Do Firms Manage Share Price to Mitigate Investor Short-Termism?

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Abstract

Recent work documents a behavioral tendency of investors to expect excessively high upside potential for low-priced stocks. Such expectations expose low-priced firms to greater pressure for short-term performance because poor earnings news leads to greater investor disappointment and larger stock price declines. We, therefore, hypothesize that firms with long-term focus, such as those that invest heavily in R&D, avoid low share prices. Consistent with our hypothesis, we find that firms with higher R&D capital decide on a higher IPO filing price, are less likely to undergo a stock split once listed, and upon a stock split, choose a higher post-split price. We establish a causal link between firms' R&D and share price management by exploiting exogenous increases in R&D induced by the staggered introduction of state-level R&D tax credits in the U.S. Our study suggests that, to shield their long-term investments from investor short-termism, R&D-intensive firms use share price management, and that share prices have an interesting role in revealing firms' strategic focuses.

JEL classification: G12, G14, G23, O31
Keywords: Investor short-termism, share price, nominal price illusion, stock splits, R&D, innovation, stock market myopia

1. Introduction

Economists and market commentators have long worried that investor short-termism pushes managers of publicly listed firms to focus on short term performance at the expense of long-term value maximization, which leads to underinvestment in innovation and slows long-term growth of the economy (Narayanan, 1985; Stein, 1989; Jacobs, 1991; Porter, 1992).[1,2] Motivated by such concerns, researchers in recent years have begun to study the actions that publicly listed firms take to shield their long-term investments from investor myopia. This literature identifies cessation of quarterly earnings announcements (Kim, Su, and Zhu, 2017), dual-class share structure (Chemmanur and Jiao, 2012), antitakeover provisions (Chemmanur, Paeglis, and Simonyan, 2011; Chemmanur and Tian, 2018), and delisting from the stock market (Lerner, Sorensen, and Stromberg, 2011; Ferreira, Manso, and Silva, 2014; Asker, Farre–Mensa, and Ljungqvist, 2015) as possible mechanisms firms adopt to deal with short-termism of stock market investors. In this paper, we extend this research and examine whether firms employ share price management as a tool to mitigate the effects of investor short-termism.

Our starting point is the premise that low nominal (per-share) share price exacerbates investor short-termism. We are motivated by the recent work of Birru and Wang (2016; hereinafter BW), which documents a behavioral tendency of investors to mistakenly associate low price with high growth expectations; for example, a $5 stock is viewed as more likely to grow to $10 than a $50 stock to grow to $100. BW label it *nominal price illusion* and shows that it is pervasive in both stock and options markets.[3] Because prior work associates excessive investor growth

[1] For instance, *The Kay Review of UK Equity Markets and Long-Term Decision Making* (2012), an official report commissioned by the UK government after the crisis of 2007–2009, concludes that "short-termism is a problem in UK equity markets … We observe a wide variety of companies that have made bad long-term decisions, and consider that equity markets have evolved in ways that contribute to these errors of managerial judgement." Similar concerns are also raised by CFA Institute (2006) in a report titled *Breaking the Short Term Cycle*. See also *The Economist* ("The profits prophets," Oct. 5, 2013).

[2] The survey evidence in Graham, Harvey and Rajgopal (2005) confirms these concerns. Most managers in their survey indicate that meeting or beating near-term earnings targets is very important for them and believe that the turmoil that can result in equity and debt markets from a negative earnings surprise can be costly. About 80 percent indicate that they would decrease spending on such items as R&D and advertising, and more than 50 percent say they would delay starting new projects to meet short-term targets even if that sacrificed long-term value creation.

[3] Using options market data to extract investors' skewness expectations, BW document that investors substantially overweight the importance of price when forming such expectations. They also find that out-of-the-money call options for low-priced stocks are overvalued relative to those of high-priced stocks. Moreover, they show that investor expectations of future skewness increase dramatically on days when a stock undergoes a split to lower its price, even though the realized skewness in fact decreases following the split. The idea that low-priced stocks are

expectations to asymmetrically larger stock price drops when quarterly earnings fall short of the expectations (Skinner and Sloan, 2002),[4] we surmise that overly optimistic expectations for low-priced firms also lead to greater investor disappointment and larger stock price declines when these firms report poor earnings, thereby increasing pressure on them to meet near-term earnings targets.[5] To avoid such pressure, firms that want to focus on long-term value creation would therefore consciously avoid low stock prices.

We follow the prior literature and identify such firms in the cross-section by relying on R&D investments. Firms that invest heavily in R&D especially require a long-term focus and a greater tolerance of failure in the short term (Porter, 1992; Manso, 2011; Tian and Wang, 2014). Specifically, short-termism can hurt innovative firms in several ways. It can lead to underinvestment in R&D because such expenditure lowers current earnings, but the benefits accrue over long-term (Narayanan 1985; Stein 1989). It can force companies to implement untimely cuts in R&D to meet near-term earnings targets (Bushee, 1998). It can also nudge publicly listed firms to abandon the pursuit of riskier breakthrough innovation in favor of incremental exploitative research that produces more predictable outcomes in the short-term (Manso, 2011; Gao, Hsu and Li, 2018; Balsmeier, Flemings, and Manso, 2017). Finally, the high uncertainty of R&D makes innovative firms more susceptible to the negative feedback effects of large stock price declines studied by theoretical works of Bond, Edmans, and Goldstein (2012), Goldstein, Ozdenoren, and Yuan (2013), Brunnermeier and Oehmke (2014) and Liu (2014). In these models, a large price drop, even when driven by investor trading rather than fundamentals, causes permanent damage to the firm because stakeholders, such as financiers, employees, and suppliers, view price drops as signal of deteriorating firm prospects, and alter their decisions. We therefore hypothesize that firms with significant R&D investments avoid a low price for their stock in order to maintain focus on

viewed as lottery-like with more room to grow has also been proposed by business press as well as by prior research (Kumar, 2009; Green and Hwang, 2009; Baker, Greenwood, and Wurgler, 2009).

[4] Skinner and Sloan (2002) interact earnings news with an indicator for glamour stocks (based on market-to-book ratio) and find that firms that investors perceive to have high growth experience asymmetrically larger price drop on the announcement of negative earnings surprises. Other studies that also document greater stock price declines on earnings announcement for stocks with excessive growth expectations include La Porta (1996), La Porta, Lakonishok, Shliefer, and Vishny (1997) and Matsumoto (2002).

[5] It is long known that low-priced stocks are disproportionally traded by small investors (Lakonishok, Shleifer, and Vishny, 1992; del Garcio, 1996; Gompers and Metrick, 2001; Dyl and Elliot, 2006; Brandt, Brav, Graham, and Kumar, 2010) and exhibit significantly higher idiosyncratic volatility (Ohlson and Penman, 1985; Brandt, Brav, Graham, and Kumar, 2010), which can further contribute to these stock responding more strongly to negative earnings surprises.

the long term and prevent disruptions induced by large stock price drops on news of lower-than-expected short-term earnings.

We begin by providing evidence that supports the key premise underpinning our hypothesis—that low share price exposes managers to greater pressure for short-term performance. We examine how stock price reaction to negative earnings surprise varies with the level of the stock price. To mitigate endogeneity concerns, we focus on stock splits that increase the number of shares outstanding and mechanically lower stock prices, without changing firm fundamentals. In a difference-in-difference (DID) analysis, we find that firms that undergo splits experience a significant increase in the sensitivity of their stock prices to negative earnings surprises relative to the matched firms, and this effect is more pronounced among firms with positive R&D. Specifically, after stock splits, firms in the full sample (positive-R&D sample) experience an average incremental drop of -1.36% (-1.43%) in their stock price over the five-day announcement window and -1.84% (-5.10%) when the window is expanded to include the subsequent six-month period. By lowering the price, stock splits appear to induce the nominal price illusion and make investors less tolerant of poor performance, and this effect is especially pronounced for R&D firms.

We then test our primary hypothesis that firms with high R&D investments consciously avoid a low price for their shares. "Price management" by publicly traded firms takes at least three forms: Price is initially set at the time of initial public offering (IPO); and post IPO, the price is managed through the binary decision to split in a given period and by the post-split price chosen by the splitters (Baker, Greenwood and Wurgler, 2009). Therefore, our hypothesis generates three corresponding predictions. First, at the time of IPO, high R&D firms would choose a higher share price compared with other firms. Second, following the IPO, firms with high R&D would engage less in stock splits to keep the price high. Finally, among the splitters, those with high R&D would choose a higher post-split price.

To test the first prediction, we examine the midpoints of the initial filing price ranges of a sample of firms that have just listed. Our evidence reveals that firms with higher R&D expenditure indeed choose a higher filing price, after controlling for profitability and firm size. An increase from the 25th to the 75th percentile of R&D expenditure is associated with a 10% higher filing price. We then use the broad cross-section of listed firms to examine the binary decision of firms to split their stock. Specifically, we estimate probit regressions using panel data and examine how the incidence of stock splits varies with the firms' R&D capital. Following Chan, Lakonishok, and Sougiannis (2001), we calculate R&D capital (*RDC*) by depreciating R&D expenditure at a 20% annual rate. We find that firms with higher R&D capital are significantly less likely to split their stocks to lower prices. The estimated coefficient implies a reduction of 1.44% in the probability of a stock split when R&D capital increases from the 25th to the 75th percentile of its distribution. This is large—about 16%—when compared with the unconditional probability of a split in a given year, which is about 9% in our sample. We also find that among the splitters, those with high R&D capital choose a high post-split stock price.

To mitigate endogeneity concerns and draw a causal inference, we exploit the staggered introduction of R&D tax credits across various states in the United States over the period 1980–2006 to identify a quasi-natural shock to R&D (Wilson, 2009). Prior studies have shown that such tax credits induce a significant increase in the R&D expenditure of firms that are headquartered in those states (Wilson, 2009; Goldman and Peress, 2019). After confirming this result for our sample, we show that following the introduction of a state tax credit, firms located in the state also engage less in stock splits as compared with other firms in the country. More specifically, we estimate that the sensitivity of the split factor to R&D expenditure is 0.6; thus, a 1% increase in R&D expenditures induces, on average, a 0.6% decrease in the split factor. Given that the mean unconditional split factor in our sample is 0.07, this represents a reduction of 8.5% in the split factor relative to its unconditional mean.

As an alternative way to address endogeneity issues, we employ the identification strategy of Lin and Wang (2006), who instrument a firm's R&D expenditure using rivals' and the public sector's spending on R&D in the state where the firm is located. While potentially related to a firm's R&D spending, both these instruments are plausibly unrelated to a firm's stock split decision. We continue to find a strong negative relationship between R&D and the incidence of splits. Together, these results present a persuasive case for a causal effect of R&D investment on firms' decision to split their stocks. We also exploit cross-sectional heterogeneity across chief executive officers (CEOs) to conduct an additional test of our hypothesis. Recent works by Islam and Zein (2020) and Bostan and Mian (2019) show that firms with greater focus on innovation are more likely to appoint CEOs that have hands-on innovation experience—labelled as inventor CEOs—and that these CEOs are better at pursuing strategies that focus on the long-term success of R&D investments. We find that the negative association between R&D capital and stock splits is strikingly more pronounced for such firms than those with non-inventor CEOs.

In our final set of analyses, we examine the timing of the split decisions by R&D-intensive firms. We find that relative to a set of matched firms, R&D firms that undergo a stock split experience a significant increase in profitability in the three-year period leading up to the year of the split. We also find that the innovation output of firms that split, measured in terms of the number of patents and patent citations, drops significantly after the split. This evidence points to the possibility that R&D-intensive firms choose to use stock splits to lower share prices when they are shifting their focus away from innovation and when it becomes optimal to attract speculative investors that focus on the firm's improved earnings. Further evidence of firms choosing a high (low) price when they have greater (less) focus on innovation comes from our IPO sample: Firms that choose a higher (lower) offer price at IPO experience superior (inferior) innovation output during the three-year post-IPO period relative to IPOs with lower offer price. However, the findings of a negative relation between stock split and future innovation and a positive relation between IPO price and future innovation also render themselves to a causal interpretation in which lower stock price impedes future firm innovation by exacerbating the pressure for short-term performance. Such causal interpretation would help understand why firms with R&D investments generally avoid low share prices.

Our evidence that R&D-intensive firms avoid low share price to mitigate the effect of investor short-termism adds to the literature that studies the actions which publicly listed firms take to shield their long-term investments from stock market myopia. Most of the actions previously identified in the literature—such as the cessation of quarterly earnings announcements (Kim, Su, and Zhu, 2017), dual-class share structure (Chemmanur and Jiao, 2012), and antitakeover provisions (Chemmanur, Paeglis, and Simonyan, 2011; Chemmanur and Tian, 2018)—may be viewed by outsiders as self-serving for managers and as evidence of their entrenchment and agency conflict. By contrast, the share price management that we study is unlikely to suffer from this problem, and hence may be viewed as a more viable mechanism to deal with investor myopia. As a practical example, by refusing to split Berkshire Hathaway's Class

A stock, Mr. Warren Buffett is perhaps the most well-known proponent of the use of high share price to mitigate investor short termism.[6]

Our results also contribute to the literature on nominal share price. In frictionless efficient markets, nominal share prices should be irrelevant. Yet most managers recognize the important role price plays in shaping investor perceptions and manage their share price actively rather than let it drift over time with returns (Weld, Michaely, Thaler, and Benartzi, 2009). Dyl and Elliot (2006) show that firms follow their industry and size peers and target specific price ranges in order to maximize their value. Baker, Greenwood and Wurgler (2009) present evidence that firms cater to time-varying preferences of investors and target low (high) price during times when investors value low-priced stocks more highly relative to high-priced stocks. The share price management that we study is novel and is linked to firms' desire to protect their long-term investments from investor myopia.

The rest of this paper proceeds as follows. Section 2 describes the data. Section 3 presents evidence that low stock price is associated with greater stock market reaction to poor short-term performance. Section 4 documents the relationship between R&D intensity and share price management by firms. Section 5 presents additional analyses to address endogeneity concerns. Section 6 discusses the timing of the split decision of innovative firms. Finally, Section 7 provides our conclusions.

2. Data and Variable Measurement

We collect data and conduct several tests to see how R&D intensity affects managers' choice of their stock's target price. First, to examine the relationship between IPO price and R&D intensity, we obtain a sample of IPO firms from the Thomson Financial SDC New Issues database for the period 1980–2018. We begin in 1980 because the calculation of R&D capital (*RDC*) in our subsequent tests requires five years of data for R&D expenses, and firms began to report R&D

[6] Buffet's reasoning is explained in an Investopedia article as follows: "Simply put: Buffett focuses on high-quality companies with long-term growth and profit potential. And by refusing to split Berkshire Hathaway's Class A stock shares, Buffett seeks to attract investors after his own heart--namely those interested in long term plays, who have extended investment horizons." ("Why doesn't Warren Buffett split Berkshire Hathaway stock?", *Investopedia*, Updated Feb 17, 2020). His lifelong reluctance to split shares has resulted in the price of the Class A shares of Berkshire Hathaway hit $306,375 per share in November 2020.

expenses from 1975. We use the midpoint of the lowest and highest initial filing price as the IPO filing price. We exclude firms that set their filing price at less than \$5. Our results remain robust to the inclusion of such firms. In addition, we obtain the IPO offer prices, that is, the prices at which IPOs are actually sold to investors. After requiring the availability of the control variables, the sample consisting of firms with valid IPO filing (offer) prices has 2,829 (4,692) observations. Panel A of Table 1 reports summary statistics of the key variables. The average filing and offer prices are around \$11 and \$12, respectively. More than half of the IPO firms in our sample did not report R&D expenditure when they went public.

To estimate the relationship between stock splits and R&D intensity, we obtain data of common stocks traded on the NYSE, AMEX, and NASDAQ stock exchanges. Stock market information on common stocks that have share codes 10 and 11 is obtained from the Center for Research on Security Prices (CRSP). The accounting data, including that of R&D, come from Compustat. Our sample period spans 1980–2018. As before, we eliminate stocks with price less than \$5 to avoid microstructure noise. We also exclude financial firms (SIC codes 6000s) and utilities (SIC codes 4900s), and firms with total assets of less than \$1 million.

We use the distribution code in the CRSP database (*Distcd*) to identify firms that engage in stock splits. Specifically, distribution codes 5523 or 5533 indicate stock splits. Because some firms have a policy of paying small annual dividends in the form of stocks, we exclude small splits with the CRSP split factor (*facshr*) less than 0.25 (Weld, Michaely, Thaler, and Benartzi, 2009; Birru and Wang, 2016). We also exclude reverse splits as they tend to be rare, and when they do occur, they mostly reflect an effort to satisfy listing requirements (Kim, Klein, and Rosenfeld, 2008; Baker, Greenwood, and Wurgler, 2009). Because much of our analysis employs yearly observations, we compute an aggregated split factor for each firm for each calendar year by cumulating the individual split factors. The main dependent variable in our regressions is *Split*, which denotes the incidence of a split during a year; it takes the value of one if the cumulative split factor for the firm during the year equals or exceeds 0.25.

Our primary measure of R&D intensity of a firm is based on its R&D capital (*RDC*). To compute *RDC*, we follow Chan, Lakonishok, and Sougiannis (2001) and depreciate R&D expenditure at the rate of 20% per year. Specifically,

$$RDC_{i,t} = RD_{i,t} + 0.8 \times RD_{i,t-1} + 0.6 \times RD_{i,t-2} + 0.4 \times RD_{i,t-3} + 0.2 \times RD_{i,t-4}, \quad (1)$$

where $RD_{i,t}$ is R&D expenditure of firm i in year t. We then measure R&D intensity alternately as the log of one plus the R&D capital (*ln*(1+*RDC*)) or R&D capital scaled by total assets (*RDC*/*TA*). Our analyses include several control variables. The details of their measurement are provided in Appendix A. Because many of the accounting variables have extreme values, we trim all our continuous variables at the 1st and 99th percentiles of the respective firm-year distribution. After requiring the availability of all control variables, our base case sample includes 52,869 firm-year observations.

Panel B of Table 1 reports summary statistics for the split sample. The mean (median) share price in our sample is about $27 ($22). The mean value of the split dummy (*Split*) is 0.09, which indicates that about 9% of the firms in our sample split their stock in a year. These numbers are consistent with those reported in other studies (Dyl and Elliott, 2006; Baker, Greenwood, and Wurgler, 2009; Minnick and Raman, 2014). As expected, R&D capital (*RDC*) has a skewed distribution. The mean R&D capital as a percentage of total assets (*RDC/TA*) is around 7%, while the median is zero.

In our subsequent analyses, we employ several additional datasets. Analyst forecasts for quarterly earnings are obtained from IBES; tax credit rates are downloaded from the website of Daniel Wilson, and inventor CEOs are identified by combining S&P Execucomp with multiple other datasets. We provide details of these data in the respective sections in which they are used. Appendix A also includes the sources of each variable.

3. Nominal Share Price and Sensitivity to Poor Quarterly Earnings

We begin our analyses by examining whether low share price levels expose firms to greater pressure for short-term performance. In their influential paper, Graham, Harvey, and Rajgopal (2005) find that managers in the US consider short-term performance important because of the fear that poor short-term performance would cause turmoil for their securities in equity and debt markets. Therefore, we use the stock price decline in response to an announcement of poor quarterly earnings to assess the pressure for short-term performance on managers.

We define poor quarterly earnings or negative earnings surprises, as those that fall below the median analyst forecast. Ceteris paribus, larger price declines on the announcement of negative earnings surprises would indicate greater disappointment of investors and more pressure on managers to meet near-term earnings targets. Previous studies find that firms with excessive growth expectations experience asymmetrically larger drop in their stock price on the announcement of negative earnings surprises (Matsumoto, 2002; Skinner and Sloan, 2002). Similarly, since nominal price illusion implies excessive investor expectations about the upside potential of low-priced stocks relative to high-priced stocks, we expect that the inability to meet the earnings expectations therefore creates greater disappointment and larger price declines for low-priced stocks than for high-priced ones.

However, a simple comparison of stock price sensitivity to negative earnings surprises across low- and high-priced firms is plagued with endogeneity issues. To mitigate such concerns, we conduct a DID analysis that focuses on firms that engage in stock splits. Stock splits provide a relatively clean setting to examine the effect of changes in nominal share price because the incidence of a split causes large changes in the stock price that have little relationship with changes in firm fundamentals. Prior works show that stock splits are not correlated with future firm profitability (Lakonishok and Lev, 1987; Asquith, Healy, and Palepu, 1989) or changes in liquidity (Schultz, 2000; Easly, O'Hara, and Saar, 2001). Therefore, several studies such as BW (2016), Green and Hwang (2009), and Baker, Greenwood, and Wurgler (2009) use stock splits as an instrument to test behavioral theories.

We compute the change in the sensitivity of the splitting firms' share price to negative quarterly earnings surprises in the 12-month period following the split compared with the 12-month period preceding the split. We drop the month of the split from our analysis. We also obtain a sample of control firms that are matched to the treatment firms based on the Fama–French 48-industry classification, and deciles of share price and past 12-month stock returns. We choose one control firm (without replacement) for each treated firm. Because control firms are matched contemporaneously—at the beginning of the split month—we control for time variation associated with any macro-factors that might affect stock price response to earnings news of both the treatment and control firms. In our DID analysis, we compare the change in the sensitivity of stock price to negative earnings surprises for the split firms relative to that of the matched firms.

Specifically, we estimate the following regression:

$$CAAR_{i,m} = \alpha_0 + \alpha_1 \, Treated + \alpha_2 \, Post + \alpha_3 \, Treated \ x \ Post$$

$$+ \beta \, ES_{i,m} + c' controls_{i,m} + \varepsilon_{i,m}. \qquad (2)$$

The dependent variable is the cumulative average abnormal stock return in percentage, $CAAR_{i,m}$, around the announcement of firm *i*'s quarterly earnings during month *m*. We examine *CAAR* over two overlapping windows. The first is a shorter window that spans the trading day -2 to +2, centered on the earnings announcement date and captures the immediate response of the stock market. The second is an extended window that spans the trading date -2 to +120 (i.e., approximately a six-month period in calendar time) and captures any drift or long-term effect of the announcement. To obtain *CAAR*, we first compute the abnormal returns on each day using the procedure in Daniel, Grinblatt, Titman, and Wermers (1997) that accounts for the size, book-to-market (*BM)*, and momentum effects in expected returns, and then add up these returns over successive days.[7] The explanatory variables include *Treated*, which is an indicator variable that takes the value of one for firms that undertake splits and zero for the matched firms. *Post* is an indicator variable that takes the value of one for the 12-month period after the split and zero for the 12-month period before it. Therefore, the coefficient on the interaction variable, *Treated x Post*, captures the DID effect. We control for the earnings surprise, *ES*, which we define as the difference between the actual earnings announced and the median analyst forecast, scaled by the absolute value of the actual earnings.[8] The data on quarterly earnings and the corresponding median forecasts come from the IBES summary file. The vector of control variables includes past earnings volatility, book-to-market ratio, institutional ownership, and the log of book value of equity. We follow Hotchkiss and Strickland (2003) and estimate the model solely based on negative earnings surprises. Specifically, we estimate the model using the negative quarterly earnings surprises of

[7] Our results remain qualitatively similar when we use buy-and-hold abnormal returns instead of cumulative abnormal returns.

[8] To avoid the problem of a small divisor when earnings are close to zero, we divide the surprise by 0.25 whenever the absolute value of actual earnings is less than 0.25 (Loh and Mian, 2006). We also experiment with using other common scalers in the literature, specifically, stock price, absolute value of median forecast, and standard deviation of actual earnings, and find similar results.

both the split and the control firms over the 12-month pre- and the 12-month post-treatment periods. Standard errors are clustered by both firm and year.

Table 2 reports the results. The estimates in Column (1) indicate that the five-day cumulative average abnormal returns associated with the announcement of negative earnings surprises for the split firms changes from a statistically insignificant 0.69% before the split to a significant -1.39% after the split.[9] To see whether this increase is over and above that for the matched firms, we look at the coefficient on the interaction variable *Treatment x Post*. The estimated coefficient is -1.36% (*t*-statistic = 4.38), indicating that the increase in the stock price sensitivity to negative earnings surprises for split firms is over and above the increase for the matched firms. When we estimate Equation (2) for the sub-sample of firms with R&D in Column (3), we obtain similar results. The decline in stock price is more pronounced after stock splits for both the total sample and for the sub-sample of R&D firms.

When we extend the event window to include the subsequent period up to 120 trading days, we obtain interesting results. In Column (2), where we look at full sample, the coefficient on the interaction variable is a statistically insignificant -1.84% (*t*-statistic = 1.39), indicating that on average it is difficult to discern a significant increase after the split in the sensitivity of the long-term returns to negative earnings surprise. Yet in Column (4), when we look at the positive R&D firms only, the coefficient becomes a significant -5.10% (*t*-statistic = 2.05). The loss in market capitalization of more than 5% is an economically large number and indicates that, among the positive R&D firms, greater initial price decline in reaction to announcing poor earnings is followed by further declines over subsequent months, which cumulatively result in very substantial price declines over the 6-month window.[10] To sum, the results in Table 2 confirm that stock splits are associated with greater sensitivity of stock price to negative earnings news, and this effect is more pronounced for R&D intensive firms.

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[9] We obtain 0.69% by adding the coefficient for *Treatment* to the intercept (i.e., -0.67 + 1.36 = 0.69). The estimate -1.36% is obtained by adding to the intercept the coefficients of *Treatment, Post*, and *Treatment x Post* (i.e., -0.67 + 1.36 – 0.72 – 1.36 = -1.39)

[10] The size of the return differential is also noteworthy because it helps us understand why the managers in the survey of Graham, Harvey, and Rajgopal (2005) believe that missing quarterly earnings targets leads to turmoil in the stock market.

A key assumption of the DID estimators in Table 2 is the parallel trends assumption. To assess if the assumption holds, one needs to examine the differences in the trends in the outcome variable for the treatment and control groups during the pre-treatment era and see if the post-treatment differences are simply due to the continuation of the pre-treatment trends. We do so in Figure 1, which plots the quarterly CAARs for negative earnings surprises for the four quarters before and after the stock splits for both the treatment and control groups. In Panel A, we look at the full sample. Here the treatment and control firms appear to have similar trend in the pre-treatment period, thus satisfying the parallel trends assumption. In Panel B, we examine the sub-sample of the positive R&D firms. Here there seems to be a difference between the trends in the CAARs for the treatment and control groups during the pre-treatment period. However, the difference is opposite to what might be needed to explain our results. That is, a simple extrapolation of the pre-treatment trends cannot explain the differences in the CAARs in the post-treatment period. Specifically, the CAAR for the treatment (control) firms is increasing (decreasing) in the pre-treatment period, and absent the treatment, we should find that the CAAR for the treatment firms is *higher* than that of control firms in the post-treatment period. We, however, find it to be *lower*. Therefore, differential trends in the pre-treatment periods cannot explain our findings.

While our focus is on negative earnings surprises, it is instructive to estimate Equation (2) using data on positive earnings surprises as a placebo test. The results are reported in the last column in Table 2. The coefficient on *Post x Treatment* is now insignificant, indicating that the greater stock price sensitivity after the split does not extend to positive earnings surprises.[11] To summarize, the results in this section are consistent with the idea that by lowering stock prices, stock splits lead to the nominal price illusion, making investors less tolerant of poor performance. They provide support to a key premise of our theory, namely, that investors are more sensitive to poor short-term performance for low-priced stocks than for high-priced stocks.

We also examine the validity of our assumption that firms with greater R&D investments face greater uncertainty about their near-term performance. We consider two proxies of the uncertainty of firms' near-term performance based on analyst forecasts of impending quarterly earnings: the absolute value of forecast errors and forecast dispersion. We regress these proxies on

[11] In untabulated results, we also conduct a DID analysis of the proportion of negative earnings surprises before and after the split and find no significant change.

R&D intensity and controls in panel regressions. The results reported in Appendix B are consistent with the commonly accepted notion that near-term earnings are more uncertain for firms with greater R&D intensity.

4. R&D Intensity and Managerial Preference for High Share Price

This section provides empirical tests of our hypothesis that firms with higher R&D intensity avoid a lower share price. We examine three major components of publicly traded firms' "price management" decisions (Baker, Greenwood, and Wurgler, 2009). Prices are initially set at the time of IPO. After the IPO, the price is managed through the binary decision to split in a given period, and by the price chosen by splitters. Accordingly, we first focus on how the IPO filing price varies with R&D intensity using a sample of firms that have just listed. Next, we look at the binary decision of firms to split their stock in a given year using a broad cross-section of listed firms. Finally, we examine the post-split price chosen by the splitters, as these firms have made an active decision in period t to split their stock and therefore, the price reflects an explicit choice, rather than simply managerial inertia. Because tolerance for failure is important for successful innovation (Porter, 1992; Manso, 2011), managers of high R&D firms want to avoid pressure for short-term performance and avoid a low share price level. Therefore, we expect this preference to be revealed in each of their price management decisions. Specifically, managers of high R&D firms would choose a higher IPO price, would engage less in price-reducing stock splits, and upon a stock split, would choose a higher post-split price.

A. R&D Intensity and IPO Filing Price

Baker, Greenwood, and Wurgler (2009) note that an important indicator of managers' preference for a certain share price level is the price they choose at the initial public offering. The IPO filing price provides a relatively clean setting to study managerial preference because managers can easily alter it by changing the number of shares on offer. The filing price is not affected by the feedback from the financial markets after firms announce their IPOs. It is also not contaminated by past stock return performance. Therefore, in this section, we examine whether R&D intensity influences managers' choice of the IPO price.

To examine whether managers choose a higher share price when their firm engages more in R&D, we regress the IPO price on R&D intensity and the control variables as follows:

$$\ln(P)_{i,IPO} = \alpha + \beta\ RD\_Intensity_{i,IPO} + c' controls_{i,IPO} + Industry\ fixed\ effects + Year\ fixed\ effects + \varepsilon_{i,IPO}. \quad (3)$$

The dependent variable is the log of the IPO filing price for firm *i*, which we measure as the mid-point of the initial filing price range. Alternately, we also check our results using the IPO offer price. Due to limitations on obtaining historical data for IPO firms, the explanatory variables are all those reported at the time of the IPO. The key explanatory variable is R&D intensity, which we measure for the IPO sample using the R&D expenditure (*RD*) of the firm in the year preceding the IPO. We alternately measure R&D intensity as the log of (1+*RD*) and *RD* scaled by total assets. We expect the coefficient on R&D intensity to be positive, reflecting that firms with greater investment in R&D prefer to set a higher share price. We include low-price premium of Baker, Greenwood and Wurgler (2009) as a control variable to capture the time-varying price incentives of managers to adjust share price to the prevailing market conditions. As in Baker et al. (2009), we compute it as the log difference between the average market-to-book ratio of low-priced firms and that of high-priced firms. We also experiment with replacing this measure with year fixed effects as an alternative mechanism to capture time-varying price preferences of firms. Other control variables include firm size, measured by the log of sales, and profitability, measured as the return on assets. A limited number of cross-sectional control variables in Equation (3) reflects the paucity of the accounting data available for firms at the time of their IPO.[12] Standard errors are clustered by year to allow for within-year correlations.

Table 3 reports the estimates of Eq. (3). In the first two columns, we use the log of the mid-point of the IPO filing price range as the dependent variable. The coefficients on *ln(1+RD)* in Column 1 and *RD/TA* in Column 2 are positive and highly significant, indicating positive association between R&D intensity and IPO filing price. The estimated coefficients are economically meaningful. For instance, the estimated coefficient on *ln(1+RD)* implies an increase

[12] We obtain similar results when we measure firm size using the log of total assets. In further robustness check, we also include the following controls: the log of the book value of equity, average equity per shareholder—computed as total book equity divided by the number of shareholders—, and earnings per share. The sample shrinks when all these variables are included, but the coefficient on R&D intensity remains positive and significant.

in the filing price of \$1.08 when we move from the 25th to the 75th percentile of R&D.[13] Compared with the average IPO filing price of \$11, this is economically meaningful. In further robustness analysis, we replace the IPO filing price with the IPO offer price in Columns (3) and (4) and obtain similar results.

Among the control variables, the coefficient on *PCME* is insignificant in the IPO filing price regressions, suggesting that the influence of Baker, Greenwood and Wurgler's (2009) low-price premium on setting IPO filing prices is insignificant. However, it is negative, and statistically highly significant when we examine IPO offer prices. This is consistent with the results in Baker, Greenwood and Wurgler (2009), who also examine IPO offer prices and find that firms set a lower offer price when investors place relatively higher valuation on low-priced stocks compared to high-priced stocks. Thus, the catering incentives documented by Baker et al. (2009) apply to IPO offer prices, but not IPO filing prices. The findings imply that Baker et al.'s catering incentives affect IPO price setting through price revisions that incorporate information obtained from road shows (Benveniste and Spindt, 1989). Even with their catering incentives, we still see very robust effects of R&D on IPO price setting.

In untabulated results, we replace *PCME* with year fixed effects and find qualitatively similar results for our R&D variables. Finally, the coefficient on *ln(Sales)*, which is a proxy for firm size, is positive and significant, confirming a prior finding that larger firms set a higher nominal share prices (Weld, Michaely, Thaler, and Benartzi, 2009).

B. R&D Intensity and the Incidence of Stock Splits

Once a firm is listed, its stock price changes passively with stock returns and actively through its decision to split the stock. Managers can avoid a low share price for their stock by shunning stock splits. Therefore, a key prediction of our hypothesis is that firms with higher R&D intensity are less likely to split their stock, compared with firms with low R&D intensity. That is,

[13] The 25th and 75th percentiles for R&D expenditure are 0 and 1.84, respectively. Therefore, a change from the 25th to 75th percentile results in *ln(1+RD)* changing from 0 to 1.044. When multiplied by the coefficient estimate of 0.076, this gives us 0.079. Taking its exponential results in 1.08.

a negative relationship exists between the incidence of stock split and a firm's R&D intensity.[14] We test this prediction by estimating the following probit model with panel data:

$$Pr\left(Split_{i,t}=1\right)=\alpha+\beta\ R\&D\_Intensity_{i,t-1}+c'controls_{i,t-1}+\text{ Industry fixed effects }+ \\ +\text{ Year fixed effects }+\varepsilon_{i,t}. \qquad (4)$$

The dependent variable takes the value of one if firm *i* engages in a stock split in year *t* and zero otherwise. The key explanatory variable is the intensity of R&D, *RD_Intensity*, which we measure alternately as the log of one plus the R&D capital (*ln*(1+*RDC*)) or R&D capital scaled by total assets (*RDC*/*TA*). The vector of control variables includes the low-price premium (*PCME*) and firm-level characteristics such as book-to-market ratio, past 12-month stock return, firm size, institutional ownership, beginning-of-the-year (pre-split) share price, the deviation of the firm's pre-split share price from the median price of the firms in in the same Fama–French 48-industry (*presplitind)* and the deviation of the firm's pre-split share price from the median price of the firms in in the same size decile (*presplitsz*). The last two controls are suggested by Weld, Michaely, Thaler, and Benartzi (2009), who find that the deviations of a firm's share price from its industry- and size-based peers are important determinants of the decision to split stock. We use *ln(Sales)* as a measure of firm size instead of market capitalization because share price is included as another control variable.[15] The regression incorporates industry (i.e., Fama–French 12-industry classification) and also year-fixed effects in specifications where we do not include *PCME*. Finally, we cluster the standard errors by both firm and year.

Table 4 reports the estimates of the model. The coefficients on the two R&D intensity variables—*ln*(1+*RDC*) and R&D capital scaled by total assets (*RDC*/*TA*)—are negative and statistically significant across all specifications, consistent with our hypothesis that R&D-intensive firms are less likely to split their stocks to lower prices. To assess the economic significance of the estimated coefficients, we calculate the probability of a firm conducting a split when *RDC* changes from the 25th to the 75th percentile of its distribution, while keeping all the control variables at their means. Focusing on the specification in Column (1), the estimated coefficient on R&D intensity,

[14] We note that we only consider regular stock splits and ignore the reverse splits.
[15] We note that market capitalization is simply the product of share price and the number of shares outstanding. Our results, nevertheless, remain robust when we include the log of market capitalization as an additional control alongside *ln(P)* and *ln(Sales)*.

log(1+RDC), is -0.045 (*z*-statistic = 5.10) implies that the probability of a firm conducting a split goes down by 1.44% when *RDC* changes from the 25th to the 75th percentile. This is large—about 16%—when compared with the unconditional probability of a split in a given year, which is 9% in our sample, as reported in Table 1. The magnitude of the effect of *RDC* is also comparable to the previously documented cross-sectional determinants of splits, used as controls in our regression.[16]

The coefficients on the control variables in Table 4 appear with the expected signs that are consistent with the prior evidence. The coefficient on *PCME* is positive and statistically significant, consistent with the findings of Baker, Greenwood and Wurgler (2009). It shows that firms strategically increase stock splits during periods when investors place higher valuation on low-priced stocks. Furthermore, consistent with the previous literature on stock splits (e.g., Lakonishok and Lev, 1987; Asquith, Healy, and Palepu, 1989), firms with higher past stock returns, higher sales growth, and a higher pre-split stock price are more likely to split their shares. The coefficient on *IO* is negative, suggesting that firms with high institutional ownership are also less likely to undergo stock splits. This is consistent with the findings of Dyl and Elliott (2006), who show that firms that can attract more institutional investors tend to have higher share price levels. The coefficient on *presplitsz* is positive and highly significant, as in Weld, Michaely, Thaler, and Benartzi (2009). Finally, the coefficient on *presplitind* is insignificant in some specifications but that is due to the inclusion of the pre-split stock price (*P*) in the model, as the two are highly correlated. In untabulated results, when we drop the pre-split stock price, the coefficient on *presplitind* becomes positive and highly significant, as in Weld et al. (2009).

To further understand the price management strategies of R&D intensive firms, in Table 5 we interact the R&D intensity variable with *PCME*, which is the Baker, Greenwood and Wurgler (2009) measure of time-varying catering incentives. The coefficient on the interaction variable is negative and statistically significant when we measure R&D intensity using *RDC/AT*. This suggests that firms with high R&D succumb less to the catering incentives documented in Baker et al. (2009). Table 5 also examines the stability over time of the reported relationships in Table 4.

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[16] The change in the probability of a split for a move from the 25th to the 75th percentile is 1.12%, -0.53%, -0.48%, -1.83%, 1.73%, 0.51%, 1.95%, 0.09%% and 2.36% for *ROA, IO, Sales, BM, R12, Sales Growth*, *P*, *presplitind* and *presplitsz*, respectively.

Specifically, Minnick and Raman (2014) show that the aggregate number of stock splits have declined significantly since the turn of the millennium, raising the possibility that the firms' decision to split has changed fundamentally in recent years. To check the consistency of our results, we divide our sample into two sub-periods: 1980–2000 and 2001–2018, and estimate the probit regression separately for the two sub-periods. The coefficients on R&D intensity are negative and significant in both sub-periods, indicating that in recent years, firms' decision to undergo a stock split continues to be negatively associated with the R&D capital. In summary, the results in this subsection are consistent with our hypothesis that high-R&D firms are less likely to split their shares to lower price levels.

C. R&D Intensity and the Post-Split Price Chosen by Splitters

Conditional on the decision to split their stock, managers can choose a certain level of post-split price by altering the split factor. As Baker, Greenwood, and Wurgler (2009) note, unlike non-split firms where the price may simply reflect past returns or managerial inertia, the split firms are those that have made an explicit decision to split their stock. Thus, their price reflects an explicit choice. Therefore, we examine the sample of split firms to see if high R&D intensity is associated with a higher post-split price. Using (from our sample) 4,815 firm-year observations with stock splits, we estimate a model similar to Equation (4) in which the dependent variable is the log of the post-split price. Following Baker et al. (2009), we define post-split price as the price at the end of the month in which the split takes place. In case of multiple splits during the year, we pick the stock price after the last split.

Table 6 reports the results. The estimated coefficients on the two alternate measures of R&D intensity—*ln(1+RDC)* and *RDC/TA*—are positive and statistically significant across all columns, indicating that among the splitters, those with high R&D target a higher post-split price. To assess the economic significance of the relationship, we note that the coefficient on *ln(1+RDC)* in Column (1) is 0.009 (*t*-statistic = 2.79), which implies that an increase in *RDC* from the 25^{th} to the 75^{th} percentile of its distribution is associated with an increase in the post-split price of $1.03.[17] This represents an increase of around 4% relative to the mean post-split price of $26.6, as reported

[17] The 25^{th} and 75^{th} percentiles for R&D capital in the sample of splitters are 0 and 19, respectively (not tabulated). Therefore, a change from the 25^{th} to the 75^{th} percentile results in *ln(1+RD)* changing from 0 to 3.04. When multiplied by a coefficient estimate of 0.009, this gives us 0.033. Taking its exponential results in 1.03.

in Table 1, Panel B. Examining the control variables, Table 6 reveals that the most important determinant of the post-split price is the pre-split price, specifically, the price that prevailed at the beginning of the year. It seems intuitive in that the higher the pre-split price of a splitter, the more likely it is that it would end up with a higher post-split price compared with other splitters. The post-split price also varies negatively with the low-price premium (*PCME*), consistent with the findings of Baker, Greenwood and Wurgler (2009). This indicates that splitters choose a lower post-split share price when investors place higher relative valuation on low-priced stocks. Among the other determinants, the post-split price increases with institutional ownership and firm size (i.e., log of sales), and decreases with recent stock returns.

In summary, this section documents evidence of avoidance of low share price by R&D-intensive firms in all their price management actions: They choose a higher IPO price at their listing, are less likely to split their stock afterwards, and upon a decision to split the stock, choose a higher post-split price. However, we note that this analysis suffers from potential endogeneity concerns, specifically the concern about correlated omitted variables. We conduct additional analysis in the next section to mitigate these concerns.

5. Identification Strategy

To establish a causal link between R&D intensity and managerial avoidance of low share price, we focus on stock splits. After an IPO, stock splits are the primary tool firms employ to manage their share price. We first examine how a quasi-natural shock to R&D associated with the introduction of state-level tax credits influences firms' decision to split their stock. Then we employ an alternative instrumental variable approach. Finally, we examine the cross-sectional heterogeneity in the relationship between R&D intensity and stock splits to strengthen our inference about the causal relationship between R&D intensity and stock splits.

A. Analysis Based on the "Exogenous" Shock of R&D Tax Credits

Beginning in Minnesota in 1982, there were 32 others states that implemented R&D tax credits by 2006 (Wilson, 2009). These states' R&D tax credits allow firms to reduce their tax liability by deducting a portion of R&D expenditure from their state tax bill. Prior work documents a positive effect of tax credits on in-state firms' R&D expenditures (Wilson, 2009; Goldman and

Peress, 2019) and on the number of high-tech establishments in the state (Wu, 2008). Therefore, these policy changes provide a source of variation in firms' R&D intensity that is plausibly exogenous to their stock split decision. Bloom, Schankerman, and Van Reenen (2013) and Goldman and Peress (2019) also use state tax credits to instrument firms' R&D activities.

We follow Goldman and Peress (2019) closely in designing our empirical strategy. We compare the change in stock splits of firms located in states that passed a tax credit with the change in stock splits of comparable firms located in the states that did not. The staggered implementation of tax credits across states allow us to control for aggregate shocks contemporaneous with the implementation of tax credits that could influence stock splits. Under the assumptions that the stock splits of firms in different states follow similar trends absent treatment and that the passage of a state R&D tax credit is not correlated with other changes driving the stock split decisions in the state, our DID estimation allows us to isolate the causal effect of R&D intensity on stock splits.

We summarize the information on state tax credits for the period 1982–2006 in Appendix B, which reports the year when the tax credit was first introduced, the size of the credit, and subsequent changes.[18] Following Heider and Ljungqvist (2015) and Goldman and Peress (2019), we reduce the potential endogeneity of a state that chooses a certain level of tax credit by abstracting from the actual levels and use a binary indicator variable that takes the value of 1 for years in which the state introduces or increases its tax credit. We do not consider reductions in tax credits, as few states implement them over time. We obtain the information on the location of headquarters of firms primarily from the web site of Bill McDonald at University of Notre Dame,[19] but supplement this with data from Compustat. We conduct our analysis for those firms that report positive R&D. To ensure that treatment firms (those headquartered in the states that introduce tax credit) are not very different from the control firms, we follow Goldman and Peress (2019) and

[18] The appendix is an extended version of Table 1 in Goldman and Peress (2019), who report similar data for the period 1990–2006. The information comes from the website of Daniel Wilson at https://www.frbsf.org/economic-research/economists/daniel-wilson/.
[19] The dataset, which contains historical information about the headquarter locations for the period 1994–2018, is downloaded from https://sraf.nd.edu/data/augmented-10-x-header-data/. The original source of the data is the header section of the companies' 10-K filings with the Securities and Exchange Commission.

estimate propensity scores using a logit regression.[20] Firms with propensity scores between 0.1 and 0.9 are retained in the analysis.

We first confirm that increases in state tax credits are indeed associated with increases in R&D expenditures for the firms headquartered in those states. Specifically, we estimate the following regression:

$$\Delta ln\left(RD_{i,s,t}\right) = \alpha + \beta\, TC_{s,t-1} + c'\Delta controls_{i,t-2} + \text{ Year fixed effects } + \varepsilon_{i,t}. \qquad (5)$$

The regression is estimated in the first difference to control for all time-invariant characteristics and because it is useful for multiple treatments[21] (Heider and Ljungqvist, 2015; Goldman, and Peress, 2019). The indicator variable *TC* takes the value of 1 only if state *s*, where firm *i* is located, implemented or increased its R&D tax credit in year *t*-1. As in Goldman and Peress (2019), the control variables include the log of sales and an indicator variable for accounting loss. Our focus is on coefficient β, which measures the difference between the change in R&D for firms in the treated states relative to the change in R&D for firms in other states. Table 7 reports the estimates of the model in Column (1). The estimate for β indicates that following the enactment of tax credits, firms headquartered in states that enact tax credits increase their R&D by 3.0% (*t*-statistic = 6.69) relative to control firms.

We next turn to test our main hypothesis that the treated firms, which experience a plausibly exogenous increase in their R&D, reduce their stock splits following the R&D tax credits. We employ a specification similar to that in Equation (5):

$$\Delta ln\left(Facshr_{i,s,t}\right) = \alpha + \beta\, TC_{s,t-1} + c'\Delta controls_{i,t-2} + \text{ Year fixed effects } + \varepsilon_{i,t}. \qquad (6)$$

Because we estimate the regression in the first difference, we do not employ probit estimation. Instead, we use OLS regression and employ change in the split factor, *Facshr*, as the dependent variable. *Facshr* combines the effects of (i) the binary decision to split and (ii) the choice of a

[20] The logit regression is estimated using cross-sectional data. The treatment indicator takes the value of one if the state in which a firm is headquartered introduces a tax credit anytime during the period 1982–2006 and zero otherwise. The covariates include industry dummies, the logarithm of sales, and a dummy variable that takes the value of one if the firm reports negative earnings before interest and taxes. The values of the covariates for each firm are taken from the first year the firm appears in the sample.
[21] As depicted in Appendix B, some states increase the tax credit more than once during the sample period.

specific split factor that leads to a certain post-split price—the two decisions we examined separately in our earlier section. If the increased R&D associated with the tax credit causes firms located in the state to target a higher share price, we expect a lower split factor and thus, a negative value for β. This DID estimate is robust to aggregate time-varying shocks because we include year-fixed effects. It is also robust to time-invariant firm characteristics because of the differencing of the data. The vector of control variables now includes the full set used in our base-case specification in Equation (4). This allows us to control for time-varying changes in firm characteristics, such as sales, book-to-market, stock returns, and the level of stock price.

Table 7, Column (2) reports the results. The estimated value of β is -0.017 (t-statistic = 2.02), which implies that after the passage of state R&D tax credits, firms in the treated states reduce their split factor by 1.7% compared with firms located in other states. Relative to the 7% unconditional mean of the split factor in our sample (reported in Table 1), this represents a decrease of 24%. Relative to the 3.0% increase in R&D after the tax credit, the 1.7% reduction in the split factor is also large. The results in Table 7, therefore, suggest a strong causal link between R&D intensity and stock splits—firms that experience a plausibly exogenous increase in their R&D significantly reduce the stock splits.

B. Instrumental Variables Approach

As a further robustness check, we employ the instrumental variable approach of Lin and Wang (2016) to examine the causal relationship between R&D intensity and stock splits. Lin and Wang (2016) employ two instruments for a firm's R&D: rivals' spending on R&D and public sector spending on R&D in the state where the firm is located. This approach follows Mortensen (1982) who argues that a firm's decision to invest in R&D depends on its competitors' R&D, and Levy and Terleckyj (1983) who note that if local governments, universities, and other non-profit organizations spend more on R&D, it can induce firms in the area to invest more in R&D to benefit from the public sector R&D spending. While potentially related to a firm's R&D spending, both these variables are plausibly unrelated to a firm's stock split decision.

As in Lin and Wang (2016), we measure the two instruments as follows. Rivals R&D is computed as the average R&D of other firms in the same industry as per the Fama–French 48-industry classification. Public sector spending is captured by *GRD*, a dummy variable that equals one if the firm's headquarter is in California, Washington, Massachusetts, Texas, or Michigan and zero otherwise. The National Science Foundation reports that these five states are at the top of the list in R&D spending from local governments, universities, and other non-profit organizations.

In the first-stage regression, we regress R&D spending on its lagged value, the two instruments and other variables as follows:

$$ln(1 + RD)_{i,t} = \alpha + \beta_1\, ln(1 + RD)_{i,t-1} + \beta_2\, ln(1 + Rivals\ RD)_{i,t-1} + \beta_3\, GRD_{i,t-1} + \beta_4\, ln\left(\frac{Cash}{TA}\right)_{i,t-1} + \beta_5\, ln(Sales)_{i,t-1} + \beta_6\, BM_{i,t-1} + Year\ fixed\ effects + \varepsilon_{i,t}. \quad (7)$$

We include the lagged value of the dependent variable in the model to capture omitted firm characteristics. Arellano and Bond (1991) and Roberts and Whited (2011) note that including lagged R&D as an instrumental variable for R&D can help deal with possible moving-average errors in the regression model. Other determinants of a firm's R&D included in the model are cash intensity, book-to-market ratio, and sales. The first-stage regression yields the predicted R&D, RD^F.

Our second-stage regression comprises a probit model similar to Equation (4) in which we regress the incidence of stock splits on predicted R&D and other controls as follows:

$$Pr\left(Split_{i,t} = 1\right) = \alpha + \beta\, RD^F_{i,t-1} + c' controls_{i,t-1} + \text{Industry fixed effects} + \text{Year fixed effects} + \varepsilon_{i,t}. \quad (8)$$

Table 8 reports the results. Panel A reports the estimates of the first-stage regression. Consistent with prior work (Lin and Wang, 2016), the coefficients on the two instruments are positive and economically large, suggesting that rivals' R&D expenditure and public sector spending in the state positively affect a firm's R&D spending. Panel B reports the results of the second-stage regression. The coefficient on the predicted R&D is -0.006 (*z*-statistic = 2.87). Therefore, the results from the instrumental variable estimation provide further confirmation that firms with higher R&D engage less in stock splits.

C. Heterogeneity in the Relationship between R&D Intensity and Stock Splits

Recent works by Islam and Zein (2019) and Bostan and Mian (2019) suggest that chief executive officers (CEOs) that have hands-on experience on innovation as inventors—that is, inventor CEOs—are more likely to pursue long-term strategies for their R&D investments to yield more impactful and breakthrough innovations. These studies also discuss a selection bias, whereby firms that prioritize innovation are more likely to have CEOs that are personally involved in innovation. Therefore, one would expect that firms with inventor CEOs are keener on shielding their R&D investments from the harmful effects of overly optimistic investor expectations for the low-priced stocks. As such, the negative relationship between R&D intensity and the incidence of splits we document earlier would be stronger for firms with inventor CEOs than those with non-inventor CEOs.

To test this prediction, we collect data for the inventor status of CEO by following a procedure similar to Islam and Zein (2020) and Bostan and Mian (2019). This procedure involves matching the CEO information available in Standard and Poor's Execucomp database with the patenting information in the inventor database of Li et al. (2014) using an elaborate process that employs both computer algorithms, as well as manual matching. The major challenge is matching the identities of the CEOs in Execucomp with the identities of the inventors in the inventor database of Li et al. (2014). We start by using a fuzzy text-matching algorithm to find names and companies across the Execucomp that match with the inventor datasets. For cases that match perfectly or that produce a high similarity score, we conduct manual verification to ensure that the CEO is indeed the same as the inventor. In cases where the name of the CEO matches with the name of an inventor but their companies cannot be matched across the patent data and Execucomp, we manually check the identities of the companies. The need for this arises sometimes because the patent data of Li et al. (2014) use PERMNO as company identifier whereas Execucomp data use CUSIP and GVKEY. Finally, for CEOs for whom we still cannot find a corresponding inventor match who work in the same company, we expand the search and look for the matching inventor names for all the previous companies in which the CEO worked as a lower-rank employee. We examine the biographies of the CEOs and the inventors available in the Capital IQ Professional Database and supplement this search with other sources (i.e., company web pages, Bloomberg, LinkedIn, Datastream, and more general Google searches) to identify whether a CEO was an inventor during his/her past employment. This elaborate process allows us to put together the innovation history, or lack thereof, for each CEO in Execucomp. The sample covers the period

1992–2010 because Execucomp is available from 1992 and the inventor dataset of Li et al. (2014) is available until 2010. Following Islam and Zein (2020), we classify a CEO as an inventor CEO if he/she has at least one patent registered in his/her name as an inventor.

Table 9 reports in Panel A the estimates of the baseline regression separately for firms with inventor and non-inventor CEOs. For firms with inventor CEOs, the estimated coefficient on our key variable R&D capital, *ln(1+RDC)*, is -0.142 (*z*-statistic = 2.41). This implies that moving from the 25th to the 75th percentile of the R&D capital, while keeping all other variables at their means, reduces the probability of a split by 2.87%. By contrast, for firms with non-inventor CEOs, the corresponding coefficient is -0.027 (*z*-statistics = 2.77), which implies that moving from the 25th to the 75th percentile of the R&D capital reduces the probability of a split by 0.97%. However, comparing the coefficients across models can be problematic in non-linear probability models, such as probit, due to potential differences in the residual variances (Allison, 2009). Therefore, we further estimate a probit model on the combined sample in Panel B, where we interact all explanatory variables (including the intercept) with an indicator variable for inventor CEO. Our focus is on the interaction term involving *ln(1+RDC)* and the indicator variable for inventor CEO. Its coefficient is negative and statistically significant, as shown in Panel B. This confirms that the negative relationship between R&D capital and the incidence of splits is stronger for firms with inventor CEOs, implying that such firms are keener to avoid a low share price to retain long-term focus for their R&D effort. This is consistent with the greater focus of these firms on the productivity of their innovation.

To summarize, the analyses in this section provides consistent evidence of a causal link between R&D intensity and a firm's decision to undergo a stock split. Firms with greater R&D intensity are less likely to split their stock to a lower price level. We obtain this evidence from our analysis of the quasi-natural shock to R&D related to state level tax credits and from using an alternative instrumental variable approach. Cross-sectional heterogeneity in the relationship between R&D intensity and the incidence of splits provides further support for the causal interpretation.

6. Timing of the Stock Split Decision by R&D-Intensive Firms

In Section 3, we show that low-priced stocks are susceptible to more negative stock market reaction in case of poor firm performance. So far, we have examined how this phenomenon discourages firms with long-term focus, such as those with high R&D, to avoid low stock price levels. However, it is possible that other firms, especially those with improving profitability and no particular need to adopt a long-term focus, target low price levels to attract investors that pay attention to good current performance and extrapolate it into high future growth expectations. Consistent with this idea, prior empirical works on stock splits document evidence that firms that undergo stock splits are those that experience significant improvements in their earnings during the period leading up to the splits (Lakonishok and Lev, 1987; Asquith, Healy, and Palepu, 1989).

While R&D-intensive firms may generally prefer a long-term focus to foster greater long-term innovation, once they or their industries mature, and the earlier R&D investments translate into high profitability, they may no longer need to keep the same focus on innovation as a key component of their competitive strategy. Instead, they may seek to enhance their market value through stock splits by attracting more speculative traders that pay attention to their improvements in earnings. This reasoning implies that when R&D intensive firms undergo a stock split, this decision coincides with a shift in their focus from the long term to the short term and from innovation to profitability. Empirically, this conjecture predicts that R&D-intensive firms that split their stock experience an improvement in their profitability in the years preceding the split, as well as a decline in their innovation after the split.

We follow Lakonishok and Lev (1987) and Asquith, Healy, and Palepu (1989) and examine the changes in profitability of firms with positive R&D in the years surrounding the split relative to a set of matched firms. From our primary sample, depicted in Panel B of Table 1, we identify firms that split their stock and have positive R&D. For each stock split observation, we look for a control firm among those with positive R&D. As before, control firms are identified contemporaneously by matching the Fama–French 48-industry classification, and deciles of nominal (per share) price and past 12-month stock returns. Our final sample includes 815 firms that have split their stocks for which we could find corresponding matched firms (without replacement). We calculate net as well as operating profitability (i.e., return on assets in percent) for each firm in each year, and compute change in profitability by simply differencing the successive yearly numbers. We then average these changes separately for "split" (those that have undergone a stock split) and control firms, and compare. The results are reported in Table 10. Panels A (B) reports the mean (median) of the yearly changes. The results indicate that regardless of the averaging method, the split firms experience increases in both net and operating profits in the years preceding the split that are over and above that of the matched firms. Our findings are consistent with those of Lakonishok and Lev (1987) and Asquith, Healy, and Palepu (1989).

Next, we examine how the split firms' innovation changes after the split relative to the matched firms. We measure a firm's innovation output using the two most commonly used measures in the innovation literature: the number of patents the firm generates and the total number of future citations, excluding self-citations, the patents receive (Hall, Jaffe, and Trajtenberg, 2005). In addition, we also look at the number of breakthrough patents the firm generates, which we define alternately as those that either fall among the top 1% or top 5% of the distribution of future citations in its technological class, as such patents especially require the pursuit of risky long-term strategies (Balsmeier, Fleming, and Manso, 2017).[22] The information on patents and citations is collected from the 2010 version of the NBER patent database compiled by Kogan, Papanikolaou, Seru, and Stoffman (2017).[23] Patent applications have a long approval process. It takes about two and a half years, on average, for a patent to be granted (Hall, Jaffe, and Trajtenberg, 2001). Therefore, some patents applied for toward the end of the sample were not granted, and therefore are not included in the sample. This makes the number of patents applications lower in the last few years. Therefore, we leave out the last two years and restrict our sample period to 1980–2008.[24]

As several variables (such as R&D intensity) can affect innovation output, we conduct our analysis of the change in innovation after the split in a multiple regression framework as specified below:

[22] We provide further detail about these measures in Appendix A.
[23] We download the data from https://sites.google.com/site/patentdataproject/Home.
[24] The number of citations received by the patents carry a similar well-known truncation problem. Because granted patents keep receiving citations many years into the future, the later it is in the sample period, the shorter the time period during which a patent can get citations. This results in fewer citations of the patents with later application dates. We correct this truncation problem using the commonly adopted fixed-effect method described in Hall, Jaffe, and Trajtenberg (2001). Citations received for each patent are divided by the average number of citations received in the applied patent's technological field and in the application year to remove all the fixed effects of year and technological field.

$$Innovation_{i,t} = \alpha_0 + \alpha_1\, Treated + \alpha_2\, Post + \alpha_3\, Treated\ x\ Post + \beta \ln(1 + RDC)_{i,t-1} + c'controls_{i,t-1} + \varepsilon_{i,t}. \quad (9)$$

The dependent variable is the innovation output of firm *i* in year *t*. It is measured alternately as the total number of patents the firm generates, total number of future non-self-citations the firm's patents receive, or total number of breakthrough patents. *Treated* is an indicator variable that takes the value of one for all years if firm *i* splits its stock at least once in the preceding three years or year *t*-2 through year *t*, and zero otherwise. *Post* is an indicator variable that takes the value of one for the post-split period and zero otherwise. The key variable in the regression is the interaction variable, *After* x *Treatment*. We expect the coefficient on it to be negative, indicating that the firms that split experience a decrease in innovation over and above that experienced by matched firms. We control for the R&D capital of a firm, as that is the primary input in generating the innovation outcomes. The vector of other controls includes those identified in the prior innovation literature, namely, institutional ownership, capital-labor ratio (*K/L*), firm size, sales growth, Amihud illiquidity, and book-to-market ratio (Aghion, Reenen, and Zingales, 2013; Fang, Tian, and Tice, 2013). Because the dependent variable is a count variable, we estimate the model as Poisson regression (Hausman, Hall, and Griliches, 1984; Sunder, Sunder, and Zhang, 2017). As before, we cluster the standard errors by both firm and year. We estimate the regression using three-year pre- and three-year post-split periods for both split and matched firms. We remove the split year from our analysis. As noted earlier, the patenting process and citations take a long time; therefore, the choice of a three-year period to examine the effect of a split seems reasonable.

Table 11 reports the results. The coefficients on the variable of interest, *Post x Treatment*, are negative and statistically significant in the first two columns for the number of patents and the citations. They are also economically significant. For instance, the coefficient in Column (1) is -0.357 (*z*-statistic =3.69), which implies that relative to the matched firms, the number of patents for the split firms drop by 30% (computed as $e^{-0.357}-1$) in the three years after the split compared with the three years before the split. There is also evidence in the last two columns that the number of breakthrough patents goes down significantly after the split. Therefore, it appears that the incidence of stock split among firms with positive R&D coincides with a significant drop in productivity in terms of both total and breakthrough innovation. Interestingly, the coefficients on the stand-alone variable, *Treatment*, are positive and significant across all columns, consistent with the idea that innovative firms split their stocks when their innovation has become mature and fruitful. Taken together, these results are consistent with the conjecture that a shift in the focus from long term to short term and from innovation to profitability plays a role in the decision of R&D intensive firms to undergo a stock split. Our conjecture implies that share prices have an interesting role in revealing firms' strategic focuses.

While we interpret the results in Table 11 as reflecting managerial choice, they are also consistent with a causal link between a firm's nominal share price and its future innovation productivity. That is, a stock split that lowers share price forces managers to focus on the short term and impedes innovation. The prevalence of myopic investors, for instance, can force a firm to underinvest in R&D (Narayan, 1985; Stein, 1989), abruptly cut such investments to meet near-term targets (Graham, Harvey, and Rajgopal, 2005), and/or force the firm to channel its R&D efforts to more predictable exploitative innovation rather than breakthrough riskier innovation (Balsmeier, Flemings, and Manso, 2017). Such casual interpretation of the positive association between nominal price and future innovation can help understand why high R&D firms avoid low share prices.

7. Conclusion

If low share price exacerbates investor short-termism, one might expect firms with long-term investments to consciously avoid low prices for their stocks. This paper provides evidence consistent with this prediction. At the time of IPO, firms with higher R&D choose higher filing prices. After the IPO, firms with higher R&D capital are less likely to split their stock. Among the splitters, those with higher R&D capital choose higher post-split prices. To establish a causal link between R&D capital and share price management, we exploit the staggered introduction of state tax credits for R&D. We find that the increases in R&D associated with these tax credits lead to a significant reduction in stock splits by the firms. An alternative instrumental variable approach yields a similar conclusion. We also find that firms with inventor CEOs are more likely to avoid low share price to shield their R&D investments from the adverse effects of the nominal price illusion, consistent with such firms' greater focus on long-term innovation.

Our findings indicate that firms manage their share price to mitigate investor short-termism. Nevertheless, we acknowledge that price management is only one among many tools managers have at their disposal. Other actions, such as the issuance of dual-class shares, stoppage of earnings guidance and antitakeover provisions could complement or replace price management in dealing with investor myopia. Future research may illuminate how managers evaluate the relative merits of each action and choose amongst them, or combine them, to encourage long-term thinking among shareholders.

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Table 1
Summary statistics

Panel A reports the summary statistics of the IPO sample we use to examine the relationship between R&D capital and IPO offer price. Panel B reports the summary statistics for the sample we use to analyze the relationship between R&D capital and stock splits. The sample period for both is 1980–2018. We trim the variables at the 1 and 99 percentiles of their pooled firm-year distributions. While most variable descriptions provided below are self-explanatory, further information about some variables follows. P_{Filing} is the mid-point of the range of IPO filing prices. *Split Dummy* is an indicator variable that takes the value of one if the firm splits its stock during the year, specifically, if the cumulative split factor during the year is greater than 0.25. *Facshr* is the cumulative split factor—the additional shares issued for each existing share—during the year. *RDC* is the R&D capital of the firm, computed by assuming a 20% annual depreciation rate for the firm's R&D expenditure. *Presplitsz* denotes the deviation of the pre-split share price from the median price of the same-size decile. *Presplitind* is the deviation of the pre-split share price from the median price of the same Fama–French (1997) industry. *PCME* is the Baker, Wurgler and Greenwood (2009) annual measure of relative valuation of low-priced stock, computed as the log difference between the average market-to-book ratio of low-priced firms and that of high-priced firms. *Post-split price* is the stock price at the end of the month in which the stock is split. Its statistics are reported for the subsample of 4,815 firm-year observations with splits. Detailed definitions of all variables are provided in Appendix A.

Panel A: IPO Sample

Variable	Description	N	Mean	S.D.	Min.	Q1	Median	Q3	Max.
P_{Filing}	IPO filing price	2,829	11.21	4.18	5.00	8.00	11.00	14.00	26.00
Sales	Total sales ($ m)	2,829	92.73	240.86	0.00	9.80	28.14	73.70	3,825.90
RD	R&D expense ($ m)	2,829	1.68	3.73	0.00	0.00	0.00	1.84	53.22
RD/TA	R&D scaled by total assets	2,829	0.10	0.18	0.00	0.00	0.00	0.13	1.25
ROA	Return on assets	2,829	-0.04	0.33	-2.47	-0.03	0.05	0.11	0.34
PCME	Low price premium	2,829	-0.16	0.27	-1.29	-0.33	-0.21	-0.05	0.27
P_{Offer}	IPO offer price	4,692	12.37	4.60	5.00	9.00	12.00	15.00	27.00

Panel B: Stock Split Sample

Variable	Description	N	Mean	StDev	Min	Q1	P50	Q3	Max
Split	Split dummy	52,869	0.09	0.29	0.00	0.00	0.00	0.00	1.00
Facshr	Split factor	52,869	0.07	0.27	0.00	0.00	0.00	0.00	8.00
RDC	R&D capital ($ m)	52,869	127	649	0.00	0.00	0.31	38	16,904
RDC/TA	R&D capital divided by total assets	52,869	0.07	0.12	0.00	0.00	0.00	0.09	0.92
ROA	Return on assets	52,869	0.05	0.07	-0.71	0.02	0.05	0.09	0.25
IO	Institutional ownership	52,869	0.51	0.29	0.00	0.27	0.52	0.75	1.09
Sales	Total sales ($m)	52,869	1,973	4,138	1	147	487	1,703	38,334
B/M	Book-to-market ratio	52,869	0.64	0.41	-0.17	0.34	0.54	0.84	2.30
Ret12	Stock returns	52,869	0.19	0.46	-0.68	-0.10	0.12	0.39	3.33
Sales Growth	Growth in sales	52,869	0.09	0.23	-5.61	0.01	0.08	0.17	4.75
P	Pre-split stock price ($)	52,869	26.84	18.84	5.00	13.00	21.58	35.38	125.18
Presplitsz	Deviation of price from the median price of the same-size decile ($)	52,869	3.48	14.05	-55.04	-3.88	1.38	8.94	106.93
Presplitind	Deviation of the price from the median industry price ($)	52,869	6.68	17.29	-81.26	-3.47	2.06	13.75	112.03
PCME	Low price premium	52,869	-0.30	0.34	-1.29	-0.48	-0.27	-0.12	0.27
Post-Split Price	Stock price at the end of the split month ($)	4,815	26.63	12.61	2.20	17.56	24.25	33.25	105.44

Table 2
Stock split and change in the sensitivity of stock price to earnings announcements: DID analysis

This table reports the estimates of the following regression.

$$CAAR_{i,m} = \alpha_0 + \alpha_1\, Treated + \alpha_2\, Post + \alpha_3\, Treated\ x\ Post + \beta\ Earnings\ Surprise_{i,m} + c'controls_{i,m} + \varepsilon_{i,m}.$$

The dependent variable is the cumulative average abnormal return in percent (*CAAR*) for firm *i* around the earnings announcement *m*. First, we compute the abnormal returns on each day using the procedure in Daniel, Grinblatt, Titman, and Wermers (1997) that accounts for the size, BM, and momentum effects in expected returns, and then add up these returns over successive days. CAAR is computed for two alternate windows: the shorter announcement window is from -2 to +2 trading days, and the longer window is from -2 to +120 trading days. *Treated* is an indicator variable that takes the value of one for firms that split their stock and zero otherwise. *Post* is an indicator variable that takes the value of one if relating to the post-split period and zero otherwise. The interaction term, *Treated* x *Post*, captures the change in the sensitivity of the stock price of firms that split relative to control firms (i.e., the DID effect). *Earnings Surprise* is calculated as the actual earnings minus the median analyst forecast scaled by the absolute value of the actual earnings. *Earnings Volatility* is the standard deviation of the actual quarterly earnings over the 12-month period before the split. *IO* is total institutional share ownership. *B/M* is the book-to-market ratio. *BV* is the book value of equity. *PCME* is the Baker, Wurgler and Greenwood (2009) annual measure of relative valuation of low-priced stock, computed as the log difference between the average market-to-book ratio of low-priced firms and that of high-priced firms. The first four columns report the results for the sub-sample of negative earnings surprises (i.e., where actual earnings fall below the median analyst forecast), and the last column reports the results for positive earnings surprises. The sample includes firms that undertake stock splits (i.e., treated firms) over the period 1985–2018. For each treated firm, we also include a control firm that is matched based on the industry, nominal (per-share) price, and past 12-month stock returns. The model is estimated using the quarterly earnings announcements of both the treated and control firms for the 12-month period before the split (i.e., pre-split period) and the 12-month period after the split (i.e., post-split period). We drop any announcements that fall in the month of the split. The *t*-statistics reported in parentheses are based on standard errors that are clustered by both firm and year. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	Negative Earnings Surprises				Positive Earnings Surprises
	All Firms		R&D Firms Only		All Firms
	Dependent Variable =				
	CAAR (-2, +2)	*CAAR* (-2, +120)	*CAAR* (-2, +2)	*CAAR* (-2, +120)	*CAAR* (-2, +2)
	(1)	(2)	(3)	(4)	(5)
Post x Treatment	-1.36***	-1.84	-1.43***	-5.10**	-0.09
	(-4.38)	(-1.39)	(-2.73)	(-2.05)	(-0.27)
Post	-0.72***	-10.86***	-0.95***	-10.79***	-1.27***
	(-2.73)	(-9.43)	(-2.82)	(-7.97)	(-4.33)
Treatment	1.36***	7.26***	1.07***	9.18***	0.74***
	(5.79)	(6.89)	(2.80)	(5.01)	(4.21)
Earnings Surprise	0.75	3.56*	2.16**	1.31	8.17***
	(1.52)	(1.93)	(2.30)	(0.67)	(6.40)
Earnings Volatility	-0.08	0.54	0.40	-2.76*	-0.42*
	(-0.60)	(0.71)	(1.31)	(-1.83)	(-1.91)
IO	-0.23	0.24	-0.11	0.56	0.12
	(-0.72)	(0.23)	(-0.32)	(0.29)	(0.45)
BM	-1.16*	1.25	-1.98*	-1.79	1.44***
	(-1.95)	(0.81)	(-1.76)	(-0.76)	(3.89)
ln(BV)	0.05	-0.16	0.12**	0.01	-0.12***
	(1.41)	(-1.00)	(2.19)	(0.04)	(-4.13)
Constant	-0.67	4.88**	-0.64	5.28*	1.90***
	(-1.35)	(2.18)	(-0.88)	(1.72)	(3.85)
Observations	4,686	4,686	2,374	2,374	9,196
R-squared	0.02	0.08	0.02	0.09	0.03

Table 3
The Relationship between R&D Intensity and IPO Share Price

This table reports the relationship between R&D intensity and the share prices firms set at their IPO. It reports the estimates from the following regression:

$$\ln(P)_{i,IPO} = \alpha + \beta\ RD\_Intensity_{i,IPO} + c'controls_{i,IPO} + \text{Industry fixed effects} + \varepsilon_{i,IPO}.$$

The dependent variable, $P_{i,ipo}$, is the log of alternately, the IPO filing price (P_{Filing}) or the IPO offer price (P_{Offer}). Subscript *i* signifies a firm and *IPO* signifies the event of the initial listing of the firm. The key explanatory variable is *RD_intensity*. It is measured alternately as the log of one plus the R&D expenditure (*ln(1+RD)*) or the R&D expenditure scaled by total assets (*RD/TA*), where both the R&D expenditure and total assets are for the year before the IPO. *PCME* is the Baker, Wurgler and Greenwood (2009) annual measure of relative valuation of low-priced stock, computed as the log difference between the average market-to-book ratio of low-priced firms and that of high-priced firms. Other control variables include the natural log of total sales, *ln(Sales)*, and return on assets, *ROA*. The *t*-statistics, reported in parentheses, are based on standard errors that are clustered by year. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	Dep. Variable = $ln(P_{Filing})$		Dep. Variable = $ln(P_{Offer})$	
	(1)	(2)	(3)	(4)
ln(1+RD)	0.076***		0.046***	
	(9.45)		(4.28)	
RD/TA		0.311***		0.153**
		(5.88)		(2.31)
PCME	-0.030	-0.049	-0.196***	-0.214***
	(-0.89)	(-1.45)	(-6.62)	(-7.70)
ROA	-0.071**	-0.025	-0.028	-0.017
	(-2.75)	(-0.92)	(-0.87)	(-0.46)
ln(Sales)	0.123***	0.132***	0.103***	0.109***
	(15.58)	(15.93)	(13.03)	(12.54)
Constant	1.934***	1.915***	1.988***	1.981***
	(48.91)	(47.75)	(49.18)	(45.02)
Observations	2,829	2,829	4,692	4,692
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No
R-squared	0.367	0.362	0.304	0.298

Table 4
The Relationship between R&D Intensity and the Incidence of Stock Split

This table reports the estimated coefficients from the following probit model:
$Pr(Split_{i,t} = 1) = \alpha + \beta\ RD\_Intensity_{i,t-1} + c'controls_{i,t-1} +$ Industry fixed effects + Year fixed effects $+ \varepsilon_{i,t}$.
The subscripts *i* and *t* signify firm and year, respectively. The dependent variable equals one if the firm splits its stock during the year and zero otherwise. The key explanatory variable is *RD_intensity*. It is measured alternately as the log of one plus the R&D capital (*ln(1+RDC)*) or the R&D capital scaled by total assets (*RDC*/*TA*), where the R&D capital, *RDC*, is defined in Equation (1). The vector of control variables includes return on assets (*ROA*), institutional ownership (*IO*), the log of dollar sales (*ln(Sales)*), book-to-market ratio (*BM*), past 12-month stock returns (*Ret12*), and year-on-year sales growth (*Sales Growth*). We also control for the level of pre-split share price using three alternate variables: the log of the beginning-of-the-year share price (*P*), the deviation of the pre-split share price from the median price of the same-size decile (*Presplitsz*), and the deviation of the pre-split share price from the median of the same Fama–French (1997) industry (*Presplitind*). The analysis is based on firm-year observations for the period 1980–2018. *PCME* is the Baker, Wurgler and Greenwood (2009) annual measure of low-price premium. The *z*-statistics, reported in parentheses, are based on standard errors that are clustered by both firm and year. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	Dependent Variable = *Pr(Split*=1*)*			
	(1)	(2)	(3)	(4)
ln(1+RDC)	-0.045***	-0.041***		
	(-5.10)	(-5.29)		
RDC/AT			-0.467***	-0.289*
			(-2.99)	(-1.80)
PCME		0.464***		0.462***
		(2.81)		(2.80)
ROA	2.007***	2.147***	2.011***	2.181***
	(9.38)	(9.50)	(9.11)	(9.53)
IO	-0.129**	-0.645***	-0.126**	-0.650***
	(-2.31)	(-7.06)	(-2.25)	(-7.02)
ln(Sales)	-0.023*	-0.067***	-0.042***	-0.083***
	(-1.73)	(-4.14)	(-3.24)	(-5.21)
BM	-0.410***	-0.231***	-0.412***	-0.228***
	(-8.24)	(-3.19)	(-8.25)	(-3.14)
R12	0.431***	0.456***	0.435***	0.459***
	(13.07)	(10.01)	(13.21)	(10.06)
Sales Growth	0.354***	0.401***	0.361***	0.409***
	(5.53)	(5.95)	(5.65)	(6.09)
ln(P)	0.226***	0.255***	0.224***	0.254***
	(4.34)	(4.95)	(4.30)	(4.91)
Presplitind	0.001	0.010***	-0.000	0.009***
	(0.42)	(5.50)	(-0.09)	(5.07)
Presplitsz	0.022***	0.009***	0.022***	0.010***
	(10.35)	(3.85)	(10.11)	(4.08)
Constant	-3.890***	-1.658***	-3.778***	-1.567***
	(-29.43)	(-12.97)	(-27.47)	(-11.78)
Observations	52,869	52,869	52,869	52,869
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No
Pseudo R-squared	0.233	0.184	0.232	0.183

Table 5
Robustness Checks on the Relationship between R&D Intensity and the Incidence of Stock Split

In the first two columns, we interact the coefficient on R&D intensity with the low-price premium of Baker, Wurgler and Greenwood (2009). In columns (3) through (6) we re-estimate the models in Table 4 separately for the two sub-periods of 1980–2000 and 2001–2018. The dependent variable equals one if the firm splits its stock during the year and zero otherwise. The key explanatory variable is *RD_intensity*. It is measured alternately as the log of one plus the R&D capital (*ln(1+RDC)*) or the R&D capital scaled by total assets (*RDC*/*TA*), where the R&D capital, *RDC*, is defined in Equation (1). *PCME* is the low-price premium as computed by Baker, Wurgler and Greenwood (2009). Other control variables include return on assets (*ROA*), institutional ownership (*IO*), the log of dollar sales (*ln(Sales)*), book-to-market ratio (*BM*), past 12-month stock returns (*Ret12*), and year-on-year sales growth (*Sales Growth*). We also control for the level of pre-split share price using three alternate variables: the log of the beginning-of-the year share price (*P*), the deviation of the pre-split share price from the median price of the same-size decile (*Presplitsz*), and the deviation of the pre-split share price from the median of the same Fama–French (1997) industry (*Presplitind*). The *z*-statistics, reported in parentheses, are based on standard errors that are clustered by both firm and year. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	Dependent Variable = *Pr(Split*=1*)*					
	Interaction with Catering Incentives		Sub-Period Analysis			
			1980–2000		2001–2018	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(1+RDC)	-0.049***		-0.033***		-0.047***	
	(-4.33)		(-2.81)		(-4.59)	
RDC/AT		-0.623***		-0.476*		-0.426**
		(-2.66)		(-1.73)		(-2.38)
PCME	0.509***	0.534***	0.855**	0.855**	0.222**	0.216**
	(3.48)	(3.50)	(2.48)	(2.48)	(2.45)	(2.39)
ln(1+RDC) x *PCME*	-0.025					
	(-1.01)					
RDC/AT x *PCME*		-0.970**				
		(-2.50)				
ROA	2.151***	2.196***	2.298***	2.308***	2.083***	2.074***
	(9.57)	(9.84)	(5.09)	(5.17)	(7.79)	(7.52)
IO	-0.642***	-0.642***	-0.265**	-0.257**	-0.296***	-0.299***
	(-7.14)	(-7.07)	(-2.53)	(-2.46)	(-2.87)	(-2.88)
ln(Sales)	-0.065***	-0.081***	-0.048**	-0.060***	-0.029*	-0.049***
	(-4.32)	(-5.25)	(-2.43)	(-2.80)	(-1.80)	(-3.05)
BM	-0.232***	-0.237***	-0.207**	-0.203**	-0.324***	-0.330***
	(-3.20)	(-3.25)	(-2.37)	(-2.35)	(-3.75)	(-3.83)
R12	0.455***	0.455***	0.357***	0.362***	0.480***	0.482***
	(10.01)	(10.08)	(7.15)	(7.20)	(8.40)	(8.39)
Sales Growth	0.401***	0.406***	0.447***	0.454***	0.293***	0.302***
	(5.95)	(6.09)	(5.38)	(5.42)	(4.24)	(4.37)
ln(P)	0.254***	0.248***	0.238***	0.228***	0.217***	0.219***
	(4.98)	(4.91)	(3.08)	(2.98)	(3.88)	(3.90)
Presplitind	0.010***	0.009***	0.003*	0.002	0.004*	0.003
	(5.63)	(5.07)	(1.72)	(1.52)	(1.80)	(1.37)
Presplitsz	0.009***	0.010***	0.013***	0.014***	0.020***	0.021***
	(4.00)	(4.24)	(6.17)	(6.19)	(8.87)	(9.13)
Constant	-1.655***	-1.543***	-2.022***	-1.921***	-1.720***	-1.612***
	(-12.94)	(-11.65)	(-9.54)	(-8.67)	(-12.05)	(-10.76)
Observations	52,869	52,869	23,495	23,495	29,374	29,374
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	No	No
Pseudo R-squared	0.184	0.183	0.178	0.177	0.176	0.175

Table 6
The Relationship between R&D Intensity and Post-Split Stock Price

This table examines the post-split price targeted by splitting firms, using the following OLS regression:

$$ln(Post\text{-}Split\,Price)_{i,t} = \alpha + \beta\ RD\_Intensity_{i,t-1} + c'controls_{i,t-1} + \text{ Industry fixed effects} + \text{Year fixed effects} + \varepsilon_{i,t}.$$

The subscripts *i* and *t* signify firm and year, respectively. The dependent variable is the stock price at the end of the month in which the firm splits its stock. The key explanatory variable is *RD_intensity*. It is measured alternately as the log of one plus the R&D capital (*ln(1+RDC)*) or the R&D capital scaled by total assets (*RDC/TA*), where the R&D capital, *RDC*, is defined in Equation (1). The vector of control variables includes return on assets (*ROA*), institutional ownership (*IO*), the log of dollar sales (*ln(Sales))*, book-to-market ratio (*BM*), past 12-month stock returns (*Ret12*), and year-on-year sales growth (*Sales Growth*). We also control for the level of pre-split share price using three alternate variables: the log of the beginning-of-the-year share price (*P*), the deviation of the pre-split share price from the median price of the same-size decile (*Presplitsz*), and the deviation of the pre-split share price from the median of the same Fama–French (1997) industry (*Presplitind*). *PCME* is the low-price premium as computed by Baker, Wurgler and Greenwood (2009). The analysis is based on firm-year observations for the period 1980–2018. The *t*-statistics, reported in parentheses, are based on standard errors that are clustered by both firm and year. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	Dependent Variable = $ln(Post\text{-}Split\ Price)$			
	(1)	(2)	(3)	(4)
ln(1+RDC)	0.009***	0.010***		
	(2.79)	(3.11)		
RDC/TA			0.266***	0.278***
			(3.47)	(3.48)
PCME		-0.109**		-0.107**
		(-2.65)		(-2.62)
ROA	0.192*	0.201*	0.222**	0.233**
	(1.71)	(1.71)	(2.03)	(2.08)
IO	0.144***	0.112***	0.140***	0.108***
	(7.82)	(4.16)	(7.20)	(3.90)
ln(Sales)	0.047***	0.041***	0.051***	0.046***
	(8.26)	(6.50)	(9.93)	(8.39)
BM	-0.022	0.016	-0.016	0.023
	(-0.89)	(0.47)	(-0.63)	(0.65)
R12	-0.039***	-0.038***	-0.039***	-0.038***
	(-4.05)	(-3.65)	(-4.01)	(-3.61)
Sales Growth	0.011	0.008	0.013	0.010
	(0.41)	(0.31)	(0.49)	(0.38)
ln(P)	0.443***	0.462***	0.445***	0.465***
	(19.17)	(21.11)	(19.50)	(21.23)
Presplitind	0.000	0.001	0.000	0.001
	(0.42)	(1.15)	(0.42)	(1.15)
Presplitsz	0.002***	0.002***	0.002***	0.002***
	(3.54)	(2.89)	(3.35)	(2.83)
Constant	1.599***	1.224***	1.575***	1.182***
	(21.21)	(18.11)	(20.85)	(17.11)
Observations	4,815	4,815	4,815	4,815
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No
R-squared	0.707	0.688	0.708	0.690

Table 7
R&D Tax Credits and Stock Splits

The analysis in this table closely follows the procedure in Goldman and Peress (2019) and examines how the introduction of state-level R&D tax credits affects R&D and stock splits. We estimate two regressions, both in first differences. Column (1) reports the estimates of the following regression:

$$\Delta ln\left(RD_{i,s,t}\right) = \alpha + \beta\, TC_{s,t-1} + c'\Delta controls_{i,t-2} + \text{ Year fixed effects } + \varepsilon_{i,t}.$$

The subscripts *i*, *s*, and *t* signify firm, state, and year respectively. The dependent variable is the log of R&D in year *t*. *TC* is an indicator variable that takes the value of 1 only if state *s* implemented or increased its R&D tax credit in year *t*-1. The control variables include the natural log of sales (*ln(Sales)*) and an indicator variable that equals one if the firm reports negative earnings before interest and taxes (*Loss*). Column (2) reports the estimates of the following regression:

$$\Delta ln\left(1 + Facshr_{i,s,t}\right) = \alpha + \beta\, TC_{s,t-1} + c'\Delta controls_{i,t-2} + \text{ Year fixed effects } + \varepsilon_{i,t}.$$

The dependent variable is the natural log of the cumulative split factor in year *t*. The control variables include the log of sales (*ln(Sales)*), return on assets (*ROA*), institutional ownership (*IO*), book-to-market ratio (*BM*), past 12-month stock returns (*Ret12*), year-on-year sales growth (*Sales Growth*), and the log of the share price *(ln(P))*. The sample spans the period 1982–2006 and includes firms that report positive R&D. Because the regressions are estimated in first differences, we control for firms' time invariant characteristics (i.e., firm-fixed effects). We also include year-fixed effects. The *t*-statistics, reported in parentheses, are based on standard errors that are clustered by firm. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	(1) DV=Δ*ln(RD)*	(2) DV=Δ*ln(1+Facshr)*
TC	0.030***	-0.017**
	(6.69)	(-2.02)
Δ*ln(Sales)*	0.149***	-0.058***
	(4.16)	(-3.86)
Δ*ROA*		0.053
		(1.55)
Δ*IO*		0.024
		(0.80)
Δ*BM*		-0.038**
		(-2.40)
Δ*R12*		-0.002
		(-0.73)
Δ*Sales Growth*		0.013
		(1.24)
Δ*ln(P)*		-0.086***
		(-12.28)
Δ*Loss*	-0.010**	
	(-2.64)	
Constant	0.081***	0.090***
	(4.49)	(4.62)
Observations	13,579	13,579
Firm fixed effects	Diff.	Diff.
Year fixed effects	Yes	Yes
R-squared	0.021	0.025

Table 8
R&D Intensity and Stock Splits: Instrumental Variables Approach

This table reexamines the relationship between R&D and stock splits using the instrumental variables approach of Lin and Wang (2016). Two instruments are used for a firm's R&D: the first is rivals spending on R&D (*Rival RD*), proxied by the average R&D spending of other firms in the same Fama–French 48-industry classification and public sector spending on R&D in the state where the firm is located, proxied by an indicator variable (*GRD*) for the five states that are known to spend the most on R&D. In the first stage, we regress a firm's R&D expenditure on its lagged value, the two instruments, the natural log of cash-to-assets ratio (*ln(Cash/TA)*), the natural log of sales (*ln(Sales)*), and book-to-market ratio (*BM*) as follows:

$$ln(1+RD)_{i,t} = \alpha + \beta_1\, ln(1+RD)_{i,t-1} + \beta_2\, ln(1+Rivals\ RD)_{i,t-1} + \beta_3\, GRD_{i,t-1} + \beta_4\, ln\left(\frac{Cash}{TA}\right)_{i,t-1} + \beta_5\, ln(Sales)_{i,t-1} + \beta_6\, BM_{i,t-1} + Year\ fixed\ effects + \varepsilon_{i,t}.$$

The subscripts *i* and *t* signify firm and year, respectively. Because the explanatory variables include lagged dependent variable, firm- or industry-fixed effects are omitted. The fitted values of R&D from the first stage, *RD_Fitted*, are then used as the key explanatory variable in the second-stage probit regression, as follows:

$$Pr\left(Split_{i,t} = 1\right) = \alpha + \beta\, RD^{F}{}_{i,t-1} + c'controls_{i,t-1} + \text{Industry fixed effects} + \text{Year fixed effects} + \varepsilon_{i,t}.$$

The dependent variable equals one if the firm splits its stock during the year and zero otherwise. The vector of control variables include return on assets (*ROA*), institutional ownership (*IO*), the natural log of dollar sales (*ln(Sales)*), book-to-market ratio (*BM*), past 12-month stock returns (*Ret12*), year-on-year sales growth (*Sales Growth*), and the log of the beginning-of-the-year share price (ln(*P*)). *PCME* is the low-price premium as computed by Baker, Wurgler and Greenwood (2009). The analysis is based on panel data of firm-year observations over the period of 1980–2018 for the firms for which we could locate headquarter-location data. The *t*-statistics in Panel A and *z*-statistics in Panel B are reported in parentheses, and are based on standard errors that are clustered by both firm and year. Statistical significance at the 10%, 5%, and 1% are denoted by *, ** and ***, respectively.

Panel A: First-stage regression

Explanatory Variables	Dependent Variable = *ln(1+RD)*
Lagged ln(1+RD)	0.944***
	(190.61)
ln(1+Rival RD)	0.078***
	(10.69)
GRD	0.054***
	(8.98)
ln(Cash/TA)	0.027***
	(6.86)
BM	-0.145***
	(-14.11)
ln(Sale)	0.028***
	(6.99)
Constant	0.153***
	(6.15)
Observations	36,229
Firm fixed effects	Lagged DV
Year fixed effects	Yes
R-squared	0.963

Panel B: Second-stage regression

Explanatory Variables	Dependent Variable=*Pr* (*Split*=1)
RD^F	-0.006***
	(-2.87)
PCME	0.037
	(1.59)
ROA	0.132***
	(7.21)
IO	-0.092***
	(-6.25)
ln(Sales)	-0.003
	(-1.27)
BM	-0.027***
	(-3.26)
Ret12	0.071***
	(8.05)
Sales Growth	0.036***
	(4.61)
ln(P)	-0.000
	(-0.01)
Presplitind	0.002***
	(4.79)
Presplitsz	0.002***
	(4.53)
Constant	0.182***
	(8.47)
Observations	30,111
Industry fixed effects	Yes
Year fixed effects	No
Pseudo R-squared	0.108

Table 9
Cross-Sectional Variation in the Relationship between R&D Intensity and Stock Splits: Inventor vs. Non-Inventor CEOs

This table investigates cross-sectional heterogeneity in the relationship between R&D intensity and the incidence of stock splits across firms with inventor and non-inventor CEOs. Panel A estimates probit regressions separately for the two sub-samples of firms. Panel B estimates the model on the combined sample but interacts all explanatory variables with an indicator variable for inventor CEO. The model we estimate is the following:

$$Pr\left(Split_{i,t} = 1\right) \text{ } or \ln(1 + Facshr)_{i,t} = \alpha + \beta\ RD\_Intensity_{i,t-1} + c'controls_{i,t-1} + \text{ Industry fixed effects} + \text{Year fixed effects } + \varepsilon_{i,t}.$$

The subscripts *i* and *t* signify firm and year, respectively. The dependent variable is the split indicator, *Split*, that equals one if the firm splits its stock during the year. The key explanatory variable is *RD_intensity*. It is measured as the log of one plus the R&D capital (*ln(1+RDC)*), where the R&D capital, *RDC*, is defined in Equation (1). The vector of control variables include return on assets (*ROA*), institutional ownership (*IO*), the natural log of dollar sales (*ln(Sales)*), book-to-market ratio (*BM*), past 12-month stock returns (*Ret12*), year-on-year sales growth (*Sales Growth*), and the level of pre-split share price ($P_{Pre\text{-}split}$). *PCME* is the low-price premium as computed by Baker, Wurgler and Greenwood (2009). The sample comprises firm-year observations for the period 1992–2010. The *z*-statistics reported in parentheses are based on standard errors that are clustered by both firm and year. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, ** and ***, respectively.

Panel A: Separate estimation for the two sub-samples

	Dep. Var. = *Pr(Split=1)*	
	Inventor CEOs	Non-Inventor CEOs
ln(1+RDC)	-0.142**	-0.027***
	(-2.41)	(-2.77)
PCME	-0.001	0.337
	(-0.00)	(1.30)
ROA	1.197	1.591***
	(0.92)	(3.13)
IO	-0.370	-0.879***
	(-0.96)	(-5.86)
ln(Sales)	0.104	-0.077***
	(1.24)	(-2.83)
BM	-1.268**	-0.407***
	(-2.07)	(-2.99)
R12	0.336**	0.495***
	(2.48)	(5.75)
Sales Growth	0.408	0.818***
	(1.41)	(4.96)
ln(P)	0.399	0.390***
	(1.57)	(4.17)
Presplitind	-0.003	0.005***
	(-0.33)	(2.66)
Presplitsz	0.011	0.014***
	(0.83)	(7.00)
Constant	-2.968***	-1.788***
	(-3.04)	(-7.00)
Observations	876	15,868
Industry fixed effects	Yes	Yes
Year fixed effects	No	No
Pseudo R-squared	0.208	0.209

Panel B: Estimation using the combined sample with the interaction effects included

Explanatory Variables	Dep. Var. = *Pr(Split=1)*
Inventor CEO x *ln(1+RDC)*	-0.115**
	(-2.07)
Inventor CEO	-1.180
	(-1.32)
log(1+RDC)	-0.027**
	(-2.32)
Constant	-1.788***
	(-6.98)
Observations	16,744
Industry fixed effects	Yes
Year fixed effects	No
Pseudo R-squared	0.210

Table 10
Change in Profitability of R&D Firms in the Years Preceding the Stock Splits

This table compares the change in profitability of the positive R&D firms that split their stock in the years surrounding the split relative to a set of control firms. From our primary sample, depicted in Panel B of Table 1, we identify firms that split their stock and have positive R&D during the period 1980–2018. For each stock split observation, we look for a control firm among the positive R&D firms. As before, control firms are identified contemporaneously based on the match with industry, nominal (per share) price, and past 12-month stock returns. Our final sample consists of 815 pairs of treatment and matched observations. We measure profitability alternately in terms of net profits (i.e., income before extraordinary items) and operating profits (i.e., revenues minus cost of goods sold minus selling and general expenses), both scaled by total assets. Change in profitability is computed as the simple difference in the consecutive yearly observations. The standard *t*-test is used to compare means whereas the Mann–Whitney test is used to compare medians. Statistical significance of the differences at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Panel A: Comparison using means

	Years Relative to the Split Year						
	-3	-2	-1	0	+1	+2	+3
Change in net profitability							
Split firms	0.22%	0.28%	0.75%	0.97%	-0.52%	-0.57%	-0.42%
Matched firms	-0.20%	-0.18%	0.25%	-0.28%	-0.65%	-0.33%	-0.19%
Difference	0.41%**	0.46%**	0.50%***	1.26%***	0.13%	-0.24%	-0.23%
Change in operating profitability							
Split firms	0.36%	0.49%	0.82%	1.11%	-1.04%	-0.91%	-0.83%
Matched firms	-0.43%	-0.25%	0.14%	-0.65%	-0.87%	-0.25%	0.23%
Difference	0.78%***	0.73%***	0.68%**	1.76%***	-0.17%	-0.67%**	-1.05%***

Panel B: Comparison using medians

	Years Relative to the Split Year						
	-3	-2	-1	0	+1	+2	+3
Change in net profitability							
Split firms	0.27%	0.28%	0.63%	0.85%	0.14%	-0.32%	-0.11%
Matched firms	-0.06%	0.03%	0.21%	-0.04%	-0.50%	-0.09%	-0.09%
Difference	0.32%**	0.25%**	0.42%***	0.89%***	0.64%**	-0.24%	-0.03%
Change in operating profitability							
Split firms	0.32%	0.37%	0.69%	0.85%	-0.17%	-0.56%	-0.34%
Matched firms	0.10%	0.06%	0.08%	-0.35%	-0.31%	-0.01%	0.04%
Difference	0.21%**	0.31%**	0.60%***	1.20%***	0.15%	-0.55%***	-0.38%**

Table 11
Stock Splits and Change in Innovation: Difference-in-Difference Analysis

This table examines how the innovation productivity of firms changes after stock splits. We compare the three-year period after the stock split to the three-year period before the split (after removing the split year). We estimate the following Poisson regression:

$$Innovation_{i,t} = \alpha_0 + \alpha_1\, Treated + \alpha_2\, Post + \alpha_3\, Treated\ x\ Post + \beta \ln(1 + RDC)_{i,t-1} + c'controls_{i,t-1} + \varepsilon_{i,t}.$$

The subscripts *i* and *t* signify firm and year, respectively. The dependent variable is the innovation output measured using four different measures: the total number of patents (*Patents*), total number of citations excluding self-citations received by the firms' patents (*Cites*), number of patents that fall among the top 1% of the distribution of future citations (*Top 1% Patents*), and number of patents that fall among the top 5% of the distribution of future citations (*Top 5% Patents*). *Treated* is an indicator variable that takes the value of one for firms that split their stock and zero otherwise. *Post* is an indicator variable that takes the value of one for the post-split period. The key variable of interest is the interaction term, *Treated* x *Post*, that captures the change in the innovation of the firms that split relative to the control firms (the DID effect). Control variables include the natural log of one plus the R&D capital (*ln(1+RDC)*), institutional ownership (*IO*), the natural log of dollar sales (*ln(Sales)*), book-to-market ratio (*BM*), year-on-year sales growth (*Sales Growth*), capital-to-labor ratio (*K/L*), and Amihud Illiquidity (*Illiquidity*). The model is estimated using three-year pre- and three-year post-split periods for positive R&D firms that split their stock during 1980–2008. For each treated firm, we also include a control firm that is matched contemporaneously based on industry, nominal (per share) price, and past 12-month stock returns. To be included, both treated and control firms must have positive R&D. The *z*-statistics, reported in parentheses, are based on standard errors that are clustered by both firm and year. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	Dependent Variable =			
	Patents	*Cites*	*Top 1% Patents*	*Top 5% Patents*
*Post*Treatment*	-0.357***	-0.508***	-0.332	-0.551***
	(-3.69)	(-3.48)	(-1.55)	(-3.56)
Post	0.173	0.272*	0.156	0.335**
	(1.52)	(1.79)	(0.84)	(2.21)
Treatment	0.421***	0.752***	0.718***	0.831***
	(3.11)	(3.84)	(2.77)	(4.20)
ln(1+RDC)	0.762***	0.917***	0.901***	0.854***
	(7.98)	(8.56)	(5.71)	(6.92)
IO	-1.155***	-1.629***	-0.514	-0.854*
	(-2.75)	(-3.09)	(-0.75)	(-1.67)
ln(Sales)	0.386***	0.206***	0.138	0.116
	(4.21)	(2.62)	(1.13)	(0.84)
Sales Growth	0.155	0.885***	1.052***	0.757*
	(0.47)	(2.90)	(2.82)	(1.91)
BM	0.067	0.095	0.130	0.022
	(0.34)	(0.51)	(0.47)	(0.08)
ln(K/L)	-0.057	-0.142	-0.020	-0.089
	(-0.69)	(-1.62)	(-0.19)	(-0.78)
Illiquidity	0.092	0.094	0.122	-0.005
	(1.29)	(1.20)	(0.92)	(-0.06)
Constant	-2.482***	1.619**	-6.376***	-4.692***
	(-4.58)	(2.32)	(-7.34)	(-7.47)
Observations	6,854	6,854	6,854	6,854
Pseudo R-squared	0.722	0.695	0.403	0.558

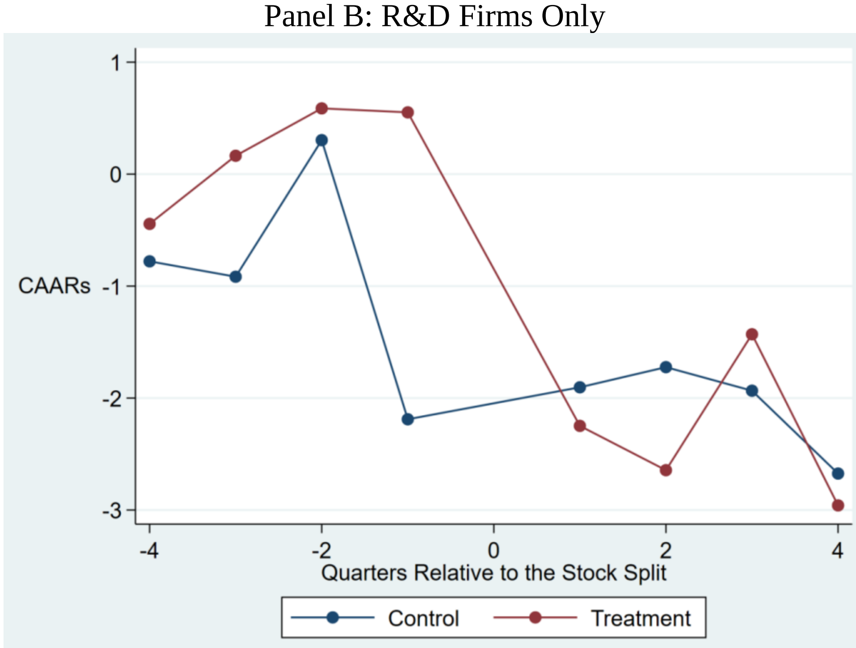
Figure 1

Quarterly Cumulative Average Abnormal Returns (CAARs) Relative to the Incidence of Stock Splits

This figure plots the average cumulative average abnormal returns (CAARs) around the announcement of earnings for the four quarters before and after the incidence of stock split. Within each quarter, we first compute cumulative abnormal returns over five days centered on the announcement of earnings for each firm, and then average it across firms separately for treated and control firms. Treated firms are those that split their stocks. Control firms are identified based on match by industry, stock price and past 12-month returns. Panel A plots the results for the full sample and Panel B for the subsample of firms with positive R&D.

Panel A: All Firms

Panel B: R&D Firms Only



Appendix A
Definitions of Variables

This appendix provides the definitions of all the variables used in our analyses. Missing values for R&D expenditures (*RD*), institutional ownership (*IO*) and *Cites* are set to zero. We trim all variables at the 1 and 99 percentiles of their pooled firm-year distributions. Variables that are capped at 0 on the lower side, that is, *RDC*, *RDC/TA*, and *IO*, are trimmed at 99 percentiles only.

Variable	Description and Source
AFE	Absolute value of forecast error. We first compute forecast error by taking the difference between actual value of quarterly earnings and the most recently available median analyst forecast in the IBES summary file. The absolute value of the forecast error is then divided by the stock price and multiplied by 100 to obtain the absolute forecast error percentage (Source: IBES Summary File).
B/M	Book-to-market ratio. Both book and market values are calculated using Compustat items as follows: Book value = Stock Equity [SEQ, CEQ+PSTK, AT-LT, or 0 depending on availability] + Deferred Taxes [TXDITC] - Preferred Equity [PSTKRV, PSTKL, PSTK, or 0 depending on availability] Market value = CSHO * PRCC_F (Source: Compustat).
BV	Book value of equity (in million $) calculated as follows: Stock Equity [SEQ, CEQ+PSTK, AT-LT, or 0 depending on availability] + Deferred Taxes [TXDITC] - Preferred Equity [PSTKRV, PSTKL, PSTK, or 0 depending on availability]. (Source: Compustat)
CAAR	*CAAR* is the cumulative average abnormal stock return in percentage around the announcement of quarterly earnings. We examine CAAR over two overlapping windows. The first is the shorter window that spans trading day -2 to +2 centered on the earnings announcement date, and the second is the extended window that spans trading day -2 to +120 (i.e., approximately a six-month period in calendar time). To obtain CAAR, we first compute the abnormal returns on each day using the procedure in Daniel, Grinblatt, Titman, and Wermers (1997) that accounts for the size, BM, and momentum effects in expected returns, and then add up these returns over successive days. The earnings announcement dates are obtained from IBES (Source: CRSP, IBES Summary File).
Cash/TA	Cash divided by total assets (Source: Compustat).
Cites	Total number of future citations, excluding self-citations, received by the patents that a firm applies for in a given year. The citation count for each patent is corrected for the well-known truncation bias, by dividing it by the average number of citations received in the same two-digit technological field in the same application year (Source: 2010 version of NBER patent data compiled by KPSS).
Disp	Analyst forecast dispersion, computed by dividing the standard deviation of analyst forecasts of quarterly earnings by the stock price. We multiply the dispersion by 100 for ease of exposition (Source: IBES Summary File).
EBIT	Earnings before interest and taxes divided by total assets. That is, (IBCOM+TXDI+ITCI+TIE) / AT (Source: Compustat).
Earnings Surprise	Computed as the difference between the actual quarterly earnings and the median analyst forecast, divided by the absolute value of the actual earnings. To avoid the problem of a

	small divisor, we set the denominator to 0.25 when it is below that number (Loh and Mian, 2006; Source: IBES Summary File).
Earnings Volatility	The standard deviation of the actual quarterly earnings per share (EPS) over the last 12-month period (Source: IBES Summary File).
Facshr	Annual split factor. If a firm splits its share more than once during a calendar year, we cumulate the split factors for the year (Π(1+facshr)-1). We remove reverse splits and set cumulative split factors between 0 and 0.25 to equal to zero (Source: CRSP).
GRD	A dummy variable that equals one if the state the firm is headquartered in incurs high public sector spending on R&D and zero otherwise. Specifically, it equals one for California, Washington, Massachusetts, Texas, and Michigan. The National Science Foundation reports that these five states are at the top of the list in R&D spending from local governments, universities, and other non-profit organizations.
Illiquidity	Amihud's illiquidity for the preceding year. It is measured daily as [abs(return)/ (abs(price)*volume))] and then averaged across the year and multiplied by 1,000,000 for ease of exposition (Source: CRSP).
Inventor CEO	A dummy variable that equals one in year t if the CEO has at least one patent in his or her name filed in year *t* or earlier and zero otherwise (Sources: Execucomp, Inventor Database of Lai, D'Amour, Yu, Sun, and Fleming (2014), Capital IQ Professional Database, Web pages of companies, Bloomberg, Datastream, Google searches, and others).
IO	Institutional ownership at the beginning of the year, computed as the aggregate shareholding of all institutions scaled by total shares outstanding. It is assumed to equal zero for firms with missing data (Source: Thomson Financial 13f).
K/L	Capital-to-labor ratio [PPENT/EMP] (Source: Compustat).
Loss	An indicator variable that takes the value of one if the firm reports negative earnings before interest and taxes and zero otherwise (Source: Compustat).
Net profitability	Same as ROA, computed by dividing the income before extraordinary items (Compustat item IB) by total assets (Source: Compustat).
Operating profitability	Computed by subtracting from revenues cost of goods sold and selling and general expenses, scaled by total assets, that is, (Sale – COGS – XSGA) / AT (Source: Compustat).
P	Share price as at the beginning of the year (Source: CRSP).
Patents	The number of patents filed by a firm in a given year that were subsequently granted. We correct for the well-known truncation problem in patent counts by using the truncation correction weights that are calculated from the application-grant lag distributions as described in Hall, Jaffe, and Trajtenberg (2001; Source: 2010 version of NBER patent data compiled by KPSS).
PCME	The annual measure of the relative valuation of low-pried stocks and high-priced stocks. It is computed following Baker, Wurgler and Greenwood (2009) as the log difference between the average market-to-book ratio of low-priced firms and that of high-priced firms.
P_{Filing}	IPO filing price. Mid-point of the price range (high and low) in IPO initial filing at which the firm expects to offer its shares (Source: SDC).

P_{Offer}	Official IPO offering price (Source: SDC).
Presplitind	The deviation of the beginning-of-the-year (or pre-split) share price from the median share price of firms in the same Fama–French (1997) 48-industry classification (Source: CRSP).
Presplitsz	The deviation of the beginning-of-the-year (or pre-split) share price from the median share price of firms in the same-size decile (Source: CRSP).
RD	R&D expenditure during the year (Source: Compustat).
RD/TA	R&D expenditure scaled by total assets (Source: Compustat).
RDC	R&D capital, computed following Chan, Lakonishok, and Sougiannis (2001) by depreciating the yearly R&D expenditure by 20% each year; [R&D capital = $R\&D_t$ + 0.8*$R\&D_{t-1}$ + 0.6*$R\&D_{t-2}$ + 0.4*$R\&D_{t-3}$ + 0.2 *$R\&D_{t-4}$] (Source: Compustat).
RDC/TA	R&D capital scaled by total assets (Source: Compustat).
Ret12	Cumulative stock returns for the preceding year (Source: CRSP).
Rivals RD	Average R&D expenditure of other firms in the same Fama–French 48-industry classification (Source: Compustat).
ROA	Return on assets, computed by dividing the income before extraordinary items (Compustat item IB) by total assets (Source: Compustat).
Split	An indicator variable that takes the value of 1 if the firm splits its stock during the year and if the cumulative split factor, *Facshr*, for the firm exceeds 0.25 and zero otherwise (Source: CRSP).
Sales	Total net sales in millions of dollars (Source: Compustat).
Sales Growth	Growth in sales [ln($Sales_t$) – ln($Sales_{t-1}$)] (Source: Compustat).
TA	Total assets in millions of dollars (Source: Compustat).
Top 1% (5%) Patents	The number of patents filed by a firm in a given year that fall in the top 1% (5%) of the distribution of future citations in the same technological field. Self-citations are excluded (Source: 2010 version of NBER patent data compiled by KPSS).

Appendix B
Relationship between R&D Intensity and Uncertainty of Near-Term Firm Performance

This appendix reports estimates of panel regressions in which we regress proxies of uncertainty of near-term firm performance on R&D intensity and controls. Two alternate measures of uncertainty are absolute forecast errors (*AFE*) and analyst forecast dispersion (*Disp*). To calculate *AFE*, we first compute forecast error by taking the difference between the actual value of quarterly earnings and the most recently available median analyst forecast in the IBES summary file. The absolute value of the forecast error divided by the stock price yields us *AFE*. *Disp* is computed by dividing the standard deviation of analyst forecasts of quarterly earnings by the stock price. Both the dependent variables are multiplied by 100 for ease of exposition. The key explanatory variable is *RD_intensity*. It is measured alternately as the log of one plus the R&D capital (*ln(1+RDC)*) or the R&D capital scaled by total assets (*RDC/TA*), where the R&D capital, *RDC*, is defined in Equation (1). We employ the same controls as in Table 2. *IO* is total institutional share ownership. *BM* is the book-to-market ratio. *BV* is the book value of equity. The results remain robust to replacing *BV* with market capitalization. The estimation sample is obtained by merging our primary sample, as depicted in Panel B of Table 1, with quarterly earnings forecast data available in the IBES summary file. The time period spans 1985–2018. The *t*-statistics reported in parentheses are based on standard errors that are clustered by both firm and year. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	Dependent Variable =			
	AFE		*Disp*	
Explanatory Variables	(1)	(2)	(3)	(4)
ln(1+RDC)	0.012***		0.004***	
	(6.65)		(3.87)	
RDC/TA		0.307***		0.194***
		(12.01)		(10.58)
IO	-0.166***	-0.166***	-0.066***	-0.066***
	(-12.53)	(-12.66)	(-7.54)	(-7.62)
BM	0.369***	0.374***	0.200***	0.204***
	(23.64)	(23.76)	(16.43)	(17.05)
ln(BV)	-0.032***	-0.028***	-0.009***	-0.007***
	(-19.67)	(-17.99)	(-9.10)	(-7.61)
Constant	0.706***	0.663***	0.266***	0.244***
	(25.03)	(24.09)	(11.02)	(10.25)
Observations	146,119	146,119	129,778	129,778
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R-squared	0.115	0.118	0.144	0.151

Appendix C
R&D Tax Credit Rate Changes Implemented by U.S. States between 1982 and 2006

This appendix provides information on the R&D tax credit rates introduced in various U.S. states over the period 1982 to 2006. The data are obtained from Daniel Wilson's website (http://www.frbsf.org/economic-research/economists/danielwilson/). Following Goldman and Peress (2019), we report the rate that applies to the highest tier of R&D spending, although the rate does not typically vary with the level of R&D spending. The last column depicts the direction of the change, which we use in our analysis. Specifically, we employ an indicator variable that equals one whenever there is an increase in the rate.

State	Year	Tax Credit	Direction of Tax Credit Rate Change
Arizona	1994	20.0%	+
Arizona	2001	11.0%	-
California	1987	8.0%	+
California	1997	11.0%	+
California	1999	12.0%	+
California	2000	15.0%	+
Connecticut	1993	6.0%	+
Delaware	2000	10.0%	+
Georgia	1998	10.0%	+
Hawaii	2000	20.0%	+
Idaho	2001	5.0%	+
Illinois	1990	7.0%	+
Illinois	2003	0.0%	-
Illinois	2004	7.0%	+
Indiana	1985	5.0%	+
Indiana	2003	10.0%	+
Iowa	1985	6.5%	+
Kansas	1988	6.5%	+
Louisiana	2003	8.0%	+
Minnesota	1982	6.3%	+
Minnesota	1987	2.5%	-
Maine	1996	5.0%	+
Maryland	2000	10.0%	+
Massachusetts	1991	10.0%	+
Missouri	1994	7.0%	+
Montana	1999	5.0%	+
Nebraska	2006	3.0%	+
New Hampshire	1993	7.0%	+
New Hampshire	1994	15.0%	+
New Hampshire	1995	0.0%	-
New Jersey	1994	10.0%	+
North Carolina	1996	5.0%	+
North Carolina	2006	3.0%	-
North Dakota	1988	4.0%	+
Ohio	2004	7.0%	+

Oregon	1989	5.0%	+
Pennsylvania	1997	10.0%	+
Rhode Island	1994	5.0%	+
Rhode Island	1998	17.0%	+
South Carolina	2001	3.0%	+
South Carolina	2002	5.0%	+
Texas	2001	4.0%	+
Texas	2002	5.0%	+
Utah	1999	6.0%	+
Vermont	2003	10.0%	+
West Virginia	1986	10.0%	+
West Virginia	2003	3.0%	-
Wisconsin	1986	5.0%	+