Firms' innovation strategy under the shadow of analyst coverage*

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Abstract

We study the effect of analyst coverage on firms' innovation strategy and outcome. By considering three different channels that allow firms to innovate: internal R&D, acquisitions of other innovative firms, and investments in corporate venture capital (CVC), we are able to distinguish between the pressure and information effect of analysts. Using the data of US firms from 1990 to 2012, we find evidence that: i) an increase in financial analysts leads firms to cut R&D expenses, and ii) more analyst coverage leads firms to acquire more innovative firms and invest in CVC. We attribute the first result to the effect of analyst pressure, and the second to the informational role of analysts. We also find that more financial analysts encourage firms to make more efficient investments related to innovation, which increase their future patents and citations. Moreover, more financial analysts and reductions in R&D spending lead to less radical innovation, whereas more investment in acquisitions and CVC leads to more radical innovation. We address endogeneity with an instrumental variables approach and a difference-in-differences strategy where exogenous variation in analyst coverage comes from brokerage house mergers.

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1 Introduction

Long-term growth in profits depends significantly on firms' investment in innovation activities.[1] However, firms may not invest in innovation in an optimal way. Some distortions arise because the decisions as to whether and how to invest in innovation are not only affected by their long-term expected benefits but also by other considerations. Among the factors that may distort firms' incentives to innovate, the recent literature has highlighted the recommendations or reports issued by financial analysts.[2]

The literature has identified two distinct effects through which analyst coverage influences firms' innovation activity. The *information effect* captures the impact of analysts on the information asymmetries between managers and the market. Analysts collect firms' information and provide it to the investors, for instance, by writing reports about company activities. By reducing the information asymmetries, analyst coverage may increase a CEO's incentives to innovate as it decreases both the possibility of market undervaluation of the investments in innovation and the firm's exposure to hostile takeovers (Stein, 1988; He and Tian, 2013). The *pressure effect* is related to the potential disciplinary actions against managers when they miss the earnings forecasts periodically issued by analysts. Missing analysts' earnings forecasts is usually punished by investors, which leads managers to focus on activities that increase earnings in the short run (Bartov, Givoly, and Hayn, 2002). Since investments in innovation do not usually generate short-term income, managers who are followed by market specialists may have an incentive to cut expenses related to innovation (Hazarika, Karpo, and Nahata, 2012; He and Tian, 2013).

In this paper we contribute to our understanding of the effect of financial analysts on firm innovation by isolating the information and pressure effects of analysts in a unified framework. To do so, we study three different channels through which firms can invest in innovation, and show that the information and pressure effects affect each of these investment channels differently.[3] We provide evidence that firms followed by more analysts adjust their innovation strategy to take advantage of the information effect while at the same time trying to mitigate the pressure effect. These adjustments have non-obvious consequences for the final innovation outcome of firms.

The three innovation channels that we consider are: research and development (R&D) expenditures, acquisitions of other innovative firms, and investments in corporate venture

[1]See, for instance, the classic work by Schumpeter (1942) and Arrow (1962).

[2]He and Tian (2013), Dai, Shen, and Zhang (2015).

[3]By focusing on three different channels that lead to innovation, we advance on the previous literature that focuses on patent-based innovation output (He and Tian, 2013). In our framework, we take into account investments in innovation which may be not protected by patents but, for example, by trade secrets.

capital (CVC) funds. R&D spending is the traditional way in which firms innovate, but firms are increasingly using external channels as a way to enhance innovation beyond organic R&D growth. Firms acquire other innovative firms to appropriate knowledge from sources beyond the boundaries of the firm (Sevilir and Tian, 2014). Managers also view CVC investments as a window of opportunity to learn about the latest innovative ideas, which may be instrumental for increasing their firms' innovation productivity (Cassiman and Veugelers, 2006; Dushnitsky and Lenox, 2005). Anecdotal evidence suggests that many firms think of acquisitions as a quick way to access innovation. For instance, in 2012 Oracle shelled out \$1.92 billion for the online recruiting platform Taleo, \$300 million to acquire the social marketing platform Vitrue, and undisclosed sums in another three firms. Similarly, evidence suggests that CEOs of innovative corporations understand the importance of investing in innovation through CVC funds to remain competitive or even to increase their market share. A prominent example is Google Ventures, which currently has \$1.5 billion under management, and has invested in more than 250 companies since its inception in 2009.[4]

We argue that the aforementioned information and pressure effects of analyst coverage vary across the different activities through which a firm innovates. First, in terms of the information effect, our argument is that analysts mitigate information asymmetries between managers and investors, but their informational impact is greater on acquisitions and CVC investments than on R&D expenditures. Analysts can more easily acquire the relevant information, understand it, and interpret it, on the former type of investments before disseminating it to the market. The reason is that the information about innovative acquisitions and CVC investments is more often verifiable, quantifiable, can more easily be compared with similar investments, or can more easily be inferred from the relevant decision-makers. In contrast, R&D expenses are less transparent, non-verifiable, and their impact on innovation productivity and firm value is difficult to quantify.[5] This greater opaqueness of R&D

[4]As Roberts (2006) highlights: "Despite having legions of talented engineers who believe that they can invent anything, these companies (*Intel, Siemens, Motorola*) know that they cannot develop all the technologies they need and realize that they need to tap innovation outside their company walls. Intel and the others typically view VC investing as one of three pillars of innovation, along with internal R&D and acquisitions."

[5]We can think of several reasons. First, as argued by Aboody and Lev (2000), R&D projects are usually unique to the firms that are developing them, whereas most capital investments share common characteristics with firms in the same industry. In this sense, it is difficult for analysts to assess the productivity and value of a firm's R&D by looking at the R&D performance of other firms, whereas the characteristics and the average performance of a target company (or a CVC fund) are easier to compare to other similar firms (or CVC funds). Second, under the Statement of Financial Accounting Standards No. 2 (SFAS 2), all R&D investments are expensed as incurred. This implies that i) all the projects in the R&D unit are recorded in the same expense account, and ii) the account combines different expenditures like labor costs, raw materials and equipments, depreciation and amortization of assets used in R&D activities, and the allocation of indirect costs related to R&D. Given this accounting treatment, financial analysts only observe a single line item in the income statement that aggregates all the costs of all existing R&D projects. Hence, it is very difficult for analysts to distinguish the effect of reallocations of resources across projects and

with respect to external innovation channels reduces analysts' ability to process information and provide valuable recommendations to the market. Therefore, the informational role of analysts may be stronger for external innovation activities than for R&D.

Second, in terms of the pressure effect, the short-term earnings targets set by analysts create pressure for managers because investors have a negative reaction (i.e., stock prices drop) if the earnings targets are not met. Based on Generally Accepted Accounting Principles (GAAP), all investments in R&D are expensed in the income statement, whereas acquisitions and CVC investments are usually capitalized. Thus, increased market pressure by analysts is more likely to distort investments in R&D because cutting R&D expenses immediately increases pre-tax earnings and may allow managers to achieve earnings targets.[6] In contrast, it should have a smaller impact on acquisitions or CVC because capitalized investments do not affect earnings in every accounting period.[7]

The previous arguments suggest the following hypotheses: the information effect of analyst coverage is smaller, while the pressure effect is larger for in-house R&D than for acquisitions and CVC. Since we argue that the information effect encourages innovation activities whereas the pressure effect discourages them, we expect analyst coverage to have a positive effect on external innovation and a negative effect on in-house R&D.

We measure the effects of financial analysts with the number of analysts that cover a firm. The idea is that the larger the number of analysts covering a firm, the more exposed the firm is in the stock market. The larger exposure is, for example, due to more analysts working for a larger number of brokerage houses, or publishing their reports in a larger

across accounting items. Moreover, SFAS 2 does not require periodic updates regarding the value of R&D. In contrast, the details about transactions related to investments in acquisitions or CVC are disclosed in footnotes of the balance sheet and firms are required to update changes in the value or productivity of these assets, thus making information more timely available for this type of investments. Third, analysts may ask for meetings with managers to obtain information related to innovation. However, due to the less transparent nature of activities within firms' R&D units and the conflict of interests between managers and the market, managers may give biased or partial information to analysts. Regarding the less verifiable nature of R&D activities, managers may be more able to hide the existence of foregone investment opportunities in R&D, but they may be less able to hide an acquisition that was finally withdrawn. Regarding the conflict of interests, the manager has no incentives to reveal the potential risks of R&D investments since these will have a direct impact on firm value, which affects his compensation. However, if for example a firm acquires a startup and reorganizes it by letting some of its employees go, the analysts can more easily extract relevant information from them, since their compensation no longer depends on the performance of the startup. Finally, empirical evidence also shows that, even after financial analysts provide information about firms' activities to the financial market, larger information asymmetries remain for R&D investments than for investments in capitalized assets (see, for example, Aboody and Lev, 2000; Kothari, Laguerre, and Leone, 2002; and Chan, Lakonishok, and Sougiannis, 2001).

[6] The SFAS 2 regulation in the US on R&D expenditures does not allow a delay of R&D expense recognition. This means that cutting an R&D expense today has a real consequence because the investment cannot be undertaken today.

[7] Acquisitions or CVC investments influence earnings through impairment loss. Such a loss exists if the fair value of acquired firms or CVC funds is lower than their costs, which may not happen for every accounting period.

number of different newspapers. Hence, this measure captures both the pressure effect to meet analysts' forecasts every period, and the information effect. In section 8, we run another set of tests where we measure analyst pressure more precisely, with the distance between analysts' consensus forecast and the firms' actual earnings per share (EPS).

We test the above hypotheses, taking into account the potential endogeneity in the coverage-innovation relationship. We use two identification strategies: an instrumental variables (henceforth IV) approach, and a difference-in-differences (henceforth DID) method. We find that firms with more analyst coverage significantly reduce R&D expenses. More interestingly, our results show that firms followed by more analysts are more active in the acquisition market, they acquire more innovative firms, and they invest more through their CVC funds. These results confirm our hypotheses that in terms of in-house R&D expenses the pressure effect is stronger than the information effect, whereas for the external innovation channels, the information effect seems to dominate.

We also conduct some split sample analysis to further provide intuition for our results. We split our sample according to the firms' level of corporate governance, their financial constraints, and whether firms belong to high- vs. low-technology industries. We find that our results are stronger in the subsamples of firms with poor corporate governance, more financial constraints, and in high-technology industries. These subsample results provide further support for the idea that the pressure and information effects of analysts influence innovation. First, financial analysts, by putting pressure on managers and by reducing information asymmetries, act as external governance mechanisms that compensate for the lack of governance in poorly governed firms. Second, since firms with low financial constraints are already able to invest in external innovation, it is the more financially constrained firms that benefit more from the effect of analysts. In this sense, financial analysts help firms ease their financial constraints, possibly due to their informational role. And third, that financial analysts have a stronger effect for firms in high-tech industries suggests that analyst coverage indeed influences innovation. Putting pressure on managers and providing information to the markets should be particularly useful for more innovative firms.

To better understand the nature of firms' change in innovation strategy due to analyst coverage, we study whether the increased investment in external innovation activities is due to a direct effect of analysts because of their ability to process and report information to the market, or to an indirect effect whereby firms increase external innovation to compensate for the reduction in in-house R&D (i.e., a substitution effect).[8] In the latter case, the increase in

[8]Several authors, including Dushnitsky and Lenox (2005) and Cassiman and Veugelers (2006), find complementarities between internal and external innovation activities. However, the resources a firm devotes to innovation are limited. The money devoted to one activity cannot be spent on another and, in this respect,

external innovation would be the result of analyst pressure rather than a consequence of their informational role. We find a positive direct effect of coverage on both future acquisitions and CVC, providing further support for the information effect.

Since our previous results provide evidence of both the positive and negative effects of financial analysts on firms' innovation strategy, we discuss their influence on firms' innovation outcomes. The literature finds that analyst coverage has a negative effect on firms' innovation outputs (i.e., patents and citations) when changes in internal R&D spending and external innovation channels are not taken into account (He and Tian, 2013). However, our results show that the effect of analysts turns out to be not significant when changes in firms' expenses in internal R&D and their investments in innovative acquisitions and CVC funds are taken into account. Interestingly, we find that firms that cut R&D spending when they are followed by more analysts see an increase in their future patent and citation count. Our interpretation is that analysts' pressure to meet earnings targets may lead to myopic behavior that leads to worse innovation outcomes, but it may also have a disciplining effect that induces managers to cut wasteful resources, which leads to better innovation outcomes. In our sample, the latter effect seems to dominate for firms that are followed by more than three analysts. Similarly, firms that acquire other innovative companies and engage in CVC investments when they are followed by more analysts also see an increase in future innovation. In this case, analyst following reduces information asymmetries between firms and the financial market, which encourages firms to make more efficient investments related to innovation, and this in turn increases their future patents and citations. Additionally, we study the effect of financial analysts and firms' innovation channels on the type of innovation, i.e., radical/explorative vs. incremental/exploitative. We find that analyst coverage and changes in R&D spending lead to less radical innovation. In contrast, external acquisitions and CVC investments are related to more radical innovation.

Finally, since the pressure effect of analysts stems from the managers' need to meet the analysts' earnings forecasts, we provide more detailed evidence of the pressure effect with another measure used in the literature: the distance between the earnings forecast set by analysts and the actual earnings per share (EPS) reported by firms.[9] Consistent with the pressure effect hypothesis, we find a discontinuity around the earnings pressure threshold, which is the point at which the actual and the forecasted earnings per share coincide. Specifically, firms that meet or beat analysts' benchmarks are more likely to have cut their R&D than those that miss the target. However, we find that this negative effect

internal and external innovation activities are substitutes (Dessyllas and Hughes, 2005).

[9] This measure, however, is less likely to capture the information effect, which is why we do not use it in our main analysis.

occurs only in the year in which managers are under pressure, and does not propagate in the long term. Consistent with this finding, our results show that the immediate cut in R&D spending, driven by managers' willingness to beat the current period forecasts, does not affect innovation in the long term.

The rest of this paper is organized as follows. Section 2 relates our contribution to the literature. Section 3 presents the sample and data. Sections 4 and 5 present the empirical strategy and the baseline results. Section 6 studies the direct and indirect effects of the number of analysts. Section 7 discusses the results on firms' innovation outputs. Section 8 uses the difference between the actual earnings per share reported by firms and the analysts' consensus forecasts as another measure of analyst pressure. Section 9 concludes.

2 Relation to the existing literature

Our paper contributes to several strands of literature. First, we contribute to the emerging literature on finance and innovation. There are relatively few papers that relate innovation to finance. A theoretical paper by Manso (2011) shows that the best way to motivate managers to innovate is by offering managerial contracts that tolerate failure in the short run and reward success in the long run.[10] Empirically, some papers analyze the effects of financial contracting like institutional ownership (Aghion, Van Reenen, and Zingales, 2013), corporate venture capital (Chemmanur, Loutskina, and Tian, 2014), financial derivatives (Blanco and Wehrheim, 2017), characteristics of board of directors (Balsmeier, Fleming, and Manso, 2017), or corporate tax (Mukherjee, Singh, and Žaldokas, 2017) on innovation. The closest paper to ours is a recent paper by He and Tian (2013) which shows that analyst coverage reduces firms' innovation output as measured by patents and citations. We contribute to this literature by studying the effect of analyst coverage on firms' innovation strategy, namely their choice of internal and external innovation, and the effects of these channels on the final innovation outcome.

We also add to the literature that studies the effect of financial markets on managerial myopia. Bushee (1998) finds that managers are more inclined to cut R&D expenses in response to a decrease in earnings and that this is more likely to happen when a large portion of institutional owners are non-dedicated (i.e., short-term) investors. A related paper by Yu (2008) finds, in contrast, that firms with more analysts manage their accrual-based earnings less, and recent work by Irani and Oesch (2016) suggests that managers decrease real earnings management but increase accrual manipulation when they are followed by

[10] A follow-up paper by Ferreira, Manso, and Silva (2014) suggests that privately-held firms are better able to innovate because lower transparency makes insiders more failure tolerant.

more analysts. We contribute to the earnings management literature by studying the effect of analysts on firms' decisions to cut R&D expenses and its consequence on the innovation output.

Our manuscript also contributes to the literature that studies the governance role of financial analysts. The recent paper by Chen, Harford, and Lin (2015) shows a positive monitoring role of analysts: following a decrease in coverage shareholders value internal cash holdings less, their CEOs receive higher excess compensation, and they are more likely to engage in value-destroying acquisitions.[11] A related paper by Derrien and Kecskés (2013) shows that a decrease in analyst coverage increases the cost of capital, which results in a decrease in firm investments such as acquisition expenses.[12] We relate to these papers in that we contrast the information and the pressure effects of financial analysts in the context of firms' innovation strategy and outcomes.

Our analysis is also related to Bena and Li (2014), who study whether acquisition decisions are based on the innovative output of acquirers and targets. We contribute to their line of inquiry by studying the effect of analyst coverage on firms' acquisitions of innovative target firms. Finally, our paper relates to the study by Dushnitsky and Lennox (2005) that analyzes firms' decisions to pursue equity investments in new ventures in order to adopt innovative ideas, instead of investing in internal R&D. We advance on this topic by studying the effect of financial market analysts on the internal versus external decision to innovate.

3 Sample selection, variables, and summary statistics

3.1 Sample selection

The sample used in this paper includes information on US public firms for the period 1990 to 2012. We start with all the companies in Compustat during the specified period. We exclude financial and utilities firms (SIC codes between 4000 and 4999, and between 6000 and 6999), and firms with total assets less than $10 million. For the remaining firms we retrieve financial statements information from Compustat. We then merge these companies with the information from the rest of the databases. We obtain financial analyst information from the Institutional Brokers Estimate Systems (I/B/E/S) database. We collect information on firms' acquisitions from the Securities Data Company (SDC) Mergers and Acquisitions

[11] See also Gentry and Shen (2013).

[12] Kelly and Ljungqvist (2012), Bradley, Jordan, and Ritter (2003), Irvine (2004), Chang, Dasgupta, and Hilary (2006), and Derrien and Kecskés (2013) also show that, by serving as external monitors, financial analysts have a positive effect on firms' investment and financing decisions, cost of capital, stock prices, liquidity, and valuation.

database. To determine firms' investments in CVC funds we first obtain the fund names and the names of the parent companies that have a CVC fund from the Thomson ONE private equity database. Then, we manually double-check the names of the parent firms using information from Google and the LexisNexis database as sometimes the parent companies provided in Thomson ONE are not the final corporate parent of the fund. Once we have obtained the correct names we manually merge the CVC funds information to our sample of Compustat firms. Our institutional ownership data comes from Thomson's CDA/Spectrum database (form 13F), and board characteristics come from BoardEx. Finally, we obtain patent and citation information from the National Bureau of Economic Research (NBER) Patent Citation database (Hall, Jaffe, and Trajtenberg, 2001). Since the NBER patent database only includes granted patents until 2006, this database suffers from two types of truncation problems. First, the lag between patent application and patent grants is two years on average but the variation is large. Second, recent patents have less time to accumulate citations than patents obtained in earlier years. We address these two problems by supplementing the NBER database with the Harvard Business School (HBS) patent database, which contains patents granted and citations through 2010. We use standardized assignee names corresponding to individual firms provided by the USPTO, and match them with the NBER assignee names. This process enables us to extend the information regarding the patenting activity of NBER firms until 2010.[13] To the extent that the patent application outcomes have been announced by 2010 for the patents filed by 2006, we mitigate the truncation problems by excluding observations after 2006 in the regressions that require patent or citation information. In case that extending the NBER database until 2010 does not fully account for the truncation bias especially in citation counts, we use the "time-technology class fixed effect" method (see Hall, Jaffe, and Trajtenberg, 2001, and Atanassov, 2013) in some specifications. In this method, citations (patents) are scaled by the average number of citations (patents) in the same technology class in the same year. Our final sample for the baseline regressions consists of $34,307$ firm-year observations and $3,352$ firms.

3.2 Variable measurement

3.2.1 Dependent variables: innovation strategy

We identify three main channels that firms can use to invest in innovation. First, firms can invest in R&D activities to increase the share of their earnings dedicated to innovation, or cut R&D to reduce their innovation expenses. We measure changes in R&D spending using

[13] Using the standardized names, we were able to identify about 220k additional patents of U.S. assignees granted after 2006.

the continuous variable *R&D Change*, which is the difference between R&D expenses (scaled by total assets) of the current year and the previous year,[14] as well as the dummy variable *R&D Cut,* which is equal to 1 if firms' R&D expenses (scaled by total assets) are lower in the current year than in the previous year, and 0 otherwise.[15]

Second, firms can acquire other innovative firms to obtain their innovation know-how, their innovative assets, and their patents. We measure firms' acquisition activity based on two variables. The first variable, *Acquisition,* is a dummy equal to 1 if a firm acquires one or more companies in a certain year, and 0 otherwise. To construct the second variable we take the raw number of acquisitions and set to zero the firm-year observations without available acquisitions information. We then compute the *LnAcquisitions* variable by taking the natural logarithm of one plus the number of acquisitions according to the previous explanation.

To investigate whether firms acquire other companies for innovation reasons, we use two variables that are proxies for the innovativeness of the acquired firms. We retrieve the names of the acquired firms from the SDC Mergers and Acquisitions database, and then we manually identify the acquired firms' patents and citations in the NBER patents database. We calculate the accumulated number of patents (i.e., the stock of patents) and the accumulated number of citations (i.e., the stock of citations) of the target firms each year up to the year they are acquired. The variable *LnTargPatent* (*LnTargCite*) measures the average number of accumulated patents (citations) of all target firms acquired by a firm that year. Both variables are adjusted for truncation problems as explained in section 3.1

Finally, firms can set up CVC funds to invest in startups related to their core business as a way to gain a window to the latest innovations. We define two variables that measure CVC investment. The first one, *CVC Setup,* is a dummy equal to 1 the first year in which the firm invests resources in its CVC fund, and 0 before that. Since this variable is meant to capture firms' decisions to set up a CVC fund, we put a missing value to the firm-years after the firm has made its first investment in start-ups. We also build the dummy variable *CVC Investments*, which is equal to 1 every year a CVC fund invests, and 0 otherwise. This variable captures firms' decisions to make investments in startups subsequently after their CVC fund has been set up.[16]

[14]The variable *R&D Change* is winsorized at the 1st and 99th percentiles to eliminate the effect of extreme values.

[15]We do not replace with 0 those observations with missing values in R&D expenses. This helps us overcome the fact that some firms might not report their R&D expenditures in their financial statements for strategic reasons. By omitting them, we minimize the bias in the estimated effect. Moreover, we exclude those observations with a reported R&D expense of zero in two sequential years because, by construction, it is not possible to cut R&D expenses in this case.

[16]We deliberately chose not to use the actual amount invested in CVC funds because this figure is some-

3.2.2 Dependent variables: innovation output

We measure innovation output of firms with their number of patents and citations per year. The variable *LnPatents* is the natural logarithm of (one plus) the yearly number of applied and eventually granted patents. The variable *LnCitations* corresponds to the natural logarithm of (one plus) the yearly number of citations. Both variables are adjusted for truncation problems as explained in section 3.1.

In order to study the radical vs. incremental nature of firms' innovative output, we follow Balsmeier, Fleming, and Manso (2017) and create three variables that categorise patents according to: i) their backward citations, ii) their future citations, and iii) their technology class. The first measure that we use, *LnBackCitations*, is the (natural logarithm of one plus) total number of citations that a firm's patents make to prior patents. Companies with patents that have a larger number of total backward citations are considered to do more incremental innovation because their patents have more direct relations to prior patents. The second measure, *LnTop1Citations*, is computed as the (natural logarithm of one plus) number of patents of a firm with citations in the top 1% in the distribution of citations, where the distribution is constructed with all the patents applied in the same technology class in the same year. This measure captures innovative outcomes that are highly successful breakthroughs, which are associated with radical innovation. Our third measure, *LnNewTechnology*, is the (natural logarithm of one plus) number of patents that are filed in technology classes previously unknown to the firm. This measure captures more radical innovations.[17] For constructing the last three measures, we consider only those firms that have a positive number of patents.

3.2.3 Independent variables: analyst coverage

Analyst coverage is the main independent variable in our regressions. We measure analyst coverage with the number of analysts that issue forecasts for a firm. Following the literature, we compute a raw measure of the number of analysts (*Coverage*) as the mean of the 12 monthly numbers of earnings forecasts that a firm receives annually, from the I/B/E/S summary file. We use this number because most analysts issue at least one earnings forecast for a firm in a year, and the majority of them issue at most one earnings forecast each month (He and Tian, 2013).[18], [19] The firm-years in which firms are not followed by financial

times not reliable in the Thomson ONE database.

[17]See Balsmeier, Fleming, and Manso (2017) for a careful discussion of these variables.

[18]We also construct an analyst coverage variable as the number of unique analysts using the I/B/E/S detail file. Our results are robust to using this variable.

[19]It is not a common practice for brokerage houses to send more than one analyst to follow the same firm in a month. Using the detail file of I/B/E/S, we find that this only happens for 0.34% of observations in

analysts have missing information in the I/B/E/S database. We set to zero the firm-year observations with missing values (Chang, Dasgupta, and Hilary, 2006; Hameed, Morck, Shen, and Yeung, 2015). Our final measure of the number of analysts is *LnCoverage*, which is the natural logarithm of one plus the raw measure of coverage computed before.

In section 8, we further study the pressure effect of analyst coverage based on the variable *EPSP*, which is the difference between the actual earnings per share (EPS) reported by firms and the analysts' consensus forecasts. EPS pressure (*EPSP*) is equal to zero when firms exactly meet analysts' consensus forecast. It is positive (negative) when firms beat (miss) the consensus forecast.

3.2.4 Control variables

Following the finance and innovation literature, we control for a rich set of firm and industry characteristics that are likely to affect firms' innovation strategy. The usual control variables are: *Firm Size*, which is the natural logarithm of the total assets; *R&D*, which is the R&D expenses scaled by total assets; *Firm Age*, which is the number of years a firm has existed in Compustat; *Leverage*, which is the ratio of firm debt to total assets; *Cash*, which is firms' cash scaled by total assets; *Profitability*, measured by the return on equity (ROE); *Tobin's Q,* which measures firm's growth opportunities; *PPE*, which is firm Property, Plant and Equipment (PPE) scaled by total assets; *Capex*, which is capital expenditures scaled by total assets; and the *KZ Index* which measures financial constraints (Kaplan and Zingales, 1997). In addition, Bushee (1998), Aghion, Van Reenen, and Zingales (2013), and Fang, Tian, and Tice (2014) show that institutional ownership is likely to affect firms' investment in innovation. We include the control variable *InstOwn*, which is the percentage of institutional ownership in the firm each year. We also include an index of corporate governance, *CGIndex*, following an approach similar to the one in Betrand and Mullainathan (2001) and García-Lara, García-Osma, and Penalva (2009). Specifically, we compute the unweighted average of the following standardized corporate governance measures: the percentage of independent directors on the firms' board, an indicator of whether the CEO is also the chairman of the board, and the G-index of managerial entrenchment by Gompers, Ishii, and Metrick (2003).[20] We develop this composite index to capture both internal (board structure) and external (G-index) determinants of firm governance.[21] Also, Aghion, Bloom, Griffith, and Howitt (2005) argue that product market competition affects innovation and that the effect

the whole database.

[20]We downloaded the G-index from A. Metrick's website. We thank the authors for making the index available.

[21]In untabulated regressions where we include each governance measure separately, we obtain similar results.

may be non-linear. We include the variables *HHI*, which is the Hirschman-Herfindahl index based on market shares, to measure industry concentration, and HHI^2, which is the square of the previous variable. To mitigate the effect of outliers, we winsorize *Profitability*, *Tobin's Q*, and the *KZ Index* at the 1st and 99th percentiles. A detailed definition of all the variables used in our analysis is provided in Table 1.

3.3 Summary statistics

Table 2 provides summary statistics of all the variables used in our analysis. Regarding R&D expenditures, the average ratio of R&D to total assets is 8.3% in our sample, and the average change in that ratio is about 0.2 percentage points. Also, 48.3% of firms in our sample cut their R&D expenses during the period studied. In terms of acquisitions, 15.4% of firms in our sample are involved in acquisition deals in a given year and, on average, 0.21 companies are acquired.[22] For those firms that acquire during our sample period (i.e., 4,204 firm-years), the average accumulated number of patents of the target firms is 4.3 and the corresponding number of citations is 70.17.[23] Also, 0.3% of the firms set up CVC funds in a given year, and around 1.4% invest in startup companies during the sample period. In terms of innovation output, firms in our sample have an average of 6 patents and 25 citations. For firms that have patents in a given year, the total number of backward citations is 812 on average. Also, firms have on average 1.14 patents with citations in the top 1% in the distribution of citations, and 1.66 patents filed in technology classes previously unknown to the firm.

In terms of coverage, firms in our sample are followed by about 6 analysts per year on average. Regarding the EPSP measure, firms are more likely to report positive EPSP (56% of the sample) than negative (35% of the sample). These statistics are consistent with other studies like Almeida, Fos, and Kronlund (2016).

The remaining variables in Table 2 enter as controls in our regressions. Firms in our sample have, on average, \$3.17 billion total assets, which corresponds to an average size (i.e., log of total assets) of 5.9. They are 19.3 years old, and have a leverage ratio of 18.4%, a ratio of cash to assets of 23.6%, a return on equity of 17.1%, a ratio of tangible assets to total assets of 22.4%, a ratio of capital expenditures to total assets of 5.1%, a proportion of institutional owners of 43.6%, a Tobin's Q of 2.98, a KZ Index of −7.5, an average corporate governance index of 0.23, and the average industry concentration in our sample is 28.7%.

[22] This average includes companies that do not acquire. The average number of acquired firms conditional on acquiring is 1.33 and the maximum is 16.

[23] As explained above, these numbers are adjusted for truncation problems.

4 Empirical strategy

To assess how analyst coverage affects firms' innovation strategy, we base our estimations on both ordinary least squares (OLS)[24] and instrumental variables (IV). Below, we also check the robustness of our results with a difference-in-differences (DID) approach. We start by estimating the following model using OLS:

$$InnovStrategy_{(i,t+k)} = \alpha + \beta LnCoverage_{(i,t)} + \gamma X_{(i,t)} + \lambda_i + \delta_t + \varepsilon_{(i,t)} \tag{1}$$

where subindexes i and t stand for firm and time, respectively. The dependent variable $InnovStrategy_{(i,t+k)}$ corresponds to our different measures of firms' innovation strategy. We use several measures, as described in subsection 3.2.1: *R&D Change* and *R&D Cut* measure changes in R&D expenditures; *Acquisition* and *LnAcquisition* measure firms' decision to acquire other companies and the number of companies acquired, respectively; *LnTargPatent* and *LnTargCite* measure the average innovativeness of the acquired companies; *CVC Setup* and *CVC Investments* measure firms' investments in start-ups. Our main independent variable is $LnCoverage_{(i,t)}$, which measures the number of analysts covering a firm. The remaining independent variables, included in $X_{(i,t)}$, capture firm and industry characteristics, as described in subsection 3.2.4. λ_i and δ_t correspond to firm and year fixed effects, respectively. Standard errors are robust to heteroskedasticity and are clustered at the firm level in all regressions. Since it may take managers more than one year to change their innovation activities, we examine the effect of analyst coverage on firms' innovation strategy one and two years ahead. Hence, the subindex k takes two values, $k \in \{1, 2\}$.[25]

The potential endogeneity problems in the analyst-innovation relationship can lead to a bias in the OLS estimates. Endogeneity in this relationship can occur in the form of both omitted variables and reverse causality. An omitted variables problem occurs if an unobservable firm characteristic affects both the innovation strategy and the number of analysts following a firm. For instance, managerial propensity for empire building may lead firms to invest more in acquisitions and CVC. At the same time, empire building managers may attract more financial analysts because this type of managers has a preference for media attention. Reverse causality might take place if, for example, firms that are more involved in acquisitions attract more analysts because they are more active in the M&A market.

[24]Since some of our dependent variables are dummy variables, we conduct a robustness test using a conditional logistic model. We obtain the same results as those obtained with OLS, except for the estimations where the dependent variable corresponds to our two CVC variables. In that case we cannot compute the value of the regression coefficients because the conditional logit model does not converge.

[25]We analyze the concurrent effect of analyst coverage by exploiting the effect of EPS pressure in section 8.

We address these endogeneity concerns mainly with an instrumental variables approach and fixed effects. We will also use a quasi-natural experiment as a robustness check. The reverse causality problem is also attenuated by the fact that our independent variables are lagged one or two periods with respect to the dependent variable.

Our instrument, *Expected Coverage*, was first introduced by Yu (2008) and exploits exogenous variation in analyst coverage.[26] This instrument uses changes in the number of analysts that work for brokerage houses over time. As argued by Yu (2008), the number of analysts that a brokerage house employs depends on the performance or profitability of the broker house but, in principle, it does not depend on the characteristics of the covered firms. In our case, it is also unlikely that the number of analysts that work for a brokerage house depends on the innovation strategy of a particular firm it covers. Therefore, a change in firms' analyst coverage driven by a change in the size of the brokerage houses covering the firm can be considered exogenous.[27]

Following Yu (2008), we construct the instrumental variable as follows:

$$ExpCoverage_{(i,t,j)} = (Brokersize_{(t,j)}/Brokersize_{(0,j)}) * Coverage_{(i,0,j)} \tag{2}$$

$$ExpCoverage_{(i,t)} = \sum_{j=1}^{n} ExpCoverage_{(i,t,j)}. \tag{3}$$

where $ExpCoverage_{(i,t,j)}$ is the expected coverage of firm i in year t from brokerage house j. $Brokersize_{(t,j)}$ and $Brokersize_{(0,j)}$ are the number of analysts employed by broker j in year t and in the benchmark year 0, respectively. We use year 1990 as the benchmark year because it is the starting year of our sample. $Coverage_{(i,0,j)}$ is the number of analysts from broker j following firm i in year 0. Hence, $ExpCoverage_{(i,t,j)}$ measures the expected number of analysts from broker j that can cover a firm i in a given year t according to the brokerage house size in that year with respect to the initial year. The instrumental variable $ExpCoverage_{(i,t)}$ is the total expected number of analysts of firm i from all the broker houses in year t. We follow the literature and drop all observations in the benchmark year (1990) since the expected coverage for that year is 1 by construction. We use $ExpCoverage_{(i,t)}$ to instrument the endogenous variable $LnCoverage_{(i,t)}$ in model (1) above and we estimate it using two-stage least squares (2SLS).

[26] The instrument has been used in other recent studies like He and Tian (2013), Chen, Harford, and Lin (2015), and Irani and Oesch (2016).

[27] As pointed out by Yu (2008), a concern with this instrument is that after a decrease in the broker house size the broker house decides which firms to stop covering, which could introduce a selection problem. However, whereas this could pose a problem for the realized coverage, it does not affect the instrument, which measures the tendency to keep covering a firm before any actual termination decision is made.

5 Baseline results

In this section we estimate the effect of the number of analysts on R&D expenditures, acquisition activity, and CVC investments using the empirical strategy explained above. As we argued in the introduction, financial analysts may have differential effects on investments in the internal and external innovation channels.

5.1 Number of analysts and R&D expenditures

We first discuss the effect of financial analysts on firms' R&D expenses. The estimated results are presented in Table 3. Panel A of Table 3 reports the OLS results and panel B shows the results of the IV strategy.[28]

The first two columns of panel A report the effect of analyst coverage on the change in R&D expenses one and two years forward. The last two columns of panel A show the effect of analysts on the indicator variable that measures a cut in R&D expenses. Column (1) of panel B shows the estimated coefficients of the first-stage regression of the IV model and the remaining columns show the IV coefficients. The results of the first-stage regression show that the coefficient of the main variable of interest, *ExpCoverage,* is positive and significant at the 1% level, which is consistent with previous work (for instance, Yu, 2008). The large t-statistic (16.45) confirms the explanatory power of our instrument. Also, the F-statistic of the regression is around 303, which is comfortably above the critical value (of 10) suggested by Stock, Wright, and Yogo (2002) for one instrument. Hence, we reject the null hypothesis that the expected coverage is a weak instrument.

Both the OLS and IV results of Table 3 indicate that firms followed by more analysts significantly reduce their expenses in R&D activities one and two years ahead. Specifically, an increase of one analyst, for a firm that initially had one analyst, decreases the change in R&D expenses by about 0.5 percentage points on average, and it increases the likelihood of cutting future R&D expenses by about 4.4 percentage points.[29] Comparing the two panels of Table 3, we can see that the coefficients of analyst coverage tend to be larger in the IV regressions, suggesting that endogeneity biases the OLS coefficients downwards.[30] The rest

[28] For the sake of brevity, we omit the coefficients of the control variables in the OLS regressions. The omitted coefficients are qualitatively similar to those of the IV regressions.

[29] An increase of one analyst represents an increase of 100% for a company that initially has one analyst. The 4.4 percentage points in the case of *R&D Cut* is computed as follows: $0.063 ln((1+1)/1) = 0.044$. The increase would be smaller for companies with initially more analysts. For example, for an average company (with six analysts), an additional analyst increases the likelihood of cutting R&D by about 1 percentage point.

[30] For example, for our dependent variable *R&D Cut* one year ahead, the coefficient in the OLS regression is 0.035 and it becomes 0.063 in the IV estimation. This suggests that an omitted variable might be simultaneously affecting coverage and R&D expenses, causing a downward bias. For instance, if managerial

of the covariates in the regressions have the expected sign. For example, firms with more cash are more likely to increase (and less likely to cut) R&D, and firms with more fixed assets are less likely to increase (or more likely to cut) R&D.

5.2 Number of analysts and acquisitions

Here, we discuss the effect of financial analysts on firms' acquisition strategy. We first study the effect on the number of acquisitions and then on the innovativeness of the acquired firms.

Table 4 reports both the OLS and IV regression results regarding the likelihood of acquiring firms and the number of acquired firms.[31] The results show that firms followed by more analysts are more likely to acquire other firms, and to acquire a larger number of firms. In the IV regressions, results are significant at the 1% level one year forward, and at the 5% level two years forward, for both variables. Specifically, if for example the number of analysts increases from 1 to 2, the likelihood of acquiring other firms one year later increases by 4.1 percentage points, and the number of acquired companies increases by about 4.2%. These effects are economically significant since the average likelihood of acquisitions in our sample is 15.4%, and the average number of acquired firms is 0.21.

Regarding the control variables, Table 4 shows that smaller and less leveraged firms are more likely to invest in acquisitions. Firms with a lower level of initial R&D expenses, more liquidity, more profitability, more growth opportunities, less financial constraints, larger percentages of institutional investors or better governed firms are also more likely to acquire other firms.

The previous results indicate that financial analysts lead firms to acquire other firms. However, acquisitions need not be part of firms' innovation strategy but rather part of, for instance, their growth strategy that is unrelated to innovation, their strategy to reduce competition, or even an empire-building strategy that reduces firm value.[32] We study the influence of financial analysts on firms' innovation strategy through acquisitions by focusing on the innovativeness of the acquired companies.

We measure the innovative value of the acquired targets using the number of accumulated patents and citations up to the moment when they were acquired. The patents and citations

style is an omitted time-varying firm-level variable, more conservative managers might be more likely to cut R&D expenses, but this type of more conservative management may also be less attractive to analysts. Alternatively, the downward bias might also be the result of measurement error.

[31] The results of the first-stage regression (not reported) are very similar to the ones in the panel B of Table 3. The same arguments hold for the first-stage regression of the number of analysts and CVC investments in the next section.

[32] A recent paper by Chen, Harford, and Lin (2015) shows that firms that experience an exogenous decrease in analyst coverage are more likely to make value-destroying acquisitions. Their result suggests that financial analysts play a governance role that leads managers to acquire better targets.

of a target reflect not only the quality of the innovation knowledge it owns but also its absorptive capacity and innovation potential. Therefore, if firms acquire with the intention of increasing their innovation capabilities, they should acquire firms with a higher number of patents and citations. In contrast, if acquisitions are made for other reasons, we should find either no effect or a negative effect on the innovation quality of the acquired firms.

We use a specification of the IV model presented above in which we include industry fixed effects instead of firm fixed effects because our sample is reduced to only those firms that acquire other companies (i.e., around 4,204 observations, an average of 2 observations per firm). Table 5 indicates a positive and significant influence of analysts on the innovativeness of acquired firms one and two years forward. Specifically, if the number of analysts increases from one to two, the average number of accumulated patents (citations) of target firms increases by 23.5% (23.8%) one year ahead. These results, together with those of Table 4 presented above, imply that analysts encourage firms to not only acquire more companies, but also more innovative ones.

5.3 Number of analysts and CVC investments

Table 6 reports the effect of analysts on firms' CVC investments. The estimated IV coefficients in panel B suggest that being followed by more analysts increases the likelihood of firms setting up a CVC fund and making subsequent investments in startups one and two years ahead. This positive effect is statistically significant at the 1% level for both *CVC Setup* and *CVC Investments*. In particular, if the number of analysts increases from one to two, the probability of setting up CVC funds and investing in startups in the future is 0.6 percentage points and 2.2 percentage points higher, respectively. After correcting for the endogeneity problem with the IV approach, financial analysts have a stronger positive effect on firms' CVC setups and investments compared to that of the OLS estimation, suggesting that OLS results are downward biased. By looking at the control variables we can see that investing in CVC funds is specific to older firms and firms with more growth opportunities.

Overall, our previous results show that stock market analysts tend to discourage R&D spending while they encourage external innovation in the form of acquisitions and CVC investments. These results are in line with our previous arguments and suggest that regarding R&D spending the pressure effect dominates, while for acquisitions and CVC investments the information effect tends to dominate.

5.4 Robustness: A quasi-natural experiment

We use a quasi-natural experiment to further address endogeneity concerns in the coverage-innovation relationship. Specifically, we follow Hong and Kacperczyk (2010) and others[33] and use brokerage house mergers as a source of an exogenous decrease in the number of analysts.[34] We also follow these papers to construct our treated and control samples (a detailed explanation of this process can be found in Appendix B).

We estimate the following difference-in-differences model, which takes into account multiple merger events:

$$\begin{aligned} InnovStrategy_{(i,m,t)} = {} & \beta_0 + \beta_1 Treated_{(i,m)} + \beta_2 Post_{(m,t)} \\ & + \beta_3 (Treated_{(i,m)} * Post_{(m,t)}) + \alpha_i + \phi_m + \delta_t + \gamma X_{(i,t)} + u_{(i,t)} \end{aligned} \tag{4}$$

where $InnovStrategy_{(i,m,t)}$ is one of our several innovation strategy variables for firm i, which is either a treatment or a control in the merger event m, in year t. $Treated_{(i,m)}$ is an indicator variable equal to 1 if a firm i is affected by a given merger event m, and $Post_{(m,t)}$ is an indicator variable equal to 1 for a firm in the post-merger period of merger m. The coefficient β_3 is the DID coefficient and captures the effect of the decrease in analyst coverage after a merger on the innovation strategy of the treated firms relative to control firms. The variables α_i, ϕ_m, and δ_t correspond to the firm, merger, and year fixed effects, respectively. Standard errors are robust and clustered at the firm-merger level to account for potential covariance of outcomes within firms over time.[35]

Results are presented in Table 7. We first use the above regression using analyst coverage as a dependent variable. The results of such a specification are presented in panel A, which shows that treated firms lose, on average, about one analyst in the first and second year after the merger relative to firms in the control group. Therefore, the DID coefficients of our regressions in panels B and C are capturing the effect of a decrease in coverage. The results of panels B and C in Table 7 correspond to our DID estimates using a sample constructed with a basic matching approach, and with a nearest neighbor matching, respectively. These matching techniques are explained in detail in Appendix B. The results in Table 7 generally show that the mergers of brokerage houses have a significant effect on the innovation strategy of firms one and two years after the mergers occur. Specifically, the DID coefficients show that after an exogenous drop in analyst coverage due to the mergers, firms are less likely to cut their R&D expenses, less likely to acquire other firms, and less likely to set up CVC

[33]Derrien and Kecskes (2013), Chen, Harford, and Lin (2015), and Irani and Oesch (2013, 2016).

[34]We thank the authors for making this list available. We report the list of mergers in Appendix B.

[35]In a more conservative approach (untabulated), we allow the firm and year fixed effects to vary by merger. The results of this approach are very similar to the reported results.

funds. These effects are economically and statistically significant, which is consistent with our OLS and IV results in the previous sections.[36]

5.5 Split sample analysis

In this section we conduct a series of split sample tests to better understand the effects financial analysts have on our main innovation channels. We first split the sample into firms with good and poor corporate governance. Firms are classified as having good (poor) corporate governance if they have a governance index above (below) the median in our sample. We then separate our sample into firms with high and low financial constraints split by the median value of the KZ index. Finally, we classify our firms into high-technology versus low-technology industries according to the OECD classification (Organisation for Economic Co-operation and Development, 2011).

Table 8 reports the split sample results. Panel A reports the results for good and poor corporate governance, panel B for high and low financial constraints, and panel C for high- and low-tech firms.[37]

Columns (1) and (2) of panel A show that the negative effect of analyst coverage on R&D expenses is significant only for poorly governed firms. As we argue throughout the paper, the effect of analyst coverage on R&D expenses mostly captures a pressure effect to meet earnings targets. An explanation for this result is that poorly governed firms may have worse earnings performance, and analysts put pressure on them to meet the targets. Alternatively, these firms might be more likely to invest in wasteful R&D projects, and analysts discipline them to cut expenses in these wasteful projects. In both cases, analysts are a form of external governance that compensates for the firms' lack of internal governance mechanisms such as independent boards.

Columns (3) to (8) of panel A report the results for the effect of analyst coverage on external investments in innovation. We argue throughout the paper that the positive effect of analyst coverage on external innovation decisions is mainly due to their role in reducing

[36]In the regressions where the dependent variable corresponds to the CVC Setup (columns (7) and (8)), we cannot include firm fixed effects due to the way in which the variable is defined (see variable definitions in Table 1). Since this variable is set to missing after firms have set up a CVC fund, taking into account the within-firm variation (i.e., including a firm fixed effect), creates a selection bias because only those firms that set up CVC funds after the merger events (i.e., those for which there is no missing data post-merger) are considered when computing the average effect. In other words, the missing data is correlated with the event. To overcome this problem, we remove the firm fixed effect. The variable *Treated*, which is less conservative than our firm fixed effect (because it imposes the same intercept for all treated and all control firms), still captures differences in the treated and control firms pre-merger. The coefficient of this variable is untabulated, but it is positive and significant in all regressions, suggesting that treated firms are more likely to set up CVC funds pre-merger, relative to control firms.

[37]Table 8 reports the effect of coverage on innovation inputs one year ahead. Untabulated results are similar when we consider the effect two years ahead.

asymmetric information. Columns (5) to (8) show that, indeed, the effect of analyst coverage is mostly significant for poorly governed firms. If investments in external innovation by poorly governed firms are more likely to suffer from asymmetric information problems, for example, due to the low reporting quality of these firms, then these results are also consistent with financial analysts compensating for the lack of governance in these firms. But columns (3) and (4) show that financial analysts have a strong significant effect on the general acquisitions for good governance firms only. A possible explanation for this result is that the type of not innovation-driven acquisitions captured in this result are acquisitions made for more strategic purposes, like gaining market power or affecting the product market structure. This type of investment might be more likely to take place in good governance firms, and the reduction of information asymmetries for these acquisitions due to financial analysts may mainly benefit these firms.

Columns (1) and (2) of panel B in Table 8 show that financial analysts only have a significant effect on the likelihood of cutting R&D expenses for firms with high financial constraints. It makes sense that these types of firms react more strongly to the pressure effect of analysts because they suffer harsher consequences for missing earnings targets. Indeed, missing the targets would make these firms even more financially constrained. In fact, meeting earnings forecast might help them get better access to the much needed funds. The results in columns (4), (7), and (8) show that the informational effect of financial analysts is also significant for the external innovation investments of highly constrained firms. These results are in line with Derrien and Kecskés (2013) who postulate that by reducing asymmetric information analysts may ease firms' financial constraints. The results of acquisitions are also significant for firms with low financial constraints, which suggests that financial analysts also play a role in reducing information asymmetries in the acquisition investments of less financially constrained firms.

Finally, all the estimates in panel C of Table 8 show that our results are mainly driven by the firms in the high-technology industries, i.e., the coefficients are larger and more often significant. These results provide further support for the main idea in this paper, which is that financial analysts play a significant role in the innovation strategy of firms. The effect of analyst coverage is particularly strong for firms in the high-technology sectors, which is where the majority of innovation activity occurs.

6 Direct vs. indirect effect of the number of analysts

The previous section shows that analyst coverage leads firms to cut investments in R&D activities, to acquire other innovative firms, and to increase investments in start-up companies. It seems clear that cutting R&D is the result of financial analyst pressure to meet earnings targets. However, the increase in innovative acquisitions and CVC investments could be due to two different effects. First, it could be driven by the informational role of analysts. As we have argued, firms may have an additional incentive to make profitable investments in acquisitions and CVC when they are followed by more analysts because analysts provide reliable information to the market regarding firms' value-enhancing operations. Second, it could be due to the analyst pressure effect. Indeed, if firms are forced to decrease R&D expenditures to meet analysts' earnings forecasts, they may invest in external innovation in order to keep up with innovation and compensate for the in-house reduction in R&D. Hence, the increase in external innovation could be the result of a direct -information- effect of analysts, or due to an indirect -pressure- effect that comes from substituting in-house R&D. We attempt to disentangle these effects in this section.

Empirically, we model the two effects with an interaction term. We estimate the effect of analysts followed by a cut in R&D expenditures on external innovation using the following equation:

$$\begin{aligned} ExternalInnov_{(i,t+k)} &= \alpha + \beta_1 LnCoverage_{(i,t)} + \beta_2 R\&DCut_{(i,t+1)} \\ &+ \beta_3 (LnCoverage_{(i,t)} * R\&DCut_{(i,t+1)}) + \gamma X_{(i,t)} + \lambda_i + \delta_t + \varepsilon_{(i,t)} \end{aligned} \tag{5}$$

where subindex i stands for firm, t stands for time, and k can take two values, $k \in \{1, 2\}$. The dependent variable $ExternalInnov_{(i,t+k)}$ corresponds to our proxies for external innovation activities: acquisitions (*Acquisition* and *LnAcquisitions*) and CVC (*CVC Setup* and *CVC Investments*). The coefficient β_1 captures the direct effect of financial analysts on external innovation, and the coefficient β_3 captures the indirect effect. According to our previous discussion, we expect the coefficient β_1 to be positive if analysts have an informational role that encourages firms to undertake value-enhancing acquisitions and CVC investments. We expect coefficient β_3 to be positive if analyst pressure leads managers to increase external innovative activities as a result of cutting R&D expenses. Alternatively, β_3 can be negative if firms also reduce external innovation after cutting internal R&D because with a smaller in-house R&D unit firms are less able to leverage the advantages of investing in innovation outside the firm. The coefficient β_2 captures the relationship between internal R&D and external innovation for firms that cut R&D but have no analyst coverage. We use the same set of covariates as in the baseline model and also include firm and year fixed effects. Errors are robust and clustered at the firm level. We estimate Equation (5) using 2SLS where the endogenous variable $LnCoverage_{(i,t)}$ is instrumented with our instrument in Equation (3).

We present the results in Table 9. Panel A reports the direct and indirect effect of analysts on acquisitions, panel B shows the results on the innovativeness of acquired firms, and panel C the results on CVC setup and investments. In the three panels, columns (1) and (3) present the direct and indirect effects of coverage on innovation outputs one year forward, and the rest of the columns present the effects two years ahead.

Panel A shows that the number of analysts has a strong and positive direct effect on the decision to acquire other firms and on the number of firms acquired, which suggests that the reason why firms increase external innovation when they are followed by more analysts is to take advantage of the informational role of analysts. The coefficient of the interaction effect is negative in all the specifications, but only appears significant (at the 10% level) for the number of acquisitions two periods forward, which suggests that the earnings pressure by analysts might have some (weak) effect on firms' external innovation. Still, the interaction coefficients are significantly smaller in absolute terms than those of the direct effect. Hence, firms that cut R&D after being followed by more analysts increase their acquisition activity, although to a lesser extent than firms that do not cut R&D. Panel B indicates that the positive effect of analysts on the innovativeness of acquired firms also comes from a direct effect related to analysts' informational role.

Finally, panel C shows that financial analysts have a positive direct effect on the CVC setup and CVC investments one and two years ahead. This effect is significant at least at the 10% level. The coefficient of the interaction term is negative and not significant. This indicates that the positive effect of financial analysts on CVC setups and investments can be attributed to their informational role.

Overall, our results indicate that for both external innovation channels the positive effect of analyst coverage is mainly due to a direct influence of analysts' actions than to an indirect effect due to the decrease in R&D.[38]

[38] We confirm these results with a multinomial logit regression model where our dependent variable is a categorical variable that captures the different possibilities of a firm's innovation strategy: doing only R&D, only making acquisitions, doing only CVC, or the various combinations among them. This model is tested with respect to the base outcome which is doing nothing. Our results show that analyst coverage makes it more likely that firms decrease R&D expenses, acquire other firms, and invest in CVC together with making acquisitions.

7 Discussion of innovation outcomes

Our results above provide evidence of a pressure effect of analysts that leads to firms cutting in-house R&D spending, and of an information effect that encourages firms to invest in innovation activities beyond the boundaries of the firm. When we take these different innovation channels into account, the final effect of analysts on firms' innovative outcome is not clear. In this section we explore the possible consequences of the change in firms' innovation strategy due to analyst coverage on the final innovation outcome.

On the one hand, firms that cut R&D should in principle see a reduction in their innovation output. Indeed, if firms devote fewer resources to R&D, their number of patents and citations should decrease. However, analyst pressure may lead to firms cutting R&D expenses only on those projects that are less productive or even wasteful. In this case, cutting R&D is efficient and it should not have a negative effect on the innovation output. In fact, innovation output may even increase if the reduction in wasteful R&D spending allows inventors to concentrate on the most efficient projects. On the other hand, increasing acquisitions and CVC investments should help firms develop and acquire new technologies, and improve their absorptive capacity. As a result, firms should be able to produce more and better innovation output. Still, acquisitions may be related to firms' growth policy or empire-building strategies, and CVC investments might be directed solely for the sake of financial returns. In these cases innovation output should be lower (if resources are diverted from innovation) or unaffected. We explore these ideas estimating the following model:

$$\begin{aligned} InnovOutcome_{(i,t+3)} &= \alpha + \beta_1 LnCoverage_{(i,t)} + \beta_2 InnovStrategy_{(i,t+1)} \\ &+ \beta_3 (LnCoverage_{(i,t)} * InnovStrategy_{(i,t+1)}) + \gamma X_{(i,t)} + \lambda_i + \delta_t + \varepsilon_{(i,t)}, \end{aligned} \tag{6}$$

where i stands for firm and t stands for time. The dependent variable $InnovOutcome_{(i,t+3)}$ corresponds to our two measures of innovation output: $LnPatents$ and $LnCitations$. Our main independent variables are: $LnCoverage_{(i,t)}$, which corresponds to the number of analysts following a firm and is instrumented throughout with our usual instrumental variable $ExpCoverage_{(i,t)}$; the innovation strategy $InnovStrategy_{(i,t+1)}$, which corresponds to firms' either cutting R&D, acquiring other firms, or investing in CVC; and their interaction. We also include our usual controls in $X_{(i,t)}$ as well as firm and year fixed effects. Errors are robust and clustered at the firm level.

Table 10 presents the results of the effect of the number of analysts and firms' innovation strategy on patents (panel A) and citations (panel B). Both panels include several specifications: column (1) shows the effect of analyst coverage and our internal and external innovation channels; in the remaining columns we also include each innovation channel interacted with analyst coverage to capture the differential effect of firms' innovation strategy on the innovation outcome for firms that are covered by analysts.

In panel A of Table 10, the coefficient of $LnCoverage_{(i,t)}$ captures the effect of coverage on future patents. This coefficient is never significant in our setting, which suggests that the negative effect of analysts previously found in the literature (He and Tian, 2013) is absorbed when we take firms' innovation strategy into account.[39] Column (1) of panel A shows that cutting R&D has a positive (although not significant) effect on patents, and that acquisitions and CVC investments have a strong positive effect on future patents, holding analyst coverage fixed.

More interestingly, columns (2), (3), and (4) show a similar pattern: the positive effect of the three firms' innovation channels on future patents observed in column (1) is driven by the interaction term in each regression. The regression in column (2) of panel A includes the interaction of analyst coverage and R&D cut. The coefficient of R&D cut captures the effect of cutting R&D on future patents, for those companies that are not followed by analysts. This coefficient is negative and significant, suggesting that cutting R&D expenses when firms are not followed by analysts is harmful for future innovation. However, the coefficient of the interaction term is positive and significant, which indicates that cutting R&D expenses is less harmful, and it can even lead to an increase in future patents for those firms that are covered by more analysts. More specifically, for example, for an average firm in our sample (i.e., followed by around six analysts), cutting R&D increases the number of future patents by 3%.[40] This result might seem surprising at first, because the intuition suggests that analyst pressure leads to myopic behavior, which should reduce the innovation output. Our results indicate that the pressure to meet analysts' forecasts leads firms to make more efficient R&D cuts the larger the analyst coverage. Such efficiency gains might come from firms cutting wasteful resources and concentrating on the most efficient projects when they are followed by more analysts.

The regression in column (3) of panel A shows a similar effect of acquisitions. Acquisitions have a negative (although not significant) impact on future patents for those firms that are not covered by analysts, suggesting that acquisitions in this case might be motivated,

[39]We are able to reproduce the results of He and Tian (2013), i.e., where coverage has a negative effect on citations and patents, using their setting.

[40]Cutting R&D has a positive effect on future patents for firms that are covered by more than three analysts, which corresponds to about 61% of our sample. For firms with less than three analysts, cutting R&D has a negative effect on future patents.

for instance, by empire-building reasons. However, acquiring other innovative firms has a positive effect (significant at the 13% level) on future patents for firms that are followed by more than three analysts. Hence, when firms are followed by more than three analysts, analyst coverage reduces information asymmetries between firms and investors in the financial market in a way that leads firms to acquire innovative targets that help them increase their future patents. Similarly, CVC investments have a strong positive influence on future patents (column (4) of panel A), specially for those firms that are covered by financial analysts. This result indicates that the more a firm is covered by analysts, the more efficient its CVC investments are in terms of generating future patents.[41]

Panel B shows similar results for citations. Whereas analyst coverage does not directly affect future citations, it does lead firms to make more efficient choices regarding their innovation strategy. Specifically, cutting R&D has a positive effect on future citations for those firms that are followed by more than three analysts. The average effect of acquisitions on future citations is also positive and significant. And investing in CVC has a strong positive effect on future citations for those firms that are followed by analysts.

We further explore the effect of coverage and innovation channels on the type of innovation output of firms. We use the variables described in section 3.2.2, namely *LnBackCitations*, *LnTop1Citations*, and *LnNewTechnology* as dependent variables in our regression model (6).

Results are reported in Table 11. Panels A, B, and C, report the effect of analyst coverage and innovation channels on the total backward citations, patents with the top 1% of citations, and patents in new technology classes, respectively. The dependent variable in the first panel captures exploitative/incremental innovations, and those of the second and third panels capture explorative/radical innovations. The coefficient of analyst coverage is negative and significant in panels B and C, suggesting that increases in analyst coverage lead to less radical innovations. If analysts put pressure on managers to meet earnings targets, then managers might choose to invest in less risky innovation activities which leads to less exploration. The results in panel A show that lower R&D spending is related to more incremental innovations. They suggest that firms that cut R&D expenses are less able to invest in projects which are more explorative in nature. Panel B results also show that cutting R&D leads to less explorative innovations. However, analyst coverage mitigates this effect as indicated by the significant coefficient of the interaction term. The coefficient of acquisitions is positive and significant in panel C. This result suggests that acquisitions are used by firms to access unknown technologies outside the firm, which enables them to

[41] As can be seen from the summary statistics table (Table 2), CVC investments are confined to a small number of firms in our sample. Hence, these results should be interpreted with caution.

produce more explorative innovation output. Finally, the results in panel A indicate that CVC investments lead to the production of more incremental innovation for those firms that are covered by few or no financial analysts. However, firms with few financial analysts are also less likely to engage in CVC investments. Hence, these firms could invest in CVC more for financial reasons than for innovation purposes. Instead, for the firms that are followed by a large number of financial analysts, which are the firms that typically invest in CVC, the informational effect of analysts seems to play a role as these firms are more likely to develop radical innovation.

Overall, our results provide evidence that having more financial analysts encourages firms to make more efficient investments related to innovation, which leads to an increase in their future patents and citations. They also indicate that analyst pressure, alongside in-house R&D spending, leads to more exploitation; whereas acquisitions and CVC investments increase exploration. We attribute this positive influence of financial analysts to their information and pressure effects, which reduce information asymmetries and the use of wasteful resources, respectively.

8 Earnings per share pressure and innovation strategy

In this section we try to isolate the pressure effect of analysts by using another measure of analyst pressure, namely the difference between the actual earnings per share (EPS) reported by firms and the analysts' consensus forecasts, for those firms that are followed. Whereas we think that this might be a less noisy measure of analyst pressure than the number of analysts, we argue that the EPS pressure measure is likely to affect only firms' R&D decisions and only in the short-term.[42] We measure EPS pressure as the difference between the firm's end of fiscal year realized EPS and the first month of the last quarter's EPS consensus forecast made by analysts. Due to the short-term nature of this measure and its direct relationship to earnings, we expect external innovation activities to be unaffected by the managers' willingness to meet earnings benchmarks.

In what follows, we first uncover a discontinuity in the likelihood of decreasing R&D expenditures around an earnings pressure threshold, and then we exploit this discontinuity to test whether cutting R&D expenses has a causal effect on firms' innovation outcomes.

Figure 1 presents graphical evidence that managers modify R&D expenses to meet analysts' consensus forecasts. Specifically, it shows that firms that meet or beat the analyst consensus forecasts are more likely to have cut R&D expenses than the firms that miss the

[42] We believe that this measure is less likely to capture the information effect of analysts and that is why we do not use it in our main analysis, where we want to study both the information and pressure effects.

forecasts. For example, the probability of cutting R&D increases from 45% to around 52% when the sign of the *EPSP* changes from negative to positive. This suggests the presence of a discontinuity in firms' R&D expenses around the *EPSP* zero threshold.

We formally analyze this discontinuity estimating the following regression:

$$\begin{aligned} R\&D_{(i.t)} = \alpha + \beta_1 I_{MeetBeat(i,t)} + \beta_2 EPSP_{(i,t)} + \beta_3 EPSP^2_{(i,t)} + \beta_4 EPSP_{(i,t)} * I_{MeetBeat(i,t)} \\ + \beta_5 EPSP^2_{(i,t)} * I_{MeetBeat(i,t)} + \beta_6 X_{(i,t)} + \lambda_i + \delta_t + \varepsilon_{(i,t)} \end{aligned} \tag{7}$$

where $R\&D_{(i.t)}$ is either *R&D Change* or *R&D Cut*. $I_{MeetBeat(i,t)}$ is an indicator variable equal to 1 for firms that meet or beat analyst consensus forecasts and 0 for firms that miss them, and $EPSP_{(i,t)}$ is the amount of EPS pressure. Consistently with Figure 1, we restrict the difference between the actual and forecasted EPS to 20 cents around the 0 threshold (i.e., $-0.2 < EPSP < 0.2$). We use a polynomial functional form and interactions so as not to impose restrictions on the underlying conditional mean functions (Angrist and Pischke, 2009). We also include our usual battery of controls in $X_{(i,t)}$ as well as firm and year fixed effects. Errors are robust and clustered at the firm level.

Table 12, panel A reports the results of regression (7). The results show show that meeting or beating analysts' consensus forecasts significantly predicts firms' likelihood of cutting R&D. Specifically, firms that meet or beat analysts' forecasts are around 3.4 percentage points more likely to have cut R&D (columns (1) and (2)). Given that the average probability of cutting R&D is 48.3%, this is an economically significant effect. The effect on R&D change is negative although not significant. The results of Table 12 also show that cutting R&D to meet or beat analysts' forecasts is only a short-term effect. Indeed, the point estimates of our main indicator variable in columns (3) and (6), which capture the effect of meeting or beating forecasts on firms' R&D behavior in the future, are not significant.

The key identification assumption behind the previous exercise is that there are no other discontinuous differences in firm characteristics around the zero EPS pressure threshold. This assumption is usually tested by studying whether there are pre-existing differences in the strategies of firms that fall on either side of the threshold. We estimate a modified version of the above equation (by lagging the dependent variable) to test for parallel trends. Results are reported in Table C.1 in Appendix B. As can be seen, firms with small positive and small negative EPS pressure have very similar pre-existing characteristics; thus, the parallel trends assumption is satisfied.

We now turn to estimate the effect of cutting R&D expenses in the short-term due to EPS pressure on firms' innovation outcomes. We do this with a fuzzy regression discontinuity framework where we exploit our previously reported discontinuity in R&D around the zero *EPSP* threshold. We estimate the following two-stage least squares regression:

$$\begin{aligned} Innov\ Outcome_{(i,t+k)} = \alpha + \gamma_1 R\&Dcut_{(i,t)} + \gamma_2 EPSP_{(i,t)} \\ + \gamma_3 EPSP_{(i,t)} * I_{MeetBeat(i,t)} + \gamma_4 X_{(i,t)} + \delta_t + \varepsilon_{(i,t)} \end{aligned} \tag{8}$$

where $R\&Dcut_{(i,t)}$ corresponds to the estimated values of a first-stage regression where we include $I_{MeetBeat(i,t)}$ as an instrument. Under the identification assumption that there are no other discontinuous differences in firm characteristics around the zero threshold, the coefficient γ_1 captures a causal effect. Regression (8) also includes a control of the amount of pressure, and its interaction with the binary variable that indicates matchers and beaters versus missers.[43] To isolate any differences around the zero threshold, we restrict the sample to a smaller window of 10 cents (i.e., $-0.10 < EPSP < 0.10$).[44] The regression includes year and industry fixed effects as well as clustered errors at the firm level.

Results are reported in panel B of Table 12. They show that cutting R&D does not influence firms' innovative outcome in the long term. This suggests that a decrease in R&D expenses that is due to the managers' willingness to meet or beat analysts' forecasts in the current period is only a short-term effect.

9 Conclusion

In this paper, we study the effect of analyst coverage on three main channels that firms can use to innovate, namely internal R&D spending, acquisitions of other innovative firms, and investment in corporate venture capital (CVC). There are two effects through which financial market analysts influence firms' innovation strategy: a pressure effect and an information effect. Analysts put pressure on firms by issuing earnings forecasts for firms to meet, and they reduce information asymmetries between firms and investors by providing the market with reliable information about firms' activities.

We find evidence that firms followed by more financial analysts are more likely to cut their internal R&D programs, which provides evidence of their pressure effect. But firms followed by more financial analysts are also more likely to start or increase CVC investments and to acquire other innovative firms, which provides evidence of their information effect. Although cutting R&D spending has a negative effect on firms' future innovation output, we find that

[43] Our results are robust to not including this interaction.

[44] The coefficient of the indicator variable $I_{MeetBeat(i,t)}$ is positively and significantly correlated with the likelihood of cutting R&D in this window. Hence, the instrument $I_{MeetBeat(i,t)}$ in the fuzzy regression discontinuity design has predictive power.

firms that cut R&D expenses after being followed by financial analysts produce more patents and citations. Similarly, firms' investments in acquisitions and CVC funds have a positive and significant impact on the future patents and citations for those firms that are followed by financial analysts. These results suggest that both the pressure and information effects of financial analysts induce firms to make more efficient decisions regarding their innovation activity. We also find that financial analysts affect the type of innovation produced. In particular, firms that are followed by more financial analysts tend to produce less radical innovation, as do firms that cut R&D. In contrast, we find that acquisitions and CVC investments enable firms to produce more breakthrough innovations.

By studying the effect of financial analysts on several innovation strategies, our results put in perspective the previous findings on the negative effect of financial analysts (like Bushee, 1998, and He and Tian, 2013): while an increase in market pressure leads to more cuts in internal R&D, which could reduce innovation, the accompanying discipling effect and increase in information encourage efficient investments in both internal and external innovation.

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A Appendix A

Table 1: **Variable Definitions.** This table describes all the variables used in our analysis.

Variables	Definitions
Innovation	
R&D Change	Ratio of R&D expenses (Compustat data item ♯46) to total assets (♯6) at t minus ratio of R&D expenses to total assets at $t-1$
R&D Cut	Indicator variable equal to 1 if R&D (♯46) (scaled by total assets (♯6)) at t is lower than that at $t-1$, and 0 otherwise
Acquisition	Indicator variable equal to 1 when a firm acquires one or more other companies, and 0 otherwise
LnAcquisitions	Natural logarithm of (one plus) the number of target companies acquired
CVC Setup	Indicator variable equal to 1 the year in which CVC fund makes its first investment, and 0 for the years preceding the first investment
CVC Investments	Indicator variable equal to 1 for each year in which CVC fund invests in a startup, and 0 otherwise
LnTargPatent	Natural logarithm of (one plus) the accumulated number of patents on average of all target firms acquired
LnTargCite	Natural logarithm of (one plus) the accumulated number of citations on average of all target firms acquired
LnPatents	Natural logarithm of (one plus) the number of granted patents per year of a firm
LnCitations	Natural logarithm of (one plus) the number of citations per year of a firm
LnBackCitations	Natural logarithm of (one plus) total number of citations that firms' patents make to prior patents
LnTop1Citations	Natural logarithm of (one plus) number of patents of a firm with citations in the top 1% in the distribution of citations.
LnNewTechnology	Natural logarithm of (one plus) number of patents filed in technology classes previously unknown to the firm
Analyst Coverage	
LnCoverage	Natural logarithm of (one plus) the arithmetic mean of the 12 monthly numbers of earnings forecasts obtained from financial analysts
EPSP	Difference between the firm's end of fiscal year realized EPS and the EPS consensus forecast made by analysts the second month in the last quarter
Control Variables	
Firm Size	Natural logarithm of book value of total assets (♯6) at the end of the fiscal year
R&D	R&D expenses (♯46) divided by book value of total assets (♯6)
Firm Age	Natural logarithm of the number of years listed on Compustat
Leverage	Book value of debt (♯9 + ♯34) divided by book value of total assets (♯6)
Cash	Cash (♯1) at the end of fiscal year divided by book value of total assets (♯6)
Profitability	Operating income before depreciation (♯13) divided by book value of total stockholders' equity (♯216)
PPE	Property, plant & equipment (♯8) divided by book value of total assets (♯6)
Capex	Capital expenditure (♯128) divided by book value of total assets (♯6)
InstOwn	Average institutional ownership percent for a firm
Tobin'sQ	Market value of equity (♯199 × ♯25) plus book value of assets (♯6) minus book value of equity (♯60) minus balance sheet deferred taxes (♯74), divided by book value of assets (♯6)

KZ Index	Kaplan and Zingales index calculated as $-1.002\times$ cash flow $[(\sharp 18+\sharp 14)/\sharp 8]$ plus $0.283\times$ Tobin'sQ plus $3.139\times$ leverage minus $39.368\times$ dividends $[(\sharp 21+\sharp 19)/\sharp 8]$ minus $1.315\times$ cash holdings $(\sharp 1/\sharp 8)$, where $\sharp 8$ is lagged
CGIndex	Average of three standardised variables: independent directors percent of a board, G-index, and CEO duality
HHI	Herfindahl-Hirschman Index calculated as sum of sales revenue scaled by sales of four-digit standard industrial classification (SIC) code
HHI^2	Squared Herfindahl-Hirschman Index

Table 2: **Summary Statistics.** This table reports the descriptive statistics for the variables of our main regressions based on the sample of US public firms from 1990 to 2012.

Variable	25th percentile	Median	Mean	75th percentile	Std. Dev.	No. of Obs.
R&D	0.008	0.038	0.083	0.109	0.127	34,307
R&D Change	−0.006	0.000	0.002	0.008	0.066	26,734
R&D Cut	0.000	0.000	0.483	1.000	0.500	26,734
Acquisition	0.000	0.000	0.154	0.000	0.361	34,307
NumofAcquisitions	0.000	0.000	0.205	0.000	0.570	34,307
CVC Setup	0.000	0.000	0.003	0.000	0.056	31,454
CVC Investments	0.000	0.000	0.014	0.000	0.118	34,307
TargPatent	0.000	0.000	4.299	0.000	77.621	4,204
TargCite	0.000	0.000	70.165	0.000	1143.696	4,204
Patents	0.000	1.000	24.545	6.000	146.720	18,191
Citations	0.000	4.000	280.027	58.000	1944.356	18,191
BackCitations	26.000	95.000	811.982	405.500	3273.194	7,968
Top1Citations	0.000	0.000	1.135	0.000	4.850	7,970
NewTechnology	0.000	1.000	1.666	2.000	2.792	7,970
Coverage	1.600	4.333	6.644	9.250	7.058	34,307
EPSP	−0.020	0.010	0.006	0.037	0.066	20,147
Positive EPSP (indicator)	0.000	1.000	0.559	1.000	0.496	20,147
Negative EPSP (indicator)	0.000	0.000	0.354	1.000	0.478	20,147
Zero EPSP (indicator)	0.000	0.000	0.087	0.000	0.281	20,147
Firm Size	4.543	5.745	5.919	7.102	1.870	34,307
Firm Age	8.000	14.000	19.273	27.000	14.877	34,307
Leverage	0.007	0.131	0.184	0.287	0.213	34,307
Cash	0.041	0.145	0.236	0.366	0.242	34,307
Profitability	0.050	0.223	0.171	0.363	0.548	34,307
PPE	0.085	0.175	0.224	0.308	0.180	34,307
Capex	0.020	0.037	0.051	0.066	0.052	34,307
InstOwn	0.093	0.432	0.436	0.709	1.495	34,307
Tobin'sQ	1.190	1.807	2.981	3.241	3.443	34,307
KZ Index	−6.696	−1.543	−7.477	0.606	20.455	34,307
CGIndex	−0.232	0.263	0.232	0.795	0.704	34,307
HHI	0.134	0.216	0.287	0.381	0.206	34,307
HHI^2	0.018	0.047	0.125	0.145	0.189	34,307

Table 3: **Number of Analysts and R&D Expenses.** This table reports both OLS (panel A) and IV 2SLS (panel B) regression results of the effect of the number of analysts on R&D expenses one and two years ahead. Robust standard errors clustered at firm level are in parentheses. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Table 1.

Panel A: OLS

Dependent variable	*R&D Change*		*R&D Cut*	
	(1)	(2)	(3)	(4)
	$t+1$	$t+2$	$t+1$	$t+2$
LnCoverage	-0.009^{***}	-0.004^{***}	0.035^{***}	0.028^{***}
	(0.001)	(0.001)	(0.009)	(0.009)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
No. of observations	26,734	24,391	26,734	24,156
R^2	0.153	0.134	0.157	0.127

Panel B: IV 2SLS

	First-stage	**Second-stage**			
Dependent variable	*LnCoverage*	*R&D Change*		*R&D Cut*	
	(1)	(2)	(3)	(4)	(5)
	t	$t+1$	$t+2$	$t+1$	$t+2$
ExpCoverage	0.373^{***}				
	(0.023)				
LnCoverage		-0.007^{**}	-0.006^{*}	0.063^{**}	0.066^{**}
(Instrumented)		(0.003)	(0.003)	(0.030)	(0.030)
Firm Size	0.425^{***}	0.018^{***}	0.013^{***}	-0.095^{***}	-0.081^{***}
	(0.015)	(0.002)	(0.002)	(0.016)	(0.016)
R&D	0.583^{***}			1.327^{***}	0.632^{***}
	(0.067)			(0.073)	(0.069)
Firm Age	0.093^{***}	-0.010^{***}	-0.001	0.045^{***}	0.007
	(0.028)	(0.002)	(0.002)	(0.016)	(0.016)
Leverage	-0.160^{***}	-0.021^{***}	-0.005	-0.038	-0.073^{***}
	(0.044)	(0.006)	(0.006)	(0.027)	(0.026)
Cash	0.219^{***}	0.035^{***}	-0.007	-0.200^{***}	-0.100^{***}
	(0.042)	(0.006)	(0.005)	(0.032)	(0.032)
Profitability	-0.004	0.008^{***}	0.006^{***}	0.025^{***}	0.021^{**}
	(0.009)	(0.002)	(0.002)	(0.008)	(0.008)
PPE	0.223^{**}	-0.028^{***}	-0.021^{**}	0.251^{***}	0.127^{**}
	(0.094)	(0.010)	(0.010)	(0.065)	(0.064)
Capex	0.833^{***}	-0.009	-0.068^{***}	0.025	0.386^{***}
	(0.128)	(0.020)	(0.019)	(0.111)	(0.115)
InstOwn	0.444^{***}	-0.003	-0.000	-0.027	-0.030
	(0.047)	(0.003)	(0.003)	(0.026)	(0.026)
Tobin'sQ	0.006^{***}	-0.001^{***}	0.000^{*}	0.001	-0.007^{***}
	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)
KZ Index	0.001^{***}	-0.000^{***}	-0.000^{***}	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CGIndex	0.043^{***}	-0.003^{***}	-0.002	0.014^{*}	0.003
	(0.013)	(0.001)	(0.001)	(0.009)	(0.009)
HHI	-0.404^{**}	0.017	0.001	0.102	-0.047
	(0.189)	(0.014)	(0.014)	(0.117)	(0.116)
HHI^2	0.289^{*}	-0.012	0.004	-0.117	-0.009
	(0.171)	(0.012)	(0.012)	(0.111)	(0.113)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
No. of observations	26,734	26,734	24,391	26,734	24,156
F-Statistic	302.7				
R^2	0.862	0.153	0.134	0.156	0.127

Table 4: **Number of Analysts and Acquisition.** This table reports both OLS (panel A) and IV 2SLS (panel B) regression results of the effect of the number of analysts on the acquisition activities one and two years ahead. Robust standard errors clustered at firm level are in parentheses. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Table 1.

Panel A: OLS

Dependent variable	*Acquisition*		*LnAcquisitions*	
	(1)	(2)	(3)	(4)
	$t+1$	$t+2$	$t+1$	$t+2$
LnCoverage	0.023***	0.016***	0.019***	0.015***
	(0.005)	(0.006)	(0.005)	(0.005)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
No. of observations	34,307	32,966	34,307	32,966
R^2	0.243	0.238	0.273	0.266

Panel B: IV 2SLS

	Second-stage			
Dependent variable	*Acquisition*		*LnAcquisitions*	
	(1)	(2)	(3)	(4)
	$t+1$	$t+2$	$t+1$	$t+2$
LnCoverage	0.059***	0.038**	0.060***	0.032**
(Instrumented)	(0.020)	(0.019)	(0.017)	(0.016)
Firm Size	−0.018*	−0.034***	−0.018*	−0.028***
	(0.011)	(0.011)	(0.010)	(0.009)
R&D	−0.135***	−0.097***	−0.120***	−0.080***
	(0.028)	(0.028)	(0.024)	(0.023)
Firm Age	−0.019*	−0.011	−0.024**	−0.009
	(0.011)	(0.012)	(0.010)	(0.010)
Leverage	−0.079***	−0.068***	−0.065***	−0.055***
	(0.015)	(0.016)	(0.013)	(0.013)
Cash	0.170***	0.104***	0.128***	0.084***
	(0.022)	(0.020)	(0.019)	(0.017)
Profitability	0.005	0.007**	0.003	0.006**
	(0.004)	(0.004)	(0.003)	(0.003)
PPE	0.032	0.024	0.021	0.030
	(0.035)	(0.034)	(0.030)	(0.029)
Capex	−0.107*	−0.030	−0.121**	−0.061
	(0.062)	(0.061)	(0.053)	(0.050)
InstOwn	0.004***	−0.000	0.003***	−0.000
	(0.001)	(0.000)	(0.001)	(0.000)
Tobin'sQ	0.003***	0.001	0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
KZ Index	−0.000**	−0.000	−0.000**	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
CGIndex	0.015**	0.013**	0.012**	0.012**
	(0.006)	(0.006)	(0.005)	(0.005)
HHI	0.090	0.031	0.106	0.041
	(0.078)	(0.077)	(0.068)	(0.067)
HHI^2	−0.045	−0.014	−0.055	−0.014
	(0.073)	(0.073)	(0.062)	(0.063)
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
No. of observations	34,307	32,966	34,307	32,966
R^2	0.242	0.237	0.270	0.266

Table 5: **Number of Analysts and Acquisition Innovativeness** This table reports IV 2SLS regression results of the effect of the number of analysts on the innovativeness of acquired firms one and two years ahead. Robust standard errors clustered at firm level are in parentheses. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Table 1.

Dependent variable	*LnTargPatent*		*LnTargCite*	
	(1)	(2)	(3)	(4)
	$t+1$	$t+2$	$t+1$	$t+2$
LnCoverage (Instrumented)	0.339**	0.319**	0.344**	0.277*
	(0.154)	(0.133)	(0.174)	(0.152)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
No. of observations	4,204	3,977	4,204	3,977
R^2	0.220	0.223	0.217	0.221

Table 6: **Number of Analysts and CVC Investments.** This table reports both OLS (panel A) and IV 2SLS (panel B) regression results of the effect of the number of analysts on CVC investments one and two years ahead. Robust standard errors clustered at firm level are in parentheses. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Table 1.

Panel A: OLS

Dependent variable	*CVC Setup*		*CVC Investments*	
	(1)	(2)	(3)	(4)
	$t+1$	$t+2$	$t+1$	$t+2$
LnCoverage	0.001	0.001**	0.007***	0.007***
	(0.001)	(0.000)	(0.002)	(0.003)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
No. of observations	31,454	30,141	34,307	32,966
R^2	0.389	0.385	0.309	0.303

Panel B: IV 2SLS

	Second-stage			
Dependent variable	*CVC Setup*		*CVC Investments*	
	(1)	(2)	(3)	(4)
	$t+1$	$t+2$	$t+1$	$t+2$
LnCoverage	0.008***	0.007***	0.032***	0.027***
(Instrumented)	(0.002)	(0.002)	(0.010)	(0.011)
Firm Size	−0.002	−0.002	−0.005	−0.005
	(0.001)	(0.001)	(0.005)	(0.006)
R&D	−0.007**	0.003	−0.018*	−0.011
	(0.003)	(0.003)	(0.010)	(0.011)
Firm Age	0.004***	0.003***	0.019***	0.019***
	(0.001)	(0.001)	(0.006)	(0.006)
Leverage	−0.001	−0.000	−0.013**	−0.010*
	(0.002)	(0.002)	(0.006)	(0.006)
Cash	−0.001	−0.002	−0.022***	−0.017**
	(0.002)	(0.002)	(0.008)	(0.008)
Profitability	−0.000*	0.000	−0.001	−0.001
	(0.000)	(0.000)	(0.001)	(0.001)
PPE	−0.001	−0.002	0.017	0.034**
	(0.003)	(0.003)	(0.015)	(0.015)
Capex	−0.007	−0.009	−0.039*	−0.040*
	(0.007)	(0.006)	(0.020)	(0.021)
InstOwn	−0.000	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Tobin'sQ	−0.000	−0.000**	0.003***	0.004***
	(0.000)	(0.000)	(0.001)	(0.001)
KZ Index	0.000	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
CGIndex	−0.002**	−0.000	−0.002	0.001
	(0.001)	(0.001)	(0.002)	(0.002)
HHI	0.008	0.011	0.089**	0.099**
	(0.009)	(0.007)	(0.044)	(0.046)
HHI^2	−0.002	−0.005	−0.053	−0.066
	(0.007)	(0.007)	(0.042)	(0.045)
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
No. of observations	31,454	30,141	34,307	32,966
R^2	0.387	0.383	0.303	0.299

Table 7: **Effect of Number of Analysts on Innovation (difference-in-differences Estimation)** This table shows the effect of the number of analysts on different innovation strategies using a difference-in-differences estimation, where the exogenous shock comes from brokerage house mergers. All panels show the effect of treatment on innovation taking into account either one year before and one year after the merger (i.e., from $t-1$ to $t+1$), or one year before and two years after the merger (i.e., from $t-1$ to $t+2$). Panel A shows the effect of brokerage house mergers on the number of analysts, and panels B and C show the effect on the innovation strategy. Panel B shows the regression results for a sample that includes all firms that appear in the I/B/E/S and Compustat files. Panel C uses a sample in which we used the nearest neighbour logit matching technique to obtain the control group. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Table 1.

Panel A: Number of Analysts

Dependent variable	*Coverage (t+1)*	*Coverage (t+2)*
	(1)	(2)
DID effect	-1.2^{***}	-1.5^{***}
	(0.24)	(0.25)
Firm fixed effect	Yes	Yes
No. of observations	21,029	31,196
R^2	0.90	0.89

Panel B: Basic Matching

Dependent variable	*R&D Cut*		*Acquisition*		*LnAcquisitions*		*CVC Setup*		*CVC Investments*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$t+1$	$t+2$	$t+1$	$t+2$	$t+1$	$t+2$	$t+1$	$t+2$	$t+1$	$t+2$
DID effect	-0.09^{**}	-0.08^{***}	-0.05^{*}	-0.05^{*}	-0.10^{***}	-0.08^{***}	-0.02	-0.03^{**}	0.02	0.004
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Year & Merger fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	21,029	31,196	21,029	31,196	21,029	31,196	19,199	28,274	21,029	31,196
R^2	0.26	0.22	0.43	0.39	0.38	0.34	0.03	0.03	0.58	0.57

Panel C: Matched Sample

Dependent variable	*R&D Cut*		*Acquisition*		*LnAcquisitions*		*CVC Setup*		*CVC Investments*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$t+1$	$t+2$	$t+1$	$t+2$	$t+1$	$t+2$	$t+1$	$t+2$	$t+1$	$t+2$
DID effect	-0.08^{*}	-0.08^{*}	-0.07^{*}	-0.07^{**}	-0.08^{**}	-0.08^{**}	-0.03^{*}	-0.03^{**}	0.001	-0.01
	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.017)	(0.01)	(0.02)	(0.02)
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Year & Merger fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	2,120	3,180	2,120	3,180	2,120	3,180	1,707	2,526	2,120	3,180
R^2	0.38	0.28	0.52	0.42	0.56	0.48	0.03	0.03	0.66	0.59

Table 8: **Median Split Sample Analysis** This table reports IV 2SLS regression results of how analyst coverage influences firms' future innovation strategies (i.e., at $t+1$) for median split sample based on high-tech vs. low-tech industries (panel A), on market competition (panel B), and on corporate governance (panel C). In all the regressions, we include control variables of our baseline model, and control for both firm and year fixed effects. Robust standard errors clustered at firm level are in parentheses. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Table 1.

Panel A: Corporate Governance

Dependent variable	*R&D Change* (1)	*R&D Cut* (2)	*Acquisition* (3)	*LnAcquisitions* (4)	*LnTargPatent* (5)	*LnTargCite* (6)	*CVC Setup* (7)	*CVC Investments* (8)
Good Governance:								
LnCoverage	−0.007	0.047	0.146***	0.132***	0.561	0.493	0.010**	0.022
	(0.005)	(0.058)	(0.042)	(0.036)	(0.441)	(0.505)	(0.004)	(0.018)
No. of obs	13,614	13,614	17,239	17,239	2,104	2,104	15,507	17,239
R^2	0.190	0.187	0.258	0.292	0.213	0.228	0.452	0.347
Low Governance:								
LnCoverage	−0.011**	0.104**	0.019	0.021	0.396***	0.419**	0.007**	0.046***
	(0.004)	(0.043)	(0.021)	(0.018)	(0.147)	(0.165)	(0.003)	(0.014)
No. of obs	13,120	13,120	17,068	17,068	2,100	2,100	15,947	17,068
R^2	0.231	0.226	0.319	0.342	0.288	0.273	0.454	0.372

Panel B: Financial Constraints

Dependent variable	*R&D Change* (1)	*R&D Cut* (2)	*Acquisition* (3)	*LnAcquisitions* (4)	*LnTargPatent* (5)	*LnTargCite* (6)	*CVC Setup* (7)	*CVC Investments* (8)
High Financial Constraints:								
LnCoverage	−0.006	0.091**	0.037	0.043**	0.064	0.089	0.011***	0.033***
	(0.003)	(0.045)	(0.025)	(0.021)	(0.196)	(0.218)	(0.003)	(0.011)
No. of obs	11,936	11,936	17,154	17,154	2,102	2,102	16,044	17,154
R^2	0.405	0.194	0.272	0.304	0.268	0.267	0.392	0.398
Low Financial Constraints:								
LnCoverage	−0.006	0.027	0.092**	0.085**	0.611*	0.547	0.007**	0.029
	(0.005)	(0.053)	(0.040)	(0.034)	(0.328)	(0.370)	(0.003)	(0.021)
No. of obs	14,798	14,798	17,153	17,153	2,102	2,102	15,410	17,153
R^2	0.235	0.219	0.302	0.330	0.237	0.248	0.479	0.352

Panel C: High-tech vs. Low-tech Industries

Dependent variable	*R&D Change* (1)	*R&D Cut* (2)	*Acquisition* (3)	*LnAcquisitions* (4)	*LnTargPatent* (5)	*LnTargCite* (6)	*CVC Setup* (7)	*CVC Investments* (8)
High-tech Industries:								
LnCoverage	−0.008**	0.074**	0.064**	0.069***	0.469**	0.505**	0.010***	0.050***
	(0.004)	(0.033)	(0.027)	(0.023)	(0.191)	(0.216)	(0.003)	(0.014)
No. of obs	21,649	21,649	23,162	23,162	3,102	3,102	20,852	23,162
R^2	0.156	0.162	0.251	0.286	0.183	0.177	0.414	0.307
Low-tech Industries:								
LnCoverage	−0.004*	0.007	0.055**	0.046**	−0.105	−0.179	0.007**	0.004
	(0.002)	(0.071)	(0.026)	(0.022)	(0.225)	(0.259)	(0.003)	(0.011)
No. of obs	5,085	5,085	11,145	11,145	1,102	1,102	10,602	11,145
R^2	0.197	0.141	0.212	0.222	0.314	0.310	0.269	0.255

Table 9: **Direct vs. Indirect Effect** This table reports IV 2SLS regression results of the interaction effect of the number of analysts and the R&D cut on acquisition activities (panel A) and CVC investments (panel B) one and two years ahead. Robust standard errors clustered at firm level are in parentheses. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Table 1.

Panel A: Acquisitions

Dependent variable	*Acquisition*		*LnAcquisitions*	
	(1)	(2)	(3)	(4)
	$t+1$	$t+2$	$t+1$	$t+2$
LnCoverage (Instrumented)	0.072***	0.047**	0.076***	0.040**
	(0.024)	(0.023)	(0.021)	(0.019)
R&D Cut	0.034**	0.031**	0.030**	0.031**
	(0.016)	(0.015)	(0.013)	(0.013)
InteractR&D (Instrumented)	−0.008	−0.015	−0.007	−0.014*
	(0.010)	(0.009)	(0.008)	(0.008)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
No. of observations	26,734	25,732	26,734	25,732
R^2	0.254	0.248	0.287	0.280

Panel B: Acquisition Innovativeness

Dependent variable	*LnTargPatent*		*LnTargPatent*	
	(1)	(2)	(3)	(4)
	$t+1$	$t+2$	$t+1$	$t+2$
LnCoverage (Instrumented)	0.455***	0.312**	0.495**	0.269
	(0.173)	(0.150)	(0.195)	(0.172)
R&D Cut	0.204	−0.181	0.224	−0.203
	(0.153)	(0.144)	(0.168)	(0.151)
InteractR&D (Instrumented)	−0.075	0.133*	−0.087	0.144*
	(0.082)	(0.079)	(0.089)	(0.081)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
No. of observations	3,533	3,415	3,533	3,415
R^2	0.209	0.212	0.201	0.209

Panel C: CVC Investments

Dependent variable	*CVC Setup*		*CVC Investments*	
	(1)	(2)	(3)	(4)
	$t+1$	$t+2$	$t+1$	$t+2$
LnCoverage (Instrumented)	0.009***	0.006*	0.035***	0.028**
	(0.003)	(0.003)	(0.012)	(0.012)
R&D Cut	0.004	0.002	0.005	0.010
	(0.004)	(0.003)	(0.009)	(0.008)
InteractR&D (Instrumented)	−0.003	−0.001	−0.004	−0.007
	(0.003)	(0.002)	(0.006)	(0.005)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
No. of observations	24,140	23,157	26,734	25,732
R^2	0.398	0.382	0.314	0.315

Table 10: **Number of Analysts, Innovation Strategies, and Innovation Outputs** This table reports IV 2SLS regression results of the interaction effect of the number of analysts and the R&D cut, acquisitions, and CVC investments on the quantity (panel A) and quality (panel B) of firms' patents three years ahead. Robust standard errors clustered at firm level are in parentheses. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Table 1.

Panel A: Patents

Dependent variable	$LnPatents(t+3)$			
	(1)	(2)	(3)	(4)
LnCoverage (Instrumented)	0.071	0.051	0.063	0.066
	(0.073)	(0.072)	(0.072)	(0.073)
R&D Cut	0.013	−0.053*	0.013	0.013
	(0.010)	(0.031)	(0.010)	(0.010)
Acquisition	0.032**	0.033**	−0.063	0.032**
	(0.015)	(0.015)	(0.060)	(0.015)
CVC Investments	0.387***	0.388***	0.381***	−0.331
	(0.062)	(0.062)	(0.062)	(0.317)
InteractR&D (Instrumented)		0.042**		
		(0.021)		
InteractAcquisition (Instrumented)			0.052	
			(0.035)	
InteractCVC (Instrumented)				0.269**
				(0.121)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
No. of observations	18,191	18,191	18,191	18,191
R^2	0.787	0.787	0.787	0.787

Panel B: Citations

Dependent variable	$LnCitations(t+3)$			
	(1)	(2)	(3)	(4)
LnCoverage (Instrumented)	0.047	0.023	0.041	0.042
	(0.075)	(0.075)	(0.075)	(0.075)
R&D Cut	0.010	−0.070**	0.010	0.010
	(0.011)	(0.033)	(0.011)	(0.011)
Acquisition	0.031*	0.032*	−0.053	0.030*
	(0.017)	(0.017)	(0.065)	(0.017)
CVC Investments	0.414***	0.416***	0.409***	−0.253
	(0.067)	(0.067)	(0.067)	(0.333)
InteractR&D (Instrumented)		0.051**		
		(0.032)		
InteractAcquisition (Instrumented)			0.045	
			(0.038)	
InteractCVC (Instrumented)				0.250**
				(0.127)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
No. of observations	18,191	18,191	18,191	18,191
R^2	0.762	0.762	0.762	0.762

Table 11: **Number of Analysts, Innovation Strategies, and Level of Novelty** This table reports IV 2SLS regression results of the interaction effect of the number of analysts and the R&D cut, acquisitions, and CVC investments on the level of novelty of firms' patents three years ahead. Control variables, firm and year fixed effects are included in all the regressions. Robust standard errors clustered at firm level are in parentheses. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Table 1.

Panel A: Total number of backward citations

Dependent variable	$LnBackCitations(t+3)$			
	(1)	(2)	(3)	(4)
LnCoverage (Instrumented)	-0.170	-0.185	-0.169	-0.160
	(0.149)	(0.149)	(0.148)	(0.149)
R&D Cut	0.043^{*}	-0.014	0.043^{*}	0.042^{*}
	(0.025)	(0.067)	(0.025)	(0.025)
Acquisition	0.007	0.007	0.030	0.008
	(0.033)	(0.033)	(0.114)	(0.033)
CVC Investments	-0.014	-0.013	-0.013	0.832^{*}
	(0.086)	(0.086)	(0.086)	(0.430)
InteractR&D (Instrumented)		0.030		
		(0.034)		
InteractAcquisition (Instrumented)			-0.011	
			(0.052)	
InteractCVC (Instrumented)				-0.309^{*}
				(0.160)
No. of observations	7,968	7,968	7,968	7,968
R^2	0.790	0.791	0.791	0.790

Panel B: Total number of breakthrough patents

Dependent variable	$LnTop1Citations(t+3)$			
	(1)	(2)	(3)	(4)
LnCoverage (Instrumented)	-0.075	-0.093^{*}	-0.072	-0.071
	(0.055)	(0.055)	(0.055)	(0.055)
R&D Cut	0.011	-0.060^{**}	0.011	0.011
	(0.010)	(0.028)	(0.010)	(0.010)
Acquisition	0.017	0.017	0.054	0.018
	(0.014)	(0.014)	(0.051)	(0.014)
CVC Investments	0.040	0.042	0.042	0.426
	(0.054)	(0.054)	(0.054)	(0.261)
InteractR&D (Instrumented)		0.038^{**}		
		(0.016)		
InteractAcquisition (Instrumented)			-0.017	
			(0.025)	
InteractCVC (Instrumented)				-0.141
				(0.100)
No. of observations	7,970	7,970	7,970	7,970
R^2	0.756	0.756	0.756	0.755

Panel C: Total number of patents of new technology classes

Dependent variable	$LnNewTechnology(t+3)$			
	(1)	(2)	(3)	(4)
LnCoverage (Instrumented)	-0.158^{**}	-0.170^{**}	-0.164^{**}	-0.158^{**}
	(0.079)	(0.079)	(0.079)	(0.079)
R&D Cut	0.024	-0.022	0.024	0.024
	(0.015)	(0.041)	(0.015)	(0.015)
Acquisition	0.038^{*}	0.038^{*}	-0.034	0.038^{*}
	(0.021)	(0.021)	(0.072)	(0.021)
CVC Investments	0.004	0.005	0.001	0.050
	(0.046)	(0.046)	(0.046)	(0.251)
InteractR&D (Instrumented)		0.025		
		(0.021)		
InteractAcquisition (Instrumented)			0.035	
			(0.034)	
InteractCVC (Instrumented)				-0.017
				(0.088)
No. of observations	7,970	7,970	7,970	7,970
R^2	0.469	0.469	0.469	0.469

Table 12: **The Effect of EPS Pressure.** This table reports the effect of EPS pressure on firms' decisions to cut R&D expenses (panel A) and on innovation output measured by patents and citations (panel B). Panel A presents OLS estimation results of the effect of EPS pressure (i.e., distance between analysts' forecasts and firms' actual EPS) and an indicator variable that equals 1 when firms meet or beat analysts' forecasts on R&D spending, in the current period and one period after. We use several specifications including 1-degree and 2-degree polynomials. Panel B exploits the discontinuity presented in panel A and uses a fuzzy regression discontinuity design to show the effect of firms' R&D cuts on firms' patents and citations three and four years later. We instrument the variable R&D cut with the indicator variable that equals 1 when firms meet or beat analysts' forecasts. We use a small window of 10 cents around the EPS pressure threshold of 0. We include our usual firm-level controls in all regressions. We also control for the level of EPS pressure and its interaction with the indicator variable in panel B. Errors are robust and clustered at the firm level, and they are reported in parenthesis below the coefficients. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Table 1.

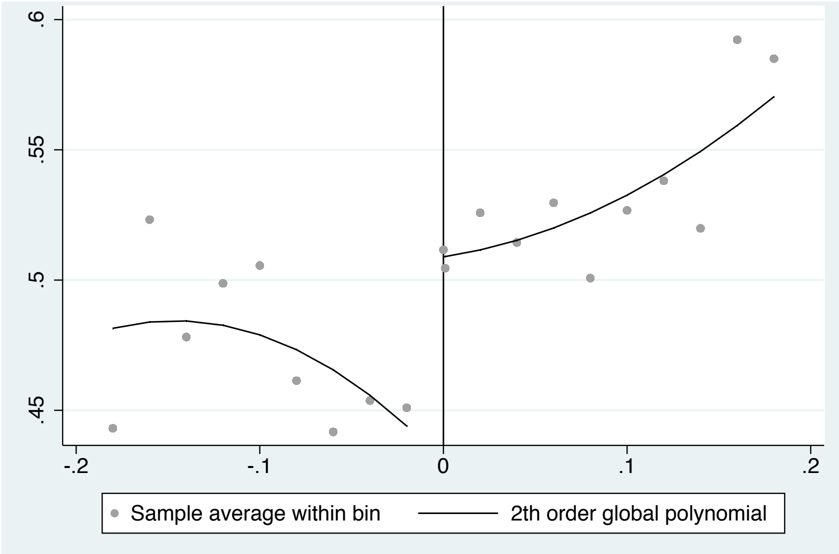
Panel A: EPS Pressure and R&D Activities

Dependent variable	*R&D Cut*			*R&D Change*		
	(1)	(2)	(3)	(4)	(5)	(6)
	t	t	$t+1$	t	t	$t+1$
$I_{MeetBeat(i,t)}$	0.034***	0.032**	−0.009	−0.000	−0.001	−0.000
	(0.011)	(0.015)	(0.016)	(0.001)	(0.002)	(0.002)
EPSP	−0.186	0.113	−0.118	−0.021	−0.058	0.024
	(0.128)	(0.426)	(0.450)	(0.017)	(0.056)	(0.053)
EPSP Polynomial	1-order	2-order	2-order	1-order	2-order	2-order
Control variables	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 observations	20,147	20,147	18,560	20,147	20,147	18,560
R^2	0.174	0.174	0.181	0.224	0.224	0.208

Panel B: EPS Pressure, R&D Cut, and Patents

Dependent variable	*LnPatents*		*LnCitations*	
	(1)	(2)	(3)	(4)
	$t+3$	$t+4$	$t+3$	$t+4$
R&D Cut	0.081	−0.904	−0.222	−1.248
(Instrumented)	(1.074)	(1.183)	(1.191)	(1.369)
EPSP Polynomial	1-order	1-order	1-order	1-order
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
No. of observations	10,963	10,963	10,963	10,963
R^2	0.492	0.339	0.456	0.222

Figure 1: **Probability of Cutting R&D.** This figure plots the probability that firms cut R&D spending by the end of the fiscal year as a function of EPS pressure measured by the distance between analysts' consensus forecasts and the actual firms' EPS. For every EPS pressure bin, the dots represent the probability of a cut in R&D –the proportion of firm-years that cut R&D from all the firm-years included in that bin (bins are of 2 cents). The lines are second-order polynomials fitted through the estimated probabilities on each side of the zero EPS pressure threshold.



B Appendix B

Following Hong and Kacperczyk (2010) and others,[45] we use the mergers of brokerage houses as an exogenous variation for analyst coverage. When two brokerage houses merge, the analysts from the two merging houses that were covering the same firms become redundant. After the merger, the surviving house usually retires some of these analysts and, as a result, after the merger the firms that had been followed by the two merging houses lose one financial analyst. As shown by Hong and Kacperczyk (2010), this loss in analyst coverage happens for reasons that are exogenous to the characteristics of the firms being covered.[46]

We take the list of 15 mergers provided by Hong and Kacperczyk (2010),[47] and we keep the 13 mergers that occur during our sample period (between 1990 and 2011). Table B.1 shows a detailed list with the characteristics of the mergers used in this study. We use these 13 events to estimate a difference-in-differences (DID) model. Our DID model presents a slight variation with the typical DID methodology because we need to handle multiple events. We follow Gormley and Matsa's (2011) "stacking" approach to construct our sample of treated and control firms. Similarly, we first construct subsamples, or cohorts, of treated and control firms for each merger event. Thus, each cohort corresponds to a merger event. We construct the cohorts in chronological order by taking into account the treated firms in the previous cohorts (see explanation below), and then we "stack" (or pool) the data across cohorts into one dataset that we will use for an estimation.

We construct each cohort as follows. For each merger event, we specify a three-month window around the merger month to account for the possibility that the merger event spanned several days or even a couple of months. Then, we use a 12-month period around this window to construct our group of treated firms. In each cohort, we classify a firm into the treated group if it was covered by both merging houses during the 12-month period before the merger window, that is, between 13 and 2 months before the merger month; and is continued to be covered in the 12-month period after the merger window, that is, between two and 13 months after the merger month.[48] For each merger, we construct a comparison group of unaffected firms (firms that were not covered by both houses before the merger)

[45] Derrien and Kecskes (2013), Chen, Harford, and Lin (2015), and Irani and Oesch (2013, 2016).

[46] In their study, Hong and Kacperczyk (2010) carefully verified that the broker house mergers were exogenous to the covered firms' characteristics. Wu and Zang (2009) also argue that when two brokerage houses merge, they typically let analysts go for reasons other than the characteristics of the firms they cover, such as merger turmoil and cultural differences in the broker houses.

[47] Using the list of mergers provided by the authors allows us to make our analysis consistent with the various studies that use the same list, and to be sure that the merger events are due to characteristics that are exogenous to the affected firms.

[48] To further ensure exogeneity, we drop all firms that were covered by both broker houses before the merger but are not covered by the surviving house afterwards as this termination decision could be endogenous.

that are present in the Compustat and in I/B/E/S databases during the event window for that merger. We use a five-year event window (two years pre- and two years post-merger) for our estimations, and hence, we require that our treated and control firms are active in Compustat and have coverage in the I/B/E/S detail file during the five-year window that corresponds to each merger. For the moment, we match firms based only on their presence in Compustat and I/B/E/S during the event window, but below we construct a group of control firms using a matching approach based on firm characteristics.

Since we use data for two years pre- and two years post-merger for our estimations, we need to address the possibility that some firm-years may overlap across two or more different events. The overlapping could be a problem if, for example, a firm appears as treated in a given year, and as a control in the same year for another event. This could happen for two mergers that occur either in the same year, or are one or two years apart. We address the possibility of overlapping as follows. Our first cohort (i.e., for merger 1 in year 1994) starts with a pool of previously untreated observations.[49] From this pool, we identify the treated firms and control firms as explained above. For the next cohort (i.e., merger 2 in year 1997), we first drop from the pool of treatment and control firm candidates the firms that we identified as treated in the previous merger, and then, from the remaining firms, we identify the treated and control firms for this merger. In general, for each cohort, we drop treated firms from previous mergers as long as the previous mergers are less than four years apart from the current one. In other words, a firm can be a control and can remain in the pool of candidate firms until it gets treated by a merger event, in which case it disappears from the sample of candidate firms for the next three years. After the three years, the previously treated firm is put back in the pool of candidates because there is no longer a risk of overlap. In the "stacked" sample, we end up with 503 treated firms and $2,922$ control firms.[50] The regression results using this sample are in Table 7 panel B.

We also construct a control group of firms using a matching technique. The results using the matched sample appear in Table 7 panel C. A matching approach is useful when one is concerned that the distributions of unobservable characteristics might be substantially different in the treatment and control samples. We match each treated firm to a set of control firms based on various firm-level characteristics measured in the previous year to the merger year. As matching variables, we choose the firm-level characteristics that determine the inclusion of a firm into the treated group. These variables correspond to those used

[49] The merger before that occurred in 1988, which is more than 3 years apart from the merger in 1994. So it is not possible that our firm-year observations overlap.

[50] Some observation units will appear multiple times in the data. For example, firm ABC might be a control in event year 1999 but a treated firm in a later event in 2005.

in the literature. We match firms on size, cash, R&D, profitability, leverage, PPE, and Tobin's Q using nearest neighbor propensity score matching. Specifically, we first estimate a logit regression in which the dependent variable equals one if a firm is treated in a given year, and zero otherwise; and the independent variables correspond to our set of matching variables. For the logit estimation, we use our panel of treated firms and the remaining firms in Compustat with valid matching variables as our control pool. Second, the estimated coefficients are used to predict propensity scores of treatment, which are then used to perform a nearest-neighbor match with replacement. We keep up to four matches per each treated firm. We end up with 229 treated and 418 control firms.

Table B.2 presents a comparison of the ex-ante characteristics of the treated and control firms for the matched sample. As Table B.2 shows, the matching procedure eliminated most of the ex-ante differences in firms' observable characteristics. We use the matched sample to estimate equation (4) again, and report the results in Table 7. The results in Table 7 show that analyst coverage significantly affects firms' innovation strategy. In particular, after a coverage termination shock, firms are less likely to cut R&D expenses, to start CVC funds, and to acquire firms. Also, when they acquire, they acquire a lower number of firms. These results are consistent with our OLS and IV results, and the previous DID results. The sign and magnitude of the coefficients in the matched sample (panel C of Table 7) are very similar to those in panel B of the same table, suggesting that potential unobservable characteristics were not causing large biases in our roughly matched sample. However, in the matched sample the significance is smaller, which might be due to the lower number of observations.

The success of the DID method relies on the so-called parallel trends assumption. This is a key identifying assumption that requires that, in the absence of treatment, the group of treated and control firms follow a similar trend. The fact that we rely on multiple treatment events is useful for mitigating concerns about the violation of the parallel trends assumption because it is hard to find a story that would argue that the parallel trends assumption is violated for each unique event. Nevertheless, we look for further support of this assumption by showing that there are no significantly different trends in the pre-event period for the two groups. Figure B.1 presents different plots of the point estimates of yearly regressions as specified in Equation (4). Each plot corresponds to various regressions of our innovation input variables against a dummy variable that equals 1 for the treated firms. In each plot we present point estimates by year, from three years before to five years after the merger events. As can be seen in Figure B.1, there is no indication of change in the innovation strategy of treated firms relative to control firms prior to the mergers. However, the change in the treated firms' innovation strategy coincides with the merger event, as shown in our previous results.

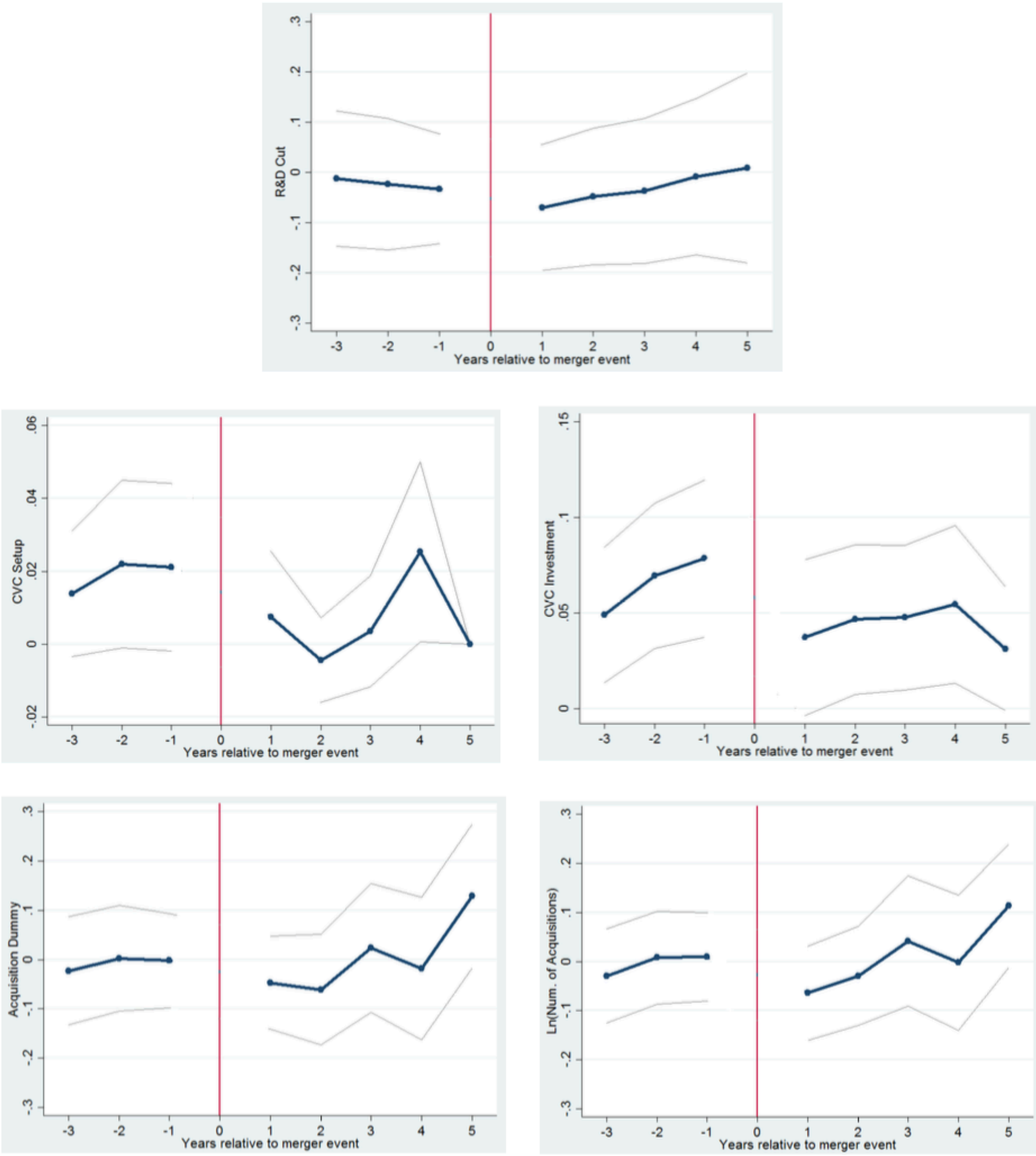
Table B.1: **Description of the Merger Events.** This table reports a description of the merger events considered in this paper. The details were compiled from Hong and Kacperczyk (2010). We include the names and dates of the merging brokerage houses as well as their I/B/E/S identifiers.

Brokerage House Name	*I/B/E/S Identifier*	*Acquirer/Target*	*Merger Date*
Paine Webber Group, Inc.	189	Acquirer	12/31/1994
Kidder Peabody & Co.	150	Target	
Morgan Stanley Group, Inc.	192	Acquirer	5/31/1997
Dean Witter Discover & Co.	232	Target	
Smith Barney	254	Acquirer	11/28/1997
Salomon Brothers	242	Target	
EVEREN Capital Corp.	829	Acquirer	1/9/1998
Principal Financial Securities	495	Target	
DA Davidson & Co.	79	Acquirer	2/17/1998
Jensen Securities Co.	932	Target	
Dain Rauscher Corp.	76	Acquirer	4/6/1998
Wessels Arnold & Henderson LLC	280	Target	
First Union Corp., Charlotte, NC	282	Acquirer	10/1/1999
EVEREN Capital Corp.	829	Target	
Paine Webber Group, Inc.	189	Acquirer	6/12/2000
JC Bradford & Co.	34	Target	
Credit Suisse First Boston	100	Acquirer	10/15/2000
Donladson Lufkin & Jenrette	86	Target	
UBS Warburg Dillon Read	85	Acquirer	12/10/2000
Paine Webber	189	Target	
Chase Manhattan	125	Acquirer	12/31/2000
JP Morgan	873	Target	
Fahnestock & Co.	98	Acquirer	9/18/2001
Josephthal Lyon & Ross	933	Target	
Janney Montgomery Scott LLC	142	Acquirer	3/22/2005
Parker/Hunter Inc.	860	Target	

Table B.2: **Ex-ante Firm Characteristics, Matched Sample.** This table reports the average values and standard errors, as well as the mean difference and t-statistic of the treated and control groups of firms in the matched sample one year before the merger event. We report the averages and difference for various firm characteristics included in our analysis. We match firms on size, cash, R&D, ROE, leverage, PPE and Tobin's Q using nearest neighbour propensity score matching. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Table 1.

	Control group	*Treated group*	
	Mean	Mean	Difference
	(Std. Err.)	(Std. Err.)	(t-stat)
Firm Size	7.01	7.68	-0.67^{***}
	(0.05)	(0.07)	(-6.9)
R&D	0.07	0.06	0.006
	(0.004)	(0.003)	(0.95)
Leverage	0.39	0.41	-0.017
	(0.007)	(0.009)	(-1.3)
Cash	0.20	0.17	0.02
	(0.008)	(0.011)	(1.43)
Profitability	0.32	0.30	0.01
	(0.01)	(0.02)	(0.51)
PPE	0.25	0.26	-0.009
	(0.006)	(0.009)	(-0.85)
Capex	0.06	0.06	-0.001
	(0.001)	(0.002)	(-0.49)
InstOwn	0.38	0.37	0.01
	(0.011)	(0.01)	(0.5)
Tobin'sQ	4.9	5.47	-0.5
	(0.19)	(0.33)	(-1.45)
$KZIndex$	-5.38	-3.9	-1.46
	(0.57)	(0.62)	(-1.55)
CGIndex	0.10	0.13	-0.028
	(0.024)	(0.034)	(-0.67)
HHI	0.18	0.18	0.001
	(0.009)	(0.012)	(0.03)

Figure B.1: **Effect of Merger Events on Innovation Strategy (Parallel Trends).** This figure includes several graphs that report the point estimates from regressions of our various innovation inputs on a dummy variable equal to 1 for firms that were affected by brokerage house mergers and 0 otherwise. The regressions follow the same specification as Equation (4) except that each point estimate corresponds to a different year, from three years before a merger event to five years after. We also include 95% confidence intervals.



C Appendix C

Table C.1: **Pre-existing Differences in R&D Expenses between Firms with a Positive or Negative EPS Pressure.** This table reports results for pre-existing differences in R&D spending around the zero EPS pressure threshold (i.e., when $EPSP = 0$). The test is performed in a sample that consists of observations in a small window around the zero EPS threshold (between -0.1 and 0.1). We control throughout for the level of EPS pressure (i.e., EPSP), interacted with the indicator variable that equals 1 for matchers and beaters and 0 otherwise. Standard errors are robust and clustered at the firm level, and are reported in parentheses below the coefficient estimates. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	*R&D Cut*		*R&D Change*	
	(1)	(2)	(3)	(4)
	$t-1$	$t-2$	$t-1$	$t-2$
$I_{MeetBeat(i,t)}$	-0.002	-0.005	0.002	0.001
	(0.012)	(0.012)	(0.002)	(0.002)
EPSP	0.151	-0.054	-0.021	-0.019
	(0.130)	(0.140)	(0.017)	(0.019)
EPSP Polynomial	1-order	1-order	1-order	1-order
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
No. of observations	19,644	18,220	19,767	18,419
R^2	0.147	0.138	0.202	0.199