovative projects via a bank loan facility best alleviates the cost of competitive disadvantage that might otherwise occur by disclosing in a public debt or equity financing.[1] Our results are significant economically. For example, a one-standard-deviation increase in our innovative efficiency variable (*IE_PA*) associates with a decrease in loan spread of 25.52 bps for managers with low external forecast accuracy. This contrasts with a 5.76 bps decrease in spread for managers with high external forecast accuracy.

Second, our findings support the corporate finance theory that high-quality young and small firms choose bilateral financing (e.g., bank loan) over multilateral financing, thus entertaining lower borrowing costs (Diamond 1991; Yosha 1995). Third, we find that private lenders are less likely to impose covenant restrictions on borrowing firms that operate their innovation projects in a more confidential way as implied by their lower management guidance accuracy. This finding comports with the view that lower management guidance accuracy provides borrowing firms with added flexibility in their innovation and financing decisions. Fourth, we provide evidence that the effects of lower management guidance accuracy on loan spreads and covenant restrictions are more pronounced for firms with greater public information uncertainty (as captured by their smaller size) and when they face greater competition from current rivals. Finally, we document that higher innovative efficiency reduces the probability of violating loan covenants, supporting the view that innovative efficiency allows firms to survive and stay competitive in the long run.

[1] While not a direct focus of this paper, we also confirm in untabulated analysis the prediction of corporate finance theory that firms generate more accurate forecasts when they receive public debt versus private debt and equity. See note 13 for details.

Our results are robust to alternative econometric and statistical specifications. While the preceding discussion suggests that while managers' forecasting quality contributes to their IE, we cannot completely remove the concern that managers endogenously determine forecast accuracy based on the expected effects of accuracy on innovative efficiency. To address the issue of whether managers' choice of forecast accuracy is independent of the forecast's effect on IE, we employ a Heckman two-stage least squares (2SLS) approach. Our results continue to hold after using 2SLS. Additionally, we follow the methods of Hall, Jaffe, and Trajtenberg (2001, 2005) to correct for the effects of truncation with data on patent applications.

Section 2 reviews the literature and states the hypotheses. Section 3 describes the data and sample and defines the variables and models. Section 4 presents the results. Section 5 summarizes additional tests, and Section 6 concludes.

2 Literature and hypotheses

Bank loans allow small, innovative firms to hide information from potential competitors compared to multilateral financing arrangements such as public bonds and equities (Campbell, 1979; Yosha, 1995). The SEC imposes different levels of mandatory disclosure on firms between bilateral versus multilateral financing arrangements. In multilateral arrangements firms are required to provide extensive documentation (often audited) to provide accurate information to public investors. Naturally, multilateral arrangements incur significant information costs, which the theoretical models (Bhattacharya, Boot, and Thakor, 2004) highlight as the "two-audience signaling problem". That is, the information disclosed by a firm will inevitably be available to the firm's competitors, thereby reducing the profitability of the borrowing firms' innovative projects. In contrast, bank loans, which are bilateral arrangements, are often characterized as a close relationship between the borrowing firm and the lending. A bilateral financing transaction, thus, generates less, possibly zero, leakage of sensitive proprietary information. The idea that bilateral financing may be caused by the desire for confidentiality was first proposed by Campbell (1979), who focused on the conflicts between equity and debt holders. Under the assumption that the terms of debt are renegotiable, Campbell (1979) contended that equity holders, which include management, may choose to borrow from a bank in order to hide positive cash flow news from debt holders. In addition to the differences in the mandatory disclosures, the two financing arrangements can also influence firms' voluntary disclosure policies. For example, small, innovative firms with high-quality innovative projects may choose the bilateral financing over the multilateral financing to protect their proprietary information. Thus, firms relying on private debt facilities are hypothesized to provide less frequent and accurate forecasts compared to firms relying on public debt and equity facilities.[2]

Firms choose their optimal disclosure policy based on the trade-off between benefits and costs of voluntary disclosure. In settings wherein entrepreneurial managers anticipate significant proprietary costs from greater outside disclosure and accuracy, firms may have an incentive not to provide accurate management forecasts. Such costs can occur when external reporting quality (e.g., from greater disclosure or accuracy) directly influences competitors' investments by providing sensitive strategic information about entrepreneurs' investment plans and payoffs (Simmonds, 1982; Bhattacharya and Ritter, 1983; Simons, 1990; Bhattacharya and Chiesa, 1995; Allen and Gale, 1999; Guilding, Cravens, and Tayles, 2000; Maiga and Jacobs, 2006; Durnev and Mangen, 2009). In such settings, managers may have fewer incentives to provide high-quality financial reporting, in that the cost-benefit trade-off between capital market and product market consequences could favor the latter.

This trade-off almost certainly applies to entrepreneurial activities, as the threat and reality of competitors' and rivals' responses can be paramount in driving an innovative firm's information disclosure decisions. Disclosures of forward-looking information that encapsulate managers' expectations of the payoffs and uncertainties of innovation would be especially relevant. We contend that the calculus of optimal voluntary disclosure applies to the setting of regularly disclosed externally reported earnings forecasts by entrepreneurial firms using private debt facilities. That is, while higher quality earnings guidance forecasts benefit investors and creditors in public capital markets (Anilowski, Feng, and Skinner, 2007; Li and Zhuang, 2012), higher quality earnings guidance forecasts could be costly for entrepreneurial firms by making their public disclosures more valuable to competitors and rivals.

Our dataset allows us to examine this cost-benefit tradeoff in the setting of private loan facilities. While much theoretical work precedes it, the formal model in Yosha (1995) most closely aligns with our research question. In this model, high-quality entrepreneurs disclose their high quality to the banker but not to outsiders,

[2] Prior studies show that firms issuing equities, for example, provide more frequent disclosure for the purpose of hyping stock prices or reducing the information costs (e.g., Lang and Lundholm 2002).

since disclosure to outsiders imposes proprietary costs that exceed the benefits of higher quality public information. The reverse also holds, namely, that low-quality entrepreneurs disclose to outsiders so as not to be perceived as being high quality because they do not want to incur the same proprietary costs of disclosure. Under this view, we predict that higher public information quality to outsiders does not strengthen (and may weaken) the relation between IE and the cost and terms of private lending. We use the accuracy of managers' earnings guidance forecasts as our proxy for public information quality. This leads to our primary hypothesis stated in the alternative form.

H_1: The relation between IE and the cost and terms of private loan facilities strengthens for firms with less accurate managers' earnings guidance forecasts.

This hypothesis, however, also requires that we understand the unconditional relation between IE and the cost and terms of private loan facilities. An extensive literature has studied this topic. Several earlier studies contend that entrepreneurial loans should cost more because the agency costs of information asymmetry and moral hazard are higher when banks lend to firms whose success depends on innovation. These firms tend to be smaller and younger (Holmstrom, 1989; Strahan, 1999). Others reason that higher loan costs might result from entrepreneurial firms' use of intangibles as collateral, which increases lenders' due diligence costs (Bradley and Roberts, 2004).

More recent studies, on the other hand, emphasize banks' incentives to lower the cost of private lending to entrepreneurs. For example, banks could accumulate expertise in lending to fund innovation, passing this on to borrowers as lower spreads and less restrictive non-price terms (Chava et al., 2015). They could also encourage borrowers to supply private lenders with better information about their operations and innovative activities. This view contends that both parties should benefit from private transparency and accuracy (Gorton and Kahn, 2000; Winton, 2003; Bharath, Sunder, and Sunder 2008). Consistent with this view, Francis, Hasan, Huang, and Sharma (2012) document that private borrowers with higher patent and citation counts benefit from lower loan spreads and fewer covenants; and Plumlee, Xie, Yan, and Yu (2014) find that bank loan spreads vary negatively with citation counts on forthcoming patents.[3]

[3] To understand the unconditional relation between IE and the cost and terms of private loan facilities and to confirm the prior results in the context of our sample and study period, we also examine the following (maintained)

3 Sample and data, variables, and models

3.1 Sample and data

We obtain our sample and data by merging four datasets: (1) the patent dataset from the National Bureau of Economic Research (NBER) patent database[4], (2) the dataset on loan pricing and loan terms from Loan Pricing Corporation (LPC)-Reuters DealScan, (3) the First Call Company Issued Guidance (CIG) datasets on managers' forecasted and actual earnings per share, and (4) Compustat North America. We use the Chava and Roberts (2008) file to link Compustat to DealScan, the Hall, Jaffe, and Trajtenberg (2001) file to link Compustat to the NBER patent database, and CUSIP codes to link First Call CIG to the other datasets.

Procedurally, we first identify all firms in the NBER patent database with available annual financial and stock price in Compustat, excluding finance, insurance, and real estate firms (i.e., those with four-digit standard industrial classification (SIC) codes between 6000 and 6999).[5] For each firm-year NBER/Compustat observation, we then identify firms in the DealScan database with a loan facility in the fiscal year following the NBER/Compustat year. Each loan facility typically contains loans made to a single borrower by multiple lenders. Those lenders also generally syndicate the package to a lead institution such as a bank, insurance company, or pension fund, to manage and underwrite the package.[6] We then eliminate firms not covered by First Call CIG. This merge of datasets generates a sample of 777 firm-year observations over 1994–2006 with details on borrowers' patents, bank loan facilities, and management earnings forecasts.

Panel A of Table 1 shows that the 777 firm-year sample covers a range of industries, based on the Fama-French 48 industry classification, constructed using firms' four-digit SIC codes as of the prior fiscal year. Pharmaceuticals (12.61%) and Machinery (10.17%) are the most represented industries. This occurs by the construction of the sample, however, as those industries are also the most patent-active industries. Panel B of

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hypothesis. This hypothesis states that proxies for the cost and terms of private loan facilities vary negatively with firms' IE independently of the accuracy of managers' earnings guidance forecasts.

[4] sites.google.com/site/patentdataproject/Home/downloads.

[5] The NBER patent data files contain detailed information on up to three million patents granted by the U.S. Patent and Trademark Office (USPTO) between 1976 and 2006. The NBER data include patent assignee names, Compustat identifiers, application dates, grant dates, and the patent's category.

[6] For a detailed description of the DealScan dataset, see Bradley and Roberts (2004) and Chava and Roberts (2008).

Table 1 shows that the sample represents an increasing number of observations each year. This is consistent with the increased use of patenting and an expanding economy.[7]

Following Hirshleifer, Hsu, and Li (2013), we measure IE as the ratio of a firm's patents granted in year *t* scaled by R&D capital based on five-year cumulative R&D expenses assumed to depreciate at 20 percent starting in year *t*-2. The formula is:

$$IE\_PA_t = \text{Patents}_t/(\text{R\&D}_{t-2} + 0.8 \times \text{R\&D}_{t-3} + 0.6 \times \text{R\&D}_{t-4} + 0.4 \times \text{R\&D}_{t-5} + 0.2 \times \text{R\&D}_{t-6}), \quad (1)$$

where Patents_t denotes a firm's number of patents granted to that firm in year *t* and $\text{R\&D}_{t\text{-n}}$ denotes the firm's R&D expenses (in millions) for the fiscal year ending *t*-n.[8] The use of cumulative R&D expenses as the denominator assumes that R&D spending over the preceding five years starting at *t*-6 contributes increasingly to successful patent applications granted in year *t.* Table 2 reports the distribution statistics for *IE_PA*, winsorized at the top and bottom two percentiles to prevent the undue influence of extreme observations. Mean and median *IE_PA* are 0.1258 and 0.0772, respectively. In economic terms, this means that $100 million dollars of R&D spending over five years generates 12.58 patents for the average firm.

3.2 Management forecast accuracy

We define *Mgt_Forecast_Acc* as the negative of the absolute difference between actual earnings per share for the fiscal year end before loan initiation and management's forecast of earnings per share deflated by stock price. Each management EPS forecast must be issued at least three weeks before the earnings announcement date to avoid the possible effects of pre-announcements. We source these data from the First Call CIG datasets.

3.3 Bank loan contracting variables

We select the variables from the DealScan dataset. The dataset, which covers approximately 65 percent of U.S. firms on Compustat North America, contains comprehensive historical information on loan facility pricing and the contract details, terms, and conditions of these facilities. The data are sourced mainly from SEC filings (10-Ks, 10-Qs, 8-Ks, and S-filing registration statements) and loan syndicators' records. Most loan facilities fund the borrower through a syndicated loan (over 70% according to DealScan), the large majority of which are used for general purposes, debt repayment, and working capital (over 60%). Most loan types involve

[7] Sec Corrado, Hulten, and Sichel (2009), Loumioti (2014), and Mann (2014) for details.
[8] Section 5 analyzes the sensitivity of the relation between innovative efficiency and bank loan contracting where the denominator of IE is based on the lagged coefficients for R&D expenditures between *t*-2 and *t*-6 years from a regression of patents on lagged R&D for each of the 48 Fama-French industries (http://mba.tuck.dartmouth.edu).

revolving lines of credit, term loans, and 364-day facilities (over 60%). We select the interest spread on the loan (called the All-in-spread, or *AIS*) at the time of loan origination (deal active date) as the key price characteristic of each loan contract. *AIS* represents the interest spread in excess of LIBOR, effectively making each loan a floating rate instrument. The other bank contracting variables listed below represent key features of the loan facility at the time of origination. We expect these variables to relate to *IE_PA* in the way hypothesized earlier, where the IE variables relate to the previous year to ensure that the IE information would be potentially available at the time of loan origination. For example, should we find that *AIS* varies negatively with *IE_PA*, this would suggest that an entrepreneurial firm with high IE could expect to pay less for its loan package compared to an entrepreneurial firm with low IE. The DealScan variables are:

AIS = Loan Spread measured as All-in-spread drawn. All-in-spread drawn describes the amount (in basis points over LIBOR or LIBOR equivalent) that the borrower pays for each dollar drawn down within the loan facility. This measure combines the loan's borrowing spread over LIBOR and any annual fee paid to the banking group.

LnMaturity = Natural logarithm of the maturity of the loan facility in months.

LnLoansize = Natural logarithm of the amount of the loan facility in millions of dollars.

Perm_pricing = Indicator variable that equals 1 if the loan facility includes performance pricing, 0 otherwise.

Num_lenders = Total number of lenders in a single loan.

Commit_Fee = Annual percentage fee payable to the lender on the undrawn portion of a committed loan package. This fee is to compensate the lender for tying up capital to a borrower.

FinCov = Number of financial covenants included in a loan contract.

GenCov = Number of general covenants included in a loan contract.

3.4 Compustat variables

In addition to the management forecast, IE, and loan contracting variables, we access firm characteristic measures from Compustat North America, which we use as control variables in the multivariate analysis. We subscript these variables to the year before the year of origination of the loan facility. These comprise the following:

SIZE = Natural logarithm of total assets for the fiscal year end before loan initiation.

Leverage = Ratio of total debt (long-term debt plus debt in current liabilities) to total assets for the fiscal year end before loan initiation.

MTB = Market-to-book ratio, measured as the market value of equity plus the book value of total debt divided by total asset for the fiscal year end before loan initiation.

Tangibility = Net property, plant, and equipment divided by total assets at the fiscal year end before loan initiation.

Profitability = Earnings before interest divided by total assets for the fiscal year before loan initiation.

Sales_Growth = Annual percentage increase in sales for the fiscal year before loan initiation.

CFvolatility = Standard deviation of quarterly cash flow from operations scaled by total assets over the last five years.

ZScore = Modified Altman's (1968) Z-score = (1.2*working capital + 1.4*Retained earnings + 3.3*EBIT +0.999*Sales)/Total Assets. As with Graham et al. (2008), we use a modified Z-score, which excludes the ratio of market value of equity to book value of total debt, because a similar term, market-to-book, enters our multivariate analysis as a separate variable.

3.5 Descriptive statistics

Table 2 summarizes descriptive statistics for these variables. For example, mean (median) *AIS* are 80.0 (37.5) basis points more than LIBOR, mean (median) *LnMaturity* are 3.40 (3.81), and mean (median) *LnLoansize* are 6.26 (6.21). Compared to a larger sample of 12,676 facilities in Bharath et al. (2008, Tables 2 and 3), assumed more representative of the DealScan population, we observe that our IE sample has lower mean *AIS* (80.0 bps versus 185.5 bps), loans of shorter maturity (30 months versus 41.6 months), and loans of greater dollar value ($521 million versus $246 million on average).[9] Our sample also comprises larger firms (total assets of $7.13 billion versus $3.183 billion) with less growth potential than the broader population (market-to-book ratio of 1.77 versus 2.0).[10] Mean debt to total assets (*Leverage*), mean property, plant, and equipment to total assets (*Tangibility*), and mean default score are, however, approximately similar to the larger sample (28.0% versus 21.2% for Leverage, 24.6% versus 27.5% for *Tangibility*, and 1.77 versus 1.927 for *ZScore*). Finally, we report mean and median *Mgt_Forecast_Acc* as -3.88% and -0.86%, respectively, which are slightly more negative than the equivalent measures of -2.40% and -0.31% for the more general capital investment sample in Goodman et al. (2014, 346). They also reflect a higher standard deviation than Goodman et al. (2014) (11.52% versus 3.1%). This wider variation in forecasting ability benefits our research

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[9] To compare with Bharath et al. (2008), we convert the mean logged variables in Table 2 to unlogged numbers using an exponential transformation.

[10] Based on SEC filing disclosures, our sample of firms also experiences much fewer covenant violations, mean = 1.08% of our sample (Table 2) versus up to 35% in the larger DealScan population (Chava and Roberts, 2008, 2094).

design, as we seek to identify whether the effects of IE on bank loan costs and terms vary with managers' external forecasting ability. Collectively, these data suggest that our sample is not representative of the larger DealScan or First Call CIG populations, especially regarding loan spread (higher on average for our sample), loan maturity (shorter for our sample), and firm size (higher for our sample). Thus, inferences about the effects of IE on bank loan costs and terms should not be generalized beyond firms with characteristics similar to those we study.

3.6 Empirical models

To test our hypothesis, we first specify the relation between *AIS* and *IE_PA* but for the effects of *Mgt_Forecast_Acc* by regressing *AIS* on *IE_PA* with controls for loan contracting and firm characteristic variables that might influence *AIS* in the absence of firms' IE. We then test whether the relation between *AIS* and *IE_PA* varies according to our prediction of the effects of manager's external forecasting ability on private loan costs and terms. We lag *IE_PA* and the firm characteristic variables by one year so that they would have been available to lenders before loan origination. The model is:

$$AIS_i = \alpha + \beta IE\_PA_i + \Sigma_j\, \delta_j LoanContracting_{ij} + \Sigma_k\, \phi_k FirmCharacteristics_{ik} + \varepsilon_i, \qquad (2)$$

where the test variable is *IE_PA*. If higher IE associates with lower *AIS*, then, independent of the effects of manager's external forecasting ability, we should observe $\beta < 0$ versus the null hypothesis that $\beta \nleq 0$. The loan contracting variables in Eq. (2) are loan maturity, loan size, an indicator variable for the use of performance pricing, the number of lenders in the facility, the number of financial covenants, the number of general covenants, and an indicator variable for the use of a commitment fee. The firm characteristic variables in Eq. (2) are firm capitalization, leverage, market-to-book ratio, the ratio of property, plant, and equipment to total assets, pretax return on total assets, the volatility of cash flow from operations, and a modified version of the Altman (1968) bankruptcy score. Given the prior literature (Chava and Roberts, 2008; Bharath, et al. 2008), we expect positive signs for the loan contracting coefficients, in that each variable represents a contract detail suggestive of higher default or information risk. For the firm characteristic variables, we expect positive signs for the variables indicating higher default or information risk and negative signs for the variables indicating profitability, growth, and lower default risk.

We also test for relations between the non-pricing loan terms and *IE_PA* using cross-sectional ordered logit analysis, where, instead of *AIS* in Eq. (2), the dependent variable is a count of the number of covenants. Independent of the effects of manager's external forecasting ability, we should observe $\beta < 0$ versus the null hypothesis that $\beta \nleq 0$, or that firms with fewer covenants reflect higher IE. We use the same loan contracting variables as before, except that we exclude the covenant variables since they are used as dependent variables. We expect the same signs for the variable coefficients in Eq. (2).

The last step of our analysis tests for predictable differences in β conditional on low and high management guidance forecast accuracy, in particular, we predict that $\beta_{Low\ Mgt\_Forecast\_Acc} < \beta_{High\ Mgt\_Forecast\_Acc} < 0$. We do this in two ways. First, we conduct separate cross-sectional regressions, where we estimate β for low and high management forecast accuracy subsamples independently. Second, we estimate a regression using all observations, where we estimate the change in β as the coefficient of an interaction variable defined as *IE_PA* = *IE_PA* for firm with low management forecast accuracy and *IE_PA* = 0 for firms with high management forecast accuracy. We also partition the observations based on public information quality as proxied by firm size. We expect the β coefficient in Eq. (2) to vary predictably by firm size ($\beta_{Small} < \beta_{Large} < 0$) (Holmstrom, 1989; Strahan, 1999). To establish the size partitions, we rank firms into quintiles based on end of year *t*-1 total assets and then assign quintiles 1 and 2 to the small firm partition and quintiles 4 and 5 to the large firm partition.

4 Results

4.1 Management forecast accuracy and IE

Table 3 regresses *IE_PA* on *Mgt_Forecast_Acc* with controls. Column 1 shows a positive coefficient of 0.1527 ($p<0.01$) for *Mgt_Forecast_Acc*, with test standard errors clustered by industry and year. Also, we observe negative coefficients for *SIZE* ($p<0.05$) and *MTB* ($p<0.05$), indicating that smaller firms and those without capitalized growth opportunities have higher IE. Because several of the control variables might be endogenous to *Mgt_Forecast_Acc*, we also estimate a two-stage regression, where the first stage uses instruments to predict *Mgt_Forecast_Acc.* Following Li and Zhuang (2012), we select *Ind_Guidance* and *Litigation_Risk* as the instruments, assuming both relate to the firm's decision to issue guidance but do not relate to its IE. The second stage regression continues to show a significantly positive coefficient for estimated

Mgt_Forecast_Acc from the first-stage equation, with a coefficient of 2.0818 ($p<0.01$). We also find that the partial F-statistic for the instrumental variables and the Hausman test for the first stage equation are both statistically significant, suggesting that a firm's guidance decision is not exogenous to the other variables. These results support the notion that innovative firms using private debt facilities have more accurate earnings guidance forecasts.

This result, however, does not answer the question of whether firms engaged in innovation with more accurate earnings guidance forecasts can borrow at lower cost and on better terms than firms with less accurate earnings guidance forecasts. We need to consider how managers' incentives to issue accurate earnings guidance forecasts relate to the cost of bank loans. For example, on the one hand, lenders would prefer to have accurate information to reduce credit risk. On the other hand, if firm managers and lenders also know that if protected or covered information were to reach the wrong hands, then this could increase the cost of credit. For example, the future cash flows from successful innovation could be subverted by the actions of competitors or rivals. Thus, it is an open question on whether loan spreads or loan terms will benefit from greater or less accuracy of management earnings forecasts to outsiders. We address this question next.

4.2 Innovative efficiency and the cost and terms of loans partitioned on management forecast accuracy

Table 4 shows the results of regressing the cost of loans or *AIS* on *IE*. We show two models for each of the forecast accuracy partitions: one includes only the loan contracting variables as regressors and the other includes both the loan contracting and firm characteristic variables. Regarding the control variables, we find that *AIS* increases in loan maturity, the number of covenants, and default risk and decreases in loan size and the use of performance pricing independent of management forecast accuracy. These results accord with the prior literature (e.g., Bradley and Roberts, 2004; Francis et al., 2012; and Plumlee et al. 2014). Table 4 also shows that the *IE_PA* coefficients are significantly more negative for the low management forecast accuracy partition than the high management forecast accuracy partition for both the reduced model ($\beta_{Low\ Mgt\_Forecast\_Acc}$ minus $\beta_{High\ Mgt\_Forecast\_Acc}$ = -118.40, $p<0.05$) and the full model ($_{Mgt\_Forecast\_Acc}$ minus $\beta_{High\ Mgt\_Forecast\_Acc}$ = -123.4523, $p<0.10$). Managers' earnings guidance forecast accuracy, therefore, conditions the effect of IE on the cost of private debt. These results support our primary hypothesis, H_1. The intuition for this result is that whereas firms' innovation success and loan costs should benefit from increased internal forecast accuracy, firms may not want to broadcast their forecasting skills publicly because of proprietary disadvantage (e.g., because competitor firms can learn about which firms are more likely to succeed). They will choose private lending to keep their information confidential. In such cases, the benefits of public disclosure such as lower cost of debt or equity capital may be outweighed by the foregone costs of competitive disadvantage. As predicted, the relation between IE and the cost and terms of private loan facilities strengthens for firms with less accurate managers' earnings guidance forecasts (H_1).

These results are also economically significant. For example, a one-standard-deviation increase in *IE_PA* associates with a decrease in loan spread of 5.76 bps for managers with high earnings guidance forecast accuracy versus 25.52 bps for managers with low external forecast accuracy. We then apply this spread difference to the average loan of our sample of $522 million with an average 29.96 month maturity assuming the average 12-month LIBOR rate for the study period. This results in a pretax interest savings (in present value) over the life of loan of $2.405 million per firm and $683 million if all 284 high accuracy management forecast firm-year observations in the sample were to enjoy this benefit. Table 5 shows similar results for the effect of management forecast accuracy on the relation between IE and the number of loan covenants. *IE_PA* associates more negatively with the number of loan covenants when managers' earnings forecasts have low accuracy versus high accuracy, and the difference in the *IE_PA* coefficients for low minus high accuracy is most significant for *FinCov* ($\beta_{Low\ Mgt_Forecast_Acc}$ minus $\beta_{High\ Mgt\_Forecast\_Acc}$ = -5.2316, p<0.01). In sum, we find that the effect of *IE_PA* on loan cost and loan terms, while negative overall, is significantly more negative for low management forecast accuracy versus high management forecast accuracy observations.

4.3 Partitioning on firm size

Smaller entrepreneurs may have more to lose from proprietary costs and competitive disadvantage and less to gain from increased transparency to capital market participants (Holmstrom, 1989; Strahan, 1999). Small firms are also those with less public information quality in general (e.g., from lower analyst coverage and institutional holdings). We test this notion by further splitting our subsamples based on low and high management forecast accuracy by firm size and predict that the benefits of less accurate management earnings forecasts will relate more to the IE of smaller firms. Table 6 shows this result, namely, that for our measures of loan cost and loan terms, the *IE_PA* coefficients are significantly more negative for the low management forecast accuracy partition than for the high management forecast accuracy partition. For example, the results show the following differences in the *IE_PA* coefficient for *AIS* as the dependent variable, namely, that $\beta_{Low\ Mgt\_Forecast\_Acc}$ minus $\beta_{High\ Mgt\_Forecast\_Acc}$ = -137.8855 ($p<0.05$) for the smaller firm observations and $\beta_{Low\ Mgt\_Forecast\_Acc}$ minus $\beta_{High\ Mgt\_Forecast\_Acc}$ = -13.8140 (not significant) for the larger firm observations. Untabulated results also show that differences in the *IE_PA* coefficients are also significantly more negative across the four measures of loan cost and loan terms for smaller firms versus larger firms conditional on low management forecast accuracy (but not for smaller firms versus larger firms conditional on high management forecast accuracy).

4.4 Partitioning on product market competition

If the threat of future or actual product market competition (PMC) from rivals helps explain our results regarding loan pricing and firms' incentives to issue management guidance forecasts, then we should also observe differences in how IE drives the cost and terms of private lending conditional on measures of PMC. We use two measures of PMC. The first is the negative of PC2 in Li (2010), who constructs PC2 to reflect barriers to market entry such as high set-up costs as reflected in industry measures of property, plant and equipment, and research and development expenses, and capital expenditures. This PC2 measure captures competition from potential entrants. The second is the PC1 measure in Li (2010) based on industry product market size, industry concentration ratio, and the number of firms in the industry. This PC1 measure captures competition from current rivals. When PC2 is low, high barriers to entry such as high set up costs serve to ensure that firms maintain their competitive advantage. In this situation, there would be little reason to reveal plans, profitability, and strategic advantage to outsiders through accurate management guidance forecasts; as such accuracy could weaken this advantage. On the other hand, when PC1 is high (e.g., there are already more firms in the industry), higher existing competition results in higher proprietary costs. This also means that firms would have less incentive to reveal plans, profitability, and strategic advantage to outsiders through guidance forecasts compared to firms with lower current competition (e.g., where there are fewer firms in the industry).[11]

[11] Li (2010) discusses the two streams of accounting literature on how product market competition might affect firm public disclosure, one stream is based on competition from potential entrants (e.g., Darrough and Stoughton, 1990), and the other is based on competition from current rivals (e.g., Verrecchia, 1983).

Panel A of Table 7 presents the results for PMC from potential entrants (the PC2 measure). For firms in the low future PMC partition, all regressions of loan cost and loan terms on *IE_PA* show *IE_PA* coefficients that are more negative for low versus high management forecast accuracy firms. For example, for the low PMC group, $\beta_{Low\ Mgt\_Forecast\_Acc}$ minus $\beta_{High\ Mgt\_Forecast\_Acc}$ = -372.75 (p<0.01) for *AIS* as the dependent variable. That is, a higher *IE_PA* associates with a greater reduction in loan spread for low accuracy firms. We reason that this occurs because low management forecast accuracy firms are those that have the least incentive to signal to outsiders the high quality of their innovative activities through accurate management guidance forecasts. On the other hand, Panel A of Table 7 shows that the effects on loan cost and loan terms are not significant for the high PMC group. These firms face higher future competition and, thus, may have less inclination to conceal the high quality of their innovative activities, as they have less competitive advantage.

Panel B of Table 7 presents the results for competition from current rivals (the PC1 measure for PMC). As discussed above, high current PMC firms would be reluctant to disclose high-quality information to outsiders through accurate management guidance forecasts, as disclosure increases the cost of competitive disadvantage by revealing plans, profitability, and strategic advantage to outsiders. These firms' guidance forecasts would, therefore, reflect lower *IE_PA* coefficients compared to firms with more accurate management guidance forecasts. For example, for the high current PMC partition, $\beta_{Low\ Mgt\_Forecast\_Acc}$ minus $\beta_{High\ Mgt\_Forecast\_Acc}$ = -300.84 (p<0.01) for *AIS* as the dependent variable. On the other hand, Panel B of Table 7 shows that the effects of forecast accuracy on loan cost and loan terms are not significant for the low current PMC group, as these firms face lower current competition. This suggests that they have relatively less concern about revealing the quality of their innovative activities to outsiders through accurate management guidance forecasts.[12]

[12] The results in Table 7 may also explain the "surprising" result in Li (2010, 665), who comments that "I find that competition from existing rivals is negatively associated with the accuracy of investment forecasts for industry followers." In contrast, when competition from existing rivals is high, this paper finds that the effect of IE on loan cost and loan terms is stronger for firms with less accurate management guidance forecasts. These are the firms whose disclosure incentives may be most affected by the proprietary costs of competitive disadvantage, which managers view as an offset to the capital market benefits of greater disclosure.

5 Robustness checks

One potential criticism of *IE_PA* is that we deflate it by a one-size-fits-all measure of lagged R&D expenditures. We, therefore, replicate Table 4 with an alternative definition of *IE_PA* that uses industry-based regressions (based on the 48 Fama-French industry classifications) to estimate the lagged relation between patents in *t* and R&D expenditures in years *t*-2 to *t*-6. With this definition, Table 8 shows results that are qualitatively equivalent to those in Table 4. Table 8 also shows that the *IE_PA* coefficient differences between the low and high management forecast accuracy partitions are significant at $p<0.01$.

A second potential criticism is that the denominator of *IE_PA* may be too narrow and not incorporate additional spending related to patents. We, therefore, re-define *IE_PA* as patents in year *t* divided by lagged *R&D* plus *S&A* expenses. Table 9 shows that *IE_PA* relates negatively to management forecast accuracy, although the negative coefficient differences are not significant at $p<0.10$. A third potential criticism is that we have not adjusted for truncation bias, in that the patents granted in the most recent years may have less effect on the cost and terms of loans since the patents have less time to foster benefits for the firm. We, therefore, delete patents granted in years 2005 and 2006 and use the truncation adjustment procedure in Hall et al. (2001). Table 10 shows that *IE_PA* relates negatively to management forecast accuracy, although the negative coefficient differences are not significant at $p<0.10$.

Fourth, as an alternative to measuring public information quality based on firm size (Table 6), we use firm accrual quality as the proxy, defined as the negative of the performance-matched *AQ* metric in Kothari et al. (2005). We assign firms annually to higher and lower *AQ* portfolios based on *AQ* terciles grouped on two-digit SIC industry code and by sorting on *ROA* measured one year before portfolio formation (Kothari et al. 2005, 174–175). Based on the same notion that managers with high-quality, innovative ability use private debt financing to curb financial statement disclosure of such ability, we predict that the effects of IE on loan cost and terms will be more negative for the low versus the high management forecast accuracy partitions for the tercile 1 (lower) *AQ* observations versus the tercile 3 (higher) AQ observations. Untabulated results show the following differences in the coefficient for *AIS*, namely, that $\beta_{Low\ Mgt\_Forecast\_Acc}$ minus $\beta_{High\ Mgt\_Forecast\_Acc} = -153.7816$ ($p<0.05$) for the lower *AQ* observations, and $\beta_{Low\ Mgt\_Forecast\_Acc}$ minus $\beta_{High\ Mgt\_Forecast\_Acc} = -56.6495$ ($p<0.10$) for the higher *AQ* observations. In sum, the effects of lower versus higher management forecast accuracy on loan spreads are also more negative for firms with lower accrual quality (in addition to being more negative for smaller firms). Thus, we confirm the results in Table 6 using a second measure of public information quality.

Finally, as an overall check on our results, rather than test whether earnings guidance forecast accuracy varies on the basis of *IE_PA* for private loan facilities only (the main focus of our paper), we test whether the accuracy of management forecasts associated with public (private) loans issued in year *t* differs from the accuracy of management forecasts in general.[13] Consistent with the view that managers have stronger capital market incentives for forecast accuracy when the loans involve outside investors, untabulated results indicate that public loans issued in year *t* associate with higher earnings guidance forecast accuracy, whereas the forecast accuracy associated with private loans issued in year *t* is the same as forecast accuracy in general.

6 Conclusion

This paper finds that the accuracy of managers' earnings guidance forecasts shapes the relation between firms' innovative efficiency (IE) and the cost and terms of their private loan facilities. Specifically, the accuracy of managers' earnings guidance forecasts significantly conditions how IE affects the costs and terms of private loan facilities. If those same entrepreneurs had used bond or equity financings, we would expect to find, consistent with prior research, that higher management guidance forecast accuracy lowers investors' cost of capital. The theory of private lending, however, considers the trade-off between more accurate forecasts for capital market participants and competitors' and rivals' reactions induced by greater accuracy. For this reason, we find that the negative relation between IE and the cost and terms of private loan facilities to entrepreneurs strengthens when managers issue less accurate earnings guidance forecasts. This negative relation also strengthens for firms with higher proprietary costs, such as smaller firms and those in industries with low barriers to entry. These effects are economically significant. For example, all else equal, innovatively-efficient

[13] To implement this test, we regress *Mgt_Forecast_Acc* on *Public_Loan* and *Private_Loan*, using all observations in a merge of the DealScan, CIG, and Compustat datasets (7,436 obs.). *Public_Loan* or *Private_Loan* is an indicator variable equal to 1 for a firm that issues a public loan (private loan) at year t, 0 otherwise. The regression also controls for *SIZE*, *MTB*, *Profitability*, *Leverage* (defined in Table 2), *Analyst following* (# analysts in year t), *Institutional ownership* (percentage of common stock at year t), and *Litigation risk* (one if the firm is in an industry with high litigation risk, namely, SIC codes 2833-2836 and 8131-8734 (bio-tech), 3570-3577 (computers), 7371-7379 (software), 3600-3674 (electronics), 4812-4813, 4833, 4841, and 4899 (communications), 4911, 4922-4924, 4931, and 4941 (utilities), and 5200-5961 (retail), and zero otherwise) (Li, 2010).

firms with less accurate earnings guidance forecasts show a loan spread reduction that is 20 basis points higher compared to innovatively-efficient firms with more accurate earnings guidance forecasts.

More generally, these results imply that studies of the effects of information quality on capital market behavior based on the accuracy of managers' earnings guidance forecasts should consider whether firms in the sample use private loan facilities. With private financing an increase in external information quality could impose significant proprietary costs that counterbalance the expected capital market benefits of that higher quality. A related implication is that firms with low-quality management forecasts are not necessarily firms with low investment efficiency. Such firms have incentives not to and, apparently, do not reveal their underlying (higher) efficiency. Our findings also relate to archival accounting research more generally, as Compustat firms routinely use private debt facilities (65 percent as of 2010, according to Wharton Research Data Services), whose use, as this study suggests, impacts their disclosure incentives.

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Table 1

Sample distribution

Panel A: Sample distribution by industry

Fama-French 48 Industry (industry number)	Frequency	Percent
Aircraft (24)	41	5.28
Alcoholic Beverages (4)	9	1.16
Apparel (10)	2	0.26
Automobiles and Trucks (23)	20	2.57
Business Services (34)	20	2.57
Business Supplies (38)	55	7.08
Chemicals (14)	68	8.75
Computers (35)	25	3.22
Construction Materials (17)	23	2.96
Consumer Goods (9)	66	8.49
Defense (26)	14	1.80
Electrical Equipment (22)	27	3.47
Electronic Equipment (36)	46	5.92
Entertainment (7)	5	0.64
Food Products (2)	32	4.12
Machinery (21)	79	10.17
Measuring and Control Equipment (37)	24	3.09
Medical Equipment (12)	18	2.32
Nonmetallic Mining (28)	5	0.64
Petroleum and Natural Gas (30)	21	2.70
Pharmaceutical Products (13)	98	12.61
Recreational Products (6)	12	1.54
Rubber and Plastic Products (15)	4	0.51
Ship Building, Railroad Equipment (25)	3	0.39
Shipping Containers (39)	10	1.29
Steel Works, Etc. (19)	29	3.73
Telecommunications (32)	15	1.93
Textiles (16)	1	0.13
Tobacco Products (5)	2	0.26
Wholesale (41)	3	0.39
Total	777	100.00

Panel B: Sample distribution by year

Fiscal year	Frequency	Percent
1994	1	0.13
1995	5	0.64
1996	17	2.19
1997	34	4.38
1998	36	4.63
1999	46	5.92
2000	60	7.72
2001	73	9.40
2002	79	10.17
2003	88	11.33
2004	107	13.77
2005	128	16.47
2006	103	13.26
Total	777	100.00

Table 2

Descriptive statistics and variable definitions

Descriptive statistics	Mean	Q1	Median	Q3	Std. Dev.
IE_PA	0.1258	0.0262	0.0772	0.1621	0.1601
AIS	79.9971	22.5000	37.5000	87.5000	95.7880
LnMaturity	3.3999	2.4849	3.8064	4.0943	0.7960
LnLoansize	6.2561	5.6908	6.2146	6.9078	1.0438
Perm_pricing	0.4401	0.0000	0.0000	1.0000	0.4969
Num_lenders	12.9644	7.0000	11.0000	18.0000	8.6357
Commit_Fee	70.6114	11.0000	23.2500	65.5000	120.2723
FinCov	1.2322	0.0000	1.0000	1.0000	1.8946
GenCov	0.9232	0.0000	2.0000	2.0000	1.1971
SIZE	8.8715	7.9537	8.7771	9.8107	1.1356
Leverage	0.2799	0.1818	0.2646	0.3573	0.1269
MTB	1.7668	1.0174	1.4434	2.1862	1.0986
Tangibility	0.2455	0.1471	0.2084	0.3126	0.1326
Profitability	0.1590	0.1180	0.1539	0.1893	0.0636
Sales_Growth	0.0727	0.0000	0.0605	0.1244	0.1459
Firm_Age	2.4700	2.3026	2.5649	2.7081	0.2651
CFvolatility	0.0320	0.0183	0.0250	0.0384	0.0231
ZScore	1.9229	1.4042	1.9121	2.4106	0.6645
Mgt_Forecast_Acc	-0.0388	-0.0273	-0.0086	-0.0030	0.1152

This table reports descriptive statistics for the full sample. The sample consists of 777 firm-year observations for a sample period between 1994 and 2006, which satisfy the data requirements. We winsorize all continuous variables at the extreme two percentiles.

Variable definitions:

AIS = Loan spread measured as All-In-Spread Drawn. All-in-Spread Drawn describes the annual spread (in basis points over 12-month LIBOR or LIBOR equivalent) that the borrower pays for each dollar drawn down. This measure combines the annualized borrowing spread of the loan over LIBOR with any annual fee paid to the bank group.

AllCov = Count of all covenants in a loan contract

CFvolatility = Standard deviation of quarterly cash flow from operations scaled by total assets over the last five years.

CommitFee = Annual percentage fee payable to the lender on the undrawn portion of a committed loan facility. This fee is to compensate the lender for tying up capital to a borrower.

FinCov = Number of financial covenants included in a loan contract.

Firm_age = Natural Logarithm of the number of years after the first appearance in Compustat

GenCov = Number of general covenants included in a loan contract.

IE_PA = Innovation efficiency by patent. Patents granted to a firm in year *t* divided by research and development (R&D) capital in year *t*-2. R&D capital is computed as the 5-year cumulative R&D expenses with 20% annual depreciation.

Leverage = Ratio of total debt (long-term debt plus debt in current liabilities) to total assets t for the fiscal year end before loan initiation.

LnLoansize = Natural logarithm of the amount of the loan facility in millions of dollars.

LnMaturity = Natural logarithm of the maturity of the loan facility in months.

Mgt_Forecast_Acc = Management guidance forecast accuracy measured as the negative of the absolute difference between actual earnings per share and management earnings forecast deflated by stock price.

MTB = Market-to-book ratio, measured as the market value of equity plus the book value of total debt divided by total asset for the fiscal year end before loan initiation.

Numlenders = Total number of lenders in a single loan

PPricing = Indicator variable that equals 1 if the loan facility includes performance pricing and 0 otherwise.

Profitability = Earnings before interest divided by total assets for the fiscal year before loan initiation.

Sales_Growth = Sales growth ratio. Percentage increase in sales over the prior fiscal year.

Firm_Age = Natural logarithm of the number of years after the first appearance in Compustat.

SIZE = Natural logarithm of total assets for the fiscal year end before loan initiation.

Tangibility = Net property, plant, and equipment divided by total assets for the fiscal year end before loan initiation.

ZScore = Modified Altman's (1968) *Z-score* = (1.2*working capital + 1.4*Retained earnings + 3.3*EBIT +0.999*Sales)/Total Assets that is estimated in the fiscal year before loan initiation. As with Graham et al. (2008), we use a modified Z-score, which excludes the ratio of market value of equity to book value of total debt, because a similar term, market-to-book, enters the regressions as a separate variable.

Table 3

Management forecast accuracy and innovative efficiency

Dependent variable = *IE_PA*	*OLS*	*Two-stage least squares*	
		First stage	Second stage
Mgt_Forecast_Acc.	0.1527***		2.0818***
	(3.11)		(3.46)
SIZE	-0.0372**	0.0058*	-0.0505***
	(-2.13)	(1.76)	(-5.58)
MTB	-0.0273**	0.0540***	-0.1298***
	(-2.04)	(7.50)	(-3.75)
Profitability	0.0781	0.4091***	-0.8487***
	(0.54)	(8.39)	(-3.30)
Leverage	0.0934	-0.0148	0.1013
	(0.82)	(-0.59)	(1.45)
Tangibility	-0.0469	0.0280	-0.0420
	(-0.61)	(1.23)	(-0.94)
CashSize	0.0369	-0.0366	0.0868
	(0.35)	(-0.90)	(0.92)
Sales_Growth	-0.0447	0.0833***	-0.2038***
	(-1.08)	(2.97)	(-2.75)
Firm_age	0.0318	0.0015	0.0792***
	(0.59)	(0.09)	(3.04)
Instrumental Variables:			
Ind_Guidance		-0.2252***	
		(-2.46)	
Litigation_Risk		-0.0150	
		(-1.47)	
Num. of obs.	777	777	777
R Square	0.2811	0.2040	0.0686
Partial F-Statistic		6.90	$p<0.01$
Diff. Mgt_Forecast_Acc Coeff. Test		$\chi^2 = 11.04$	$p<0.01$
Hausman Test		$\chi^2 = 6.86$	$p<0.01$

This table presents the effect of the management forecast accuracy on the Innovation efficiency for the maximum samples of 777 firm-year observations. We regress innovative efficiency (*IE_PA*) on management forecast accuracy and other control variables. The two-stage least squares tests report results of two-stage regressions of the relation between management forecast accuracy and innovative efficiency. We use two instrumental variables (Li and Zhuang, 2012), namely, *Industry_Guidance* and *Litigation_Risk*. *Industry_Guidance* is the percentage of firms in the same industry that issue management guidance. *Litigation_Risk* is an indicator variable that equals one if the firm is in an industry with a high litigation risk, and zero otherwise. Industries with the SIC codes: 2833-2836, 3570-3577, 7370-7374, 3600-3647, 5200-5961, and 8131-8734 are classified as high-litigation risk industries. We report *t*-statistics in parentheses with standard errors clustered by industry and year. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Table 2 states the definitions of the variables.

Table 4

Innovative efficiency and bank loan spread (*AIS*)

Dependent variable = *AIS*	*Low management forecast accuracy*		*High management forecast accuracy*	
IE_PA	-155.0681***	-159.4276**	-36.6650	-35.9753*
	(-3.15)	(-2.53)	(-1.63)	(-1.68)
Difference (Low – High)	-118.4031**	-123.4523*		
(t-statistic)	(-2.19)	(-1.86)		
LnMaturity	20.8939**	19.9498***	0.1491	0.4587
	(2.38)	(3.22)	(0.07)	(0.17)
LnLoansize	-36.6691***	-32.0382***	-10.7103***	-10.9239**
	(-4.86)	(-3.08)	(-3.18)	(-2.09)
PPricing	-58.5246***	-52.5106**	-29.4847**	-32.1856**
	(-2.75)	(-2.40)	(-2.09)	(-2.18)
Numlenders	-0.7843	-0.7689	0.1053	0.0740
	(-0.89)	(-0.78)	(0.24)	(0.17)
FinCov	11.6872	13.8236*	17.3846	17.2273
	(1.48)	(1.78)	(1.58)	(1.61)
GenCov	14.7941**	11.3914**	12.9483	14.0509**
	(2.40)	(2.14)	(2.09)	(2.23)
CommitFee	0.2618***	0.2284**	0.2717*	0.2406*
	(2.77)	(2.28)	(1.75)	(1.69)
SIZE		-4.4432		-0.9144
		(-0.42)		(-0.15)
Leverage		51.7821*		-3.6336
		(1.72)		(-0.10)
MTB		-6.6560		-2.7904
		(-0.58)		(-0.77)
Tangibility		88.9315		24.1267
		(1.04)		(0.73)
Profitability		37.4736		32.7936
		(0.26)		(0.42)
CFvolatility		102.7401		240.6809**
		(0.24)		(2.02)
ZScore		-27.5914*		-14.7969**
		(-1.97)		(-2.11)
Num. of obs.	253	253	284	284
R Square	0.7614	0.7877	0.7493	0.7714

This table presents the effect of *IE_PA* on bank loan spread (*AIS*) for the maximum samples of 537 firm-year observations for *IE_PA*. We regress bank loan spread (*AIS*) on innovative efficiency (*IE_PA*) and other control variables. We report *t*-statistics in parentheses with standard errors clustered by industry and year. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Table 2 states the definitions of the variables. All regressions include industry-level fixed effects.

Table 5

Innovation efficiency and non-pricing loan terms conditional upon management forecast accuracy

	Low management forecast accuracy			*High management forecast accuracy*		
Dependent variable =	*AllCov*	*GenCov*	*FinCov*	*AllCov*	*GenCov*	*FinCov*
IE_PA	-4.3049***	-4.2785***	-5.5624***	-0.9433	-0.5998	-0.3308
	(-3.03)	(-2.60)	(-3.49)	(-0.76)	(-0.35)	(-0.32)
Diff.	-3.3616*	-3.6787	-5.2316***			
(t-statistic)	(-1.78)	(-1.55)	(-2.75)			
LnMaturity	0.1411	0.0046	0.4291	0.1636	0.1343	0.2867**
	(0.46)	(0.02)	(0.98)	(0.69)	(0.51)	(2.12)
LnLoansize	0.3738**	0.4350**	0.4027	-0.4780**	-0.6735**	-0.2586
	(2.50)	(2.19)	(1.38)	(-2.34)	(-2.13)	(-0.62)
PPricing	3.1037***	3.2709***	3.1611***	4.4751***	4.7292***	3.9810***
	(4.15)	(5.36)	(3.59)	(4.76)	(5.65)	(5.06)
Numlenders	-0.0301	-0.0426	-0.0298	0.1146**	0.1100*	0.1339**
	(-0.80)	(-1.17)	(-0.68)	(2.46)	(1.68)	(2.32)
SIZE	-1.2095***	-1.1816***	-1.4423***	-0.9509***	-0.4276	-1.5593***
	(-5.32)	(-3.53)	(-5.78)	(-2.93)	(-1.10)	(-3.67)
Leverage	3.5677	1.4126	5.3517	-3.3076	-8.7119**	0.0921
	(1.32)	(0.62)	(1.65)	(-0.99)	(-2.06)	(0.03)
MTB	-0.2077	0.0655	-0.4952	-0.5931*	-0.4128	-1.1030
	(-0.26)	(0.08)	(-0.53)	(-1.82)	(-1.54)	(-1.66)
Tangibility	-3.1916	-1.1002	-5.4178***	1.4036	0.0842	6.0538***
	(-1.57)	(-0.41)	(-2.65)	(0.87)	(0.03)	(6.16)
Profitability	-4.5517	-2.6788	-8.0651	-3.8349*	-0.2098	-7.2554
	(-0.94)	(-0.37)	(-1.29)	(-1.89	(-0.05)	(-1.62)
CFvolatility	-6.0955	-11.5830**	-1.4375	5.7434	9.3057	-0.4687
	(-0.72)	(-2.29)	(-0.08)	(0.39)	(0.83)	(-0.02)
ZScore	-0.8190*	-1.5085***	-0.2454	0.1055	-0.2187	0.2157
	(-1.71)	(-2.87)	(-0.57)	(0.40)	(-0.42)	(0.42)
Num. of obs.	267	267	267	286	286	286
Pseudo R^2	0.2672	0.3208	0.3712	0.4240	0.5223	0.5409

This table presents the logit (the ordered logit) regression coefficients and two-sided *t*-values for the maximum samples of 553 observations for the number of debt covenants. We regress debt covenant (*AllCov*, *GenCov*, and *FinCov*) on innovative efficiency (*IE_PA*) and other control variables. We report *t*-statistics in parentheses with standard errors clustered by industry and year. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Table 2 states the definitions of the variables. All regressions include industry-level fixed effects.

Table 6

Innovative efficiency and loan cost and non-pricing terms conditional on management forecast accuracy and firm size

		Smaller firms			*Larger firms*		
Dep Var		*Low management forecast accuracy*	*High management forecast accuracy*	*Low minus high*	*Low management forecast accuracy*	*High management forecast accuracy*	*Low minus high*
AIS	*IE_PA*	-200.3404***	-62.4550***	-137.8855**	-9.1089	4.7052	-13.8140
	t-statistic	(-2.92)	(-3.63)	(2.00)	(-0.14)	(1.00)	(0.21)
	Num. of obs.	144	119		111	147	
	R Square	0.8133	0.8712		0.8176	0.9272	
AllCov	*IE_PA*	-7.3338***	-0.6986	-6.6352**	-11.7089*	-5.3237	-6.3852
	t-statistic	(-3.93)	(-0.51)	(2.66)	(-1.93)	(-1.09)	(0.94)
	Num. of obs.	150	119		119	149	
	Pseudo R^2	0.3576	0.4681		0.3499	0.5951	
GenCov	*IE_PA*	-7.2466***	0.5556	-7.8021***	-7.8973	-16.3891**	8.4918**
	t-statistic	(-3.69)	(0.35)	(2.94)	(-1.18)	(-1.64)	(-1.06)
	Num. of obs.	150	119		119	149	
	Pseudo R^2	0.4226	0.4620		0.4598	0.7580	
FinCov	*IE_PA*	-5.2385**	-0.4629	-4.7755**	-5.5132	-2.6007	-2.9126
	t-statistic	(-3.37)	(-0.47)	(2.28)	(-1.47)	(-0.81)	(0.64)
	Num. of obs.	150	119		119	149	
	Pseudo R^2	0.2641	0.3713		0.2652	0.4593	

This table presents the effect of *IE_PA* on bank loan spread (*AIS*) and non-pricing loan terms. We categorize observations into the lowest two and the highest two firm size quintiles, and then regress bank loan spread (*AIS*) and other non-pricing loan terms on *IE_PA* and other control variables for these two groups. We report *t*-statistics with standard errors clustered by industry and year. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Table 2 states the definitions of the variables. All regressions include industry-level fixed effects and firm-level control variables as per Table 4.

Table 7

Innovative efficiency and loan cost and non-pricing terms conditional on management forecast accuracy and type of product market competition (PMC)

Panel A: Product market competition from potential entrants

		Low PMC			*High PMC*		
Dep Var		*Low management forecast accuracy*	*High management forecast accuracy*	*Low minus high*	*Low management forecast accuracy*	*High management forecast accuracy*	*Low minus high*
AIS	*IE_PA*	-378.9017***	-6.1485	-372.7532***	-89.3231*	-56.4106***	-32.9125
	t-statistic	(-5.05)	(-0.59)	(4.92)	(-1.89)	(-3.21)	(-0.65)
	Num. of obs.	101	124		118	122	
	R Square	0.9085	0.9384		0.7905	0.8456	
AllCov	*IE_PA*	-7.2823	6.5091**	-13.7914**	-4.1551*	-6.9718**	2.8167
	t-statistic	(-1.50)	(2.05)	(-2.38)	(-1.78)	(-2.22)	(0.72)
	Num. of obs.	111	126		120	118	
	Pseudo R^2	0.2715	0.6077		0.3783	0.5368	
GenCov	*IE_PA*	-8.5946**	7.1868	-15.7814***	-4.1509	-7.5153***	3.3644
	t-statistic	(-2.11)	(2.13)	(-2.98)	(-1.46)	(-4.64)	(1.03)
	Num. of obs.	111	126		120	118	
	Pseudo R^2	0.3321	0.8475		0.4249	0.6214	
FinCov	*IE_PA*	-3.5110	6.0786***	-9.5896	-7.7137***	-5.6723***	-2.0414
	t-statistic	(-0.54)	(2.78)	(1.40)	(-3.07)	(-2.82)	(-0.63)
	Num. of obs.	111	126		120	118	
	Pseudo R^2	0.3826	0.7043		0.5287	0.6940	

Panel B: Product market competition from current rivals

		Low PMC			*High PMC*		
Dep Var		*Low management forecast accuracy*	*High management forecast accuracy*	*Low minus high*	*Low management forecast accuracy*	*High management forecast accuracy*	*Low minus high*
AIS	*IE_PA*	18.6474	-17.6671	36.3145	-325.9719***	-25.1270***	-300.8449***
	t-statistic	(0.43)	(-1.37)	(0.79)	(-3.66)	(-3.05)	(-3.37)
	Num. of obs.	119	100		100	146	
	R Square	0.8746	0.9025		0.9210	0.8594	
AllCov	*IE_PA*	-9.0132*	-5.8860**	-3.1272	-7.6987**	6.7286***	-14.4274***
	t-statistic	(-1.71)	(-2.74)	(-0.55)	(-2.30)	(2.86)	(-3.53)
	Num. of obs.	127	101		104	146	
	Pseudo R^2	0.3272	0.5735		0.4201	0.6332	
GenCov	*IE_PA*	-6.9591*	-5.9519**	-1.0072	-9.8167***	23.0019	-32.8186*
	t-statistic	(-1.73)	(-2.13)	(-0.21)	(-3.19)	(1.22)	(-1.72)
	Num. of obs.	127	101		104	146	
	Pseudo R^2	0.3737	0.6528		0.4106	0.8258	
FinCov	*IE_PA*	-13.7489*	-2.1019	-11.6470	-6.2262	12.1155**	-18.3417**
	t-statistic	(-1.78)	(-1.33)	(-1.47)	(-1.08)	(2.30)	(-2.35)
	Num. of obs.	127	101		104	146	
	Pseudo R^2	0.4958	0.4656		0.5298	0.7286	

This table presents the effect of *IE_PA* on bank loan spread (*AIS*) and non-pricing loan terms. We split the observations into the low product market and high product market partitions based on the PC1 and PC2 measures in Li (2010), and then regress bank loan spread (*AIS*) and other non-pricing loan terms on *IE_PA* and other control variables for these two groups. We report *t*-statistics with standard errors clustered by industry and year. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Table 2 states the definitions of the variables. All regressions include industry-level fixed effects and firm-level control variables as per Table 4.

Table 8

Robustness check: Innovative efficiency and the bank loan spread (*AIS*) by using as the denominator of IE the lagged coefficients for R&D expenditures between *t*-2 and *t*-6 years from a regression of patents on lagged R&D for each of the 48 Fama-French industries

Dependent variable = *AIS*	*Low management forecast accuracy*		*High management forecast accuracy*	
IE_PA	-15.0743***	-15.7840***	-0.0001	-0.0906
	(-3.75)	(-6.04)	(0.00)	(-0.08)
Diff.	-15.0742***	-15.6934***		
(t-statistic)	(-3.54)	(-5.51)		
LnMaturity	19.4529**	-8.5837	0.8025	-1.0184
	(2.50)	(-1.35)	(0.30)	(-0.22)
LnLoansize	-34.7480***	30.1204	-9.0946***	3.4534
	(-3.33)	(0.81)	(-2.70)	(0.11)
PPricing	-59.9574***	-9.1766	-30.6032**	-3.7906
	(-3.79)	(-0.84)	(-2.31)	(-1.22)
Numlenders	-0.6451	99.3306	0.2595	19.9519
	(-0.75)	(1.48)	(0.49)	(0.76)
FinCov	14.0887**	34.9346	15.3553*	65.2393
	(2.36)	(0.26)	(1.71)	(1.54)
GenCov	15.7422***	17.5976	14.0458**	226.7750***
	(3.27)	(0.05)	(2.07)	(4.20)
CommitFee	0.2560***	-34.3551	0.2805*	-14.9094**
	(2.92)	(-1.57)	(1.90)	(-2.28)
SIZE		17.8366***		1.1721
		(3.07)		(0.43)
Leverage		-29.6536***		-9.6055**
		(-2.73)		(-2.15)
MTB		-56.3409***		-33.3991**
		(-3.65)		(-2.47)
Tangibility		-0.5728		0.2556
		(-0.58)		(0.48)
Profitability		16.5046**		15.4918*
		(2.41)		(1.91)
CFvolatility		11.7214***		15.1701**
		(3.05)		(2.12)
ZScore		0.2156**		0.2483*
		(2.31)		(1.87)
Num. of obs.	286	286	315	315
R Square	0.7539	0.7901	0.7537	0.7748

This table presents the effect of *Mgt_Forecast_Acc* on *IE_PA* (Panel A) and effect of *IE_PA* on bank loan spread (*AIS*) (Panel B) for the maximum samples of 601 firm-year observations for *IE_PA* by using as the denominator of IE the lagged coefficients for R&D expenditures between *t*-2 and *t*-6 years from a regression of patents or citations on lagged R&D for each of the 48 Fama-French industries. We report *t*-statistics in parentheses with standard errors clustered by industry and year. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Table 2 states the definitions of the variables. All regressions include industry-level fixed effects.

Table 9

Robustness check: Innovative efficiency and the bank loan spread (*AIS*) by using R&D+S&A expenditures as the denominator for *IE_PA*

Dependent variable = *AIS*	*Low management forecast accuracy*		*High management forecast accuracy*	
IE_PA	-556.4577***	-690.3894***	-138.9235	-187.9159
	(-2.75)	(-4.88)	(-0.42)	(-0.63)
Difference	-417.5342	-502.4735		
(t-statistic)	(-1.08)	(-1.51)		
LnMaturity	15.0977***	-5.3955	-0.5965	-0.2749
	(2.17)	(-0.50)	(-0.26)	(-0.10)
LnLoansize	-24.7452**	57.2779**	-8.2413***	2.0060
	(-2.07)	(2.00)	(-2.72)	(0.07)
PPricing	-65.5345***	-13.3824	-33.5240***	-2.8632
	(-5.46)	(-1.19)	(-2.63)	(-0.92)
Numlenders	-1.1167	82.3087	0.3722	29.6845
	(-1.22)	(1.55)	(0.94)	(1.54)
FinCov	15.5071***	-77.5257	17.2155**	28.1006
	(3.12)	(-0.43)	(2.09)	(0.36)
GenCov	13.5144***	520.3644***	11.2598**	138.6505*
	(2.79)	(3.06)	(2.24)	(1.76)
CommitFee	0.2850***	-18.7452	0.3179**	-13.3452*
	(2.90)	(-1.50)	(2.24)	(-1.71)
SIZE		15.2980***		-0.2539
		(3.00)		(-0.12)
Leverage		-21.0088		-8.8289**
		(-1.58)		(-2.16)
MTB		-61.2949***		-34.3318**
		(-4.30)		(-2.49)
Tangibility		-0.9091		0.3576
		(-1.15)		(0.81)
Profitability		12.7534**		17.1835**
		(2.15)		(1.99)
CFvolatility		12.7815***		12.0225**
		(2.98)		(2.29)
ZScore		0.2385**		0.2876**
		(2.33)		(2.19)
Num. of obs.	343	343	376	376
R Square	0.6970	0.7416	0.7810	0.7967

This table presents the effect of *Mgt_Forecast_Acc* on *IE_PA* (Panel A) and effect of *IE_PA* on bank loan spread (*AIS*) (Panel B) for the maximum samples of 719 firm-year observations for *IE_PA* by using R&D+S&A expenditures as the denominator of *IE_PA*. We regress bank loan spread (*AIS*) on innovative efficiency (*IE_PA*) and other control variables. We report *t*-statistics in parentheses with standard errors clustered by industry and year. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Table 2 states the definitions of the variables. All regressions include industry-level fixed effects.

Table 10

Robustness Check: Innovative efficiency and the bank loan spread (*AIS*) by deleting patents granted in years 2005 and 2006 and using truncation adjustment factors to compute innovative efficiency

Dependent variable = *AIS*	*Low management forecast accuracy*		*High management forecast accuracy*	
IE_PA	-69.4999***	-66.3531**	-35.9646*	-36.5395*
	(-3.21)	(-2.21)	(-1.86)	(-1.90)
Difference	-33.5354	-29.8136		
(t-statistic)	(-1.16)	(-0.84)		
LnMaturity	25.7005***	-2.8507	-1.0769	-3.9465
	(2.86)	(-0.21)	(-0.63)	(-0.66)
LnLoansize	-39.5848***	57.2791***	-10.0297***	-25.4310
	(-2.66)	(4.81)	(-2.83)	(-0.52)
PPricing	-43.9459**	-7.4168	-34.4553**	-2.3111
	(-2.01)	(-0.79)	(-2.48)	(-0.62)
Numlenders	-1.1208	104.0829**	0.1081	14.7510
	(-0.93)	(2.25)	(0.18)	(0.51)
FinCov	14.0125*	-35.8551	28.6731**	51.5330
	(1.76)	(-0.19)	(2.29)	(0.69)
GenCov	15.0519**	-42.1373	10.0258***	155.9973**
	(2.25)	(-0.13)	(2.91)	(2.49)
CommitFee	0.2126**	-29.2215	0.2434**	-15.0836***
	(2.42)	(-1.45)	(1.98)	(-2.68)
SIZE		23.6963***		-1.6830
		(3.29)		(-0.80)
Leverage		-37.1973**		-9.5272**
		(-2.33)		(-2.11)
MTB		-39.5445		-37.5404**
		(-1.60)		(-2.26)
Tangibility		-1.2568		0.2769
		(-0.90)		(0.36)
Profitability		15.4520		27.3645**
		(1.50)		(2.20)
CFvolatility		12.1759*		9.9828***
		(1.84)		(3.06)
ZScore		0.1799*		0.2358**
		(1.87)		(2.22)
Num. of obs.	210	210	236	236
R Square	0.7872	0.8122	0.7831	0.7954

This table presents the effect of *Mgt_Forecast_Acc* on *IE_PA* (Panel A) and effect of *IE_PA* on bank loan spread (*AIS*) (Panel B) for the maximum samples of 446 firm-year observations for *IE_PA* by deleting patents granted in years 2005 and 2006, and using truncation adjustment factors to compute *IE_PA*. We report *t*-statistics in parentheses with standard errors clustered by industry and year. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Table 2 states the definitions of the variables. All regressions include industry-level fixed effects.