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RESEARCH INTENSITY AND FINANCIAL ANALYSTS EARNINGS FORECAST: SIGNALING EFFECTS OF PATENTS

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Abstract

In this paper, we study how R&D investment affect financial analyst?s earnings forecasts and how intellectual capital endowments moderate this effect. We argue that high information asymmetry and uncertainty associated with R&D investment increase a financial analysts? earnings forecast error. Patents can remedy this relationship by signaling the ability of a firm in transforming research investments into new and valuable knowledge. Using a panel of 2,253 publicly listed U.S firms, we find that higher R & D intensity is positively correlated with financial analysts? earnings forecast error. The endowment of intellectual capital (i.e. patents) moderates this relationship negatively. However we do not find any moderating effect for the value of patents measured as forward citations.

Jelcodes:O32,O34

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ABSTRACT

In this paper, we study how R&D investment affect financial analyst's earnings forecasts and how intellectual capital endowments moderate this effect. We argue that high information asymmetry and uncertainty associated with R&D investment increase a financial analysts' earnings forecast error. Patents can remedy this relationship by signaling the ability of a firm in transforming research investments into new and valuable knowledge. Using a panel of 2,253 publicly listed U.S firms, we find that higher R & D intensity is positively correlated with financial analysts' earnings forecast error. The endowment of intellectual capital (i.e. patents) moderates this relationship negatively. However we do not find any moderating effect for the value of patents measured as forward citations.

Keywords: R&D intensity; Analyst forecasts; Patent, information asymmetry, uncertainty, Capital market

JEL: O32, O34, G24

INTRODUCTION:

Innovation not only plays an important role in economic growth (Solow, 1957) but is also a key factor in creating a firms competitive advantage (Katila & Ahuja, 2002) and long-term success (Cohen & Levinthal, 1990). Investment in research and development (R&D) is the main source of innovation for a firm and is the main input for the creation of intangible capital, product innovation and differentiation (David, Hitt, & Gimeno, 2001). Despite the importance of R&D investments in creating and maintaining rent-producing innovative capabilities, the information asymmetry between managers and capital market can lead to the high cost of capital and underinvestment in innovative projects (Hall, 2002).

A recent stream of research focuses on the role of capital markets on innovation and R&D investment. There are two competing argument regarding the effect of capital market on R&D investment. First, capital markets can improve the efficiency of capital allocation by relieving financial constraints and creating incentives for firms to pursue innovative projects (Atanassov, 2014). Second, capital markets may create short-termism which weakens a manager's incentive to invest in novel and innovative projects (He & Tian, 2013). Given these arguments, this paper investigates how capital markets react to R&D investments and how a firm's intellectual capital endowments moderate this effect.

In this paper, we focus on financial analysts as one key ingredient of the capital market. More specifically, we investigate how R&D investments affect the earnings forecasts by financial analysts and how intellectual capital endowments moderate this effect. Analyst forecasts are considered a proxy for investors' expectations of future earnings (Brown, 1993; Kasznik & McNichols, 2002). Financial analysts are active market intermediaries that produce information for investors and set performance benchmark (He & Tian, 2013). Prior literature has shown the role of financial analyst on investment in innovative projects. For example, He and Tian (2013), found that firms covered by a larger number of analysts produce fewer patents and patents with lower citations. In the same vein, Gentry & Shen, (2013) take an agency theory perspective and illustrate how firms reduce their R&D intensity in response to either missing or exceeding analyst forecasts. Additionally, Palmon and Yezegel, (2012) show that analyst recommendations are more valuable for R&D intensive firms. They argue that analysts with knowledge in acquiring and processing private information are better able to identify mispricing in environments with exacerbated information asymmetry. Along this stream of research we argue that high information asymmetry and uncertainty associated with R&D investment increase the earnings forecast error of financial analysts (Gu & Wang, 2005). Since the increase in earnings forecast error can lead to suboptimal investment decisions (Gentry & Shen, 2013), we investigate how patents can remedy this relationship by signaling the ability of a firm in transforming research investments into new and valuable knowledge.

Using a panel of 2,253 publicly listed U.S firms in manufacturing sectors, we find that higher R&D intensity is positively correlated with the earnings forecast error of financial analysts. The endowment of intellectual capital (i.e. patent) moderates this relationship negatively. We do not find any moderating effect for quality of patents measured as forward citations.

Overall, this study contributes to the literature in two ways. First, it complements the literature on the relationship between capital markets and R&D investment. In doing so, this study confirms the findings of prior work which conclude that R&D investment is associated with high uncertainty and is difficult to evaluate it by external parties. This study also supports the role of patents as signals of quality in financial markets by extending prior studies in the context of informed financial intermediaries (i.e. financial analysts). This paper is also related to a more general literature on signaling in financial market (Bhattacharya & Ritter, 1983; Leland & Pyle, 1977; Ross, 1977).

The structure of this article is as follows. In the following section we review the literature on the importance of financial analyst forecasts, and their relationship to R&D investments and intellectual capital endowment to develop our hypotheses. In the third section we introduce our dataset, methodology and analysis. Finally we conclude with discussion of the findings, contributions, and limitations.

THEORY AND HYPOTHESIS:

The Importance of Financial Analysts Forecasts

Financial analysts are intermediaries that provide earnings forecasts and stock recommendations (hold, buy and sell) based on private information. They gather information through several activities such as interrogating top managers, conference participation, analyzing financial and scientific reports, interacting with industry experts, etc. (Asquith, Mikhail, & Au, 2005; Palmon & Yezegel, 2012; Rao & Sivakumar, 1999). The finance and accounting literature argue that analyst's stock recommendation and earnings forecasts are informative and valuable and their information has been incorporated into share price (e.g. (Francis & Soffer, 1997; Frankel, Kothari, & Weber, 2006; Palmon & Yezegel, 2012; Womack, 1996).

Analyst not only impact investors' decision but also can shape the decision and strategies of top managers (Knyphausen-Aufsess, Mirow, & Schweizer, 2011). Empirical evidence reveals that in order to attract more coverage by analysts, managers adopt common strategies rather than unique strategies, and receive higher valuations (Litov, Moreton, & Zenger, 2012). Nicolai, Schulz, & Thomas, (2010) illustrate the important role of analysts in the spreading popular management concepts. Furthermore, Benner & Ranganathan (2012) argue that analysts' recommendations lead to changes in strategic investments. Managers also face pressure from analysts to de-diversify their corporate strategies (Zuckerman, 2000).

Analyst can have two opposite effects on firm strategies and top management decisions. First, analysts can function as an external monitoring mechanism (Gentry & Shen, 2013) and reduce the agency cost associated with the separation of ownership and control (Fama & Jensen, 1983). In this instance, analyst can help increase the value of a firm by disciplining managers and forcing them to take projects which create value for shareholders. They also create external benchmarks which allow shareholders to evaluate the performance of managers. There is evidence that the probability of CEO dismissal is larger when a large number of analysts follow the firm (Farrell & Whidbee, 2003), when analyst issue negative recommendation (Wiersema & Zhang, 2011) and when firms miss the analyst forecasts (Puffer & Weintrop, 1991). Second, financial analysts can create excessive pressure on managers and lead to short-termism (He & Tian, 2013). This can be especially exacerbated when managers consider the analysts' short term earning forecast as an important target. Graham, Harvey, & Rajgopal, (2005) in a survey of 401 financial executives show that the majority of firms view earnings forecasts as an important indicator and are willing to sacrifice long-term value in order to meet a short-term earnings target. Both arguments imply that analyst's earnings forecasts are an important performance target for firms and top managers (Barth & Kasznik, 1999; Bartov, Givoly, & Hayn, 2002; Kasznik & McNichols, 2002).

Since divergence of opinions is likely to increase with risk (Miller, 1977), the importance of financial analyst forecasts and recommendations tend to increase with information asymmetry. In a similar vein it has been shown that in environments of higher (lower) uncertainty analyst's earning forecast and recommendations tend to diverge (converge) and generate (no) abnormal return (Ackert & Athanassakos, 1997).

Financial Analysts and R & D Investment

R&D investment has two peculiar characteristics that differentiate them from other investments (Hall, 2002). First, the majority of R&D investments are due to the cost of highly educated individuals. Hence, inventions are products of organizational tacit knowledge embedded in the human capital of the firm's employees (Henderson & Cockburn, 1994) and are not easily transferable and tradable. This means that R&D investments are unique thus making it difficult for investors to evaluate them (Aboody and Lev, 2000). Second, the outcomes of R&D investment are highly uncertain (Mansfield, 1968).

Aforementioned characteristics lead to what is called the "lemon problem" (Akerlof, 1970) in which external investors are not able to evaluate R&D investments and inventive efforts of a firm. Hence, capital markets will not be able to differentiate between market value of a high-quality firm and the average firm. This situation raises the cost of capital for the high-quality firm and leads to underinvestment in profitable investments (Myers & Majluf, 1984).

Consistent with this argument, prior studies show research-intensive firms tend to hoard a large amount of cash and other liquid assets (Opler, Pinkowitz, Stulz, & Williamson, 1999). The cash holdings allow them to reduce the cost of investment and facilitate experimentation which is a necessary part of inventive efforts. Similarly, it has been shown that for R&D intensive firms insider gain is larger (Aboody & Lev, 2000), they experience higher bid-ask spread (Boone & Raman, 2001) and use more share repurchase (Barth & Kasznik, 1999).

The unique characteristics of innovative projects lead to information complexity which may create problems for analysts to process the information and therefore increase analyst forecast error. Gu and Wang (2005) show that analyst forecast error increases by the value of intangible assets, technology diversity and originality.

Therefore, we expect that high R&D intensity is associated with higher uncertainty and information complexity:

> *Hypothesis 1. There is a positive relationship between a firm's R & D in*tensity and *analyst's earning forecast error.*

Patent and Financial Analysts

The high analyst earning forecast error can lead to suboptimal decisions that do not create value for shareholders. Gentry and Shen (2013), adopting an agency theory lens, have shown both positive and negative bias in analyst earning forecasts is proceeded with reduction in R&D intensity.

Prior research has shown firms tend to communicate information about the innovative projects in order to reduce information asymmetry associated with R & D investments (Anton & Yao, 2002; Guo, Lev, & Zhou, 2004; Jones, 2007). This voluntary disclosure might be costly and reduce informational advantages of the firm (Bhattacharya & Ritter, 1983). In this section we investigate the role of patenting activities in reducing information asymmetry specific to R&D investment. While patents provide a monopoly in using patented technology they also create opportunity for "investing around" (Bhattacharya & Ritter, 1983). The latter give patents characteristics similar to partial information disclosure argued in Bhattacharya and Ritter (1983). In this case, patents serve as an observable attribute that are signals of unknown quality (Long, 2002).

A signal is positively correlated to unobservable characteristics of quality and it is less costly for high-quality ventures to generate than low quality ones (Spence, 1973). Granted these conditions, a quality signal, by reducing information asymmetry, assists investors to mitigate adverse selection problems. Firms that possess more quality signals are desirable to investors, and are more likely to receive higher valuations (for a review of signaling theory in management and economics see Connelly, Certo, Ireland, & Reutzel, 2011 and Riley, 2001).

One of these signals is patents (Long, 2002). Patents are resources performing a dual role mechanism. The patent not only allows a firm to appropriate the rents of invention, but they also signal the value of technological capabilities and its effectiveness in transforming R & D investment to tangible outcomes (Griliches, 1990; Levitas & McFadyen, 2009).

A series of recent studies have highlighted the signaling value of patents in venture capital markets (Conti, Thursby, & Thursby, 2013; Haeussler, Harhoff, & Mueller, 2014; Hsu & Ziedonis, 2013), initial public offerings (Cao, Jiang, & Ritter, 2013; Heeley, Matusik, & Jain, 2007), debt financing (Czarnitzki, Hall, & Hottenrott, 2014; Hochberg, Serrano, & Ziedonis, 2014), and equity markets (Hall, Jaffe, & Trajtenberg, 2005; Levitas & McFadyen, 2009). Along these studies we expect patents to also serve as signals of quality for financial analysts and reduce information asymmetry associated with R&D intensive firms. Hence we hypothesis that:

> Hypothesis 2. A *firm's patenting activity negatively moderates the relationship between a firm's R & D intensity and analyst's earning forecast* error.

In the previous section we argued that patenting activity of firms can send signals of quality and reduce information asymmetry associated with R & D investment. However, not all signals have equal value (Spence, 1973). It is especially true about patents which have a skewed value in which only few patents are commercially valuable (Hall et al., 2005).

The prior research has shown that financial analysts that cover R&D intensive firms evaluate firm technological capabilities closely by going to academic conferences, reading scientific papers and interacting with scientists (Palmon & Yezegel, 2012). In addition, investment banks are hiring analysts with specialized industry related training and skills. The specialized industry related knowledge and interaction with researchers may allow analysts to separate the value of a firm with high quality patents from a firm producing low quality patents. Hence we hypothesis that:

> *Hypothesis 2b. A firm's* level of patent value negatively moderates the relationship *between a firm's R & D intensity and analyst's earning forecast error.*

RESEARCH DESIGN AND METHODOLOGY:

Sample:

We build our sample based on three databases from COMPUSTAT, Institutional Brokers Estimate System (I/B/E/S) and Kogan, Papanikolaou, Seru, & Stoffman's (2012) patent database. First, we extract all manufacturing companies (Standard Industrial Classification (SIC) 2000-3999) which meet the following criteria: i) they have assets more than $ 10 million ; ii) do not report R&D expenses more than sales, and iii) they are in industries with at least five companies in the four-digit SIC code (Chen & Miller, 2007; Gentry & Shen, 2013). Second, we match our data with the patent database created by Kogan et al., (2012)[1], which contains information on patent applications and grants, and the identifications of patent assignees and citations. This data set consists of all U.S. patents granted during the period 1926-2010 (7.8 million patents). The database has PERMNO identifiers for each assignee that allows for matching with firm level financial data extracted from COMPUSTAT. Finally, we use I/B/E/S to extract data on analyst's earnings forecasts. I/B/E/S includes data on analyst's earnings forecast from 1976 on, however data from the early years are not reliable, hence we limit our sample to 1979-2005. Furthermore, since we look at innovations in prior years we need at least 3 years lagged observations. Our final

[1] Available at https://iu.app.box.com/patents

sample includes 16,422 firm-year observations from 2,253 firms in 213 industries (four-digit SIC) between 1982 and 2005.

Variables:

Analysts forecast error. The exacerbated uncertainty about the prospect of firm can make analyst adjust the earning forecasts. In this paper we measure analyst forecast error as the absolute value of difference between the last forecast of analysts and actual earning normalized by earning forecast. Similar measure has been used in prior research (Gentry & Shen, 2013; Gu & Wang, 2005; Nicolai et al., 2010).

$$Analyst\ forecact\ error_{it} = |\frac{(actual\ EPS_{it} - EPS\ forecast_{it})}{EPS\ forecast_{it}}|$$

In each year, analysts issue more than one forecast per year. It has been shown that markets assign higher value to the last forecast preceding the actual earnings announcement (Bartov et al., 2002). In order to measure EPS $forecast_{it}$ we use the last forecasts before the end of fiscal year (Gentry & Shen, 2013). Using absolute value helps to avoid negative and positive values that cancel each other out and capture the uncertainty and deviations in the forecasts (both positive and negative). Hence for each year we use the mean of analyst forecast error for all analysts covering the firm.

R&D intensity. Following Chen and Miller (2007) we use R&D expenditures divided by sales as a proxy for R&D intensity. R&D intensity captures the importance of R&D and knowledge creation in firm strategy (Cohen & Levinthal, 1990). In order to be sure our results are not driven by denominator alternatively we use R&D expenditure divided by total assets (Levitas & McFadyen, 2009), the results are qualitatively similar. About 30 percent of our observations have missing values in R&D expenditure. This is due to the fact that firms are not obliged to separate R&D expenditure from sales and general administrative (SG&A) expenses if they are less than 10 percent of SG&A. Following prior research we replace the missing values with zero (Chen, Hambrick, & Pollock, 2008; Gentry & Shen, 2013; Henderson, Miller, & Hambrick, 2006). The assumption here is that the R&D expenditures are negligible. In order to control that our results are not driven by this choice we run separate analysis for firms that report their R&D expenditures and results are qualitatively similar.

Patenting activity**.** In order to measure the patenting activity of firms we count number of patent applications. Applications are used instead of number of grants because the application date is closer to the innovation date (Hall et al., 2005). We create a yearly patent count for each firm. Then by adding up the patent count of the last three years we create 'stock of patents'. The stocks of recent years allow us to measure the signaling affect remains from previous years. Due to the skewed nature of patents, we use natural logarithm of patent counts. In order not to loose observations with zero patents we use the logarithm of patent count plus one (Log+1).

Patent value**.** Using a straight forward count of patents cannot capture the commercial value and importance of patents. It has been shown that patent commercial values are extremely skewed with several patents producing very little economic values and only very few patents are able to create significant commercial value for firms. Hall, Jaffe and Trajenberg (2005) highlighted the role of patent citation as measure of patent importance and its relation to the market value of a firm. Thus, we measure patent value with forward citations that patents of a firm receive. The patent citations usually face two truncation problems. First the citation information for patents in the last few years of a sample decreases, since patents appear in a database if they have been granted till 2010. Hence we limit our analysis to patent applications until 2005 allowing for five years since the last grant year. Secondly, patents tend to receive citations over a period of time but we see only citations received until 2010. In this situation using simple citation count will bias our measure since older patents are more likely to receive more citation. It has been shown that the citations received in the first years are a strong predictor of later citations (Fleming, 2001). In the main analysis we use number of citations patent received 3 years after application but in a separate analysis we use five year citations (available upon request) and obtain the same results. For each year we add all patent citations and create a yearly patent value for each firm. Then by adding up the patent value of the last three years we create a 'stock of patent value'. Due to the skewed nature of a patent value we use the natural logarithm (Log+1) of patent value.

It is likely that the '*stock of patent value'* is highly correlated with 'stock of patents' since as the number of patents increases, it is also more likely that the sum of citations they receive also increases. In order to consider this issue we also use two measures of citation efficiency. First we calculate citation efficiency for each year by normalizing total number of citations with number of patents and then create 'stock of patent efficiency' by adding up the last three years citation efficiency. Second we normalized total number of citation with average number of citations that patent of companies in the same industry (four-digit SIC code) received. We create 'stock of patent efficiency *(industry)'* by adding up the value created for the last three years.

Control variables: We include several control variables that may affect analyst earnings forecasts. Number of securities analyst that cover a firm can increase the level of publicity of firm, which in turn can increase scrutiny of investors. Hence we include in our model Analyst coverage which measure number of security analysts that track and issue earnings forecasts for firm. Cash holdings can be considered as risk free investment which can help companies to deal with unpredicted issues. Hence holding cash might affect the uncertainty about firm earning forecast. We include in our model cash measured by natural logarithm of cash holding in million USD. The probability of bankruptcy can affect the uncertainty in analyst forecasts. Hence we include *Altman's Z* (Altman, 1968) as measure of firm's distance from bankruptcy[2]. Similarly the performance of company in comparison to its competitors can shape the earnings forecasts of analyst. We measure the performance as return on assets (ROA) defined as ratio of net income before extraordinary items to average value of assets. We include in our model the difference between performance of firm in last year and average of industry level ROA at four-digit SIC code. We also include two time varying characteristics of industry (four-digit SIC). First we include the industry level analyst forecast error. Second we include industry sales growth in our model. In order to take into account macroeconomic changes that might affect earnings forecast we also include year fixed effects[3].

Statistical analysis:

In this paper we argue that security analyst earning forecast error is determined by R&D intensity of a firm and this relationship can be moderated by patenting activity and the patent value of a firm. In all models the subscript i refers to firms, while the subscript t refers to time.

$$\text{Analyst forecast error}_{it} = \beta_0 + \beta_1 \text{ research intensity}_{it} + \beta_2 \text{ paten stocks}_{it} + \beta_3 \text{ research intensity}_{it} * \text{paten stocks}_{it} + \beta_{4.} Z_{it} + \beta_5 Y_t + \varepsilon_{it}$$

In this model, analyst earning error (Analyst earning error_{it}) is dependent on research intensity (research intensity_{it}), patenting activity or patent value in the prior three years (paten stocks_{it}),

[2] The Altman's Z is calculated as following *Altman's Z = (1.2*(Working Capital / Total* Assets) + 1.4*(Retained Earnings / Total Assets) + 3.3*(Earnings Before Interest and Taxes / Total Assets) + 0.6*(Market Value of Equity / Total Liabilities) + 0.999*(Sales/ Total Assets)). The higher the Altman's Z the lower is risk of bankruptcy.

[3] In a separate analysis we also included *Tobin's Q* and firm size as natural logarithm of sales. The results obtained are similar. Since they are highly correlated with analyst coverage and cash holding in order to avoid multicollinearity problem we did not include them in the main analysis.

interaction between research intensity and patenting activity or patent value (research intensity$_{it}$ * paten stocks$_{it}$). Z_{it} is a vector of time varying control variables mentioned in previous section and Y_t include year fixed effect.

Since our data has both cross-sectional and time series elements, we estimate our model using panel data regressions (Wooldridge, 2002). We use fixed effect model which allow us to take into account the time-invariant firm effect and also consider time effect. While random effects assume all regressors are exogenous, the fixed effect model allow for possible correlation between regressors and time invariant firm-level effects. We also used Hasuman test in which null hypothesis is that firm-effects are random hence both fixed effect and random effect generate consistent estimators. The Hausman test verifies superiority of fixed effect model ($p<0.01$). Furthermore since we are using panel data and error terms may be serially correlated for a firm, we use cluster-robust standard errors, where the errors are clustered around firms. Table 1 reports all variables and their definition.

[Table 1 about here]

ANALYSIS AND RESULTS:

Descriptive statistics:

Table 2 reports descriptive statistics including mean and standard deviation in addition to correlation of variables. As we can see in table 1 there is on average around a 60 percent gap between analyst earnings forecast and actual earnings (Analysts forecast error). Firms invest 3.4 percent of their sales in R&D. Firms in our sample invest on average $110 million in R&D and have sales of $3,200 million. The firms have on average patents stocks (citation) of 86 (153) with minimum zero (zero) and maximum of 11,118 (15,990). Similarly in the last three years, patents receive a total of 1.9 citations per patents and 2.9 citations relative to similar patents in the same industry (four-digit SIC code). Around 10 analysts cover firms in our sample with a minimum of one and maximum of 66 analysts. Firms hold on average $212 million in cash. Altman's Z on average is equal to 4.5 implying that average firm is in the safe zone (Altman, 1968). Furthermore firms in our sample on average have 1.4 percent larger ROA than average of industry, their industry experience 59.6 percent analyst earnings forecast error and 20 percent sales growth. Table 3 shows the distribution of firm in different industries. Majority of firms are clustered in 2 digits SIC code of 36, 35, 38 and 28.

[Table 2 and 3 about here]

Multivariate analysis:

Table 4 shows the results obtained from the fixed-effect panel data regression models that regress analysts earning forecast error on R&D intensity of firm, patenting activities and interaction between R&D intensity and patenting activities. The F-statistics for all models are statistically significant ($p<0.01$). In model 1 we consider only the effect of control variables on analyst earning forecast error. In model 2 we also consider R & D intensity, patent stock and interaction between them. As we can see the coefficient for R&D intensity is positive ($p<0.05$) providing support for hypothesis one. The positive and statistically significant coefficient of R & D intensity holds across all models. The negative coefficient of interaction term in model 2 also confirms hypothesis 2a ($p<0.05$). Model 3 includes the citation stocks and similarly the interaction term has a negative coefficient which provides support for hypothesis 2b. In model 4 instead of citation stocks we used citation efficiency measured as number of citations per patents. In this model we can see the interaction term is negative but it is not statistically significant. Finally in model 5 we used citation efficiency as a ratio of forward citation of firm relative to average citation of patents belonging to firms in the same industry (four-digit SIC code). The results show that the interaction term is not statistically significant. Hence we find support for H1, H2a but we do not find robust support for H2b.

Regarding control variables as we can see with increase in the *Altman's Z* the analyst error is reducing ($p<0.01$). It implies when company is facing lower probability of bankruptcy the analyst error is closer to actual value. When we look at performance of firm (ROA) in comparison to industry, we observe that better performing firms have lower analyst error ($p<0.01$). We also notice the positive correlation between industry analyst error ($p<0.01$) and industry sales growth with analyst error ($p<0.1$). These findings hold across all models.

[Table 4 about here]

DISCUSSION AND CONCLUSION:

In this paper we investigate how capital markets react to R&D intensity and what is the role of patents in moderating this effect. Specifically, we focus on financial analysts as one key ingredient of the capital market. Financial analysts are important actors in capital markets which not only affect the investors' decisions but also shape the strategies of a firm.

In the theoretical section we argue the unique characteristics of R&D investment lead to high uncertainty and information complexity. So we expect that an analyst's earning forecast error increases with R&D intensity. We further argue that patents can serve as a signal of quality and effectiveness of the R&D processes and reduce the information asymmetry and uncertainty associated with R&D intensity. However not all patents are valuable and since financial analysts have specialized skills and knowledge about technology and industry we expect that they are able to differentiate firms that generate valuable patents from those with less valuable patents. Hence patent value should also reduce the information asymmetry and consequently the analysts forecast error.

We build a panel of 2,253 US publicly listed firm in manufacturing sectors using three sources of data , COMPUSTAT, I/B/E/S and patent database of Kogan et al. (2012). In the multivariate analysis we use a fixed effect model and control for time invariant characteristics of the firm, we also include several time variant variables related to the firm and industry and time dummies. Our results show that higher R&D intensity is positively correlated with financial analysts' earnings forecast error. The endowment of intellectual capital (i.e. patent) moderates this relationship negatively. However we do not find any robust moderating effect for quality of patents measured as forward citation.

This study contributes to three important streams of literature. First, we contribute to the literature on the determinant of analyst forecast error. Prior literature has shown that analyst forecast error increases by uncertainty, information complexity and intangible-related assets (Brown, 1993; Choi, Chen, Wright, & Wu, 2014; Gu & Wang, 2005; Plumlee, 2003; Salva & Sonney, 2011). We contribute to this literature by confirming these findings and providing additional evidence that R&D intensity leads to larger analyst forecast error. However, we also show that patents can serve as an additional source of information and moderate the effect of the information complexity associated with R&D intensity on analyst forecast error.

Second, we contribute to the growing body of literature that investigates the signaling value of patents in financial markets (Cao et al., 2013; Conti et al., 2013; Czarnitzki et al., 2014; Haeussler et al., 2014; Heeley et al., 2007; Hochberg et al., 2014; Hsu & Ziedonis, 2013; Levitas & McFadyen, 2009). The main idea in this stream of research is that patents are not only used for appropriating value from underlying technologies, but are also able to signal the quality of a firm to external investors. Long (2005) argues that if the patent were used only for rent seeking then companies would only patent when they see a commercial value associated with a patent. However companies patent several inventions with little private value. We provide further evidence for the use of patents as a signal in an environment where information complexity and asymmetry is high (i. e. R&D intensity). By doing so we show the informational value of patent signals in the financial analysts forecasts. While patenting activity provides valuable information, the value of a patent, which is hard to evaluate, does not seems to have any effect in reducing analysts forecast error.

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Table 1- List of variables

Variables	Definition	Source
Independent Variable		
R&D intensity	R&D expenditures divided by sales	COMPUSTAT
Patent stock	natural logarithm of patent count of the last three years	Kogan et al, (2012)
citation stock	natural logarithm of patent forward citation of patents in the last three years	Kogan et al, (2012)
citation efficiency stock	Citation stock divided by patent stock	Kogan et al, (2012)
Citation efficiency stock relative to industry	Citation stock divided by average number of citations of patents of companies in the same industry	Kogan et al, (2012)
Dependent Variable		
Analyst forecast error	Average absolute value of difference between the last forecast of analyst and actual earning normalized by earning forecast	I/B/E/S
Control Variables		
Analyst coverage	Number of securities analyst that cover a firm	I/B/E/S
Cash	Natural logarithm of cash holding in million USD	COMPUSTAT
Altman's Z	(1.2*(Working Capital / Total Assets) + 1.4*(Retained Earnings / Total Assets) + 3.3*(Earnings Before Interest and Taxes / Total Assets) + 0.6*(Market Value of Equity / Total Liabilities) + 0.999*(Sales/ Total Assets))	COMPUSTAT
ROA- industry ROA	the difference between performance of firm in last year and average of industry level ROA	COMPUSTAT
Industry level analyst gap	Average of analyst forecast bias for industry	I/B/E/S
Industry level sales growth	Average of sales growth for industry	COMPUSTAT

Table 2- Simple statistics and correlation (N=16011)

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11
1-Analyst forecast error	0.595	3.563	1										
2- R&D intensity	0.038	0.066	0.03	1									
3- Patent stock	1.974	1.993	-0.04	0.31	1								
4- citation stock	1.982	2.189	-0.04	0.37	0.96	1							
5- citation efficiency stock	0.749	0.763	-0.03	0.40	0.79	0.89	1						
6- citation efficiency stock relative to industry	0.747	0.958	-0.04	0.17	0.84	0.86	0.73	1					
7- Analyst coverage	9.568	9.324	-0.05	0.18	0.51	0.5	0.36	0.47	1				
8- Cash	2.942	2.256	-0.02	0.08	0.33	0.32	0.16	0.25	0.22	1			
9- Altman's Z	4.48	5.472	-0.07	0.18	0.03	0.07	0.12	0.01	0.1	0.00	1		
10- ROA- industry ROA	0.014	0.104	-0.11	-0.09	0.04	0.04	0.02	0.05	0.12	0.04	0.22	1	
11- industry level analyst gap	0.596	1.672	0.39	0.02	-0.02	-0.03	-0.02	-0.02	-0.01	-0.02	-0.04	-0.02	1
12- industry level sales growth	0.193	1.396	0.00	-0.01	-0.03	-0.02	-0.02	-0.01	0.00	-0.01	0.00	-0.01	-0.01

Table 3- Industry distribution of firms in sample

SIC Code	Industry	N	Frequency (%)
20	Food And Kindred Products	123	5.56
21	Tobacco Products	14	0.63
22	Textile Mill Products	55	2.49
23	Apparel And Other Finished Products Made From Fabrics	57	2.58
24	Lumber And Wood Products, Except Furniture	30	1.36
25	Furniture And Fixtures	44	1.99
26	Paper And Allied Products	76	3.44
27	Printing, Publishing, And Allied Industries	78	3.53
28	Chemicals And Allied Products	224	10.13
29	Petroleum Refining And Related Industries	47	2.12
30	Rubber And Miscellaneous Plastics Products	73	3.30
31	Leather And Leather Products	19	0.86
32	Stone, Clay, Glass, And Concrete Products	48	2.17
33	Primary Metal Industries	112	5.06
34	Fabricated Metal Products	87	3.93
35	Industrial And Commercial Machinery And Computer Equipment	328	14.83
36	Electronic And Other Electrical Equipment And Components,	359	16.23
37	Transportation Equipment	139	6.28
38	Measuring, Analyzing, And Controlling Instruments; Photographic, Medical And Optical Goods; Watches And Clocks	241	10.90
39	Miscellaneous Manufacturing Industries	58	2.62
Total		2,212	100

Table 4- Firm fixed-effect panel regression of the impact of R&D intensity on analyst earnings forecast error

	(1)	(2)	(3)	(4)	(5)
R&D intensity		5.699**	5.416**	4.460*	3.280*
		(2.256)	(2.341)	(2.368)	(1.778)
Analyst coverage	0.001	-0.001	-0.001	-0.000	-0.001
	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)
Cash	0.038	0.036	0.037	0.039	0.037
	(0.045)	(0.044)	(0.044)	(0.045)	(0.045)
Altman's Z	-0.027***	-0.025***	-0.025***	-0.025***	-0.025***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
ROA- industry ROA	-2.291***	-2.287***	-2.285***	-2.287***	-2.274***
	(0.588)	(0.586)	(0.585)	(0.587)	(0.586)
Industry analyst gap	0.799***	0.798***	0.798***	0.798***	0.798***
	(0.200)	(0.200)	(0.200)	(0.200)	(0.200)
Industry sales growth	0.012*	0.013*	0.013*	0.013*	0.013*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Patent stock		0.105			
		(0.068)			
R&D intensity * patent stock		-0.890**			
		(0.403)			
Citation stock			0.075		
			(0.062)		
R&D intensity* Citation stock			-0.660*		
			(0.354)		
Citation efficiency stock				0.023	
				(0.099)	
R&D intensity* Citation efficiency stock				-0.972	
				(0.886)	
Citation efficiency stock (industry)					0.092
					(0.100)
R&D intensity * citation efficiency stock (industry)					-0.478
					(0.927)
Constant	0.184	-0.135	-0.028	0.035	0.020
	(0.286)	(0.352)	(0.338)	(0.302)	(0.306)
Number of firms	2,212	2,212	2,212	2,212	2,212
N	16,011	16,011	16,011	16,011	16,011
Model F	2.67***	2.55***	2.56***	2.52***	2.47***
R^2	0.15	0.15	0.15	0.15	0.15