Seoul Journal of Business
Volume 27, Number 2 (December 2021)
DOI: https://doi.org/10.35152/snusjb.2021.27.2.003

Does Analyst Coverage Encourage Firm Innovation? Evidence from Korea*

WOOJIN KIM**
Seoul National University
Seoul, Korea

YOONYOUNG CHOY***
Seoul National University
Seoul, Korea

ABSTRACT

This paper examines whether analyst coverage affects firm innovation in an economy dominated by family-controlled business groups. Using a sample of Korean publicly traded firms from 2010 to 2018, we find that an increase in financial analysts leads covered firms to cut investments in corporate venture capital and R&D. Moreover, reduction in innovation through acquisitions is more pronounced when analysts are from chaebol (family-controlled large business group) affiliated brokerages. These findings suggest that unlike in U.S., analyst coverage puts pressure on managers to meet the analysts' forecasts, thereby impeding innovation under such environment.

Keywords: corporate venture capital, financial analysts, innovation, acquisition, R&D

* I appreciate support from the Institute of Management Research at Seoul National University. We appreciate Euna Cho, Hyundong Kim and seminar participants at the Joint Conference with the Allied Korea Finance Associations for helpful comments.

** Professor of Finance, Seoul National University Business School, 1 Gwanak-Ro, Gwanak-gu, Seoul, 08826, Korea; email: woojinkim@snu.ac.kr, Tel: +82-2-880-5831

*** Seoul National University Business School, 1 Gwanak-Ro, Gwanak-gu, Seoul, 08826, Korea; email: yy.choy@snu.ac.kr, Tel: +82-10-9437-5401

INTRODUCTION

A growing body of literature has highlighted the factors and outcomes of firm innovation. Recently, the literature has presented two conflicting views on analyst coverage and its effect on firms' innovation strategy. Specifically, He and Tian (2013) support the so-called "pressure effect" of analyst coverage on managers to meet analysts' earnings forecasts, thereby inducing managers to cut long-term expenses related to innovation. On the other hand, Guo, Pérez-Castrillo and Toldrà-Simats (2019) find that "information effect" also exists, which makes the opposite prediction that analyst coverage can mitigate managerial myopia and increase a CEO's incentive to innovate by reducing information asymmetry.

Motivated by this, this paper investigates whether such information and pressure effects of financial analysts on firm innovation exist in an emerging market where many companies are group-affiliated. Due to the characteristics of family-owned business, the informational role of financial analysts in emerging markets can be different from those in developed counterparts, since it may be difficult to obtain trustworthy information about such companies (Chan and Hameed 2006).

Our analyses focus on Korea, which is dominated by family–controlled business groups, often referred to as chaebols. (Kim, Ko and Wang 2019). As most chaebols are conglomerates in that they run many lines of different businesses, some are engaged in stock brokerage business and as such have their own securities firms as member companies. This may induce business group-affiliated analysts to issue more positive estimates for member companies within the same group (Mantecon and Altintig 2012). The existence of group-affiliated analysts may either exacerbate the pressure effect by forcing managers to meet even higher earnings forecasts with a positive bias, or mitigate it by allowing managers to largely ignore non-arm's length forecasts, which clearly deserves attention in Korean market.

Secondly, investigating Korean market is relevant in the sense that it is one of the most up-to-date for innovative startups, rarely seen in other economies. Specifically, there are innovative Korean start-ups that grows into competitive giants over a short period of time. For instance, Naver was established with only seven engineers in 1998 and stands out as domestic premier portal space, clearly substituting Google or Yahoo in 2003.

Thirdly, as technological innovation was one of the engines of the Korean economic development, Korea has adopted various corporate strategies to promote innovation, including R&D, acquisition and corporate venture capital (CVC). Especially, Korean market is vertically integrated as well as horizontally, so CVC is one of important channel to innovate. That is, corporate investors are likely to be in a better position to provide complementary resources to investees, thereby obtaining innovative knowledge and products externally. For instance, many corporations like Samsung are committing a large amount of money to discover innovators around the world through venture capital. Specifically, Samsung Venture Investment Corporation actively invests in future-oriented businesses based on new innovative technologies which are expected to serve as new growth engines. Overall, these market features in Korea provides us with an ideal setting to identify the relevant consequences and the final outcome of firm innovation, which we believe is worth an investigation.

Using publicly traded non-financial firms in Korean stock market between 2010 and 2018, we consider how the information and pressure effect of analyst coverage vary across CVC, R&D and acquisition, following Guo, Pérez-Castrillo and Toldrà-Simats (2019). Firstly, our result is different from Guo, Pérez-Castrillo and Toldrà-Simats (2019) in that analyst coverage leads to not only the cut in R&D but also negative CVC investment, supporting that the short-term earnings targets estimated by analysts put pressure on managers, since investors can punish managers who miss the earnings forecasts. The reason is that CVC as an innovation vehicle has only recently entered emerging economies. Given that successful outcomes of venture capital investments are generally limited in these markets, companies may be careful to choose CVC investment as their innovation strategies (Rajamani and Velamuri 2014). As a result, we argue that the pressure effect works as disciplinary actions to cut such uncertain investment as CVC in Korea.

Secondly, the pressure effect is also observed in acquisitions when firms are followed by group-affiliated analysts. The pressure effect exists both when group-affiliated analysts estimate firms in the same business groups and when those analysts follow firms in other business groups. This is due to the positive bias in group-affiliated estimates (Lim and Kim 2019), which puts more pressure on managers to cut long-term expenses including innovation.

Thirdly, in terms of innovation outcome, the change in innovation strategies due to analyst coverage *even decreases* the innovation output. That is, the sources of pressure exerted on managers by financial analysts cause the CEO to focus heavily on the short-term performance, and this may affect the long-term innovation output, which differs from the case in U.S. Overall, our analysis implies that the pressure effect of analyst coverage dominates in Korea.

Finally, we also perform several subsample analyses as well as robustness tests: We split the sample according to the level of corporate governance, whether or not a firm belongs to high-technology industries, and if a firm is a recent start-up. It turns out that analyst coverage has pressure effects on the likelihood of decreasing innovation for firms in low-tech industries and with good corporate governance. The exception occurs when a recent start-up firm is followed by financial analysts, since analyst coverage increases the relevant firm innovation. In order to alleviate the potential endogeneity problem, we also employ an instrumental variable (IV hereafter) approach, based on the finding of Yu (2008) and Guo, Pérez-Castrillo and Toldrà-Simats (2019). Specifically, we impose the expected number of analyst coverage as our IV variable. The IV regressions generate consistent result although it does not perfectly rule out endogeneity as a confounding factor.

Our study contributes to studies on the relation between finance and firm innovation. While prior research merely suggests that group-affiliated analysts' estimates have positive bias, this study further develops how the bias can increase pressure effect on group-affiliated firms' managers, thereby impeding innovation. That is, the bias in group-affiliated analysts' estimates put extra pressure on managers to cut long-term expenses. Moreover, this paper shows that higher uncertainties associated with CVC investment for emerging economies and different accounting standard may lead to different strategic adjustment from managers. Whereas previous studies highlight the pressure from such internal strategies as R&D, this paper shows that the external innovation channel can be another candidate for the pressure effect. Although the information effect on acquisition exists, the long-term output stemming from the pressure effect is stronger, implying that different innovation channels can absorb potential positive impact of analyst coverage, suggested by previous studies (He and Tian 2013). Given that IFRS has been adopted in many jurisdictions, including the European Union, and that many emerging markets face the difficulty in CVC investment, our findings are not restricted to Korean market setting but rather a general phenomenon in emerging markets.

Our paper is organized as follows. Section 2 discusses prior research on analyst coverage and firm innovation. Section 3 describes the data and empirical strategy. Section 4 presents our empirical results. Section 5 concludes.

LITERATURE REVIEW

This study contributes to the following three broad streams of literature: innovation, financial analysts, and managers' short-termism. A growing body of literature examines various economic forces that may affect innovation. Some of the factors that have been documented to affect innovation of public firms are acquisitions (Teece 2010; Seru 2014), external financial dependence, and corporate venture capital. For example, Acharya and Xu (2017) find that public firms financing through internal cash flows (Rajan and Zingales 1996) invest less on R&Ds and less patents outcome. Recent studies focus on CVC, or corporate venture capital, as an important innovation channel through which established firms may conduct external R&Ds (Gaba and Bhattacharaya 2012). González-Uribe (2020) finds that venture capital can influence innovation among companies within the same venture capital portfolios. Ma (2020) finds that firms have motivation to invest in CVCs in order to fix their innovation weaknesses. We add to this literature by relating analyst coverage to firm innovation strategies mentioned above in an emerging market setting.

This paper also adds to a substantial body of research that studies the role of financial analysts. While traditional analyst research has focused more on asset pricing implications, recent studies extend this literature and focus on how improvement in information environment led by analyst coverage may reduce uncertainty over firm information and ultimately affect firm performance (Lee and So 2017). There are two conflicting explanations regarding how financial analysts may affect firm investment. Derrien and Kecskes (2013) find that more analyst coverage leads to increase in capital expenditures due to a decrease in information asymmetry. However, other studies show that analysts may distort corporate investment out of the pressure effect on managers to beat short-term earnings targets (Benner and Ranganathan 2012; He and Tian 2013). Merkley, Michaely and Pacelli (2017) reconcile these two views by arguing that analysts' informativeness depends on factors such as the number of analysts covering an industry.

Another criticism on the validity of analysts' forecasts is potential bias from investment banking relationships. For example, Corwin, Larocque and Stegemoller (2017) finds that the change in investment bank-firm relationships affects analysts to issue biased coverage. In our setting, an additional source of potential bias due to conflict of interest is the existence of chaebol-affiliated brokerages. Lim and Kim (2019) show that long-term investment strategies based on analyst recommendations may be more profitable when investors discount a positive bias in chaebol-affiliated analysts' recommendations. Whether chaebol-affiliated brokerages may encourage or discourage corporate investment is unclear, *ex ante*. Since chaebol-affiliated brokerages firms may attract analysts with better ability, they may improve information environment thereby increasing corporate investment in innovation. On the other hand, non-arm's length forecasts may impose a strict pressure on managers who are *de facto* accountable to the joint controlling shareholder of both the covered firm and the brokerage.

Perhaps the paper that is closest to ours is a recent study by Guo, Pérez-Castrillo and Toldrà-Simats (2019) who show that the effect of analyst coverage on U.S. firms' innovation varies across R&D, acquisition and CVC investment, thereby influencing the long-term outcomes. Our paper complements and extends their study by analyzing the effect of financial analysts on innovation in a representative emerging market and how this relationship may be affected by the existence of chaebol-affiliated brokerages.

Finally, this paper also builds on the prior literature on managers' incentives for "short-termism." For instance, Kolasinski and Yang (2018) suggest that managerial myopia may be one of the factors that led to the subprime mortgage crisis, since CEOs with short-term incentives may decide to take on riskier exposure to subprime mortgage-backed securities. Such managerial short-termism has been one suspect of distortions in firm innovation. Dechow and Sloan (1991) find that managers tend to cut R&D investment by the end of their tenure, resulting in a decrease in the firm's reported earnings. This paper complements these studies by connecting the effect of analyst coverage and mangers' decisions to adjust their innovation strategy, and then examining the long-term innovation outcome to further verify whether managers' decisions were indeed short-term based or not.

DATA AND METHODOLOGY

Sample Construction

Our sample consists of publicly traded firms in Korea from 2010 to 2018, available on DataguidePro, our primary local dataset comparable to Compustat and IBES combined. Following Guo, Pérez-Castrillo and Toldrà-Simats (2019), we exclude financial and utility firms with KSIC codes of 64-66 and 35-36, respectively. The financial analyst information is also obtained from DataguidePro. Since the analyst information is incomplete prior to 2009, our sample period starts from 2010.

Our key innovation channel variables taken from the previous literature are R&D, acquisitions, and CVC investment. While R&Ds are directly taken from DataguidePro, the latter two variables are constructed as follows: Since most arm's-length acquisitions in Korea take the form of a block trade between the old, outgoing controlling shareholder and the incoming controlling shareholder, we first identify all changes in the largest shareholder maintained by the Korea Investor's Network for Disclosure (KIND) database (downloadable via http://kind.krx.co.kr, which is the website operated by the Korea Exchange (KRX)). KIND is one of electronic systems managed by the Korea Stock Exchange to provide corporate disclosure information. We then exclude the following cases: cases when commercial banks become the new largest shareholder; control changes that occur due to unilateral declines in the equity stakes of the previous largest shareholder; cases where control block transactions are withdrawn after the initial disclosure as well as miscellaneous cases such as SPAC listings where actual control remains unchanged; cases in which the value of the acquired stock is less than 5% of the market value or the new largest shareholder's ownership is less than 5%; deals with less than 1 billion KRW, roughly 1 million USD (Cho and Kim 2019).

To assemble CVC investment data, we first obtain the fund names and the names of the parent companies, defined as the largest equity investor of the fund from the Disclosure Information of Venture Capital Analysis (DIVA, downloadable via http://diva.kvca.co.kr, which is the website operated by KVCA) and DART database. The former is a comprehensive dataset of venture capital funds and their investment targets whereas the latter is a disclosure platform similar to EDGAR in U.S. DIVA is provided by Korea Venture Capital Association (KVCA) and is the only accredited database which contains information about company governance, financial statements, funds and investment information in South Korea. The sample period ends in 2018, since the periodic annual reports from venture capital funds are available until 2018. Then we manually collect the names of venture capital funds' investment targets and classify them into three mutually exclusive sets of start-ups based on their age: those that are (1) less than three years old, (2) at least three but less than seven years old, (3) and at least seven years old. Once we have identified the targets and the age group they belong to, we locate the target with the largest investment amount within each fund, i.e. the start-up with the largest portfolio weight, and assign that target's age group as the age group of the fund. Once we have a list of parent companies that are participating in venture capital funds, we then merge this list with our sample firms from DataguidePro to identify those firms that engage in CVC investment.

Finally, we obtain patent information from the WIPS ON database (equivalent to WIPS patent database available from http://wipson.com). This database offers the list of documentation of patents by individuals and firms designated by the Korean Patent Office. Since the information on patent citation is unavailable in Korea, we use granted patents from the WIPS ON instead. This leaves us the final sample of 18,351 firm-year observations and 2,039 unique firms.

Variables

Our dependent variables are three innovation channels as well as an innovation output, following Guo, Pérez-Castrillo and Toldrà-Simats (2019). We first compute three measures for CVC investment: *CVC*1 is a dummy variable equal to 1 when a firm invests in CVC fund for a start-up with less than three years old and zero otherwise; *CVC*2 is an indicator variable equal to 1 for CVC investment for a firm with at least three but less than seven years old and zero otherwise; *CVC3* is a dummy variable equal to one for CVC investment for a firm with at least seven years old and zero otherwise.

Unlike in U.S. where capital market is the primary financing source for both public firms and start-ups, vast majority of financing in Korea are mediated through commercial banks which provide collateral-based loans. Even start-ups' initial external financing is typically a loan from a commercial bank, guaranteed by either one of the two government organizations, namely, Korea Credit Guarantee Fund (KODIT) and Korea Technology Finance Corporation (KOTEC). Since these loans stand first in line prior to any other external financier in case when the start-up fails, it is difficult for Korean venture capital to invest in an early stage start-up, since they stand in line behind commercial lenders. As a result, only a limited number of start-up firms are successful in attracting CVC investment, and the timing of receiving investments ranges from the initial stage to the later stage of start-up growth. To accommodate this unique feature of the Korean venture capital market, we classify CVC investment into three categories based on the investee's growth stages.

We next measure R&D investment using *RDchange*, which is the difference between the ratio of R&D expenses to total assets at time t and $t - 1$. Another measure of R&D is the dummy variable *RDcut*, which equals one if a firm's R&D expenses divided by total assets are lower in time t than in $t - 1$, and zero otherwise. We replace missing observations with zeros in R&D expenses, following Lewis and Tan (2016) among many others in the R&D literature.

Our last measure of innovation channel, namely acquisitions, is captured by two variables: *Acquisition* is a dummy variable equal to one if a firm engages in an acquisition of a controlling stake in another firm in time t, and zero otherwise. We also use *lnAcq*, defined as the natural log of one plus the number of targets which a firm acquires in a given year. As for the degree of innovativeness of targets, we follow Guo, Pérez-Castrillo and Toldrà-Simats (2019) and compute the natural log of one plus the total number of patents applied for by the target at the Korean Intellectual Property Office in a given year (*lnTargPatent*), and the natural log of one plus the total number of granted patents held by the target up to the year when a given acquisition takes place (*lnTargGrant*).

Finally, as a measure of innovation output to check if the long-term output gets affected by any changes in innovation efforts, we calculate patent variables for our sample firms similar to those obtained for acquisition targets. Specifically, we apply the natural log of one plus the number of both patents filed during a given year and patents granted held up to a given year, indicated as *lnPatents* and *lnGranted*, respectively.

Our key independent variable is the number of analysts per firm, *lnCoverage*, computed as the natural log of one plus the coverage. As a robustness test, we consider an alternative measure of analyst pressure, *EPSD*, defined as the difference between the actual EPS and analysts' consensus EPS estimate, divided by the stock price. Consensus EPS estimate is the arithmetic mean of a firm's earnings forecasts by financial analysts following each firm.

Our control variables include firm size (*Size*), R&D ratio (*RDRatio*), firm age (*Age*), leverage (*Leverage*), cash (*Cash*), return on equity (*ROE*), property, plant and equipment (*PPE*) ratio, capital expenditure (*CAPEX*), institutional ownership (*InstOwn*), Tobin's Q (*Q*), Kaplan-Zingales index (*KZIndex*), corporate governance index (*CGIndex*), market share (*MktShare*) computed as sales divided by the sum of sales of all firms within the two-digit Korean Standard Statistical Classification (KSIC) code and Hirshman-Herfindahl Index (*HHI*), all lagged by one year. We obtain institutional ownership information from TS-2000, a local dataset similar to DataguidePro, as well as DART. *ROE*, *Q*, *RDChange* and the *KZIndex* are winsorized at the 1st and 99th percentiles. Definitions of all variable are described in detail in the appendix.

Table 1 provides summary statistics for our data. The average *RDRatio* is 1.6% in our sample, and the average change in that ratio is about -0.004 percentage points. The second measure for R&D investment, *RDCut*, implies that 29.6% of our sample firm-years decide to cut their R&D expenses. As for the acquisition measure, 1.2% of firms in the sample are engaging in an acquisition in a given year, and 0.009 companies are acquired. For 897 firm-years that do acquire targets, the average total number of patents of the target is 5.5, and that of granted patents are 5.2. The final measure for our innovation strategies or channels is CVC investment. The results from table 1 indicates that 4.7% of sample firms invest in early stage start-ups through CVCs, 4.4% in mid-stage start-ups and 4.2% in relatively mature start-ups. With respect to the innovation output,

Table 1. Descriptive Statistics

This table reports the summary statistics, including number of observations, mean, standard deviation, 25th percentile, median, and the 75th percentile of variables used in the analyses. The data corresponds to Korean non-financial firms for the period 2010-2018. All variable definitions are described in the appendix.

Variable	N	Mean	Std Dev	p25	Median	p75
RDratio	17,099	0.016	0.039	0.000	0.002	0.018
RDchange	17,139	-0.00004	0.013	-0.0003	0.000	0.0003
RDcut	16,312	0.296	0.457	0.000	0.000	1.000
Acq	18,351	0.012	0.109	0.000	0.000	0.000
lnAcq	18,351	0.009	0.080	0.000	0.000	0.000
*CVC*1	18,351	0.047	0.211	0.000	0.000	0.000
*CVC*2	18,351	0.044	0.206	0.000	0.000	0.000
*CVC*3	18,351	0.042	0.201	0.000	0.000	0.000
lnTargPatent	897	1.878	1.897	0.000	1.386	3.135
lnTargGrant	897	1.820	1.803	0.000	1.386	3.135
lnPatents	18,305	1.005	1.413	0.000	0.000	1.609
lnGranted	18,305	0.986	1.319	0.000	0.693	1.609
lnCoverage	18,351	1.839	3.263	0.000	0.000	0.000
EPSD	14,978	-0.038	2.765	-0.066	-0.0008	0.061
Size	17,099	18.737	1.451	17.812	18.541	19.458
Age	18,351	24.133	17.808	12.000	19.000	37.000
Leverage	17,099	0.371	0.232	0.198	0.358	0.517
Cash	17,099	0.088	0.102	0.020	0.054	0.118
ROE	17,188	0.059	0.195	0.004	0.056	0.135
PPE	17,099	0.265	0.192	0.106	0.246	0.392
CAPEX	17,095	0.038	0.122	0.001	0.018	0.057
InstOwn	18,351	5.169	8.661	0.000	0.000	8.320
Q	17,099	1.293	0.977	0.751	1.005	1.474
KZIndex	15,001	-20.709	105.999	-3.231	0.002	1.322
CGIndex	18,351	28.023	44.605	0.000	0.000	65.000
MktShare	18,351	0.004	0.026	0.0001	0.0002	0.0006
HHI	18,351	0.001	0.015	0.000	0.000	0.000

firms on average applies for 1 patent during a given year and holds roughly similar number of granted patents at a given point in time. In terms of coverage, firms on average are followed by 5.3 analysts per year. Normalized difference between actual earnings and earnings consensus earnings forecasts is -3.8% on average, which implies that earnings forecasts tend to biased upwards.

Methodology

Following Guo, Pérez-Castrillo and Toldrà-Simats (2019), we use ordinary least squares (OLS) to estimate how analyst coverage may affect firm innovation. Since analyst coverage is clearly not random, the causality may well run the other way around. Specifically, there may be more analyst coverage for firms that engage in more innovation activities, namely more acquisitions, more R&D, and more CVC investments. To address this potential reverse causality, we consider 'expected' coverage as an instrument variable and implement a two-stage least squares (2SLS) approach. The baseline estimation based on OLS is as follows:

$$Innovation_{(i,t+k)} = \alpha + \beta lnCoverage_{(i,t)} + \gamma X_{(i,t)} + \delta_i + \mu_t + \varepsilon_{(i,t)} \quad (1)$$

where subindex i and t represent firm and year throughout this paper, respectively. The dependent variables $Innovation_{(i,t+k)}$ stands for different measures of innovation channels: *RDChange* and *RDCut* for the R&D investment; *Acq* and *lnAcq* for firms' acquisition activities; *lnTargPatent* and *lnTargGrant* for how innovative the target firms are; and *CVC*1, *CVC*2 and *CVC*3 for firms' CVC investment. The main independent variable is $lnCoverage_{(i,t)}$, which represents the number of analysts following a firm. The remaining control variables in $X_{(i,t)}$ are firm size (*Size*), R&D ratio (*RDRatio*), firm age (*Age*), leverage (*Leverage*), cash (*Cash*), return on equity (*ROE*), property, plant and equipment (*PPE*) ratio, capital expenditure (*CAPEX*), institutional ownership (*InstOwn*), Tobin's Q (*Q*), Kaplan-Zingales index (*KZIndex*), corporate governance index (*CGIndex*), market share (*MktShare*) and Hirshman-Herfindahl Index (*HHI*), as described in the previous section. δ_i and μ_t represent to firm and year fixed effects, respectively. We examine innovation activity up to two years (k = 1, 2). Year fixed effect should be included in the regression, since this method can eliminate omitted variable bias caused by excluding unobserved variables that evolve over time. Since this study is interested in analyzing the impact of analyst coverage that varies over time on firm innovation, we believe that fixed effect model should be included for our analyses.

In order to address the non-randomness of coverage, we consider 'expected' coverage as an instrument variable (IV). Expected coverage is obtained by first applying the increase in brokerage size to the firm-brokerage level coverage at the beginning of the sample period and then summing them up across the brokerages as in Yu (2008) and Guo, Pérez-Castrillo and Toldrà-Simats (2019). As explained in Yu (2008) and previous studies, we believe that this is legitimate instrument since it exploits exogenous variation in analyst coverage, namely the change in the size of the brokerage houses, which should be independent from any characteristics of covered firms. Specifically, we construct our IV, *ExpectedCoverage*, as follows.

$$ExpectedCoverage_{(i,t,j)} = \left(\frac{Brokersize_{(t,j)}}{Brokersize_{(0,j)}}\right) * Coverage_{(i,0,j)} \quad (2)$$

where $ExpectedCoverage_{(i,t,j)}$ is the expected coverage of firm i in year t from brokerage j. $Brokersize_{(t,j)}$ and $Brokersize_{(0,j)}$ are the number of analysts working for broker j in year t and the benchmark year 0, respectively. The benchmark year is 2010, the first year in our sample period. $Coverage_{(i,0,j)}$ is the number of analysts following firm i in year 2010 working for brokerage j. $ExpectedCoverage_{(i,t,j)}$, therefore, is the expected number of analysts from brokerage j following firm i at time t with respect to the initial year 2010 that is attributable to the change in brokerage size. Once we obtain the firm-brokerage level expected coverage extrapolated from natural increase (or decrease) in brokerage size, we sum up $ExpectedCoverage_{(i,t,j)}$ across all brokerage firm j's to get the aggregate expected number of analysts following firm i as below:

$$ExpectedCoverage_{(i,t)} = \sum_{j=1}^{n} ExpectedCoverage_{(i,t,j)} \quad (3)$$

where n is the total number of brokerages in year t. Since *ExpectedCoverage* is based on original coverage and changes in brokerage size, we expect this variable to be well correlated with actual coverage. However, we do not see a direct relationship between this variable and our measures of current innovation activities. Hence, we argue that this is a valid instrument for actual coverage and use this IV to instrument for $lnCoverage_{(i,t)}$ in equation (1) and incorporate the estimated $\widehat{lnCoverage}_{(i,t)}$ in the second stage regression as follows:

$$lnCoverage_{(i,t)} = \alpha + \beta ExpectedCoverage_{(i,t)} + \gamma X_{(i,t)} + \delta_i + \mu_t + \varepsilon_{(i,t)} \quad (4)$$

$$Innovation_{(i,t+k)} = \alpha + \beta \widehat{lnCoverage}_{(i,t)} + \gamma X_{(i,t)} + \delta_i + \mu_t + \varepsilon_{(i,t)} \quad (5)$$

where $\widehat{lnCoverage}_{(i,t)}$ is the fitted value of $lnCoverage_{(i,t)}$ from the first stage regression in equation (4).

In the cross-sectional sub-sample analyses, we divide our sample into two groups based on four dimensions: corporate governance based on *CGIndex*; high-tech industries according to the OECD classification (Organisation for Economic Co-operation and Development 2011), if a firm is a recent start-up (*Startup*) with age no older than 10 years (Hellman and Puri 2002), and whether covering brokerage belongs in a large business group or chaebol.

The unique feature of our sample allows us to classify both covered firms and analysts into those that are affiliated with chaebols and those that are not. Based on the list of firms provided by the Korea Fair Trade Commission (KFTC), we identify both brokerages and firms into group-affiliated and non-group-affiliated categories, and define group-affiliated (*GA*) analysts as analysts in a group-affiliated brokerage estimating group-affiliated firms. That is, *GA* is a dummy variable defined at analyst-firm-broker level. Note that this variable does not require the covered firm and covering brokerage to be from the same business groups. As such, this variable reflects the general level of reputation of the covered firm and the covering brokerage. However, we would expect potential conflict of interests to be more severe when both the firm and the brokerage belong to the same business group. To capture this possibility, we consider another dummy variable, *SameGA*, which equals one if both the firm and the broker are from the same business group.

Based on *CGIndex*, we create *GoodGov*, a dummy variable set equal to one if a firm's corporate governance index (*CGIndex*) is higher than the sample mean value of *CGIndex* and zero otherwise. *CGIndex* is collected and summated from Korea Corporate Governance Service (KCGS) when evaluates firms' governance practices in terms of sub-categories including protection for shareholder rights, board independence and managerial transparency for disclosures and audit. So, higher *CGIndex* implies that the firm has higher level of corporate governance.

To define a recent start-up, *Startup* is defined as a dummy variable equal to 1 if a firm's age is no older than 10 years and 0 otherwise, following Hellman and Puri (2002).

Lastly, we split the sample in high-tech industries, following industry classification of OECD (2011). As a result, firms with KSIC codes 20, 21, 26-31, 35, 49, 61, 62, 70 and 86 belong to high-tech industries, and high-tech dummy (*HT*) is set equal to 1 for these firms in high-tech industries and zero otherwise.

Once we create these four dummies, we then interact them with the instrumented $lnCoverage_{(i,t)}$ in equation (5) as follows

$$\begin{aligned} Innovation_{(i,t+k)} &= \alpha + \beta_1 CharDummy + \beta_2 ln\widehat{Coverage}_{(i,t)} \\ &+ \beta_3 ln\widehat{Coverage}_{(i,t)} \cdot CharDummy + \gamma X_{(i,t)} \\ &+ \delta_i + \mu_t + \varepsilon_{(i,t)} \end{aligned} \quad (6)$$

where *CharDummy* represents three distinct cross-sectional dimensions, namely corporate governance, group-affiliation, and membership in high-tech industries as mentioned. Specifically, this variable is equal to one for firms under good corporate governance, group-affiliated, and high tech, and 0 otherwise. Here, our key coefficient of interest is β_3, since it measures how analyst coverage may affect innovation activities of firms in each sub-group.

In addition, we perform several robustness tests to disentangle the direct and the indirect effect of analyst coverage. Specifically, we include interaction term to capture the indirect substitution which comes from any decrease in innovation channels:

$$\begin{aligned} Innovation_{(i,t+k)} &= \alpha + \beta_1 ln\widehat{Coverage}_{(i,t)} + \beta_2 Cut_{(i,t+1)} \\ &+ \beta_3 \left(ln\widehat{Coverage}_{(i,t)} * Cut_{(i,t+1)} \right) + \gamma X_{(i,t)} \\ &+ \delta_i + \mu_t + \varepsilon_{(i,t)} \end{aligned} \quad (7)$$

where $Cut_{(i,t+1)}$ corresponds to the decrease in other two innovation channels, if any. Our key variables of interest are β_1 and β_3, since the two variables capture the direct and the indirect effect of analysts on innovation increased. If β_1 is positive, analysts have a direct informational effect on acquisition strategies; if β_3 is positive, the indirect pressure effect of analysts forces managers to increase innovation to substitute the decrease in other innovation strategies, if any. The coefficient β_2 represents the increased innovation strategies and the decreased counterparts of firms without any analyst coverage. $\widehat{lnCoverage}_{(i,t)}$ is instrumented coverage variables from 2SLS in equation (4).

We also analyze how innovation output is affected from the adjustment of innovation strategies out of analyst coverage as below:

$$\begin{aligned} Outcome_{(i,t+3)} = {} & \alpha + \beta_1 \widehat{lnCoverage}_{(i,t)} + \beta_2 Innovation_{(i,t+1)} \\ & + \beta_3 \left(\widehat{lnCoverage}_{(i,t)} * Innovation_{(i,t+1)} \right) \\ & + \gamma X_{(i,t)} + \delta_i + \mu_t + \varepsilon_{(i,t)} \end{aligned} \tag{8}$$

where $Outcome_{(i,t+3)}$ are two measures of innovation output, which are *lnPatents* and *lnGranted*. $\widehat{lnCoverage}_{(i,t)}$ is the instrumented coverage variable from equation (4). $Innovation_{(i,t+1)}$ corresponds to the three innovation channels which are R&D, acquisition and CVC investment after one year. We also include control variables and fixed effects as before. β_1 represents the effect of analysts on future patents; β_2 corresponds to the effect of three innovation strategies on long-term output when the amount of analyst coverage firms obtained is changed; and β_3 captures the differential effect of firm innovation for firms covered by analysts.

Instead of using *lnCoverage*, we apply another measure of analyst pressure, *EPSD*, the difference between the actual EPS and analysts' EPS estimates, divided by stock price. If analysts' estimates have negative effects on innovation strategies, it is important to see if such reduction affects long-term innovation output:

$$\begin{aligned} Innovation_{(i,t)} = {} & \alpha + \beta_1 I_{Meet(i,t)} + \beta_2 EPSD_{(i,t)} + \beta_3 EPSD^2_{(i,t)} \\ & + \beta_4 EPSD_{(i,t)} * I_{Meet(i,t)} + \beta_5 EPSD^2_{(i,t)} * I_{Meet(i,t)} \\ & + \beta_6 X_{(i,t)} + \delta_i + \mu_t + \varepsilon_{(i,t)} \end{aligned} \tag{9}$$

where $Innovation_{(i,t)}$ is the innovation channel that might decrease from the pressure effect. $I_{Meet(i,t)}$ is a dummy variable equal to one if firms meet estimated EPS and zero for firms that miss the target. Here, our key coefficient of interest is β_1. If β_1 is negative, it implies that firms that meet analysts' estimate are likely to cut one of their innovation strategies, which supports the pressure effect of analysts. As in equation (8), we also estimate the effect of cutting innovation investment because of *EPSD* on firms' patent outcomes. Following Guo, Pérez-Castrillo and Toldrà-Simats (2019), we use $I_{Meet(i,t)}$ as IV to estimate innovation channel that declines due to the pressure effect, based on equation (9), then put the instrumented innovation into the estimation below:

$$\begin{aligned} Outcome_{(i,t+3)} &= \alpha + \beta_1 \widehat{Innovation}_{(i,t)} + \beta_2 EPSD_{(i,t)} \\ &+\beta_3 \left(EPSD_{(i,t)} * I_{Meet(i,t)} \right) + \gamma X_{(i,t)} \\ &+\delta_i + \mu_t + \varepsilon_{(i,t)} \end{aligned} \tag{10}$$

where $\widehat{Innovation}_{(i,t)}$ is from the first stage regression, which is equivalent to the equation (9). The key coefficient of interest is β_1, which corresponds to the causal effect of cutting innovation on firms' long-term innovation outcome.

FINDINGS

Baseline Results

In this section, we report our main empirical findings. We first document the effect of analyst coverage on firms' innovation strategies. The result from R&D expenditure is presented in table 2. Panel A reports the OLS results while panel B reports the 2SLS results. The first two columns of panel A reports the effect of an analyst coverage on the change in R&D expense while columns (3) and (4) report the effect on a cut in R&D. Column (1) of panel B reports the results of the first-stage regressions and columns (2) to (4) reports the second stage estimation.

Column (1) of panel B indicates that the coefficient of IV, *ExpectedCoverage*, is positive and significant at the 1% level, consistent with the previous studies (Yu, 2008; Guo, Pérez-Castrillo

Table 2. Number of Analyst and R&D Expenses

This table shows OLS (panel A) and 2SLS (Panel B) estimation results of the effect of analysts (*lnCoverage*). The dependent variables are: the change in the ratio of R&D expense to total assets one and two years ahead (*RDChange*) in column (1) and (2); and the dummy equal to one if a firm reduces its R&D ratio and zero otherwise one and two years ahead (*RDCut*) in column (3) and (4). In Panel B, column (1) shows the first-stage regression where *lnCoverage* is instrumented, and column (2) to (5) shows the result from the second-stage of R&D change and R&D cut, respectively. Control variables include *Size, RDRatio, Age, Leverage, Cash, ROE, PPE, CAPEX, InstOwn, Q, KZIndex, CGIndex, MktShare* and *HHI.* Standard errors are in parentheses, and ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All variable definitions are in appendix.

Panel A: OLS

Dependent	*RDChange*		*RDCut*	
	(1) *t* + 1	(2) *t* + 2	(3) *t* + 1	(4) *t* + 2
lnCoverage	0.00002 (0.00004)	-0.00006 (0.00007)	-0.0029 (0.0020)	0.0021 (0.0024)
Control Variable	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
No. of obser	12,976	10,800	11,004	9,106
R^2	0.14	0.17	0.38	0.31

Panel B: IV 2SLS

Dependent	First-Stage	Second-Stage			
	LnCoverage	*RDChange*		*RDCut*	
	(1) *t*	(2) *t* + 1	(3) *t* + 2	(4) *t* + 1	(5) *t* + 2
ExpectedCoverage	0.1335*** (0.0026)				
$\widehat{lnCoverage}$		-0.0004*** (0.0001)	-0.0002 (0.0002)	-0.0066 (0.0047)	0.0067 (0.0057)
Size	0.8327*** (0.0612)	0.0051*** (0.0004)	0.0016*** (0.0006)	-0.0444** (0.0180)	-0.0450** (0.0212)
RDratio	3.4848*** (1.0192)			5.1578*** (0.2651)	2.5004*** (0.3603)
Age	-0.1842*** (0.0643)	-0.0003 (0.0003)	0.00006 (0.0005)	-0.0086 (0.0134)	-0.0183** (0.0078)

Table 2. (continued)

Dependent	First-Stage	Second-Stage			
	LnCoverage	*RDChange*		*RDCut*	
	(1) t	(2) $t+1$	(3) $t+2$	(4) $t+1$	(5) $t+2$
Leverage	-0.9333*** (0.1462)	-0.0032*** (0.0008)	-0.0035*** (0.0013)	-0.0720* (0.0378)	-0.0002 (0.0454)
Cash	-0.5862** (0.2624)	-0.0033** (0.0015)	0.0002 (0.0023)	-0.0451 (0.0690)	-0.0142 (0.0859)
ROE	0.5576*** (0.1160)	0.0034*** (0.0006)	-0.0003 (0.0010)	-0.0507* (0.0283)	-0.0446 (0.0336)
PPE	0.2740 (0.2603)	-0.0043*** (0.0015)	0.0016 (0.0024)	0.2324*** (0.0721)	0.1226 (0.0849)
CAPEX	0.1154 (0.1674)	0.0026*** (0.0009)	-0.0004 (0.0013)	-0.0750* (0.0394)	0.0351 (0.0462)
InstOwn	0.0052* (0.0031)	-0.00003** (0.00002)	-0.00002 (0.00003)	-0.0005 (0.0008)	-0.0004 (0.0009)
Q	0.2660*** (0.0273)	0.0003** (0.0002)	0.0002 (0.0002)	-0.0002 (0.0073)	-0.0085 (0.0094)
KZIndex	-0.0007*** (0.0002)	-0.000001 (0.000001)	-0.000001 (0.000002)	0.00001 (0.00005)	-0.0001 (0.0001)
CGIndex	-0.0025** (0.0010)	-0.00001** (0.000005)	0.00001 (0.00001)	0.0001 (0.0003)	0.0006* (0.0004)
MktShare	11.8821* (6.2153)	-0.0768** (0.0343)	-0.0135 (0.0500)	4.5701*** (1.5153)	3.6135** (1.7299)
HHI	-44.1626** (17.6457)	0.1348 (0.0943)	0.0671 (0.1311)	-11.7007*** (3.9736)	-9.7218** (4.5183)
Year Fixed	Yes	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	Yes	Yes	Yes
No. of Obs	14,997	12,976	10,800	11,044	9,106
F-statistic	15.27				
R^2	0.71	0.14	0.17	0.38	0.31

and Toldrà-Simats 2019). The large *t*-statistic (51.20) and F-statistic above the critical value of 10 confirms that our IV is not a weak instrument (Stock, Wright and Yogo 2002).

The results from panel A suggests that the effect of analyst coverage on R&D is largely insignificant. However, the result from panel B implies that firms followed by more analysts significantly decrease their R&Ds one year ahead at 1% significance level. Like in the case of U.S., the one-year forward *RDChange* turns out to be negative; what is different from U.S. is that the pressure effect is short-term, whereas the reduction in *RDChange* in U.S. sustains for two years. Comparing the two panels, the coefficients of *lnCoverage* is larger in the 2SLS regressions, suggesting that there is downward bias in OLS estimation.

The rest of coefficients on control variables results in expected sign: firms with fixed assets are more likely to reduce or cut their R&Ds. The negative sign of cash might be due to the fact that firms may rely on cash holdings to smooth R&D, which results in the negative coefficient of cash holdings, as suggested in Brown and Petersen (2011).

Table 3 reports the effect of analysts on firms' CVC decision. The OLS coefficients in panel A suggest that firms followed by more analysts reduce firms' CVC investment for mid-stage and final-stage firms, and making the relevant investment in a start-up. Due to the unique feature of Korean venture capital market mentioned in section 3.2, the result from *CVC*1 reports an early start-up's difficulties in obtaining external finance. The same result applies to the coefficient from the 2SLS analysis, since the signs for CVC investment for mid- and final-stage firms are significantly negative. The result is different from Guo, Pérez-Castrillo and Toldrà-Simats (2019), since the analyst coverage increases CVC investment in U.S. Another difference is that while the positive effect of analyst coverage only occurs in external innovation in U.S., we show that negative pressure can distort such external innovation as CVCs in an emerging market setting. This may be due to the fact that firms in emerging markets may face higher probability of CVC funds failed (Teppo and Wüstenhagen 2009), so that firms followed by financial analysts may feel pressure to decrease such uncertain investments. By looking at the control variables, it implies that big firms with less leverage tend to invest via CVC channel. Also, the coefficients for Age in column (1), (3) and (5) from the 2SLS analysis are negative and significant, implying that younger firms are more likely to use CVCs, meaning that venture capital is a key player for a young venture to innovate when capital markets are not accessible yet. Later, we investigate whether the decrease in CVC, as well as in R&D affects

Table 3. Number of Analyst and CVC Investments

This table shows OLS (panel A) and 2SLS (Panel B) estimation results of the effect of analysts (*lnCoverage*). The dependent variables are: a dummy variable equal to one if a firm starts its CVC for a firm with less than three years old and zero otherwise in column (1) and (2) (*CVC*1); a dummy variable equal to one if firms's CVC invests in a start-up with at least three but less than seven years old and zero otherwise in column (3) and (4) (*CVC*2); and a dummy variable equal to one if firms's CVC invests in a start-up with at least seven years old and zero otherwise in column (5) and (6) (*CVC*3). In Panel B, column (1) to (6) shows the result from the second-stage of the three dependent variables, respectively. Control variables include *Size, RDRatio, Age, Leverage, Cash, ROE, PPE, CAPEX, InstOwn, Q, KZIndex, CGIndex, MktShare* and *HHI*. Standard errors are in parentheses, and ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All variable definitions are in appendix.

Panel A: OLS

Dependent	*CVC*1		*CVC*2		*CVC*3	
	(1) t + 1	(2) t + 2	(3) t + 1	(4) t + 2	(5) t + 1	(6) t + 2
lnCoverage	-0.0003 (0.0005)	-0.0005 (0.0006)	-0.0005 (0.0005)	-0.0013** (0.0005)	0.0002 (0.0005)	-0.0011** (0.0005)
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	14,996	14,995	14,996	14,995	14,996	14,995
R^2	0.61	0.49	0.59	0.48	0.60	0.48

Panel B: IV 2SLS

Dependent	Second-Stage					
	*CVC*1		*CVC*2		*CVC*3	
	(1) t + 1	(2) t + 2	(3) t + 1	(4) t + 2	(5) t + 1	(6) t + 2
$\widehat{lnCoverage}$	-0.0002 (0.0013)	-0.0009 (0.0014)	-0.0011 (0.0013)	-0.0027** (0.0013)	0.00004 (0.0013)	-0.0022* (0.0013)
Size	0.0109** (0.0044)	0.0218*** (0.0046)	0.0116*** (0.0044)	0.0248*** (0.0045)	0.0077* (0.0043)	0.0190*** (0.0044)
RDRatio	0.0141 (0.0686)	0.0104 (0.0711)	0.0179 (0.0688)	0.0326 (0.0700)	-0.0017 (0.0667)	0.0270 (0.0687)
Age	-0.0416*** (0.0043)	-0.0017 (0.0045)	-0.0354*** (0.0043)	-0.0023 (0.0044)	-0.0380*** (0.0042)	-0.0017 (0.0043)

Table 3. (continued)

Dependent	Second-Stage					
	*CVC*1		*CVC*2		*CVC*3	
	(1) t + 1	(2) t + 2	(3) t + 1	(4) t + 2	(5) t + 1	(6) t + 2
Leverage	-0.0011 (0.0099)	-0.0052 (0.0102)	0.0042 (0.0099)	-0.0083 (0.0101)	-0.0006 (0.0096)	-0.0201** (0.0099)
Cash	0.0045 (0.0176)	0.0224 (0.0182)	-0.0132 (0.0176)	0.0077 (0.0180)	0.0109 (0.0171)	0.0175 (0.0176)
ROE	-0.0150* (0.0078)	-0.0054 (0.0081)	-0.0074 (0.0078)	-0.0107 (0.0080)	-0.0127* (0.0076)	-0.0030 (0.0078)
PPE	-0.0254 (0.0175)	0.0087 (0.0181)	-0.0392** (0.0175)	0.0099 (0.0178)	-0.0051 (0.0170)	0.0066 (0.0175)
CAPEX	0.0177 (0.0112)	-0.0568*** (0.0116)	0.0090 (0.0112)	-0.0448*** (0.0114)	0.0165 (0.0109)	-0.0392*** (0.0112)
InstOwn	-0.0003 (0.0002)	-0.00001 (0.0002)	-0.0002 (0.0002)	-0.0001 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)
Q	-0.0002 (0.0019)	0.0011 (0.0019)	0.0002 (0.0019)	0.0010 (0.0019)	-0.0010 (0.0018)	0.0009 (0.0019)
KZIndex	-0.0001 (0.00001)	0.00004** (0.00001)	0.00001 (0.00002)	0.00004** (0.00001)	-0.00001 (0.00002)	0.00001 (0.00002)
CGIndex	0.0001 (0.0001)	0.0005*** (0.0001)	0.0001* (0.0001)	0.0005*** (0.0001)	0.0002** (0.0001)	0.0005*** (0.0001)
MktShare	-0.1586 (0.4175)	0.2363 (0.4321)	0.3803 (0.4182)	0.2093 (0.4258)	0.7491* (0.4055)	0.5746 (0.4180)
HHI	0.7011 (1.1852)	-0.2287 (1.2268)	-0.6359 (1.1873)	-0.4358 (1.2089)	-1.5059 (1.1512)	-0.9356 (1.1867)
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	14,996	14,995	14,996	14,995	14,996	14,995
R^2	0.61	0.49	0.59	0.48	0.60	0.48

long-term innovation outcomes.

In table 4, we report both the OLS and 2SLS regression results to discuss the effect of analyst coverage on firm's acquisition. The results show that firms followed by more analysts are more likely to acquire targets and to increase their number of target firms in

Table 4. Number of Analyst and Acquisition

This table shows OLS (panel A) and 2SLS (Panel B) estimation results of the effect of analysts (*lnCoverage*). The dependent variables are: a dummy variable equal to one if a firm acquires one or more targets and zero otherwise (*Acq*) in column (1) and (2); and the natural log of one plus the number of targets (*lnAcq*) in column (3) and (4). In Panel B, column (1) to (4) shows the result from the second-stage of the two dependent variables, respectively. Control variables include *Size, RDRatio, Age, Leverage, Cash, ROE, PPE, CAPEX, InstOwn, Q, KZIndex, CGIndex, MktShare* and *HHI*. Standard errors are in parentheses, and ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All variable definitions are in appendix.

Panel A: OLS

Dependent	*Acq*		*lnAcq*	
	(1) $t + 1$	(2) $t + 2$	(3) $t + 1$	(4) $t + 2$
lnCoverage	0.000002 (0.0005)	0.0010* (0.0006)	0.0001 (0.0004)	0.0008* (0.0004)
Control Variable	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
No. of obser	12,985	11,002	12,985	11,002
R^2	0.18	0.20	0.19	0.20

Panel B: IV 2SLS

Dependent	Second-Stage			
	Acq		*lnAcq*	
	(1) $t + 1$	(2) $t + 2$	(3) $t + 1$	(4) $t + 2$
$\widehat{lnCoverage}$	0.0035*** (0.0012)	0.0005 (0.0014)	0.0024*** (0.0009)	0.0003 (0.0010)
Size	-0.0095** (0.0043)	-0.0061 (0.0052)	-0.0076** (0.0031)	-0.0052 (0.0038)
RDratio	-0.0773 (0.0663)	0.0243 (0.0761)	-0.0594 (0.0481)	0.0121 (0.0554)
Age	0.0045 (0.0037)	-0.0015 (0.0039)	0.0034 (0.0027)	-0.0010 (0.0028)
Leverage	0.0094 (0.0094)	0.0080 (0.0108)	0.0084 (0.0069)	0.0062 (0.0079)
Cash	0.0655*** (0.0168)	0.0213 (0.0198)	0.0457*** (0.0122)	0.0111 (0.0144)

Table 4. (continued)

Dependent	Second-Stage			
	Acq		*lnAcq*	
	(1) *t* + 1	(2) *t* + 2	(3) *t* + 1	(4) *t* + 2
ROE	-0.0026 (0.0072)	-0.0166** (0.0081)	-0.0015 (0.0052)	-0.0122** (0.0059)
PPE	0.0270 (0.0170)	0.0398* (0.0207)	0.0188 (0.0124)	0.0309** (0.0151)
CAPEX	-0.0317*** (0.0103)	0.0129 (0.0113)	-0.0231*** (0.0075)	0.0093 (0.0082)
InstOwn	0.00005 (0.0002)	0.0003 (0.0002)	0.0001 (0.0001)	0.0003 (0.0002)
Q	0.0032* (0.0018)	0.0041** (0.0021)	0.0029** (0.0013)	0.0031** (0.0015)
KZIndex	0.00001 (0.0001)	0.00002 (0.0001)	0.00001 (0.00001)	0.00001 (0.00001)
CGIndex	-0.0002** (0.0001)	-0.0002** (0.0001)	-0.0001*** (0.00005)	-0.0001** (0.0001)
MktShare	-1.2580*** (0.3842)	0.2809 (0.4347)	-0.8964*** (0.2791)	0.1252 (0.3168)
HHI	3.2227*** (1.0543)	-0.5515 (1.1400)	2.3194*** (0.7660)	-0.2282 (0.8307)
Year Fixed	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	Yes	Yes
No. of Obs	12,985	11,002	12,985	11,002
R^2	0.19	0.20	0.19	0.20

two years forward in panel A; In panel B, the results is same except that the likelihood of acquisition and the number of target firms are higher in one year forward. Overall, both results indicate that analyst coverage makes firm acquire other targets, and that the number of acquisition increases. This is consistent to the case in U.S., since analyst coverage increases acquisition as well. What differs from U.S. is that their exists only one-year-forward effect on acquisition in Korea. As for control variables, small firms and firms with more cash and more growth opportunities are more likely to

Table 5. Number of Analysts and Acquisition Innovativeness

This table shows the 2SLS regressions for the effect of analyst coverage on the acquisition of innovative target firms. The dependent variables are: the natural log of one plus the total number of patents on average of all target firms when they are acquired (*lnTargPatent*) in column (1) and (2); and the natural log of one plus the total number of granted patents of all targets up to the acquisition (*lnTargGrant*) period in column (3) and (4). Control variables include *Size, RDRatio, Age, Leverage, Cash, ROE, PPE, CAPEX, InstOwn, Q, KZIndex, CGIndex, MktShare* and *HHI*. Standard errors are in parentheses, and ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All variable definitions are in appendix.

Dependent	*lnTargPatent*		*lnTargGrant*	
	(1) $t + 1$	(2) $t + 2$	(3) $t + 1$	(4) $t + 2$
$\widehat{lnCoverage}$	0.1336*** (0.0390)	0.0238 (0.0401)	0.1214*** (0.0367)	0.0252 (0.0380)
Control Variable	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
No. of obs	787	633	787	633
R^2	0.24	0.19	0.26	0.20

acquire other firms. The fact that smaller firms with higher growth opportunities are more likely to engage in acquisitions implies that external growth strategies including M&As may help recent start-ups to innovate much faster. The negative coefficient of *ROE* and *CGindex* indicate that firms with low profitability and bad governance pursue more acquisition. For those firms, acquisition may not be out of their innovation strategy but for their growth, which necessitates the analysis of the analyst effect on innovative acquisitions as in table 5.

Table 5 shows the evidence that analyst coverage encourages firms not only to invest more in acquisition but also to acquire more innovative targets. The innovativeness of target firms is measured by the number of patents and granted patents of targets. If acquisitions are part of firms' growth strategy, there should be either insignificant or negative effect on the patents generated by targets. Since the number of firm-year observation reduced, we apply industry fixed effects instead. The positive and significant coefficient of instrumented *lnCoverage* indicates that financial analysts help firms to acquire more innovative firms, which can be seen in U.S. as well. What differs from U.S. is that the effect in Korea is short-term, since the relevant effect sustains for two years in U.S.

Overall, our main findings imply that analysts discourage R&D and CVC investment while their coverage encourages acquisitions. That is, the pressure effect dominates in R&D and CVC channel, whereas information effect exists in acquisitions.

Cross-sectional Variation and Robustness Test

In this section, we conduct several cross-sectional and robustness tests to further support the effect of analyst on firm innovations. In table 6, we split the sample into firms with group-affiliation, high-tech firms, and firms with good corporate governance. Following the standard of Fair Trade Commision (FTC) in Korea, we define group-affiliated analysts as analysts in a group-affiliated brokerage. In terms of industry classification, we follow the OECD standard (2011), and divide the firm according to their KSIC codes of which the code 20, 21, 26-31, 35, 49, 61, 62, 70, 86 belong to high-tech industries. Corporate governance is based on *CGIndex*, and higher *CGIndex* indicates firms with good governance.

Panel A reports the effect of group-affiliated analyst coverage (*GA*) on innovation strategies by group-affiliated firms. For instance, LG electronics followed by analysts working for Samsung securities belongs to this category. It shows that the estimate from group-affiliated analysts have pressure effects on acquisition. Based on previous studies, the positive bias in group-affiliated analysts may have higher pressure effect on firms, so that those firms have higher incentive to cut expenses related to acquisition.

Panel B is the result for group-affiliated analyst coverage following a firm in the same business group (*SameGA*). Identical group affiliation requires the covered firm and coverage brokerage to be from the same business groups. For instance, Samsung Electronics followed by a financial analyst in Samsung Securities belongs to this category. It shows that the identical group affiliation leads to pressure on managers to cut acquisition, which further supports the pressure effect resulting from the positive bias of group-affiliated analysts. This is consistent to previous findings (Lim and Kim 2019), which finds that markets react to an optimistic bias in group-affiliated analysts. The reason why we do not see any difference between the effects of *GA* and *SameGA* is that same-group affiliated analysts tend to give positive opinion on their peer group firms but their estimates do not differ much from GA's estimates. Some might wonder whether the analyses in panel A and B are limited to a selected group of companies and industries, since group-affiliated brokerage houses are mostly found for larger group-affiliated companies. That is, young start-ups do not have affiliated brokerage houses, which necessitates the analysis on comparing analysts' effects on firm innovation for traditional companies and more recent start-ups as in panel C. Panel B also shows that the analyst coverage from identically group-affiliated brokerage leads to higher CVC investment for mid-stage start-ups at 10% significance level. This may due to managers' incentive to compensate for the reduction in acquisition. In this case, there exists indirect substitution effect between CVC and acquisition, which we investigate later in table 7.

To distinguish analysts' influence on firm innovation for traditional companies and more recent start-ups, panel C shows the result for the impact of analyst coverage on recent start-ups' innovation. It turns out that as the amount of analyst coverage firms obtained increases, R&D investment decreases, supporting the pressure effect. However, recent start-ups' managers increase their investment in both acquisition and innovative acquisitions. That is, analyst coverage to some extent helps recent start-ups' innovation, since it increases managers' (innovative) acquisition efforts.

Estimates in panel D show that firms in the high-tech industries tend to invest more in CVCs when more financial analysts follow those firms. Given that most of innovation occurs in high-tech industries, it is reasonable that financial analysts motivate innovation strategy of firms in high-tech industries. The results from panel D imply that analyst coverage increases information transparency, thereby motivates managers to increase their investment in CVC, supporting the information effect to some extent. This is consistent to the case in U.S, since analyst coverage increases CVC investment in high-tech industries as well. What differs from U.S. is that U.S. firms in high-tech industries reduce R&D but increases acquisition as well as CVC investment. Moreover, by comparing the result from panel A, B and D, it turns out that high-tech firms are more likely to cut R&D and utilize CVC while traditional family-owned companies

Table 6. Split Sample Analysis

This table reports the 2SLS regression on the effect of financial analysts on one-year forward innovation by splitting the sample. In panel A, we define group affiliated analysts(*GA*) as analysts working for a group-affiliated brokerage estimating group-affiliated firms, based on Fair Trade Commision (FTC); In panel B, we define same group affiliated analysts(*SameGA*) as analysts working for a group-affiliated brokerage estimating firms in the same business groups; in Panel C, we define recent start-ups (*Startup*) as firms with age no older than 10 years, following Hellmann and Puri (2002); in Panel D, we split the sample in high-tech industries (*HT*), following industry classification of OECD (2011); in panel E, we split the sample by the mean value based on *CGIndex* (*GoodGov*). In all regressions, we include control variables which are *Size, RDRatio, Age, Leverage, Cash, ROE, PPE, CAPEX, InstOwn, Q, KZIndex, CGIndex, MktShare* and *HHI*, and firm and year fixed effects. Standard errors are in parentheses. ***, **, and * shows significance at the 1%, 5%, and 10%, respectively. All variable definitions are in appendix.

Panel A: Group Affiliated Analysts (*GA*)

Dep.	*RDChange*	*RDCut*	*Acq*	*lnAcq*	*lnTargPatent*	*lnTargGrant*	*CVC2*	*CVC3*
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*lnCoverage*GA*	0.0002 (0.0001)	-0.0077 (0.0067)	-0.0038** (0.0016)	-0.0027** (0.0012)	-0.0116 (0.0450)	-0.0064 (0.0471)	0.0010 (0.0018)	-0.0027 (0.0017)
No.Obs	12,976	11,004	12,985	12,985	787	787	14,996	14,996
R^2	0.14	0.38	0.19	0.19	0.24	0.26	0.59	0.60

Panel B: Group Affiliated Analysts estimating the same business groups (*SameGA*)

Dep.	*RDChange*	*RDCut*	*Acq*	*lnAcq*	*lnTargPatent*	*lnTargGrant*	*CVC2*	*CVC3*
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*lnCoverage*SameGA*	0.0001 (0.0002)	-0.0060 (0.0075)	-0.0034* (0.0018)	-0.0023* (0.0013)	-0.0569 (0.0513)	-0.0468. (0.0483)	0.0032* (0.0019)	-0.0028 (0.0018)
No.Obs	12,976	11,004	12,985	12,985	787	787	14,996	14,996
R^2	0.14	0.38	0.19	0.19	0.24	0.26	0.59	0.60

Table 6. (continued)

Panel C: Recent start-ups (*Startup*)

Dep.	*RDChange*	*RDCut*	*Acq*	*lnAcq*	*lnTargPatent*	*lnTargGrant*	*CVC2*	*CVC3*
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*lnCoverage*Startup*	-0.0003** (0.0001)	0.0023 (0.0060)	0.0041** (0.0018)	0.0027** (0.0013)	0.1316*** (0.0482)	0.1249*** (0.0456)	-0.0025 (0.0024)	-0.0006 (0.0023)
No.Obs	12,976	11,004	12,985	12,985	787	787	14,996	14,996
R^2	0.14	0.38	0.19	0.19	0.24	0.26	0.59	0.60

Panel D: High-tech (*HT*) industries

Dep.	*RDChange*	*RDCut*	*Acq*	*lnAcq*	*lnTargPatent*	*lnTargGrant*	*CVC2*	*CVC3*
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*lnCoverage*HT*	-0.00001 (0.00004)	-0.0036* (0.0021)	0.0005 (0.0001)	0.0002 (0.0004)	0.0296 (0.0323)	0.0346 (0.0304)	0.0024*** (0.0007)	0.0016** (0.0007)
No.Obs	12,976	11,004	12,985	12,985	787	787	14,996	14,996
R^2	0.01	0.08	0.01	0.01	0.27	0.29	0.16	0.16

Panel E: Good Corporate Governance (*GoodGov*)

Dep.	*RDChange*	*RDCut*	*Acq*	*lnAcq*	*lnTargPatent*	*lnTargGrant*	*CVC2*	*CVC3*
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*lnCoverage*GoodGov*	0.00003 (0.0001)	-0.0017 (0.0056)	-0.0051*** (0.0013)	-0.0042*** (0.0009)	-0.0546 (0.0346)	-0.0257 (0.0325)	-0.0109*** (0.0008)	-0.0121*** (0.0008)
No.Obs	12,976	11,004	12,985	12,985	787	787	14,996	14,996
R^2	0.14	0.38	0.19	0.20	0.25	0.27	0.17	0.17

are more likely to cut acquisitions. It implies that traditional family-owned business groups and more recent start-ups are different in their efforts to innovate.

Finally, in panel E of table 6, the result for corporate governance shows that firms with higher *CGIndex*, or firms with good governance decrease acquisition and CVC investment. An explanation is that market participants tend to be positively surprised by the actual earnings of good-governance firms (Bebchuk, Cohen and Wang 2013), which makes managers get higher pressure from financial analysts to meet the targets. As a result, managers decide to cut their acquisition and CVC investment. At the same time, the result shows that the effect of analyst coverage on external innovation is positively significant for poorly governed firms. That is, firms with poor corporate governance tend to suffer from information asymmetry, so analyst coverage, to some extent, compensate for the lack of governance in these firms (Guo, Pérez-Castrillo and Toldrà-Simats 2019). This is different from the case in U.S., since U.S. firms with good governance increases acquisition when they are followed by financial analysts.

In table 7, we estimate the two effects by including an interaction term of *lnCoverage* and reduced investment, which are R&D and CVCs, following equation (7). As mentioned, the interaction term captures the indirect effect and the coefficient of *lnCoverage* represents the direct counterpart. Panel A.1 and A.2 reports the direct and indirect effects of analyst on acquisition and innovative acquisitions, respectively. It shows that the number of analysts hold a positive effect on the acquisition decision and on the number of firms acquired as well as the innovative acquisitions, which implies that firms' increased acquisition is due to analysts' informational role. The coefficient of the interaction terms is not significant in two panels, consistent to the case in U.S.

Finally, Panel B.1 shows that financial analysts both have direct effect on acquisition and the number of firms acquired. However, the coefficient of interaction term indicates that the indirect effect from cutting CVC investment is also significant. This is different from the case in U.S., since there exists only a direct influence of analyst coverage and no indirect effect due to the decrease in CVCs in U.S. The possible explanation is that firms reduce innovation after cutting their CVC investment because those firms are less able to leverage to do acquisitions. However, the larger coefficient

Table 7. Direct Versus Indirect Effect

This table reports the 2SLS estimation results of the effect of interaction between analyst coverage and R&D Cut (Panel A.1 and Panel A.2) as well as CVC investment for mid-age start-ups (*CVC*2, Panel B). Panel A.1 is the effect on acquisitions and panel A.2 is on innovative acquisitions. Dependent variables are: a dummy variable (*Acq*) equal to one if a firm acquires one or more targets and zero otherwise in column (1) and (2); and the natural log of one plus the number of targets (*lnAcq*) in column (3) and (4) for panel A.1 and B.1; the natural log of one plus the total number of patents on average of all target firms (*lnTargPatent*) when they are acquired in column (1) and (2); and the natural log of one plus the total number of granted patents of all targets (*lnTargGrant*) up to the acquisition period in column (3) and (4) for panel A.2. and B.2. In all regressions, we include control variables which are *Size, RDRatio, Age, Leverage, Cash, ROE, PPE, CAPEX, InstOwn, Q, KZIndex, CGIndex, MktShare* and *HHI,* and firm and year fixed effects. Standard errors are in parentheses, and ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All variable definitions are in appendix.

Panel A.1: R&D and acquisitions

Dependent	*Acq*		*lnAcq*	
	(1) $t+1$	(2) $t+2$	(3) $t+1$	(4) $t+2$
$\widehat{lnCoverage}$	0.0036*** (0.0013)	0.0003 (0.0014)	0.0024** (0.0009)	0.0002 (0.0010)
RDCut	0.0004 (0.0089)	-0.0066 (0.0094)	-0.0003 (0.0064)	-0.0017 (0.0068)
$\widehat{lnCoverage}$**RDCut*	0.0005 (0.0007)	0.0008 (0.0007)	0.0004 (0.0005)	0.0003 (0.0005)
No. of Obs	11,004	11,002	11,004	11,002
R^2	0.22	0.20	0.23	0.20

Panel A.2: R&D and innovative acquisitions

Dependent	*lnTargPatent*		*lnTargGrant*	
	(1) $t+1$	(2) $t+2$	(3) $t+1$	(4) $t+2$
$\widehat{lnCoverage}$	0.1877*** (0.0448)	0.0314 (0.0410)	0.1670*** (0.0427)	0.0313 (0.0388)
RDcut	0.5350 (0.4607)	0.3084 (0.4392)	0.3218 (0.4392)	0.2564 (0.4156)
$\widehat{lnCoverage}$**RDCut*	-0.0227 (0.0385)	-0.0313 (0.0356)	-0.0150 (0.0367)	-0.0254 (0.0337)
No. of Obs	665	633	665	633
R^2	0.28	0.19	0.28	0.20

Table 7. (continued)

Panel B.1: CVC and acquisitions

Dependent	*Acq*		*lnAcq*	
	(1) $t+1$	(2) $t+2$	(3) $t+1$	(4) $t+2$
$\widehat{lnCoverage}$	0.0034*** (0.0012)	0.0008 (0.0014)	0.0024*** (0.0009)	0.0005 (0.0010)
CVC2	0.0012 (0.0163)	0.0212 (0.0198)	0.0009 (0.0118)	0.0145 (0.0145)
$\widehat{lnCoverage}*CVC2$	0.0013 (0.0021)	-0.0042* (0.0025)	0.0008 (0.0015)	-0.0029 (0.0018)
No. of Obs	12,985	11,002	12,985	11,002
R^2	0.19	0.20	0.19	0.20

Panel B.2: CVC and innovative acquisition

Dependent	*lnTargPatent*		*lnTargGrant*	
	(1) $t+1$	(2) $t+2$	(3) $t+1$	(4) $t+2$
$\widehat{lnCoverage}$	0.1377*** (0.0391)	0.0271 (0.0402)	0.1241*** (0.0369)	0.0273 (0.0381)
CVC2	0.1088 (0.6918)	0.4278 (0.7746)	-0.0962 (0.6517)	0.3094 (0.7338)
$\widehat{lnCoverage}*CVC2$	0.0446 (0.0941)	0.0201 (0.0963)	0.0468 (0.0886)	0.0076 (0.0912)
No. of Obs	787	633	787	633
R^2	0.24	0.19	0.26	0.20

of *lnCoverage* than that of interaction term implies that the direct effect from analyst coverage dominates in acquisition, consistent to previous studies (Guo, Pérez-Castrillo and Toldrà-Simats 2019). Panel B.2 shows that the positive effect of analyst coverage on innovative acquisition is only attributable to a direct effect of financial analysts.

Table 7 above shows that the result from pressure effect on CVC investment is mixed, given that both direct information and indirect pressure effect exist in the investment. Firms cutting R&D and CVC investment may see the decrease in innovation output. However, as seen in subsample analysis, analyst coverage provides firms with reallocating their resources, since the firm may cut inefficient innovation investment. Moreover, if CVC investment is for the sake of their growth, the final innovation outcome should not be unaffected. In order to investigate the final outcome from the reduction in the two strategies, table 8 shows the possible consequences of firms' adjustment on three innovation strategies, following the equation (8).

According to panel A in table 8, three-year-forward number of patents by a firm in the sample is affected by analyst coverage. Except for CVCs, the differential effect of R&D cut and acquisition is unrelated to their innovation, meaning that some firms acquire other firms out of their growth and that cut down their R&D expenses to save their businesses. Moreover, when we include the interaction term between acquisition and analyst coverage, the negative partial effect from acquisition is absorbed. However, the effect of three innovation strategies when firms are followed by financial analysts is significantly negative, which is different from U.S. Note that the effect of analyst coverage remains to be significantly negative. It means that the negative effect from the pressure of analysts persists even when we take innovation strategies of firms followed by analyst coverage into account.

Panel B shows similar results for granted patents. The coefficient for interaction term implies that the differential effect of firms' external strategies on the innovation outcome for firms followed by analysts are negative. Moreover, the effect of analyst coverage on granted patents remains to be negative, even when three innovation channels are taken into account. Those results in panel A and B are different from the case in U.S., since negative effect of financial analysts on patents turns out to be insignificant when interaction term between U.S. firms' three innovation strategies and analyst coverage are included. Overall, it supports our argument that the reduction in innovation channels *negatively affects* the final innovation outcomes.

In table 9, we apply another measure of analyst pressure, *EPSD*, which is the difference between the actual EPS and the estimated counterparts, divided by stock price, to support our argument that the pressure effect exists. Although this measure is better estimation for the pressure effect (Guo, Pérez-Castrillo and Toldrà-Simats 2019), the difference between the actual EPS and the estimates are widely dispersed and this is why we do not use it as our main variable. Moreover, we believe that (expected) analyst

Table 8. Number of Analysts, Innovation Strategies, and Innovation Outputs

This table reports the 2SLS regression results on the effect of analyst coverage interacted with the three innovation channels on future innovation outcomes: RD Cut, acquisition and CVCs for mid-age start-ups (*CVC2*). In column (2) to (4), we include interaction term between analyst coverage and R&D, acquisition and CVC, respectively. The dependent variables are: the natural log of one plus the number of three-year-forward patents (*lnPatents*) and granted patents by firms in the sample (*lnGranted*), respectively. In all regressions, we include control variables which are *Size, RDRatio, Age, Leverage, Cash, ROE, PPE, CAPEX, InstOwn, Q, KZIndex, CGIndex, MktShare* and *HHI,* and firm and year fixed effects. Standard errors are in parentheses. ***, ** and * indicate the significance level of 1%, 5% and 10%, respectively. All variable definitions are in appendix.

Panel A: Patents

Dependent	*lnPatents* (*t* + 3)			
	(1)	(2)	(3)	(4)
$ln\widehat{Coverage}$	-0.1114*** (0.0153)	-0.1075*** (0.0154)	-0.1072*** (0.0153)	-0.1034*** (0.0155)
RDCut	-0.0715** (0.0337)	0.1203 (0.1051)	-0.0706** (0.0336)	-0.0731** (0.0336)
Acq	-0.2366* (0.1257)	-0.2323* (0.1257)	1.0433*** (0.3196)	-0.2267* (0.1256)
CVC2	-0.1496 (0.1212)	-0.1535 (0.1212)	-0.1517 (0.1211)	0.5412** (0.2351)
$ln\widehat{Coverage}$*RDCut*		-0.0160* (0.0083)		
$ln\widehat{Coverage}$*Acq*			-0.0920*** (0.0211)	
$ln\widehat{Coverage}$*CVC2*				-0.0972*** (0.0284)
Control variables	yes	yes	yes	Yes
Year Fixed Effect	yes	yes	yes	yes
Firm Fixed	yes	yes	yes	yes
No. Obs	9,058	9,058	9,058	9,058
R^2	0.49	0.49	0.50	0.49

Table 8. (continued)

Panel B: Granted Patents

Dependent	*lnGranted* (*t* + 3)			
	(1)	(2)	(3)	(4)
$ln\widehat{Coverage}$	-0.1051*** (0.0144)	-0.1003*** (0.0145)	-0.1022*** (0.0144)	-0.0974*** (0.0145)
RDCut	-0.0450 (0.0315)	0.1903* (0.0985)	-0.0443 (0.0315)	-0.0465 (0.0315)
Acq	-0.2627** (0.1177)	-0.2574** (0.1177)	0.6321** (0.2997)	-0.2533** (0.1177)
*CVC*2	-0.1049 (0.1136)	-0.1097 (0.1135)	-0.1064 (0.1135)	0.5502** (0.2203)
$ln\widehat{Coverage}*RDCut$		-0.0196** (0.0078)		
$ln\widehat{Coverage}*Acq$			-0.0643*** (0.0198)	
$ln\widehat{Coverage}*CVC2$				-0.0922*** (0.0266)
Control variables	yes	yes	yes	Yes
Year Fixed Effect	yes	yes	yes	Yes
Firm Fixed	yes	yes	yes	Yes
No. Obs	9,058	9,058	9,058	9,058
R^2	0.49	0.49	0.49	0.49

coverage is more legitimate measure for analyzing both pressure and information effect, since analyst forecasts for EPS in emerging countries are generally biased towards overstatement (Jaggi and Jain 1998). Since we are interested in both the pressure and the information effect, we believe that analyst coverage is more unbiased measure for this study. Panel A.1 and panel B.1 reports the results of the equation (9), and panel A.2 and B.2 represents the estimation from the equation (10). Panel A.1 indicates that meeting the estimated EPS (I_{meet}) increases the likelihood of cutting R&D expenditure, similar to the case in U.S. However, note that the pressure effect is short-term phenomenon, since column (3) and (6) of panel A.1, turns out to be significantly positive, which differs from the case in U.S. On the other hand, the result from CVC investment turns out to be insignificant, meaning that the pressure effect on CVC investment is

Table 9. The Effect of EPSD

This table reports the effect of the difference between actual EPS and EPS estimates (*EPSD)* on firm's R&D (Panel A.1) and that on long-term output (Panel A.2); Panel B.1 is the EPSD effect on CVCs for mid- and final-stage start-ups (*CVC*2 and *CVC*3) and Panel B.2 is for their long-term outcomes. Panel A.1 and B.1 is from the OLS estimation of the effect of the indicator variable equal to one if a firm meets EPS forecast and zero otherwise (I_{Meet}), and *EPSD*. The dependent variables are: the change in R&D (*RDChange*) in column (1) to (3); and the dummy equal to one if a firm reduces its R&D ratio and zero otherwise (*RDCut*) in column (4) to (6). For panel A.2 and B.2, the dependent variables are: the natural log of one plus the number of three-year-forward patents (*lnPatent*, column (1)) and granted ones (*lnGranted*, column (2)). In all regressions, we include control variables which are *Size, RDRatio, Age, Leverage, Cash, ROE, PPE, CAPEX, InstOwn, Q, KZIndex, CGIndex, MktShare* and *HHI,* and firm and year fixed effects. Standard errors are in parentheses. ***, ** and * indicate the significance level of 1%, 5% and 10%, respectively. Variable definitions are in appendix.

Panel A.1: EPSD and R&D

Dependent	RDChange			RDCut		
	(1) t	(2) t	(3) $t+1$	(4) t	(5) t	(6) $t+1$
I_{Meet}	-0.0004 (0.0003)	-0.0004 (0.0003)	0.0004* (0.0002)	0.0275*** (0.0096)	0.0269*** (0.0096)	-0.0296** (0.0115)
EPSD	0.00001 (0.00005)	-0.00007 (0.0001)	-0.00005 (0.0001)	0.0015 (0.0018)	0.0064 (0.0045)	-0.0087* (0.0052)
EPSDpolynomial	1-order	2-order	2-order	1-order	2-order	2-order
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes	Yes	Yes	Yes
No.Obs	13,353	13,353	11,403	13,353	13,353	9,540
R^2	0.14	0.14	0.14	0.36	0.36	0.40

relatively weak.

Panel A.2 and panel B.2 is the result for the effect of cutting R&D and CVC investment on innovation outcomes, respectively. Following Guo, Pérez-Castrillo and Toldrà-Simats (2019), we use the indicator variable (I_{meet}) to instrument R&D cut and CVC investment, and report the result from the second-stage regression. Both panels indicate that a decrease in R&D and CVC investment does not

Table 9. (continued)

Panel A.2: EPSD, R&D investment, and patents

Dependent	*lnPatent*	*lnGranted*
	(1) *t* + 3	(2) *t* + 3
$\widehat{RDCut}$	-1.4019 (1.5177)	-0.8599 (1.4300)
Control variable	Yes	Yes
Year fixed	Yes	Yes
Firm Fixed	Yes	Yes
No.Obs	7,747	7,747
R^2	0.50	0.49

Panel B.1: EPSD and CVC investment

Dependent	*CVC2*			*CVC3*		
	(1) *t*	(2) *t*	(3) *t* + 1	(4) *t*	(5) *t*	(6) *t* + 1
I_{Meet}	0.0027 (0.0032)	0.0029 (0.0032)	-0.0028 (0.0034)	-0.0048 (0.0030)	-0.0047 (0.0030)	0.0021 (0.0033)
EPSD	-0.0005 (0.0006)	-0.0027* (0.0015)	-0.0010 (0.0016)	-0.0001 (0.0006)	-0.0002 (0.0014)	0.0003 (0.0015)
EPSDpolynomial	1-order	2-order	2-order	1-order	2-order	2-order
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	Yes	Yes	Yes	Yes
No.Obs	13,353	13,353	13,352	13,353	13,353	13,352
R^2	0.70	0.70	0.59	0.72	0.72	0.60

Panel B.2: EPSD, CVC investment, and patents

Dependent	*lnPatent*	*lnGranted*
	(1) *t* + 3	(2) *t* + 3
$\widehat{CVC2}$	-178.7367 (193.5118)	-109.6357 (182.3279)
Control variable	Yes	Yes
Year Fixed	Yes	Yes
Firm Fixed	Yes	Yes
No.Obs	7,747	7,747
R^2	0.50	0.49

increase the innovation outcomes, further supporting our previous argument that the pressure effect on managers to cut the two channels persists. This is consistent to the case in U.S., since the reduction in R&D does not affect innovation output of U.S. firms either.

CONCLUSION

This paper relates to the growing body of literature to address how financial markets influence efforts and outcomes of innovation by firms. Among factors that affects corporate long-term innovation, there are conflicting views regarding the information effect and the pressure effect of financial analysts. Specifically, analysts release reliable information to the market, managers have stronger incentive to pursue innovative projects, whereas the short-term pressure to meet the estimated EPS makes them cut the long-term expense such as R&Ds. This paper adds on this literature by examining the effect of analyst on firms in emerging markets where firms face higher uncertainties to take innovative long-term strategies and large conglomerates hold higher comparative advantage to undertake innovations as well as successful start-ups that grows into innovative giants.

Using publicly traded non-financial Korean firms in 2010-2018, we establish the following patterns: analysts put pressure on firms' R&D and CVC investments; analyst coverage encourages a firm to undertake acquisitions as well as acquiring innovative targets. In appendix 2, we provide a table summarizing our findings with Korean data against those with U.S. counterparts. The former result out of the pressure effect of analyst coverage is more pronounced when group-affiliated firms are followed by analysts from group-affiliated brokerage. We further examine if increased acquisitions are due to the direct effect from analysts, and find that the substitution out of the decrease in CVC investment exists unlike the case in U.S. Moreover, innovation outcomes, as measured in three-year-forward number of patents, are negatively affected by the decrease in R&D and CVC investment, even when we take the analyst effect on the two strategies into account. Additionally, we apply another measure, *EPSD* instead and show the evidence that the pressure effect exists in the R&D cut. That is, R&D change and R&D cut out of the alternative coverage measure turns out to be negative and positive, respectively. Additionally, the pressure effect on both CVC and R&D investment *even decrease* the long-term outcomes, meaning that the pressure effect is stronger in Korean market.

Overall, our findings support the argument that analyst coverage is a disciplinary tool against managers to reallocate long-term expenses. Even if financial analysts increase firms' acquisition activity, the increase results from indirect substitution of the decrease in R&D. What is unique about Korean firms is that the uncertainty faced by firms on CVC investment makes managers to cut the external innovation out of the pressure they get from the analyst coverage. Moreover, the chaebol structure provides analysts with extra incentive to increase their estimates on their affiliated companies, thereby increasing the pressure effect on managers to decrease acquisitions. We believe that these findings are not restricted to Korean market, since its market structure and group-affiliation can be seen in many emerging economies. The contribution of this paper is that firms in emerging market that higher difficulties in undertaking long-term innovation efforts faced by those markets may result in the pressure effect of analyst coverage; the positive bias in group-affiliated analysts hold higher impact on firms' decision to innovate; higher uncertainties associated external innovation such as CVC investment can be either substituted via increased acquisition or out of the pressure effect from financial analysts.

Nevertheless, our findings do not necessarily deny the information effect and subsequent impact on innovation outcomes. As shown in the sub-sample analysis, the information effect exists in firms from high-tech industries. Given that the indirect effect on acquisition from substituting the decrease in CVC investment exists, the final outcome depends on whether parent firms' innovation recovers when they reduce or terminate CVCs (Ma 2020). Rather, this paper highlights the fact that the short-term analysts' forecasts can have an impact on firm's long-term decision. Moreover, the benefit cannot be only measured at the firm level, given that the technological development benefits not only a firm, but also the spillover benefits other participants in the industry and their subsequent innovation efforts, which we leave for future research.

APPENDIX A

Variable Definitions

This table describes the definitions for all variables used on the sample of Korean public firms from 2010 to 2018. Variable constructions are based on Guo, Pérez-Castrillo and Toldrà-Simats (2019).

Variable	Definition
RDChange	The difference between R&D expense / total assets at time t and that at time $t-1$
RDCut	Dummy variable equals to one if the R&D / total asset at time t is lower than that at time $t-1$, and zero otherwise
Acq	Dummy variable that equals one if a firm acquires one or more targets in a given year, and zero otherwise
lnAcq	Natural log of one plus the number of target firms acquired in a given year
*CVC*1	Dummy variable that equals one when a firm invests in a CVC fund whose portfolio start-up with the largest weight is less than three years old and zero otherwise.
*CVC*2	Dummy variable that equals one when a firm invests in a CVC fund whose portfolio start-up with the largest weight is at least three but less than seven years old and zero otherwise
*CVC*3	Dummy variable that equals one when a firm invests in a CVC fund whose portfolio start-up with the largest weight is at least seven years old and zero otherwise
lnTargPatent	Natural log of one plus the total number of patents of all target firms
lnTargGrant	Natural log of one plus the total number of granted patents of all target firms
lnPatents	Natural log of one plus the number of annual patents of a firm
lnGranted	Natural log of one plus the number of annual granted patents of a firm
lnCoverage	Natural log of one plus the annual average number of earnings estimates from financial analysts
EPSD	The difference between the actual EPS and EPS forecast / stock price
Size	Natural log of total assets
RDratio	R&D expense / total assets
Age	The number of years since a firm first appears in DataguidePro

Variable	Definition
Leverage	Total debt / total assets
Cash	Cash / total assets
ROE	Operating income before depreciation / total stockholders' equity
PPE	Property, plant and equipment / total assets
CAPEX	Capital expenditure / total assets
InstOwn	The combined shareholding of institutional investors for a firm as provided in TS-2000 and Data Analysis, Retrieval and Transfer System (DART) database
Q	(Market value of equity + total assets – book value of equity – deferred tax) / total assets (Guo, Pérez-Castrillo and Toldrà-Simats 2019)
KZIndex	-1.002 * cash flow [(income before extraordinary item + depreciation) / property, plant and equipment]+ 0.283 * Tobin's Q (*Q*) + 3.139 * leverage (*Leverage*) – 39.368 * dividends [(common dividends + preferred dividends) / property, plant and equipment] – 1.315 * cash holdings [cash / property, plant and equipment] (Guo, Pérez-Castrillo and Toldrà-Simats 2019)
CGIndex	Collected and summated from Korea Corporate Governance Service (KCGS) which evaluates firms' governance practices in terms of sub-categories including protection for shareholder rights, board independence, and managerial transparency for disclosures and audit.
MktShare	Market share computed as sales divided by the sum of sales of all firms within the two-digit Korean Standard Statistical Classification (KSIC) code
HHI	Herfindahl-Hirschman index for sample firms' two-digit KSIC code, calculated as $\sum_{i=1}^{N} MktShare_i^2$, where N is the number of firms in the two-digit KSIC industry.
GA	A dummy variable set equal to one if a covered firm and an estimating analyst's brokerage belongs to a business group during a given firm-year, and zero otherwise. Business groups are identified from the list of large business groups designated by the Korea Fair Trade Commission (KFTC) every year.
SameGA	A dummy variable set equal to one if both the covered firm and the estimating analyst's brokerage belong to the same business group during a given firm-year, and zero otherwise.
HT	A dummy variable set equal to one if a firm belongs to high-tech industries, defined as firms with KSIC codes 20, 21, 26-31, 35, 49, 61, 62, 70. 86, and zero otherwise, following industry classification of OECD (2011).

Variable	Definition
Startup	A dummy variable set equal to one if a firm's age is no older than 10 years, and zero otherwise
GoodGov	A dummy variable set equal to one if a firm's corporate governance index (*CGIndex*) is higher than the sample mean value of *CGIndex*, and zero otherwise.
I_{Meet}	A dummy variable equal to one if firms meet estimated EPS and zero for firms that miss the target.

APPENDIX B

Comparison of Findings Between U.S. and Korea.

This table compares the findings based on U.S. data (Guo, Pérez-Castrillo and Toldrà-Simats 2019) to those based on Korean data. It compares the result from the increase in analyst coverage.

Innovation strategies	Sub-sample	The increase in analyst coverage results in	
		Korea	U.S (Guo, Pérez-Castrillo and Toldrà-Simats 2019)
R&D		(-)	(-)
Acquisition		(+)	(+)
Innovative Acquisition		(+)	(+)
CVC		(-)	(+)
Patents (Long-term impact)		(-)	insignificant
Sub-sample	Group-affiliated	(-)	None
	Same-Group-affiliated	(-)	None
	Early start-ups	(+)	None
	High-tech	(+)	(+)
	Good governance	(-)	(+)

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Received April 29, 2021
Revised June 10, 2021
Accepted December 1, 2021