

Innovation Under Pressure

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Abstract

Firms become more efficient at innovation activities when they face pressure to meet Earnings Per Share (EPS) targets using stock repurchases. Using a regression-discontinuity framework, we find that incentives to engage in "EPS-motivated buybacks" are followed by more citations and higher values for firms' new patents. We trace these effects to improved allocation of R&D resources and a greater focus on novel innovation. The positive effects are concentrated among ex-ante "innovation-efficient" firms that achieve better patenting outcomes after reorganizing (but not cutting) their R&D investments. Our findings illustrate that short-term earnings pressure can act through a free cash flow channel that motivates more efficient spending.

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I. Introduction

A valuable feature of public equity markets is that they provide listed firms with improved access to external financing (Bernstein (2015), (2022)). But at the same time, equity markets expose managers to various short-term performance pressures. Such pressures may stem from stock analysts (He and Tian (2013), Guo, Pérez -Castrillo, and Toldrà -Simats (2019)), transient institutional investors (Bushee (1988), Giannetti and Yu (2021)), takeover threats (Stein (1988), Chemmanur and Tian (2018)), or from managers' compensation and contracts (Dechow and Sloan (1991), Darrough and Rangan (2005), Chen, Cheng, Lo, Wang (2015), Edmans, Fang, and Lewellen (2017), Ladika and Sautner (2020)). Previous research has argued that these kinds of short-term pressures have the potential to harm firms in the long run (Stein (1989), Lerner, Sorensen, and Stromberg (2011), Kraft, Vashishtha, and Venkatachalam (2018), Bernstein (2022)).

Investments in innovation, being among a firm's most long-term-oriented activities, are often believed to suffer when firms prioritize short-term goals. For example, Jamie Dimon and Warren Buffett argue that WSJ (2018) public firms increasingly experience “...*an unhealthy focus on short-term profits at the expense of long-term strategy, growth and sustainability.*”¹ Yet, many sources of short-term pressures identified in the literature—such as takeovers, institutional investors, or analysts—also play a vital role in corporate governance, potentially supporting rather than hindering a firm's long-term investments (e.g., Chen et al. (2015)). The literature that has studied how these sources of short-term pressures affect innovation activities offers mixed evidence.²

¹ Wall Street Journal, June 6, 2018. “Short-Termism Is Harming the Economy.” <https://www.wsj.com/articles/short-termism-is-harming-the-economy-1528336801>

² Regarding takeover threats, Chemmanur and Tian (2018) find that anti-takeover provisions predict more patents, while Meulbroek, Mitchell, Mulherin, Netter, and Poulsen (1990) and Atanassov (2013) find that anti-takeover laws lead to less R&D and patents, respectively. For equity analysts, He and Tian (2013) show that a reduction in analyst

The goal of this paper is to study the effects of a common type of short-term pressure to meet quarterly earnings targets—specifically, an incentive to engage in *EPS-motivated buybacks* (for brevity, we will regularly refer to these incentives as “earnings pressure”)—on firms’ future innovation outputs. To identify these effects, our empirical framework exploits a discontinuity in firms’ incentives to engage in share repurchases to “just meet” the analyst earnings consensus (Hribar, Jenkins, and Johnson (2006), Almeida, Fos, and Kronlund (2016)). Specifically, we compare differences in future innovation outcomes for firms that would just miss their EPS target by a small margin without doing a buyback (and who are more likely to engage in repurchases to bring their EPS just above the target) versus firms that would narrowly meet the target anyway.³ Under the identification assumption that there are no discontinuous changes in other variables that may independently affect innovation output around this same threshold, this empirical strategy can identify the effect of such pressure to meet earnings on innovation outputs.⁴

We focus on firms’ incentives to beat their EPS targets since EPS is the short-term performance measure that tends to matter the most to both firms and investors (Graham, Harvey, and Rajgopal (2005)). While firms also have other earnings management tools (such as accruals management), there are several reasons why we focus specifically on the role of EPS-motivated buybacks. First, the incentive to use buybacks to boost EPS above the analyst target represents a

coverage leads to more patents, while Derrien, Kecskés, and Thesmar (2013) and Gentry and Shen (2013) show that fewer analysts lead to lower R&D. Regarding institutional investors, Bushee (1988) shows that transient institutional investors are related to R&D cuts used to meet earnings expectations, while Giannetti and Yu (2021) show that short-term institutional investors improve product innovation, especially in competitive industries. Hackbarth, Rivera, and Wong (2022) highlight that shareholders can exploit debtholders through myopic decisions.

³ Our analysis importantly only exploits the discontinuity in whether the EPS surprise would have been negative absent buybacks; that is, we do not condition any part of the analysis on actually doing (or not doing) buybacks.

⁴ A candidate confounder that we examine in a robustness test is whether the same threshold that predicts a discontinuous increase in buybacks is contemporaneously related to jumps in the use of other earnings management tools, such as cuts to R&D or increases in accruals. Consistent with the identification assumption, we find that there are no discontinuities in these other earnings management tools around the same threshold.

form of short-term pressure that we can readily isolate. Second, this setting differs conceptually from the existing literature on short-termism in that it does not involve changes in firms' investor base, analyst coverage, takeover risk, or managerial contracts. Instead, the variation in the current paper comes from differences in firms' short-term incentives to beat the EPS estimate through buybacks in a particular quarter while holding the other sources of short-termism constant.⁵ Third, EPS-motivated buybacks are economically important: they require significant cash outlay even when the impact on EPS is relatively small (Almeida et al. (2016)). We might, therefore, expect this setting to be especially relevant in causing significant knock-on effects on the firm's operational decisions. Finally, this setting has practical importance in light of the active policy debate around the consequences of earnings-motivated buybacks. Political leaders and the media often single out these buybacks as a prime example of corporations caving to short-term earnings pressure.⁶

How might we expect firms' future innovation outputs to be affected by incentives to engage in EPS-motivated buybacks? On the one hand, previous research suggests that the effects could be negative. Innovation is often viewed as the first thing that suffers when firms focus on the short run (Dechow and Sloan (1991)), even though innovation and patents are critical for a firm's future long-run value and profitability (Griliches (1981), Deng, Lev, and Narin (1999), Pandit, Wasley, and Zach (2011)). Almeida et al. (2016) find that EPS-motivated buybacks, on average, tend to be followed by lower spending on capital expenditures, employment, and R&D;

⁵ This is a natural feature of our research design which is based on time-series variation in whether firms happen to fall within a narrow range of "pre-repurchase" EPS (the "counterfactual EPS" absent buybacks). Additionally, we find empirically that there is no significant difference in analyst coverage and institutional ownership across the two sides of the threshold in untabulated tables; similarly, it seems unlikely that variables such as takeover risk or managerial contracts would differ as these tend to be persistent over time for a firm.

⁶ For example, in the US, the Biden administration has introduced a tax on buybacks, partly as a means to counter perceived short-termism (see, e.g., <https://crsreports.congress.gov/product/pdf/R/R47397>). U.S. Senator Elizabeth Warren, who is among the proponents of such a view, has argued that "...buybacks create a sugar high for the corporations. It boosts prices in the short run, but the real way to boost the value of a corporation is to invest in the future, and they are not doing that."

and if such reduced spending also negatively affects the firm's most promising innovation projects, we might expect to see lower innovation outputs down the road, e.g., in the form of fewer and less influential patents. Several industry leaders have also pointed out that short-term pressure to meet earnings targets can harm firms' innovation activities. For example, Michael Dell, describing his experience as a public-company CEO, noted that WSJ (2014) "*shareholders increasingly demanded short-term results to drive returns; innovation and investment too often suffered as a result,*" and he argued that this was an underlying motivation for taking his company private.⁷

On the other hand, pressure to meet earnings by engaging in EPS-motivated buybacks can push firms to make more efficient use of resources (*i.e.*, a "free cash flow" channel). Firms with abundant financial resources have been shown to be more likely to make wasteful or inefficient investments (e.g., Jensen (1986), (1993)); in that case, incentives to do EPS-motivated buybacks can help counteract such agency problems and thus improve the efficiency of firms' spending on innovation projects. The idea is that, by introducing an urgent incentive to spend money on buybacks and thus reducing financial slack, firms need to focus their activities, and they may do so by prioritizing only those activities that they are particularly good at. For example, firms may choose to cut innovation activities for projects that have low potential value, while maintaining or increasing their relative focus on those projects that are the most promising. In that case, firms' innovation output could even increase.

To capture the effects of earnings pressure on both the quantity and quality of a firm's future innovation outputs, we use the rich content in patent databases, which allows us to measure firms' innovation activities and performance across multiple dimensions (Lev (2001)).

⁷ Wall Street Journal, Nov. 24, 2014. "Going Private Is Paying Off for Dell." <https://www.wsj.com/articles/michael-dell-going-private-is-paying-off-for-dell-1416872851>

As suggested by Griliches ((1990), p. 1702), “[n]othing else even comes close in the quantity of available data, accessibility, and the potential industrial, organizational, and technological detail.” We employ conventional patent measures such as patent count and forward citations (Griliches (1981), Hall (1993)), and also the measure of patents’ value of Kogan, Papanikolaou, Seru, and Stoffman (2017), which is based on stock market reactions to patent grants. Finally, we measure the novelty of firms’ innovation activities to examine changes to their innovation strategy.

Our baseline findings show that over the four quarters after firms face pressure to do EPS-motivated buybacks, the average effect on future innovation outputs is significantly *positive*, consistent with improved efficiency in innovation activities. We observe both increases in forward citations for firms’ new patents and a higher economic value for these patents. We also find a statistically significant increase in the raw number of new patents produced by these firms. These positive effects happen despite these firms spending less on R&D in aggregate.⁸ In sum, earnings pressure, in the form of an incentive to engage in EPS-motivated buybacks, does not appear harmful to innovation outputs because it can spur increased innovation efficiency.

We next investigate two candidate (non-exclusive) mechanisms that could explain the positive effects on innovative efficiency. First, we examine whether resource allocation improves in a way such that overall R&D dollars are spent on more productive projects. To do so, we separate our sample into two groups: firms that are ex-ante efficient at innovation vs. those that are not, based on measuring the extent to which firms previously have been able to translate R&D spending into new patents (Hirshleifer, Hsu, and Li (2013)). Consistent with improved resource allocation, we find that the positive effect of earnings pressure on innovation outcomes

⁸ This finding was first documented by Almeida et al. (2016), and we also confirm this finding of a negative effect on R&D spending in the current sample of firms that can be linked to patent databases.

is driven entirely by firms that previously have been better at executing innovative projects—the ‘innovation-efficient’ firms. On average, these innovation-efficient firms do not cut their R&D spending, which is consistent with these projects having higher NPV. Conversely, only those firms that have been inefficient at creating patents in the past tend to cut R&D spending in response to earnings pressure. This pattern across firms is consistent with efficient reallocation: When firms must choose which internal projects to cut to finance EPS-motivated buybacks, they reduce spending on their least productive projects first.

Second, we study the extent to which the firms subject to earnings pressure are more likely to increase their relative focus on more novel innovation, i.e., whether we observe a shift in the *nature* of innovation. To this end, we employ measures for the ratio of patents in unknown fields, and the scope of backward citations (Katila and Ahuja (2002), Balsmeier, Fleming, and Manso (2017)).⁹ Consistent with more novel innovation, we find that firms with earnings pressure on average exhibit an increase in the ratio of patents in areas that are previously “unknown” to them, along with an increase in the use of new knowledge sources (measured as new backward citations that firms have not used before). This is consistent with firms creating more influential patents by increasing their relative focus on new technologies. In addition to our first mechanism that showed an improved allocation of R&D spending *across* firms, these findings thus suggest a re-prioritization of projects *within* firms.

To shed more light on the underlying mechanisms behind the findings that firms focus more on novel research, we analyze detailed plant-level data from the annual volumes of the ‘R. R. Bowker Directory of American Research and Technology,’ which track the number of

⁹ *Patents in unknown fields* are those that are classified in technology fields that a firm has never filed in before, and *Patents in known fields* are those that are classified in technology fields that a firm has filed in previously (Balsmeier et al. (2017)). *Scope* denotes the ratio of backward citations that have not previously been cited in prior patents from the same patent assignee to all backward citations, and thus reflects the use of new knowledge in innovation activities (Katila and Ahuja (2002)).

scientists and technicians at the plant level (Png (2019)). We find evidence that firms subject to earnings pressure exhibit a change in the composition of their R&D spending toward increased hiring of primary researchers. To examine the downstream effects of these activities on ultimate product market outcomes, we next exploit USPTO trademark data to measure whether the breadth of firms' product lines changes (Sandner and Block (2011), Nasirov (2020)). We find a positive effect of earnings pressure on product line breadth, consistent with these firms expanding into new product areas.¹⁰

We conduct two cross-sectional tests to further support the hypothesis that an underlying mechanism behind our results is that firms adopt a more efficient innovation strategy. First, we partition our sample into firms in industries with long vs. short innovation life cycles, and we find that the positive effect of earnings pressure on future innovation is concentrated in firms with shorter innovation life cycles.¹¹ This finding is intuitive because it is less costly and more feasible for firms with shorter innovation life cycles to switch their R&D focus. Second, we partition the sample of firms based on the ex-ante diversity of their patent portfolios, and we find that the effect is concentrated among firms with more diversified patent portfolios; this result is consistent with a hypothesis that firms that are more technologically diversified are better able to re-prioritize resources toward relatively more promising projects (Hsu, Lee, Peng, and Yi (2018)).

This paper adds to the literature in several ways. First, we contribute to the literature on how short-termism influences corporate innovation by exploring a new channel and a novel identification strategy. This fundamentally distinguishes our findings from other papers in the

¹⁰ We also test if these results on innovation "novelty" come about because firms undertake "riskier" innovation projects (as measured by the standard deviation of the future variation in citations across patents), but we find that the average riskiness remains similar.

¹¹ Firms in industries with short innovation life cycles (e.g., storage drives; see Christensen (1997)), can more easily change their innovation strategy compared to firms with long innovation life cycles (e.g., firms in the pharmaceutical industry).

related literature that have studied the link between short-termism and innovation by focusing on variation in firms' investor base, number of analysts, takeover risk, or managerial contracts.¹² While this related literature largely focuses on governance/monitoring channels, our setting and empirical evidence instead emphasize a possible bright side of short-term earnings pressure that can be explained by a free cash flow channel.

To the best of our knowledge, we are also the first in this literature to dig deeper into whether productive projects (vs. only marginal projects) suffer when firms cut R&D due to short-term pressures. We do so by splitting firms into those that are likely to be efficient at translating dollars into innovation vs. those that are not. Our evidence shows that it is the “right firms” (i.e., ones with seemingly mostly marginal-NPV projects) that are taking money away from innovation projects. In contrast, firms that are already good at producing innovation become even more efficient by further refocusing their R&D dollars toward relatively more novel projects.

Our paper further speaks to the literature on the real effects of earnings targets. Previous findings have suggested that managers may sacrifice their firms' investments to meet earnings targets (e.g., Graham et al. (2005), Edmans et al. (2017), Ladika and Sautner (2020), Terry (2023)). Yet, there is less evidence regarding the longer-term consequences that result from actions firms take to meet these targets. Our analysis suggests that firms with pressure to meet earnings using buybacks tend to exhibit improvements in innovative efficiency, thus highlighting a potentially positive aspect of firms' desire to meet earnings targets. This is especially important given that stock buybacks—particularly those motivated by EPS management—have long been

¹² While our empirical setting limits the sample to only firms that have analysts, the source of variation critically differs from He and Tian (2013) and Chen, Harford, and Lin (2015) who exploit variation in the *number* of analysts. Instead, the variation in the current paper comes from a sudden short-term incentive to beat the EPS estimate using buybacks in a particular quarter, while holding the number of analysts and other sources of short-termism constant.

portrayed by the media and politicians as a leading example of a type of myopia that is detrimental to the overall economy.

Finally, this study offers new evidence that speaks to the literature on the effect of earnings management on firms' innovation activities. Prior studies in this literature suggest that earnings pressure leads to significant cuts in R&D due to managers' accruals management and/or real activities manipulation (Roychowdhury (2006), Gunny (2010), Dichev, Graham, Harvey, and Rajgopal (2013)), which may lead to weaker innovation performance (Bereskin, Hsu, and Rotenberg (2018)). Our results highlight that firms can respond to short-term earnings pressure through changes in their innovation strategy and resource allocations, and we describe how these differential responses, in turn, can moderate the downstream effects of short-term incentives.

II. Data

A. Sample

Our sample consists of firms in the intersection of the CRSP/Compustat, patent, and Institutional Brokers Estimate System (I/B/E/S) databases. We start with all U.S. public firms in the CRSP/Compustat dataset. We only include companies headquartered and incorporated in the United States, and we further exclude firms in the financial (SIC codes 6000-6999) and utility industries (SIC codes 4900-4999), as these industries are subject to different accounting standards and regulatory environments. We obtain analysts' earnings forecasts from the I/B/E/S database. We require firms to be covered by analysts because our empirical strategy hinges on measuring analyst EPS forecasts. Following Almeida et al. (2016), we additionally limit the sample to only firms for whom a repurchase would raise EPS.¹³

¹³ For firms that have either a very high or a negative price-to-earnings ratio, buybacks can lower rather than raise their EPS.

We use patent data to construct several measures of firms' innovation-related outputs (e.g., Kamien and Schwartz (1975), Griliches (1990)). We collect data for all patents granted by the U.S. Patent and Trademark Office (USPTO) from 1976 to 2017 from the PatentsView database. This database includes detailed information about each patent's assignee (i.e., firms), technology classification, filing date, grant date, and references (backward citations). We then match each patent assignee to U.S. public firms using the link provided by Noah Stoffman that ends in 2017 (Kogan et al. (2017), Stoffman, Woepfel, and Yavuz (2022)).¹⁴ To focus our study on firms involved in innovation activities, we drop firm-year observations from our sample if the firm has not filed any patents in the past two years.¹⁵

After merging these data sets, our sample consists of 2,312 unique firms.¹⁶ Our sample period starts in 1988 due to the availability of analyst coverage data. We end our sample period in 2015 to ensure that most of the patents that are applied for have been granted by the USPTO before 2017 and thus exist in the patent database.

In addition to patent data, we exploit several other datasets related to firms' product lines, R&D staff, and plant-level activities. First, we collect trademark information from the USPTO trademark database.¹⁷ We follow the procedure of Hsu, Li, Li, Teoh, and Tseng (2022) to match each trademark assignee to U.S. public firms.

Second, we collect data on the number of scientists hired in each plant from the annual volumes of the "R. R. Bowker Directory of American Research and Technology." We follow

¹⁴ The data is available from the website of Noah Stoffman: <https://kelley.iu.edu/nstoffma/>.

¹⁵ It is common in the economics literature to focus on firms with patent records (see, for example, Lerner, Sorensen, and Strömberg (2011), Aghion, Van Reenen, and Zingales (2013), Bloom, Schankerman, and Van Reenen (2013)).

¹⁶ The unique number of firms is calculated based on the sample in a narrow range around a zero pre-repurchase EPS surprise ($-0.003 \leq Sue_{adj, it} \leq 0.003$); as we describe in more detail in Section III, this range constitutes the main sample for our analysis.

¹⁷ Details of this database are provided by Graham, Hancock, Marco, and Myers (2013).

Png (2019) in matching this dataset to U.S. public firms in the CRSP/Compustat dataset. These data are nevertheless only available from 1989 to 1995 and for a smaller subset of firms.

Finally, we collect plant-level information, including the estimated revenue and the number of employees, from the National Establishment Time-Series (NETS) database (2017 version) of Walls & Associates. This dataset allows us to capture each plant's size and the timing when a plant was established or closed.

B. Measures of innovation activities

Innovation is critical for a firm's long-term value and profitability (Griliches (1981), Deng, Lev, and Narin (1999), Pandit, Wasley, and Zach (2011)). To measure innovation outputs, we consider several measures based on firms' patents: the number of forward citations, the value of patents, and the number of patents.

Our first measure, *Forward citations*, is the sum of all future citations received by all granted patents that the firm applied for in a quarter; that is, the frequency of these patents being listed in the references of other subsequent patents.¹⁸ For example, if a firm applies for three patents in a given quarter, and each of these will receive ten citations in the future from other patents, the forward citation measure for that firm-quarter is 30. The forward citations measure thus reflects the technological importance of the patents that a firm applies for over a given period (Trajtenberg, Henderson, and Jaffe (1997), Harhoff, Narin, Scherer, and Vopel (1999), Hall et al. (2005), Aghion et al. (2013)). Note that for later quarters in our sample period (which ends in 2015), the forward citations will be mechanically lower for all firms since newer patents have not yet had equally many years to be cited by others as older patents; to account for this effect, we include year-quarter (time) fixed effects throughout our analysis.

¹⁸ We consider the timing of the application of a patent (and not the grant date) as the time when its associated invention occurs, as is common in the literature (Hall, Jaffe, and Trajtenberg (2005)).

Our second measure of firms' innovation outputs, the *Value of patents*, is calculated as the market value of all granted patents that the firm applies for (and that are eventually granted) during a given quarter. We calculate the market value of each patent following Kogan et al. (2017), by using the stock market reactions (relative to Fama-French 30 industry returns) around the patent grant announcement, after adjusting for return volatility, day-of-week fixed effects, and firm-year fixed effects. The underlying idea behind this measure is that the stock market reaction to the news of a firm receiving a patent is an estimate of the future economic profits associated with that patent. By summing this measure across all patents that a firm applies for during a quarter, this measure thus reflects the total market value of a firm's innovation outputs in that quarter (Almeida, Hsu, Li, and Tseng (2021), Stoffman et al. (2022)).

Our third measure for firms' innovation outputs, *Number of patents*, denotes the raw number of granted patents the firm applies for in a quarter.¹⁹ On the one hand, an advantage of this measure is that it is arguably the simplest measure of innovation outputs. On the other hand, compared with the forward citation and patent value measures, a relative downside of this measure is that it does not account for the 'quality,' *i.e.*, the technological importance or the economic value of each patent.

In addition to these three measures for innovation outputs, we also construct several measures to capture the novelty of the innovation projects a firm focuses on, *i.e.*, whether a firm's patents reflect technology that is new to the firm. The first of these measures, *Scope*, is the ratio of the number of 'new backward citations' as a fraction of all backward citations made across all patents filed by a firm in a quarter, following Katila and Ahuja (2002) and Gao, Hsu, and Li (2018). We categorize a backward citation as 'new' if it has never been cited by the firm's

¹⁹ The patent count measure, despite its simplicity, has been widely used in the economics literature to capture firm-level innovation outputs (e.g., Griliches (1981)).

other patents filed over the past five years. For example, if a firm files for one patent in a quarter, and the application makes ten references, five of which have not been previously cited in any of the firm's other patent filings in the last five years, *Scope* for that firm-quarter is 50%. *Scope* thus reflects the extent to which a firm explores new technology opportunities outside of its current expertise.

Our second measure of innovation novelty is *Ratio of patents in unknown fields*, which measures the fraction of patents that the firm files in “unknown fields.” Following Balsmeier et al. (2017), a patent in an unknown field is one that is filed in a technology class that is new to the firm.

Finally, we use trademark data to measure whether firms venture into new product market categories. We calculate the *Breadth* of a firm's product lines as the number of unique product classes covered by all active product trademarks owned by a firm in a quarter (Sandner and Block (2011), Nasirov (2020)).²⁰ A growth in *Breadth* suggests that the firm is expanding into a larger number of unique product spaces. While this measure is not patent-based, it offers a complementary perspective of the extent to which firms engage in novel projects.

III. Empirical Strategy

A. Identification Strategy

Our empirical strategy for studying the effects of earnings pressure follows the ‘fuzzy regression discontinuity’ framework in Almeida et al. (2016), which focuses on the pressure firms face to engage in EPS-motivated buybacks. The key idea is that firms have a strong incentive to meet or beat analysts' EPS forecasts, and firms can use stock buybacks to raise their EPS to achieve the analyst target when they might otherwise just miss. This empirical strategy

²⁰ Each trademark can be registered in one or multiple product/service classes. There are 45 product/service classes: <http://www.wipo.int/classifications/nice/nclpub/en/fr/home.xhtml>.

allows us to identify the effect of such earnings pressure by comparing changes to future outcomes for those firms that would “just miss” without a buyback versus other firms that narrowly meet the EPS target even without a buyback.

We start by calculating a variable, pre-repurchase EPS surprise, which captures the difference between each firm’s EPS and the consensus analyst forecast if the firm had not engaged in any buybacks.²¹ Confirming the intuition that firms do more buybacks if they otherwise would have missed, Hribar et al. (2006) show that firms with pre-repurchase EPS surprise that fall just below the zero threshold are discontinuously more likely to engage in share repurchases that raise EPS—a finding that we also confirm for our sample period and set of firms.

In our main specification, we use this discontinuity in firms’ incentives to do buybacks when they fall just below the pre-repurchase EPS surprise threshold to examine the effects on the firm’s future innovation-related outcomes.²² Specifically, we estimate equation (1), which represents the reduced form of the fuzzy regression discontinuity framework:

²¹ The pre-repurchase EPS surprise is the difference between the repurchase-adjusted EPS and the median analyst forecast as of the end of the quarter that is being forecasted, where the repurchase-adjusted EPS is calculated as follows: $EPS_{adj} = \frac{E_{adj}}{S_{adj}} = (E + I)/(S + \Delta S)$ where E is reported earnings, I is the estimated foregone interest due to the repurchase, S is the number of shares at the end of the quarter, and ΔS is the estimated number of shares repurchased (the repurchase amount divided by the average daily share price). The foregone interest is the after-tax interest that alternatively would be earned on the funds equal to that used to repurchase shares if those funds were instead invested in a 3-month T-bill.

²² To understand the discontinuity, consider the following example. Suppose that the analyst EPS consensus forecast is \$3.00 a share, and that the company has one billion shares outstanding. A manager learns that the actual reported EPS number is going to be \$2.99 a share. The manager can meet the forecast by increasing share repurchases. For example, using \$600 million to repurchase stock at an assumed price of \$60 per share would reduce shares outstanding to 990 million. The company’s earnings would also decrease because the company forgoes interest payments on its cash holdings. Assuming, for example, that the interest rate is 5%, the firm’s marginal tax rate is 30%, and the company forgoes one quarter of interest, the foregone interest is $1.25\% \times (1-30\%) \times \$600 \text{ million} = \$5.25 \text{ million}$. Thus, total earnings would decrease from \$2.99 billion to \$2.98475 billion, resulting in a new EPS equal to \$3.01 (rounded to the nearest cent). This example illustrates how firms can move from an EPS (before repurchases) of \$2.99 to an actual EPS of \$3.01, or equivalently, moving the EPS surprise (relative to the analyst consensus) from -1 cent to +1 cent.

$$(1) \quad \bar{Y}_{i,(t+1,t+4)} - \bar{Y}_{i,(t-4,t-1)} = \alpha + \beta_1 I_{Negative\ pre-repurchase\ EPS\ surprise_{i,t}} + \beta_2 Sue_{adj_{i,t}} \\ + \beta_3 Sue_{adj_{i,t}} \times I_{Negative\ pre-repurchase\ EPS\ surprise_{i,t}} + \theta_t + \epsilon_{it}$$

$Y_{i,t}$ represents the innovation-related outcome variables for firm i in quarter t . $\bar{Y}_{i,(t+1,t+4)}$ denotes the average of the outcome variable between the first and fourth quarters after the focal quarter ($t = 0$) when we measure the pre-repurchase EPS surprise ($Sue_{adj_{i,t}}$), while $\bar{Y}_{i,(t-4,t-1)}$ is the average over the four quarters preceding the focal quarter. The rolling four-quarter averages mitigate any seasonality in the innovation measures. To measure the impact on the dependent variables, we calculate the change in a firm's future innovation outcomes relative to its own past; this also eliminates any time-invariant firm-level characteristics that could confound our results. Because the outcome variables (e.g., number of patents, forward citations, etc) tend to increase with firm size, we first scale the sum of innovation outputs in quarters $t + 1$ to $t + 4$ by the pre-focal-quarter total assets to mitigate the size effect and then take the log of one plus these values to be $\bar{Y}_{i,(t+1,t+4)}$, and similarly for the lagged variable $\bar{Y}_{i,(t-4,t-1)}$.²³ θ_t denotes time (year-quarter) fixed effects.

The pre-repurchase EPS surprise ($Sue_{adj_{i,t}}$) is the difference between the “pre-repurchase” EPS (*i.e.*, the estimate of what EPS would have been absent buybacks) and the median EPS forecast as of the end of the quarter that is being forecasted; this difference is normalized by the end-of-quarter stock price. $I_{Negative\ pre-repurchase\ EPS\ surprise_{i,t}}$ is an indicator for having a negative pre-repurchase EPS surprise.²⁴ The main coefficient of interest is

²³ The logarithmic transformation is consistent with a Cobb-Douglas production function for innovation outputs, see Griliches ((1981), (1987)) and Kortum and Lerner (1998) and mitigates the skewness in patent outputs (Lerner (1994)). We need to include one because there is a chance that a firm does not produce any patent in a 4-quarter period.

²⁴ We do not condition the sample based on whether a firm actually does a buyback in response to their incentive to raise EPS; so even if a firm does not engage in any share repurchases but it has a negative pre-repurchase EPS surprise, it is still included in the sample and its $I_{Negative\ pre-repurchase\ EPS\ surprise_{i,t}} = 1$.

β_1 , which captures the relation between the outcome variables and earnings pressure (*i.e.*, whether the pre-repurchase EPS surprise is just below zero). Because we control for the level of $Sue_{adj,it}$, this empirical specification accounts for the possibility that higher earnings surprises may proxy for stronger future economic fundamentals. To isolate the effects close to the threshold around the zero pre-repurchase EPS surprise, we constrain the sample throughout our analysis to a narrow symmetric window of $-0.003 \leq Sue_{adj,it} \leq 0.003$. In total, there are around 22,000 firm-quarter observations on either side of the threshold in this window.

Our baseline specification in equation (1) captures how earnings pressure influences firms' innovation activities over the next four quarters. Such a one-year lag is reasonable in light of prior studies that have shown that a one-year window is sufficient to capture the effect of corporate policies on innovation outputs (e.g., Pakes and Griliches (1984), Griliches (1990), Lerner and Wulf (2007), Balsmeier et al. (2017)).²⁵ In addition, we also examine the effects in the second, third, and fourth years after the focal quarter to describe the longer-run dynamics.

Because this paper focuses on a sample of firms that are actively involved in innovation-related activities (*i.e.*, we exclude firms that have not patented in the last two years, as described in Section II.A), we first verify that the “first-stage” discontinuity in the level of repurchases around the zero pre-repurchase EPS surprise threshold, which was first shown by Hribar et al. (2006), also holds in the current sample. We do so by estimating equation (1) using share repurchases in the focal quarter ($t=0$), normalized by previous-quarter assets, as the dependent variable. As an alternative dependent variable, we also use an indicator variable for whether

²⁵ Pakes and Griliches ((1984), p.64): “*This evidence is summarized in terms of mean gestation lags in Pakes and Schankerman (this volume) The average of the mean gestation lags presented in the latter paper was 1.34 years.*” Griliches ((1990), p.1674): “*Nevertheless, the evidence is quite strong that when a firm changes its R&D expenditures, parallel changes occur also in its patent numbers. The relationship is close to contemporaneous with some lag effects which are small and not well estimated (Hall, Griliches, and Hausman (1986)).*” De Rassenfosse and Jaffe (2018) document that about 80% of patents granted by the European Patent Office (EPO) are filed within one year from the initiation of corresponding R&D projects.

firms do an accretive repurchase, where a buyback is defined as accretive if it has the effect of raising EPS by at least one cent. Figure 1 and Panel A of Table IA.1 in the Internet Appendix show a strong discontinuity in the extent to which firms engage in accretive buybacks just around the zero pre-repurchase EPS surprise threshold. This result thus helps establish in our sample the finding that firms engage in significant additional buybacks if they would miss analysts' earnings estimates absent such buybacks.²⁶

B. Identification Strategy Assumptions

The empirical strategy makes the following identification assumptions. First, this strategy assumes that—in the absence of the discontinuous jump in the incentive to engage in share repurchases around the zero pre-repurchase EPS surprise threshold—there are no other discontinuous changes in firms' policies around this threshold that directly affect the outcome variables. To support this identification assumption, we show that firms that fall just above and below the zero pre-repurchase EPS surprise threshold display similar trends in the dependent variables in the quarters before the focal quarter ($t=0$). In addition, we show that firms that fall just above and below the threshold do not differ in their contemporaneous real- and accruals-based earnings management. This suggests that no other discontinuities in these other contemporaneous earnings management activities are happening that could spuriously drive future changes to innovation outcomes.

A related assumption is that spurious changes in other firm characteristics (e.g., number of analysts, fraction of short-term-oriented investors, nature of compensation contracts, takeover risk) do not confound the empirical strategy. Supporting this assumption, we find no significant

²⁶ Panels B and C of Table IA.1 additionally show that this relation is significant in subsamples formed on a median split of innovative efficiency, which we will examine in more detail in Section VI.A. The coefficient is slightly higher for the low-innovation-efficiency firms, meaning that they appear to do more buybacks in response to incentives to just-beat the EPS forecast; however, the difference between these two subsamples is not statistically significant.

difference in analyst coverage and institutional ownership across the two sides of the zero pre-repurchase EPS surprise threshold. Because the empirical strategy is based on whether a firm falls just below the pre-repurchase EPS threshold at a particular point in time, it is also unlikely to be confounded by contemporaneous changes in takeover risk or managerial contracts that tend to be more persistent across time. And even though some firms—e.g., those with many analysts, short-term-oriented investors, short-term compensation contracts, or that face takeover risk—may “care” more about their EPS and thus be more likely to respond to these incentives by conducting buybacks, this possibility is nevertheless not a threat to the internal validity of the empirical strategy. However, it does imply that our findings may not generalize to firms that do not care about beating earnings.

Finally, we acknowledge that the pre-repurchase EPS surprise is imperfectly estimated, as it involves accurately estimating both firms’ EPS in the absence of buybacks and the exact EPS target that firms (and analysts) have in mind. However, if there were “too much” noise in this measure, we would likely be unable to observe any discontinuity in firms’ responses around the threshold.

IV. Summary Statistics

We present summary statistics of the key variables in Table 1. These summary statistics are calculated based on the average over four quarters before the ‘focal quarter’ for those firm-quarters that end up in the narrow window around the pre-repurchase EPS surprise that we use for our main tests ($-0.003 \leq Sue_{adj,it} \leq 0.003$).

On average, each firm-quarter observation has 11.3 new patents, 141.5 future (‘forward’) citations across those same patents, and a total patent value of \$137.2 million.²⁷ On average,

²⁷ Harhoff et al. (1999) and Hall et al. (2005) estimate the value of each forward citation at \$1 million. Kogan et al. (2017) estimate the value of each patent at \$17.66 million. Table 1 indicates that in our sample, each forward citation is valued at \$0.97 million (\$137.2 million / 141.5 citations), and each patent is valued at \$12.14 million

67% of backward citations are new (*'Scope'*), and 20% of patents are in unknown fields. These statistics suggest that more than half of knowledge sources are new to firms but that firms are more likely to patent in known rather than unknown technology classes. Moreover, the trademark portfolio for the firms in the sample covers almost 11 different product classes on average.

Table 1 further compares firms that fall on either side of the zero pre-repurchase EPS threshold. We find that these firms have broadly similar characteristics and innovation outputs (in levels) before the focal quarter. These findings also help support the identification assumptions described in Section III.B.

V. Overall Effects on Innovation

A. Innovation Outputs

To measure the effect of earnings pressure on firms' future innovation activities, we estimate equation (1) within the limited window around the zero pre-repurchase EPS surprise threshold ($-0.003 \leq Sue_{adj,it} \leq 0.003$). Table 2 reports results for the effect on our baseline innovation output variables: the number of citations, the value of patents, and the number of patents. The coefficients on $I_{Negative\ pre-repurchase\ EPS\ surprise}$ represent the differences in changes to a firm's future innovation output across firms that fall narrowly on the negative vs. positive side around the zero pre-repurchase EPS surprise threshold.

The results show significant increases in innovation outputs in the four quarters after firms are subject to earnings pressure. In column (1), for the number of forward citations, the coefficient of 0.0137 (significant at the 1% level) suggests that forward citations increase by

(\$137.2 million / 11.3 patents), and these estimates are thus broadly similar to the previous estimates in the literature.

eight citations per year after firms are exposed to earnings pressure.²⁸ In column (2), for the value of patents, the coefficient of 0.0125 (significant at the 5% level) suggests that the value of patents increases by \$7 million in the period after firms are exposed to earnings pressure.²⁹ Finally, in column (3), where the dependent variable is the number of patents, the coefficient of 0.0038 remains positive (and statistically significant); however, the economic magnitude of this effect is comparatively smaller than the effects on patent citations and values.

These results suggest that after firms are exposed to earnings pressure, they exhibit an overall increase in the technological influence and economic values for the patents they subsequently file. Figure 2 shows graphical evidence of the discontinuous effects on innovation outcomes, showing that firms just below the zero-pre-repurchase EPS surprise threshold exhibit an increase in their innovation outputs.

In column (4) of Table 2, we find that these positive effects on innovation outputs take place despite lower average spending on R&D. These results on R&D are broadly similar to those of Almeida et al. (2016), the main difference being that the samples are quite different, as the current paper focuses exclusively on innovative firms (those that have patented in the last two years). As in Almeida et al. (2016), these average decreases in R&D spending are nevertheless quite small in economic terms despite being statistically significant. Yet, the fact that R&D is lower on average, while firms also produce more influential patents on average, suggests that these affected firms are becoming more efficient at producing innovation outputs

²⁸ Specifically, $(0.0137 \times 141.5 \text{ average number of patents} \times 4 \text{ quarters} = 8)$. The increase of 8 forward citations is economically meaningful because one forward citation is worth \$1 million, according to the estimates of Harhoff et al. (1999) and Hall et al. (2005). This finding is also broadly in line with the economic magnitudes found in related papers that have studied the effect on patents. Giannetti and Yu (2021) show that a one-standard-deviation increase in short-term institutional ownership is associated with a 6.8% increase in the number of patents that follow after increases in competition from tariff cuts. He and Tian (2013) find that when a firm's analyst coverage increases by one standard deviation, its number of patents decreases by 4.8%. Atanassov (2013) shows that after the passage of a Business Combination law in a state, the number of patents by firms decreases by 11.23% over three years.

²⁹ Specifically, $(0.0125 \times 137.2 \times 4 \text{ quarters} = \$7 \text{ million per year})$.

overall.³⁰

How can such an effect happen whereby average R&D spending goes down, but overall innovation goes up? Two assumptions are needed for an efficiency improvement: (1) firms have marginal R&D projects that are not productive (as suggested by, for example, Jensen (1993)), and (2) firms endogenously decide to make cuts to these marginal projects instead of making cuts to their more productive projects. Section VI. examines two mechanisms that can cause such efficiency improvements, broadly supporting these assumptions.

Our results are noteworthy in light of prior evidence (Almeida, Ersahin, Fos, Irani, and Kronlund (2020)) that EPS-motivated buybacks can result in lower total factor productivity (TFP) among manufacturing firms, which they relate to frictions (e.g., union bargaining) that can impede the process of prioritizing a firm's highest NPV projects. Comparing their findings to the evidence in the current paper supports the hypothesis that innovation-intensive firms are more agile and face fewer frictions in reallocating their resources (such as intangible assets) toward their most productive projects.

B. Longer-Run Dynamics and Pre-Trends

Next, we study the dynamic effects of earnings pressure on innovation outputs over longer time horizons to examine how long-lasting these effects are. While our baseline model investigates changes over four quarters after the focal quarter compared with four quarters before ($\bar{Y}_{i,(t+1,t+4)} - \bar{Y}_{i,(t-4,t-1)}$), we now replace the dependent variable with the change in the second year ($\bar{Y}_{i,(t+5,t+8)} - \bar{Y}_{i,(t-4,t-1)}$), the third year ($\bar{Y}_{i,(t+9,t+12)} - \bar{Y}_{i,(t-4,t-1)}$), and the fourth year

³⁰ As a robustness test, we also examine alternative measures for forward citations and the value of patents. In Table IA.2 in the Internet Appendix, we consider forward citations that are further adjusted by the number of forward citations received by other patents in the same technology class and subsection (in columns (1) and (2)), respectively. We also consider patent values based on alternative adjustments for market return and industry return (2-digit SIC code) in columns (3) and (4), respectively. The results in this analysis are consistent with the baseline results in Table 2. Moreover, the coefficients presented in Table IA.2 are similar in economic magnitude to their counterparts in Table 2, suggesting that our baseline results are not sensitive to such empirical choices in measuring forward citations and patent values.

$(\bar{Y}_{i,(t+13,t+16)} - \bar{Y}_{i,(t-4,t-1)})$ following the focal quarter. We present the results in Panel A of Table IA.3 in the Internet Appendix.

We find that the positive effect on innovation lasts for three years and dissipates by the fourth year. For forward citations, we find the coefficients on $I_{Negative\ pre-repurchase\ EPS\ surprise}$ are 0.0137, 0.0088, 0.0114, and 0.0060 in the first, second, third, and fourth years, respectively. For the value of patents, we find the coefficients on $I_{Negative\ pre-repurchase\ EPS\ surprise}$ are 0.0125, 0.0084, 0.0136, and 0.0032 in the first, second, third, and fourth years, respectively. The results presented in Panel A of Table IA.3 support the intuition that any factors influencing a firm's innovation projects can have lasting impacts for several years.

To support the identification assumptions, we also examine pre-focal-quarter changes in the innovation outputs. In Panel B of Table IA.3, we use lagged innovation output changes compared to the previous four quarters (e.g., $\bar{Y}_{i,(t-4,t-1)} - \bar{Y}_{i,(t-8,t-5)}$) and $\bar{Y}_{i,(t-8,t-5)} - \bar{Y}_{i,(t-12,t-9)}$) as the dependent variable in equation (1), and find that there is no relation between these lagged changes in innovation outputs and incentives to engage in EPS-motivated buybacks in the focal quarter. These results support a 'parallel trends' assumption around the discontinuity, i.e., firms that end up just below the zero pre-repurchase EPS surprise threshold had similar pre-trends in the outcome variables as the firms just above this threshold in the quarters leading up to the focal quarter.

Figure 3 shows graphical evidence of the dynamics of the estimated effects of earnings pressure on innovation outputs. This figure also illustrates that the effects last around three years after the focal quarter, and supports parallel trends in the periods leading up to the focal quarter.

VI. Examining the Mechanisms behind Higher Innovative Efficiency

The results in the previous section show that earnings pressure does not appear harmful to innovation but instead appears to spur higher innovative efficiency, thus resulting in higher-value

and better-cited patents. This section examines two possible (non-exclusive) mechanisms that can help explain this positive effect on innovative efficiency. First, we test whether the resource allocation of R&D spending across firms improves when firms need to choose whether and how to finance EPS-motivated buybacks. Second, we examine the extent to which earnings pressure can engender a sense of urgency that focuses a firm's innovation efforts toward more novel areas.

A. More Efficient Allocation of R&D Resources across Firms

The first mechanism we examine hinges on improved allocation of R&D spending across firms. In particular, we study whether earnings pressure results in relatively more dollars being spent by those firms that are good at translating R&D dollars into new patents while relatively fewer R&D dollars are spent by those firms that are not good at translating R&D dollars into patents.

To test this mechanism, we separate our sample of firms into two groups: those that are “innovation-efficient” and those that are not. Innovative efficiency is calculated, following Hirshleifer et al. (2013), as the log of one plus the number of patents filed by a firm in a quarter minus the log of one plus a firm's R&D capital, where the firm's R&D capital is defined as the five-year sum of its annual R&D expenditures with an obsolescence rate of 15% (Hall (1993)). This measure represents how each dollar of a firm's R&D spending has translated into new patents in the past. We calculate each firm's innovative efficiency before the focal quarter, and split the sample based on the median to study the effects on innovation outcomes and R&D across these two sub-groups. An implicit assumption in this analysis is that firms that were efficient in the past are likely to continue being efficient also in the future. The results are reported in Table 3.

Table 3 shows that the positive effect from earnings pressure on future innovation outputs (the value of patents, forward citations, and the number of patents) is driven entirely by firms that were ex-ante more efficient at translating R&D dollars into new patents—the innovation-efficient firms (columns (1)–(3) in Panel A). Panel A of Figure IA.1 shows these findings graphically, and further shows that these effects persist for several years ($t + 1$, $t + 2$, and $t + 3$). Table 3 (column (4) of Panel A) also shows that the innovation-efficient firms on average do not cut total R&D spending when subject to earnings pressure, likely because these activities are relatively high-NPV for them. While their overall R&D spending doesn't significantly change, as we will discuss in the next sections, we do observe changes in the focus across different types of innovation, consistent with a changing composition of R&D spending within firms.

By contrast, Panel B of Table 3 shows that the firms that were ex-ante less efficient at innovation on average do tend to cut R&D spending when subject to earnings pressure (column (4)). Furthermore, we do not observe any evidence of a positive effect from earnings pressure on future patent outputs (columns (1)–(3)) among this subset of firms that have lower innovative efficiency. It might seem puzzling why these 'inefficient' firms do not experience a drop in patent outputs given that they do reduce spending on R&D. One possible explanation for this finding is that because the average productivity of R&D spending in these firms is low, then any marginal R&D project has an especially low likelihood of successfully being turned into future patents. Cutting R&D thus represents the “least-costly” funding source for these innovation-inefficient firms when they are subject to earnings pressure. Likewise, Panel B of Figure IA.1 does not show any positive effect on innovation outputs in future years $t + 1$, $t + 2$, and $t + 3$.

Overall, these findings are consistent with heterogeneous effects on R&D spending and future innovation outputs across firms depending on their ex-ante innovative efficiency, whereby earnings pressure can improve the overall allocation of R&D resources across firms. These

findings are thus broadly consistent with the idea that a firm's marginal R&D projects can be either more or less productive (as suggested by, for example, Jensen (1993)), and that firms endogenously are less likely to make cuts to these projects when they are more productive, and vice versa.³¹

B. Focus on Novel Innovation

One way that firms can produce more impactful innovation is by shifting resources away from incremental innovation related to their legacy projects/products, and instead focusing more on relatively novel innovation projects. If earnings pressure pushes firms to re-evaluate how they allocate resource dollars across projects within the firm, that could represent a second channel for why we observe higher future innovative output. The idea is that when firms are faced with earnings pressure, they experience a sense of urgency in better prioritizing which of their projects to fund (similar to the channel that drives the reallocation across firms, as documented in the previous section), resulting in a larger share of the firm's R&D dollars being allocated toward relatively higher-impact projects.

To examine this mechanism, we estimate equation (1) for two outcome measures that capture the degree of novelty of firms' innovation projects: (1) patent scope, and (2) the ratio of patents in unknown fields. Patent scope denotes the fraction of backward citations used in a patent that has not been cited by prior patents of the same patent assignee and thus reflects the use of new knowledge in innovation activities (Katila and Ahuja (2002)). Patents in unknown fields are those in technology fields where a firm has not filed a patent before (Balsmeier et al. (2017)). Table 4 presents results.

³¹ For the high-efficiency firms, while they are not spending more net dollars, one possible explanation for higher innovation output is that the resource constraint spurred by the pressure to do EPS-motivated buybacks helps improve the allocation of R&D dollars also within each firm in a similar way that it does across firms. Such a mechanism is nevertheless difficult to directly test since we cannot easily observe a proxy for the NPV of individual R&D projects within firms.

Column (1) of Table 4 Panel A presents the results for changes in firms' patent scope as the dependent variable. Consistent with an increased focus on more novel innovation when firms are subject to earnings pressure, the coefficient on $I_{Negative\ pre-repurchase\ EPS\ surprise}$ is 0.0249 (statistically significant at the 5% level). In economic terms, this finding indicates that the ratio of using new knowledge increases by around 2.5%, which is meaningful compared with the sample mean of 67%.

Column (2) of Panel A of Table 4 further shows that the ratio of patents in unknown fields also significantly increases after firms are subject to earnings pressure. In particular, the coefficient on $I_{Negative\ pre-repurchase\ EPS\ surprise}$ is 0.0309 (statistically significant at the 1% level), implying that the ratio of patents in unknown fields increases by 3%. This effect is also economically substantial relative to the sample mean of the ratio of patents in unknown fields, which is 20%. Taken together, these findings support a hypothesis whereby one of the underlying mechanisms behind the baseline results from Table 2 is that firms switch their innovation efforts toward newer technology areas, which in turn creates more valuable and influential patents.

We next use trademark data to study whether firms also expand into new product areas. Finding such an expansion in product areas would be consistent with a greater focus on more types of innovation, rather than a focus on incremental innovation for already-existing projects/products. To measure the number of product markets that firms operate in, we use newly available trademark data from the USPTO, which has been used in recent papers to measure firms' new products (e.g., Hsu et al. (2022), Giannetti and Yu (2021)). Specifically, we use a measure of a firm's trademark *Breadth*, defined as the number of unique product classes covered by active trademarks owned by a firm in a quarter (Sandner and Block (2011)).

Column (3) of Table 4 Panel A shows results based on equation (1) using changes in the trademark breadth around the focal quarter as the dependent variable. We find that firms subject to earnings pressure significantly increase trademark breadth, which implies an expansion of their product lines into new areas. In economic terms, the coefficient of 0.0408 suggests that firms' product lines cover a 4% greater fraction of different areas.³²

Further, we know from Table 3 that it is especially the innovation-efficient firms that are primarily responsible for the positive effects of earnings pressure on future innovation outputs. In Panels B and C of Table 4, we thus compare the measures that capture changes to scope, patenting in unknown areas, and trademark breadth across the subsets of firms that are ex-ante innovation-efficient vs those that are not.³³ Consistent with our previous findings, Panel B of Table 4 shows that the increased focus on more novel types of innovation when subject to earnings pressure is concentrated among the ex-ante innovation-efficient firms. Even so, there is also some evidence of internal shifting of resources toward more novel projects among the firms that were ex-ante less efficient at innovation (Panel C), at least based on patenting in unknown areas, which grows by 2.52 percentage points when these firms are subject to earnings pressure (column (2) of Panel C).

Overall, these findings are consistent with better prioritization of projects *within* firms when they are subject to earnings pressure. As these firms venture into new technologies and put more weight on more novel innovations, they become better at creating more influential patents. Such a mechanism can thus help explain our baseline results from Tables 2 and 3 that showed that firms subject to earnings pressure exhibited an increase in their future innovation output.

C. Composition of R&D Staff

³² Our finding is related to Giannetti and Yu (2021), who find that firms with more short-term institutional investors launch more new products as measured by trademarks when subject to heightened competitive pressure.

³³ We exclude observations with trademarks but without patents from this comparison.

To provide additional evidence for the hypothesis that firms subject to earnings pressure are allocating relatively more resources toward more novel types of innovation, we next collect detailed plant-level data from the R. R. Bowker Directory of American Research and Technology, which tracks the number of scientists in each plant over time (Png (2019)). Specifically, this database lists the numbers of ‘technicians’ and ‘professionals;’ the latter category is what we label ‘scientists.’³⁴ One limitation is that these data are only available from 1989 to 1995, and for a smaller subset of firms.

In Table 5, we present results from estimating equation (1) using the change in the number of scientists in the R. R. Bowker Directory from before to after the focal quarter as the dependent variable. We also present results on R&D spending, as the firms for which this data are available could exhibit different results for such spending compared with the broader sample.

In Panel A of Table 5, we find evidence that firms subject to earnings pressure tend to increase the number of scientists they hire (column (1)). This finding—which indicates firms are changing their hiring practices of R&D personnel—is also consistent with the findings from the previous section that firms are putting relatively greater emphasis on more novel types of innovation.

Next, in Panels B and C, we split the sample based on each firm’s ex-ante innovative efficiency. We find that the increase in the number of scientists is concentrated in the high innovative efficiency subsample (Panel B). This is consistent with our findings in Tables 3 and 4 that showed that the positive effects on innovation impact (future patent value, future citations) are primarily found among these firms. By contrast, the low-innovation-efficiency firms do not

³⁴ Similar to our previous patent output variables, we scale the number of research technicians/professionals by total assets from the quarter before the focal quarter ($t = -1$).

hire more scientists, and we see a slight cut in R&D spending among the low-innovation-efficiency firms in the part of our sample that we can match to the R.R. Bowker directory.

In sum, Table 5 provides corroborating evidence based on human capital changes for how firms can switch their innovation focus and produce more influential patents. Our results are consistent with the hypothesis that earnings pressure can make firms rethink their hiring practices and focus away from legacy projects toward newer types of innovation. By hiring more scientists, firms are better positioned to access more new knowledge sources and explore new technologies, thus becoming more likely to create higher-impact patents.

D. Alternative Hypothesis: Innovation-Based Window Dressing

Our results point to a bright side of earnings pressure, as it can raise firms' innovation efficiency and shift their focus toward newer technologies. As an alternative hypothesis, we consider the possibility that our results could be driven by a "window-dressing" hypothesis, whereby earnings pressure encourages firms to manage the appearance of their innovation outputs. In that case, the increase in future patents we observe might be only chimeric and not representative of real advances. In this spirit, Kedia and Philippon (2009) find that managers who might want to mask reduced productivity tend to over-invest in innovation.

While such a window-dressing hypothesis is difficult to rule out conclusively, our results on patents' economic and technological importance nevertheless point to real advances. That is, the fact that the actual economic value of future patents and the number of forward citations increase (Table 2) is mostly consistent with true increases in the impact of firms' innovation outputs and difficult to reconcile with the alternative hypothesis that firms are merely filing for more 'lightweight' patents as a window-dressing measure. The fact that the firms' innovation focus changes to newer areas, and that firms are allocating more resources to hire scientists also points to substantial changes to firms' underlying innovation processes.

In Section VII, we provide complementary cross-sectional evidence that the improvement in innovative focus is driven by firms that are better able to reallocate their innovation focus across alternative areas, further supporting the hypothesis that these changes represent real advances in innovation and are not merely illusory.

E. What do the Innovation-Efficient Firms Cut Instead?

The evidence that innovation-efficient firms subject to earnings pressure on average do not cut R&D investments raises an interesting question: When these firms make EPS-motivated repurchases that help them meet the target, how are they financing these buybacks? Previous evidence (Almeida et al. (2016)) suggests that firms cut investment and employment to help finance these repurchases; thus, one natural hypothesis is that firms that do not cut R&D may be cutting other types of investment.

To examine this hypothesis, we collect detailed data on firms' plants and employment from the NETS database. Then, within the sample of high-innovative-efficiency firms, we estimate equation (1), with the change in employment (scaled by the pre-focal-year level of employment) as the dependent variable. We additionally examine an indicator for whether a plant was separated (i.e., sold or closed) in the three years after the focal year as an alternative dependent variable. Table IA.4 in the Internet Appendix presents the results. The unit of observation in each regression is plant-year.

We find that these firms tend to cut the number of employees and sell/close some plants when they are subject to earnings pressure. These cuts can thus help explain how innovation-efficient firms may finance any EPS-motivated buybacks without necessarily cutting their (relatively productive) R&D functions. The fact that these firms are cutting investments in their existing legacy plants may also be a contributing motivation for why the R&D functions of these firms put additional emphasis on creating innovations in technologies that are new to the firm.

VII. Cross-Sectional Evidence

To shed additional light on the underlying mechanisms for how firms are able to switch the focus of their innovative activities, this section investigates how heterogeneity across different firms and industries in the opportunities to make such reallocations can amplify or moderate the effect of earnings pressure on firms' innovation activities. Our cross-sectional measures are based on: (1) innovation life cycle length, and (2) patent diversity. The idea is that these measures can capture differences in firms' relative ability to shift their innovation focus between different types of projects.³⁵

A. The Role of Patent Life Cycles

We first investigate the role of the length of a firm's innovation life cycle. The underlying idea behind this test is that firms in industries with short innovation life cycles (e.g., storage drives; see Christensen (1997)) can more easily change their innovation focus than firms in industries with long life cycles (e.g., pharmaceuticals).

We measure innovation life cycles at the industry level and begin by calculating the innovation life cycle for each individual patent as the difference in years between its grant year and the average grant year of the patents that it cites (Trajtenberg et al. (1997)). We then average this difference across all patents granted to firms within each Fama-French 30 industry and split the sample of firms based on the industry median. We then estimate equation (1) for our three main patent output variables (changes to future citations, patent values, and the number of patents) and for R&D spending separately among the short-life-cycle firms vs. the long-life-cycle firms. Since Table 3 showed that the changes in the patent outputs are concentrated in

³⁵ We have verified that there are significant increases in accretive repurchases just below the zero pre-repurchase EPS threshold across all of the subsamples in these cross-sectional tests, similar to the results for splits on innovative efficiency in Panels B and C in Internet Appendix Table IA.1.

firms that are ex-ante more efficient at innovation, we perform these cross-sectional tests within the subsample of firms characterized by high innovative efficiency. Table 6 presents the results.

Table 6 shows that the positive effects of earnings pressure on innovation are concentrated among firms in industries with short innovation life cycles. For example, in column (1) in Panel A, the coefficient on $I_{Negative\ pre-repurchase\ EPS\ surprise}$ is 0.0323 (statistically significant at the 1% level). This estimate indicates that, after firms are exposed to earnings pressure, firms' forward citations increase by 3.2% among the subset of the innovation-efficient firms that also can change their technological focus more quickly. By contrast, the coefficient is only 0.0025 (i.e., more than 10 times smaller) and statistically insignificant for firms in the long life-cycle group (Panel B). We observe qualitatively similar results when considering the effects on the value and number of patents in columns (2) and (3), respectively.

The results reported in Table 6 are intuitive because firms with short innovation life cycles are more used to fast changes in technological development and have greater flexibility around reallocating resources across different kinds of innovation projects.

B. The Role of Patent Portfolio Diversity

Next, we consider heterogeneity based on the diversity of each firm's existing patent portfolio. The previous literature has suggested that technologically diversified firms can more easily switch focus and adapt to changes (Hsu et al. (2018)). To measure technological diversity, we calculate the number of unique technology sections covered by a firm's patents granted each year. As in the previous analysis, we limit the sample to the ex-ante high-innovation-efficiency firms. We then separately estimate equation (1) for the patent output variables and R&D spending for the low-diversity and high-diversity groups. Results are reported in Table 7.

As shown in Table 7, the positive effects on innovation outputs are concentrated among firms with a diversified patent portfolio. For example, comparing the results in column (1) across

Panel A (high patent diversity firms) and Panel B (low diversity firms), we see that after firms are exposed to earnings pressure, technologically diversified firms' forward citations increase by around 2.3% (Panel A), compared to around 1.4% for the low patent diversity firms (Panel B). We observe similar findings directionally for the value and number of patents, although these differences are not statistically significant.

Table 7 is consistent with the idea that firms that are familiar with a wider range of technologies can more easily change their innovation activities and adopt new technologies faster when they need to urgently prioritize among competing resource needs. These findings are also consistent with prior studies that have documented that firms' innovation strategies are affected by managers' diversity of skills (Custódio, Ferreira, and Matos (2013)). Overall, these results support the argument that the positive effects of earnings pressure on innovation depend on firms' ability to efficiently re-prioritize resources toward relatively more promising projects.

VIII. Robustness Tests

A. Potential Confounding Effects

One potential concern regarding whether our findings can be explained by firms' incentives to do EPS-motivated buybacks is whether the pre-repurchase EPS threshold could be related 'contemporaneously' (i.e., during the focal quarter itself) to other earnings management tools, such as accruals-based earnings management or forms of real earnings management (e.g., cuts to R&D). Specifically, a possible confounding factor might be if firms on either side of the threshold do discontinuously more or less of these other forms of earnings management in the focal quarter, and those differences independently affect future innovation output. A possible link with future patent outcomes would be easiest to imagine for any contemporaneous changes to R&D, while it seems more difficult to imagine a direct causal link between accruals-based earnings management and changes to future patenting outputs. To help address this possible

concern, in Table IA.5 in the Internet Appendix, we examine whether there are any contemporaneous discontinuities in either of these other earnings management variables around the same threshold. The results show that firms on both sides of the threshold do similar amounts of real- and accruals-based earnings management. These results support the identification assumption that no other discontinuities in these other contemporaneous earnings management activities are happening that might spuriously drive future changes to innovation outcomes.

B. Risk-taking

A potential alternative interpretation for our baseline findings is increased risk-taking. That is, firms facing earnings pressure might choose to engage in riskier innovation projects, and such a mechanism could help explain the baseline findings showing that firms subject to earnings pressure produce higher-impact innovation outputs and shift toward more novel innovation projects. We therefore examine whether firms subject to earnings pressure pursue higher-risk innovation strategies.

To measure the riskiness of innovation projects, we follow Amore, Schneider, and Žaldokas (2013) and Mukherjee, Singh, and Žaldokas (2017) and use the standard deviation of forward citations. Table IA.6 in the Internet Appendix reports the findings. Table IA.6 shows that the riskiness of innovation projects does not appear to change significantly. That is, while the innovation strategy shifts to become more novel, it does not appear measurably riskier, at least as measured by the standard deviation of citation outcomes.

IX. Conclusion

In this paper, we study how firms' innovation activities change after firms are subject to earnings pressure in the form of a short-term incentive to raise EPS through buybacks. Our main finding is that stronger incentives to spend money on buybacks to meet current-quarter EPS targets lead to higher future innovation outputs in the form of higher forward citation counts and

higher economic value of patents. This result is driven by firms that are ex-ante efficient at creating patenting outputs.

We also find that the positive effects on innovation are linked to a shift in firms' innovation strategies: Firms subject to greater earnings pressure are more likely to explore newer technologies, increase the scope of their innovation activities, and expand the breadth of new products. These firms also increase the share of scientists on their staff, consistent with a shift in their research focus. Cross-sectional evidence further shows that the positive effects on innovation are concentrated in firms that can more easily shift their focus, as measured by shorter innovation life cycles and greater patent diversity. The paper thus highlights a potential bright side of earnings pressure: An incentive to spend money on EPS-motivated buybacks can constrain firms' free cash flow and push firms to reprioritize by focusing more on those activities they are particularly good at.

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Appendix: Variable Definitions

FORWARD CITATIONS: The sum of all forward citations received by all granted patents the firm applies for in a quarter.

VALUE OF PATENTS: The sum of the market value of all granted patents that the firm applies for in a quarter. We use the market value following Kogan et al. (2017), based on stock market reactions to the announcement of patent grants after adjusting for return volatility, day-of-week fixed effect, and firm-year fixed effects, using Fama-French 30 industry returns as the benchmark return.

NUMBER OF PATENTS: The number of patents that the firm applies for in a quarter that are eventually granted.

R&D/ASSETS: R&D expenses scaled by lagged total book assets.

INNOVATIVE EFFICIENCY: The log of one plus the number of patents filed by a firm in a quarter minus the log of one plus a firm's R&D capital, following Hirshleifer et al. (2013). A firm's R&D capital is defined as the five-year sum of its annual R&D expenditures with an obsolescence rate of 15%.

PATENT SCOPE: The ratio of the number of new citations made by all patents filed by a firm within a certain period (year or quarter) to the number of all citations made by all patents filed by the firm in the same period, following Katila and Ahuja (2002) and Gao et al. (2018).

UNKNOWN PATENT RATIO: The number of patents in unknown fields to the number of all patents filed by the firm. Following Balsmeier et al. (2017), the number of patents in unknown fields denotes the number of patents that are filed in a technology class that the firm has never patented in before.

TRADEMARK BREADTH: The number of unique product categories spanned by the firm's active trademarks.

SCIENTISTS: The sum of the number of scientists across all the firm's facilities. Based on data from annual volumes of the 'R. R. Bowker Directory of American Research and Technology.'

INDUSTRY PATENT LIFE CYCLE (YEARS): The average years between a patent's grant year and the grant years of patents it cites; we average this measure across all patents granted to firms within each Fama-French 30 industry.

INNOVATION DIVERSITY: The number of unique technology sections covered by a firm's patents granted in a year.

PRE-REPURCHASE EPS SURPRISE: The difference between the 'pre-repurchase EPS' and the median analyst estimate as of the end of the quarter that is being forecasted, normalized by the end-of-quarter stock price. The pre-repurchase EPS is calculated as follows: $EPS_{adj} = \frac{E_{adj}}{S_{adj}} = (E + I)/(S + \Delta S)$ where E is reported earnings, I is the estimated foregone interest due to the repurchase, S is the number of shares at the end of the quarter, and ΔS is the estimated number of shares repurchased (the repurchase amount divided by the average daily share price). The foregone interest is the after-tax interest that alternatively would be earned on the funds equal to that used to repurchase shares if those funds were instead invested in a 3-month T-bill.

ACCRETIVE REPURCHASE: A share buyback that increases EPS by at least one cent.

Figure 1

Pre-Repurchase EPS Surprise and Probability of Accretive Share Repurchases Among Patenting Firms

This figure plots the probability of doing an accretive share repurchase as a function of the pre-repurchase earnings surprise. For every pre-repurchase EPS surprise bin (along the x-axis), the dot represents the probability of an accretive share repurchase (i.e., the fraction of firm-quarters with an accretive repurchase out of all firm-quarters in that bin). Pre-repurchase EPS surprise is the difference between the pre-repurchase EPS and the median analyst estimate as of the end of the quarter that is being forecasted, normalized by the end-of-quarter stock price. The pre-repurchase EPS is calculated as follows: $EPS_{adj} = \frac{E_{adj}}{S_{adj}} = (E + I)/(S + \Delta S)$ where E is reported earnings, I is the estimated foregone interest due to the repurchase, S is the number of shares at the end of the quarter, and ΔS is the estimated number of shares repurchased (the repurchase amount divided by the average daily share price). The foregone interest is the after-tax interest that alternatively would be earned on the funds equal to that used to repurchase shares if those funds were instead invested in a 3-month T-bill. Accretive repurchases are defined as buybacks that increase EPS by at least one cent. The lines are second-order polynomials fitted on each side of the zero pre-repurchase earnings surprise.

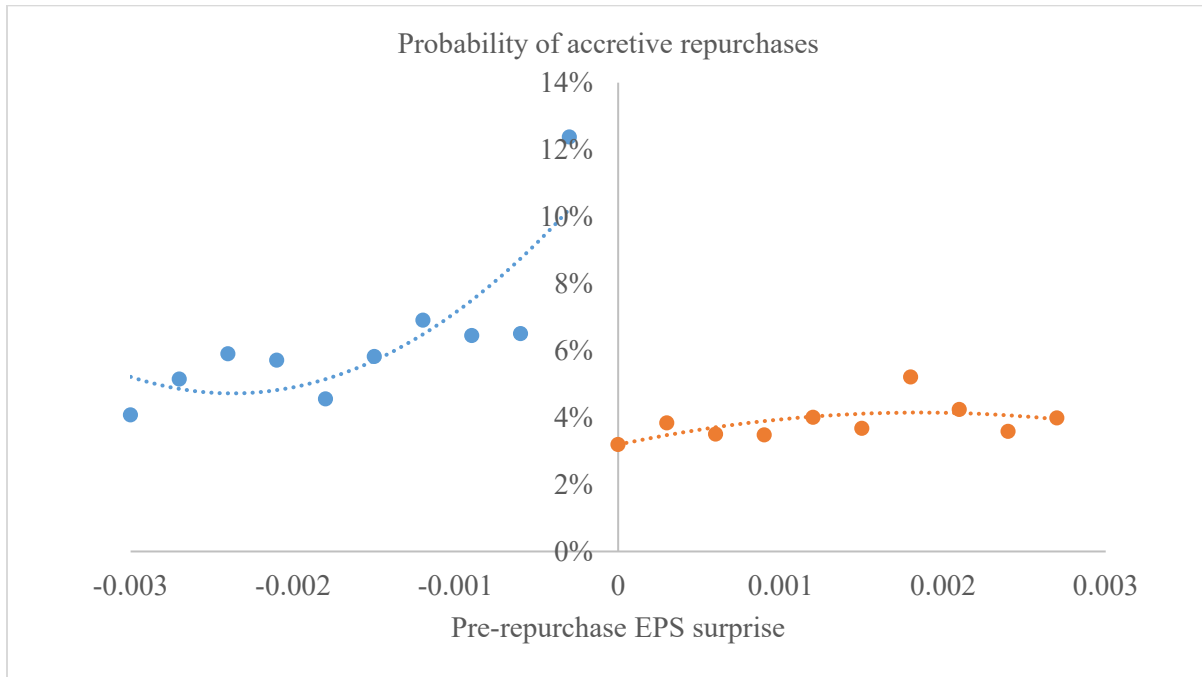


Figure 2

Pre-Repurchase EPS Surprise and Innovation

This figure plots the change (average from four quarters before compared with the average over the four quarters after the focal quarter) in innovation outputs variables as a function of the pre-repurchase earnings surprise. Panel A plots the result for changes in forward citations. Panel B for changes in the value of patents. Panel C for changes in the number of patents. For each pre-repurchase EPS surprise bin (along the x-axis and defined in Figure 1), the dot represents the change in the outcome variable, net of the fiscal quarter average across all firms in the sample. The lines are second-order polynomials fitted on each side of the zero pre-repurchase earnings surprise. All variables are defined in Section II and Appendix.

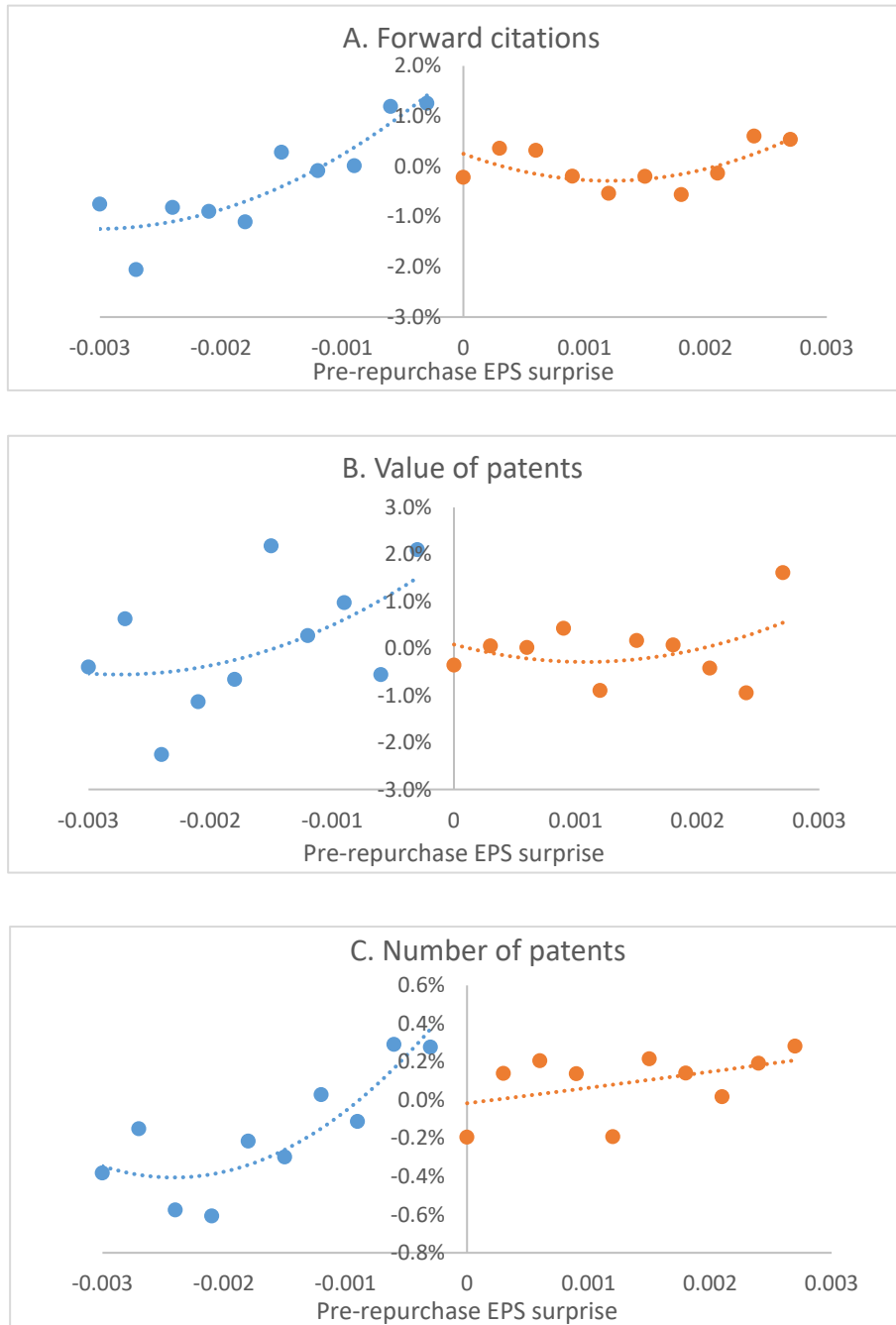


Figure 3
Dynamic Effects

This figure presents the dynamics of the effects of incentives to engage in EPS-motivated buybacks on innovation outputs. The outcome variables after the focal quarter are measured as a difference by comparing the innovation outputs in the first, second, third, and fourth year after the focal quarter, to the four quarters before the focal quarter for firms just below the zero pre-repurchase EPS surprise compared to firms just above this threshold. The outcome variable before the focal quarter is measured as a difference by comparing the innovation outputs in the first, second, and third years before the focal quarter to the previous year. Panel A shows results for forward citations, Panel B for the value of patents, and Panel C for patent counts. Standard errors are clustered at the firm level, and the figures show the 95% confidence intervals.

A. Forward Citations

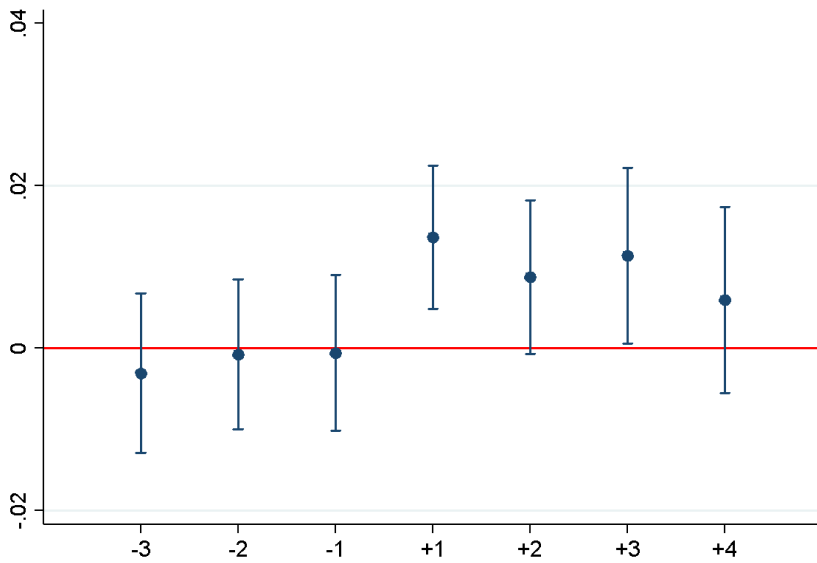
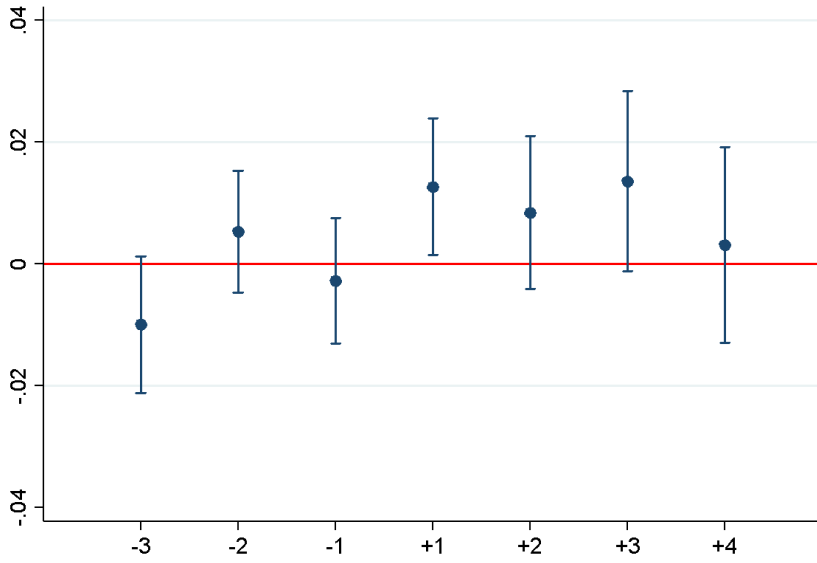


Figure 3, continued

B. Value of Patents



C. Number of Patents

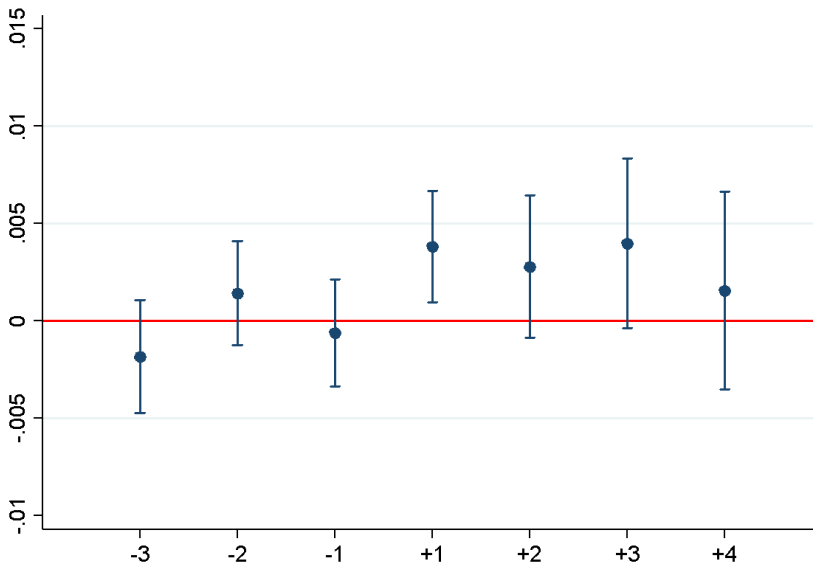


Table 1
Summary Statistics

This table reports summary statistics. We also present statistics separately for the sample with slightly negative ($-0.003 \leq Sue_{adj,it} < 0$) vs. slightly positive ($0 \leq Sue_{adj,it} \leq 0.003$) pre-repurchase EPS surprise. All variables are defined in Section II and Appendix.

	N	Mean	Std.	N	Mean	Std.	N	Mean	Std.
	Full Sample			Pre-Repurchase EPS Surprise:					
				Negative		Positive			
FORWARD CITATIONS	22,061	141.5	429.2	6,177	144.7	450.3	15,884	140.3	420.7
VALUE OF PATENTS (\$M)	22,061	137.2	457.0	6,177	125.5	448.6	15,884	141.7	460.2
NUMBER OF PATENTS	22,061	11.3	33.4	6,177	10.5	32.0	15,884	11.6	33.9
R&D/ASSETS	22,061	0.04	0.05	6,177	0.04	0.05	15,884	0.04	0.05
INNOVATIVE EFFICIENCY	22,061	-1.72	1.77	6,177	-1.63	1.77	15,884	-1.76	1.77
PATENT SCOPE	22,061	0.67	0.34	6,177	0.67	0.34	15,884	0.67	0.34
UNKNOWN PATENT RATIO	22,061	0.20	0.32	6,177	0.20	0.31	15,884	0.20	0.32
TRADEMARK BREADTH	29,445	10.90	9.27	8,468	11.01	9.21	20,977	10.85	9.30
SCIENTISTS	410	450	1088	75	622	1536	335	411	959
PATENT LIFE CYCLE (YEARS)	22,061	7.73	2.35	6,177	7.77	2.45	15,884	7.72	2.30
INNOVATION DIVERSITY	22,061	0.41	0.26	5,375	0.41	0.26	13,896	0.41	0.27

Table 2
Innovation Outcomes

This table presents the estimated effects on innovation outputs of firms having an incentive to boost short-term EPS using share repurchases. We estimate equation (1) using a small window around a zero pre-repurchase EPS surprise ($-0.003 \leq Sue_{adj,it} \leq 0.003$). The dependent variables are the log differences between the pre-period (average of four quarters before the focal quarter) and post-period (average of four quarters after the focal quarter) patenting variables, where both the pre- and post-variables are scaled by the firm’s assets as of the quarter before the focal quarter. These patenting outcome variables are defined in Section II and the Appendix. $I_{\text{Negative pre-repurchase EPS surprise}}$ is an indicator for whether the difference between the pre-repurchase EPS and the median analyst estimate as of the end of the quarter that is being forecasted is negative. The pre-repurchase EPS is calculated as described in the Appendix and Figure 1. We include a linear control in the pre-repurchase EPS surprise, which is further interacted with the sign of this variable, and time fixed effects. All variables are winsorized at the 1% and 99% levels each year. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable			
	FORWARD CITATIONS	VALUE OF PATENTS	NUMBER OF PATENTS	R&D
	1	2	3	4
$I_{\text{NEGATIVE PRE-REPURCHASE EPS SURPRISE}}$	0.0137*** (0.0045)	0.0125** (0.0057)	0.0038*** (0.0015)	-0.0003** (0.0002)
Linear controls in pre-repurchase EPS surprise	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
N	22,061	22,061	22,061	22,061
R ²	0.0186	0.0267	0.0367	0.0501

Table 3
The Role of Innovative Efficiency

This table presents the estimates of the effects on innovation across subsamples formed based on a firm's ex-ante (measured before the focal quarter) innovative efficiency. We partition our sample by the median of the innovative efficiency, defined as the log of one plus the number of patents filed by a firm in a quarter minus the log of one plus a firm's R&D capital. A firm's R&D capital is defined as the five-year sum of its annual R&D expenditures with an obsolescence rate of 15%. All other variables and the methodology are as described in Table 2. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable			
	FORWARD CITATIONS	VALUE OF PATENTS	NUMBER OF PATENTS	R&D
	1	2	3	4
<i>Panel A: High Innovative Efficiency</i>				
	0.0240***	0.0188**	0.0050**	-0.0001
Δ NEGATIVE PRE-REPURCHASE EPS SURPRISE	(0.0071)	(0.0091)	(0.0022)	(0.0002)
Linear controls in pre-repurchase EPS surprise	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
N	10,657	10,657	10,657	10,657
R ²	0.0182	0.0196	0.0207	0.0304
<i>Panel B: Low Innovative Efficiency</i>				
	0.0031	0.0068	0.0026	-0.0006***
Δ NEGATIVE PRE-REPURCHASE EPS SURPRISE	(0.0061)	(0.0076)	(0.0021)	(0.0002)
Linear controls in pre-repurchase EPS surprise	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
N	10,751	10,751	10,751	10,751
R ²	0.0299	0.0344	0.0391	0.0820

Table 4
Innovation Strategy

This table presents the estimated effects on innovation strategy in the full sample (Panel A) and subsamples formed based on the firm's innovative efficiency (measured before the focal quarter) in Panels B and C, respectively. Dependent variables are the differences in the outcome variables between the pre- and post-period (the average over the four quarters after the focal quarter vs. the average over four quarters before the focal quarter). The definitions of these variables are included in the Appendix. All other variables and the sample are described in Table 2. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable		
	PATENT SCOPE	UNKNOWN PATENT RATIO	TRADEMARK BREATH
	1	2	3
<i>Panel A: Full Sample</i>			
Δ NEGATIVE PRE-REPURCHASE EPS SURPRISE	0.0249** (0.0113)	0.0309*** (0.0087)	0.0408* (0.0221)
Linear controls in pre-repurchase EPS surprise	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
N	22,061	22,061	29,447
R ²	0.0064	0.0072	0.0143
<i>Panel B: High Innovative Efficiency</i>			
Δ NEGATIVE PRE-REPURCHASE EPS SURPRISE	0.0354* (0.0182)	0.0391*** (0.0145)	0.0422 (0.0392)
Linear controls in pre-repurchase EPS surprise	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
N	10,657	10,657	7,385
R ²	0.0093	0.0115	0.0260
<i>Panel C: Low Innovative Efficiency</i>			
Δ NEGATIVE PRE-REPURCHASE EPS SURPRISE	0.0184 (0.0141)	0.0252** (0.0107)	-0.0027 (0.0348)
Linear controls in pre-repurchase EPS surprise	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
N	10,751	10,751	7,638
R ²	0.0110	0.0101	0.0179

Table 5

Changes to the Composition of the Firm's Innovation Labor Force

This table presents the estimated effects on the number of scientists and R&D in the full sample of firms that we can link to the R.R. Bowker Directories (Panel A). We also report results separately in subsamples formed based on a firm's innovative efficiency (Panels B and C). The sample period is limited to 1989-1995 due to data availability. Dependent variables are the difference in the number of scientists (model 1) and R&D expense (model 2), both scaled by the pre-focal-quarter assets. All other variables and the sample are constructed as described in Table 2. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable	
	SCIENTISTS	R&D
	1	2
<i>Panel A: Full Sample</i>		
Δ NEGATIVE PRE-REPURCHASE EPS SURPRISE	0.0525** (0.0264)	-0.0077 (0.0234)
Linear controls in pre-repurchase EPS surprise	Yes	Yes
Time fixed effects	Yes	Yes
N	410	550
R ²	0.0147	0.0321
<i>Panel B: High Innovative Efficiency</i>		
Δ NEGATIVE PRE-REPURCHASE EPS SURPRISE	0.0929* (0.0480)	0.0184 (0.0465)
Linear controls in pre-repurchase EPS surprise	Yes	Yes
Time fixed effects	Yes	Yes
N	166	271
R ²	0.0500	0.0336
<i>Panel C: Low Innovative Efficiency</i>		
Δ NEGATIVE PRE-REPURCHASE EPS SURPRISE	0.0098 (0.0182)	-0.0295* (0.0170)
Linear controls in pre-repurchase EPS surprise	Yes	Yes
Time fixed effects	Yes	Yes
N	157	273
R ²	0.0146	0.0750

Table 6

The Role of Innovation Life Cycle

This table presents split-sample results based on Table 2 across subsamples formed on innovation life cycle (measured at the industry level as described in the Appendix). We partition our sample by the median of innovation life cycles. All other variables and the sample are as described in Table 2. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable			
	FORWARD CITATIONS	VALUE OF PATENTS	#OF PATENTS	R&D
	1	2	3	4
<i>Panel A: Short Innovation Life Cycle</i>				
Δ _{NEGATIVE PRE-REPURCHASE EPS SURPRISE}	0.0323*** (0.0086)	0.0246** (0.0106)	0.0071** (0.0028)	0.0000 (0.0003)
Linear controls in pre-repurchase EPS surprise	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
N	8,282	8,282	8,282	8,282
R ²	0.0235	0.0242	0.0246	0.0349
<i>Panel B: Long Innovation Life Cycle</i>				
Δ _{NEGATIVE PRE-REPURCHASE EPS SURPRISE}	0.0025 (0.0123)	0.0061 (0.0185)	0.0000 (0.0033)	-0.0002 (0.0002)
Linear controls in pre-repurchase EPS surprise	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
N	2,375	2,375	2,375	2,375
R ²	0.0412	0.0484	0.0548	0.0694

Table 7
The Role of Innovation Diversity

This table presents split-sample results based on Table 2 across innovation diversity subsamples. We partition our sample by the median innovation diversity (measured at the firm level as described in the Appendix). All other variables and the sample are as described in Table 2. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable			
	FORWARD CITATIONS	VALUE OF PATENTS	NUMBER OF PATENTS	R&D
	1	2	3	4
<i>Panel A: High Innovation Diversity</i>				
$I_{\text{Negative pre-repurchase EPS surprise}}$	0.0227** (0.0090)	0.0089 (0.0111)	0.0063* (0.0032)	-0.0002 (0.0003)
Linear controls in pre-repurchase EPS surprise	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
N	5,051	5,051	5,051	5,051
R ²	0.0361	0.0298	0.0324	0.0437
<i>Panel B: Low Innovation Diversity</i>				
$I_{\text{Negative pre-repurchase EPS surprise}}$	0.0139 (0.0122)	0.0029 (0.0152)	-0.0001 (0.0037)	-0.0001 (0.0004)
Linear controls in pre-repurchase EPS surprise	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
N	4,068	4,068	4,068	4,068
R ²	0.0321	0.0408	0.0381	0.0479