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Strategic R&D Investment around Seasoned Equity Offerings: Evidence from High-Technology Industries

by

Yu Wang

A dissertation submitted in partial satisfaction

of the requirements for the degree of

Doctor of Philosophy

in

Business Administration

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Patricia M. Dechow, Co-Chair Professor Richard G. Sloan, Co-Chair Professor Stavros Gadinis Assistant Professor Alastair N. Lawrence Associate Professor Panos N. Patatoukas Professor Xiao-Jun Zhang

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Strategic R&D Investment around Seasoned Equity Offerings: Evidence from High-Technology Industries

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by

Yu Wang

Abstract

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Yu Wang

Doctor of Philosophy in Business Administration

University of California, Berkeley

Professor Patricia Dechow and Professor Richard Sloan, Co-Chairs

Focusing on high-technology issuers, this study provides new evidence that managers strategically overinvest in research and development (R&D) projects prior to seasoned equity offerings (SEOs). It corroborates the theoretical prediction that managers with short-term valuation pressure tend to overinvest in long-term projects to elevate investors' growth expectations (Bebchuk and Stole, 1993). I find that issuers with more intensive pre-SEO R&D expenditures exhibit lower productivity in terms of innovative output and operating performance following offerings, which is a primary manifestation of overinvestment. Such issuers also have higher price run-ups prior to offerings and lower long-term stock returns thereafter, suggesting that investors initially overestimate the future benefits of R&D expenditures but are subsequently disappointed by their low productivity. In additional analysis, I document that analysts make higher long-term growth forecasts prior to offerings for R&D intensive issuers, whereas such issuers are more likely to miss analysts' sales forecasts subsequently relative to non-intensive issuers. This evidence suggests that analysts fare no better than investors in correctly anticipating the future benefits of pre-SEO R&D expenditures. Further analysis of managers' disclosure of the intended use of proceeds indicates that R&D intensive issuers tend to provide more nonfinancial R&D information to reinforce investors' growth expectations. Finally, I provide evidence that the documented strategic R&D investment behavior among seasoned issuers is not explained by managerial overconfidence.

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Chapter 1

Introduction

In spite of its important role in firm growth, research and development (R&D) has long been established as a tool for real earnings management (e.g., Roychowdhury, 2006). Two recent studies further suggest that, cross-sectionally, managers suppress R&D expenditures to inflate earnings around seasoned equity offerings (SEOs) (i.e., Cohen and Zarowin, 2010; Kothari, Mizik, and Roychowdhury, 2016). This evidence of opportunistic R&D curtailment is consistent with the notion that earnings are the primary focal point for investors. However, when earnings become less of a focal point and the market puts more weight on growth related metrics, do managers still cut R&D investment to boost bottom line numbers? Theory suggests that, in such circumstances, mangers faced with short-term valuation pressure tend to strategically overinvest in long-term projects, R&D in particular, to elevate investors' growth expectations (Bebchuk and Stole, 1993).¹

In this study, I examine managers' R&D investment decisions among high-technology firms seeking seasoned equity financing. Compared to peers in other sectors, high-technology firms report losses more frequently, which shifts investors' attention from bottom line numbers toward growth related metrics, especially R&D expenditures.² Moreover, high-technology firms, with assets concentrated in intangibles, have limited collateral value for debt financing and thus depend heavily on equity financing following the exhaustion of internal cash (e.g., Brown, Fazzari, and Petersen, 2009). The SEO setting therefore ensures that managers have a strong incentive to maximize short-term valuation.³

Using a sample of 902 seasoned offerings by high-technology firms between 1975 and 2005, I find that high-technology issuers, on average, increase rather than reduce their R&D expenditures prior to the offering, which contrasts with the cross-sectional evidence of R&D curtailment from previous research (i.e., Cohen and Zarowin, 2010; Kothari et al., 2016). Specifically, R&D intensity, measured as a percentage of beginning total assets, rises significantly during the fiscal year immediately prior to the offering, with the increase in R&D expenditures accounting for nearly four percent of total assets. Breaking down this sample into three groups (terciles) on the basis of R&D intensity for the year immediately prior to the

¹ Likewise, Aghion and Stein (2008) offer a theory whereby the market pays more attention to growth related metrics. Opportunistic managers, correspondingly, tend to overinvest to cater to the market's preference for high growth, especially when they have a strong incentive to maximize stock prices in the short term.

 $^{^{2}}$ R&D is one of the most important means through which firms compete and grow, which is especially the case for high-technology industries (e.g., Hall, 2016).

³ This study focuses on seasoned offerings rather than initial public offerings (IPOs). Initial issuers, unlike seasoned issuers, are mostly young firms with relatively short track records of R&D activities. Therefore, their intensive R&D expenditures tend to be associated with higher information asymmetry and valuation uncertainty, which might adversely affect valuation at the time of initial offerings (e.g., Guo, Lev, and Shi, 2006).

offering, I demonstrate that issuers in the top tercile (R&D intensive issuers) exhibit an anomalous pattern of rising prior to the offering and declining immediately thereafter, while other issuers maintain a relatively flat time series of R&D expenditures around the offering. To ensure that this decline is not a mechanical consequence of an increased asset base following the offering, I measure R&D intensity alternatively as a percentage of SG&A expenses and find this pattern to be robust.

This anomalous pattern observed for R&D intensive issuers raises the question of whether such issuers are more likely to strategically overinvest or invest in less productive R&D projects prior to offerings to inflate their valuation. As overinvestment ultimately manifests itself in lower R&D productivity. I expect that R&D intensive issuers will exhibit lower productivity in terms of innovative output and operating performance. I employ data on firms' patenting activities from the U.S. Patent and Trademark Office (USPTO) since patents capture the productivity of a firm's R&D expenditures and are recognized as the most important measure of corporate innovative output (e.g., Griliches, 1990). Patents, however, vary widely in their technological influence and economic value (e.g., Hall, Jaffe, and Trajtenberg, 2005; Kogan, Papanikolaou, Seru, and Stoffman, 2016). Therefore, both the quantity and the quality of patents factor into the measurement of innovative output. I find that, for R&D intensive issuers, each million dollars spent on R&D generate not only significantly fewer patents but also patents of lower quality, and are associated with significantly lower sales over the three years following the offering, which is a primary manifestation of overinvestment. For example, moving from an average issuer with low pre-SEO R&D intensity to an average issuer with high pre-SEO R&D intensity, the cumulative number of patents filed with the USPTO over the three years following the offering drops significantly from 43 to 22, and the number of patents generated by each million dollars of R&D expenditures drops significantly from two to fewer than one. The difference-in-differences analysis of R&D productivity further confirms that the lower productivity of R&D intensive issuers is attributable to their investments in less productive R&D projects prior to the offering rather than certain firm characteristics that are systematically associated with low productivity.

These findings indicate that managers, with a short-term goal of maximizing SEO valuation, strategically overinvest or invest in less productive R&D projects prior to offerings to elevate investors' growth expectations. I next investigate whether this overinvestment is correctly anticipated by investors or results in mispricing of R&D information. The evidence suggests that investors are initially optimistic about the future benefits of pre-SEO R&D expenditures at the time of offerings but grow disappointed with the low productivity over the ensuing years.

I find that stock prices run up 42 percent over 60 trading days prior to the offering for R&D intensive issuers, while stock prices for non-intensive issuers increase by only 29 percent. This difference in price run-up (13 percent) is significant and equivalent to 37 percent of the average price run-up (36 percent) for all issuers in the sample. However, the higher price rises preceding offerings associated with R&D intensive issuers are followed by lower long-term stock returns over the three years following offerings. The average buy-and-hold size adjusted three-year return of R&D intensive issuers (-30 percent) is significantly lower than that of non-intensive issuers (-12 percent), with a difference of -18 percent. The significantly lower long-term stock return of R&D intensive issuers is also robust to the risk adjustment based on Fama

and French's (1993) three-factor model. In addition to R&D intensity, I also break down the sample into three groups (terciles) on the basis of R&D surprise for the year immediately prior to the offering. R&D surprise is measured as the change in R&D expenditures from the previous year scaled by beginning total assets. I find consistent evidence that issuers with high R&D surprise have lower R&D productivity in terms of innovative output and operating performance, higher price run-ups prior to offerings and lower long-term stock returns thereafter.

The evidence so far suggests that strategic investment in R&D projects serves to inflate SEO valuation, and eventually results in value destruction following the offering. Managers' R&D investment decision, however, might be driven by their optimistic bias rather than opportunistic intent. As suggested by Malmendier and Tate (2005), optimistic judgments often lead to managerial overconfidence, which in turn affects corporate investment decisions. In additional analyses, I examine whether R&D intensive issuers are more likely to have overconfident managers. Using overconfidence measures based either on managers' option holdings or on their corporate decisions, I do not find overconfidence to be significantly more prevalent among R&D intensive issuers. This evidence indicates that managers' pre-SEO R&D overinvestment is more likely to be associated with their opportunistic intent to elevate investors' growth expectations.

Managerial opportunism is further confirmed by a comparison between SEO firms and a matched sample of non-SEO firms. I find that R&D intensive issuers, with size, sales growth, R&D intensity, and investment opportunities similar to their non-SEO peers, have a more abrupt increase in R&D during the year immediately prior to offerings and exhibit lower R&D productivity and lower long-term stock returns over the three years following offerings, indicating that these issuers strategically overinvest in R&D for short-term valuation benefits.

To provide more direct support for the link between pre-SEO R&D expenditures and growth expectations, I examine analysts' forecasts made prior to the offering and issuers' subsequent frequency of missing analysts' forecasts. I document that analysts make more aggressive long-term growth forecasts for R&D intensive issuers relative to non-intensive issuers. R&D intensive issuers, however, exhibit significantly higher likelihoods of falling short of analysts' sales forecasts over the three years following the offering.⁴ This evidence suggests that analysts indeed pay attention to R&D expenditures when making growth forecasts for high-technology companies. Analysts, however, fare no better than investors in correctly anticipating the future benefits of pre-SEO R&D expenditures.

In addition to the pre-SEO R&D numbers, how might managers provide other R&D related information to help elevate investors' growth expectations? In particular, I study managers' disclosure of the intended use of proceeds in the prospectuses. I find that R&D intensive issuers are significantly more likely to state that their proceeds are for R&D plans and

⁴ I/B/E/S provides analysts' long-term growth forecasts which represent an expected annual increase in operating earnings over the company's next full business cycle. These forecasts often refer to a period of between three and five years. I/B/E/S, however, does not provide data on realized long-term growth rates. I examine analysts' sales forecasts for two reasons. First, unlike long-term growth rates, both forecasted and actual values of sales are available from I/B/E/S. Second, sales are a better growth related metric than earnings for high-technology firms which are characterized by frequent loss reporting.

that they also tend to provide more concrete information on product lines and research programs related to their R&D plans. This evidence suggests that these managers may strategically use voluntary nonfinancial disclosure to complement pre-SEO R&D numbers and thereby reinforce investors' growth expectations.

Finally, I examine the robustness of my results to alternative variable measurement, sample selection, and industry classification. Specifically, I provide evidence that the main results are robust to (1) an expanded measurement window of five years for R&D productivity; (2) alternative measurement of R&D output without scaling; (3) an alternative measure of R&D surprise estimated from discretionary expense model in Cohen and Zarowin (2010); (4) the exclusion of SEOs affected by internet bubble bursting; (5) the exclusion of software companies; and (6) the alternative classification of high-technology issuers based on Loughran and Ritter (2004).

Overall, by examining R&D productivity in terms of innovative output and operating performance, this study provides initial evidence that high-technology firms strategically overinvest or invest in less productive R&D projects prior to seasoned offerings. It corroborates Bebchuk and Stole's (1993) theoretical prediction that managers with a strong incentive to maximize short-term valuation will overinvest in long-term projects to elevate investors' growth expectations. Focusing on high-technology industries where earnings are less of a focal point and the market puts more weight on growth related metrics, this study highlights the role of R&D expenditures as a means of elevating investors' growth expectations rather than a real earnings management tool as established by previous research (e.g., Roychowdhury, 2006).

This paper also offers new insights into R&D mispricing. Mounting evidence of higher subsequent returns to R&D intensive firms suggests that investors underreact to R&D information (e.g., Lev and Sougiannis, 1996; Chan, Lakonishok, and Sougiannis, 2001). This study, however, provides direct support for Jensen's (1993) conjecture that investors' optimism about the prospect of inefficient R&D investments leads to the overpricing of R&D intensive firms.⁵ It also echoes Curtis, McVay, and Toynbee's (2016) cross-sectional finding that investors overestimate the growth implications of R&D investments which have become less profitable during recent years. One major takeaway for investors is that, in order to better assess firms' future operating and stock performance, they should not take at face value high R&D expenditures occurring shortly prior to SEOs.

The rest of the dissertation is organized as follows. Chapter 2 provides the background and develops predictions. Chapter 3 describes the sample and research design. Chapter 4 presents the main empirical results followed by additional analyses in Chapter 5. Chapter 6 summarizes robustness tests, and Chapter 7 concludes.

⁵ In a related study, Daniel and Titman (2006) find that the lower return to growth stocks is concentrated in stocks with significant "intangible" information. Their findings suggest that investors overreact to intangible information. However, they do not define or identify the exact content of intangible information.

Chapter 2

Prior Literature and Hypothesis Development

2.1 Prior research on SEO and earnings management

It is a stylized fact that SEO firms have high stock returns in the year before the offering, price drops around the offering announcement, and negative long-term stock returns following the offering. Specifically, Loughran and Ritter (1995) report an average return of 72 percent in the year before the seasoned offering. Asquith and Mullins (1986) document an abnormal two-day return of -2 percent around SEO announcement. Following the offering, SEO firms significantly underperform non-SEO firms matched on industry membership and firm size (e.g., Spiess and Affleck-Graves, 1995; Loughran and Ritter, 1995). Rangan (1998) further shows that the abnormal return for the first year following the offering is –7.4 percent.

The literature on SEO firms' long-term underperformance is centered on managers' earnings manipulation. Managers engage in both accruals and real activities manipulation to inflate earnings prior to the offering. Investors, however, do not anticipate this opportunistic behavior and are surprised when future earnings reverse following the offering. For example, evidence suggests that discretionary accruals are abnormally high before the offering and that issuers with higher discretionary accruals have lower long-term stock returns thereafter (e.g., Rangan, 1998; Teoh, Welch, and Wong, 1998). DuCharme, Malatesta, and Sefcik (2004) show that SEOs with subsequent shareholder lawsuits have much higher pre-SEO abnormal accruals and higher post-SEO accrual reversals. Cohen and Zarowin (2010) and Kothari et al. (2016) examine managers' use of real activities to inflate earnings around SEOs, which will be discussed in more detail in Section 2.2.

In addition to investors' inability to adjust for managers' earnings manipulation, analysts appear to be overly optimistic about the future performance of SEO firms. Teoh and Wong (2002) find that analysts' earnings forecast errors are predicted by prior year's accounting accruals and analysts tend to be more optimistic about future earnings for issuers reporting higher pre-SEO accruals. Dechow, Hutton, and Sloan (2000) show that analysts systematically make overly optimistic long-term earnings growth forecasts around equity offerings and that issuers with higher growth forecasts exhibit more pronounced stock market underperformance following the offering.

2.2 Prior research on R&D and real earnings management

The studies on managers' R&D investment decisions primarily focus on their opportunistic reduction of R&D expenditures to increase earnings. For example, evidence suggests that managers cut R&D expenditures to avoid reporting small losses (e.g., Roychowdhury, 2006), to beat prior year's earnings (e.g., Baber, Fairfield, and Haggard, 1991; Bushee, 1998), and to meet analysts' forecasts (e.g., Bhojraj, Hribar, Picconi, and Mcinnis, 2009; Asker, Farre-Mensa, and Ljungqvist, 2014). Two recent studies provide cross-sectional evidence

that managers reduce R&D expenditures to inflate earnings around SEOs (i.e., Cohen and Zarowin, 2010; Kothari et al., 2016). In particular, Cohen and Zarowin (2010) pool R&D expenditures together with advertising and SG&A expenses, and find that discretionary expenses, the portion not explained by past sales, are negative preceding and positive following the offering for 1,511 SEOs over the period from 1987 to 2006. Kothari et al. (2016) extend Cohen and Zarowin (2010) by focusing on R&D expenditures. They document that the proportion of firms with negative R&D surprises and positive earnings surprises is much higher in the years of SEOs compared to non-SEO years.

Two other concurrent papers, in contrast, illustrate that R&D expenditures may not necessarily serve as a real earnings management tool. Focusing on a small sample of firms subject to the SEC's Accounting and Auditing Enforcement Releases, Sun (2016) finds that in order to maintain high stock market valuation these alleged manipulators cut SG&A but increase R&D during the years in which they overstate earnings. Fedyk, Singer, and Soliman (2016) document that science and technology firms tend to inflate sales and R&D expenditures rather than earnings to boost IPO valuation. They, however, find no association between discretionary R&D and one-year ahead stock returns for these firms.

2.3 Hypothesis development

The evidence of opportunistic R&D reductions is consistent with the notion that earnings are the primary focal point for investors. However, when earnings become less of a focal point and the market puts more weight on growth related metrics, do managers still cut R&D investment to boost bottom line numbers? Theory suggests that, in such circumstances, managers overinvest in R&D projects rather than cut them. In particular, Bebchuk and Stole (1993) model managers' long-term investment decisions in the presence of short-term valuation pressure and information advantage over uninformed investors. The information advantage lies in that investors can observe the level of long-term investments but not their productivity.⁶ In turn, to create a rosy outlook for short-term valuation benefits, managers strategically overinvest in long-term projects, particularly R&D.

This study focuses on managers' R&D investment decisions among high-technology firms seeking seasoned equity financing for two reasons. First, compared to peers in other sectors, high-technology firms report losses more frequently. Evidence from the Compustat universe indicates that 42 percent of high-technology firms report operating losses, compared to 25 percent for firms in other sectors. As a result, investors' attention is shifted from bottom line numbers to other relevant "intangible" value drivers, especially R&D related information. For

⁶ R&D productivity is not observable at the time of spending and takes time to unravel. Though productive R&D expenditures can ultimately translate into a firm's future growth and competitiveness (e.g., Pandit, Wasley, and Zach, 2011), many R&D expenditures turn out to be unproductive in the long run (Jensen, 1993). For example, General Motors spent virtually \$40 billion on R&D during the 1980s but reported a loss of \$6.5 billion in the early 1990s. Although R&D productivity is ex ante unobservable, it is not completely unpredictable. For example, Cohen, Diether, and Malloy (2013) find that firms with track records of unsuccessful R&D activities will continue to make unsuccessful R&D investments. Investors, however, appear to ignore or have difficulty in processing this productivity information embedded in the firm's history of R&D investments.

example, Chan, Martin, and Kensinger (1990) study the market response to firms' announcement of plans to increase R&D expenditures between 1979 and 1985, and find that these R&D announcements are associated with positive stock returns for high-technology firms. Second, high-technology firms have limited collateral value for debt financing as intangibles account for a significant portion of their asset base. Consequently, they depend mostly on equity financing when internal cash is exhausted (e.g., Brown et al., 2009). The SEO setting thus ensures that managers have a strong incentive to maximize short-term valuation. Managers' incentive to maximize short-term valuation is even stronger when they have aligned personal interests. For example, Lang and Lundholm (2000) show that when SEO firms have selling shareholders participating in the offering, managers are more likely to dramatically increase disclosure activities beginning six months before the offering to inflate the stock prices.

Based on the overinvestment prediction from Bebchuk and Stole (1993), I expect that high-technology issuers aiming to maximize SEO valuation will increase rather than cut investment in R&D projects prior to their offerings. To begin with, I examine the time series of R&D expenditures around SEOs. In contrast to the cross-sectional evidence from Cohen and Zarowin (2010), I find that, on average, high-technology issuers significantly increase their R&D expenditures during the year immediately preceding the offering, but significantly decrease their R&D expenditures during the year immediately thereafter.⁷ Moreover, breaking down high-technology issuers into three groups (terciles) on the basis of R&D intensity for the fiscal year immediately preceding the SEO filing day, I show that only R&D intensive issuers exhibit an anomalous pattern of rising prior to the offering and declining immediately thereafter, whereas non-intensive issuers' time series of R&D expenditures remain relatively flat around the offering.

This evidence confirms the relevance of the overinvestment theory for high-technology issuers. Also, the anomalous time series pattern raises the question of whether R&D intensive issuers are more likely to strategically overinvest or invest in less productive R&D projects prior to offerings to elevate investors' growth expectations. Since investment beyond the efficient level eventually results in lower productivity, I expect that R&D intensive issuers will exhibit lower R&D productivity over the years following the offering.

Prediction I: Issuers with high pre-SEO R&D expenditures have lower R&D productivity.

Next, I examine the valuation impact associated with high pre-SEO R&D expenditures. That is, if there is evidence of opportunistic overinvestment among R&D intensive issuers, do investors correctly anticipate this or misprice R&D information? Previous research provides evidence that investors underreact to R&D information (e.g., Lev and Sougiannis, 1996; Chan et al., 2001). Jensen (1993), however, conjectures that investors are overly optimistic about the future profitability of inefficient R&D investments, leading to the overpricing of R&D intensive firms. Consistent with Jensen (1993), Curtis et al. (2016) document that investors overestimate the growth implications of R&D investments at the aggregate level during recent years. Clearly,

⁷ This finding is based on the level of R&D expenditures scaled by beginning total assets. I also use the same discretionary expense model as in Cohen and Zarowin (2010), and find positive discretionary R&D preceding the offering and negative discretionary R&D following the offering for high-technology issuers.

whether investors under- or overreact to R&D information hinges on the productivity of R&D investments. As R&D productivity is ex ante unobservable, I expect that overinvestment or investment in less productive R&D projects initially serves to elevate investors' growth expectations, leading to higher price run-ups prior to the offering for R&D intensive issuers.

Prediction II: Issuers with high pre-SEO R&D expenditures have higher price run-ups prior to the offering.

As the strategic R&D investment manifests itself in lower productivity, investors impound its negative implications into prices, resulting in lower long-term stock returns following the offering for R&D intensive issuers.

Prediction III: Issuers with high pre-SEO R&D expenditures experience lower long-term stock returns following the offering.

Chapter 3

Sample and Research Design

3.1 Sample selection

The SEO sample is obtained from the Securities Data Company (SDC) Global New Issues database. The sample selection starts with seasoned issues of common stocks by high-technology firms that are listed on NYSE, NASDAQ, and AMEX, excluding (i) SEOs with offer prices lower than \$5, (ii) spin-offs, reverse LBOs, closed-end funds, unit investment trusts, REITs, and limited partnerships, (iii) right issues and unit offerings, and (iv) nondomestic and simultaneous domestic-international offers. High-technology firms are identified using 4-digit SIC codes as in Qian, Zhong, and Zhong (2012).⁸ I further restrict the sample to SEOs with non-missing R&D expenditures for the two years prior to the SEO filing day, and exclude SEOs with missing financial data from Compustat and stock return data from CRSP. The final sample consists of 902 SEOs from 1975 to 2005. Table 1, Panel A summarizes the sample selection. It is important to note that observations with missing R&D expenditures (Compustat item *xrd*) are not included by setting missing values to zero. Eleven percent of firms with missing R&D from Compustat actually have active patenting activities (Koh and Reeb, 2015), suggesting that many firms with R&D activities could choose not to report R&D, and therefore setting missing R&D to zero will give a biased measure of R&D intensity.

The sample period begins in 1975 and ends in 2005 to accommodate the use of patent data for the measurement of R&D productivity.⁹ This paper employs the updated KPSS patent dataset constructed by Kogan et al. (2016), which covers the details of patents applied to and granted by the USPTO from 1926 to 2010.¹⁰ However, Kogan et al. (2016) note that the official records of patent grants in high quality text files from the USPTO are only available for the

⁸ Fama and French's (1997) 49-industry classification identifies nine high-technology related sectors, including business services, computers, computer software, electrical equipment, electronic equipment, measuring and control equipment, medical equipment, pharmaceutical products, and telecommunication. Qian et al. (2012) refine the identification of high-technology firms by excluding relatively low-technology industries from business services and electrical equipment. Within the sector of business services, only computer and R&D related services (SIC codes 7374, 7376-7379, 7391, and 8730-8734) are identified as high-technology. Within the sector of electrical equipment, only communication equipment, electrical machinery, and storage batteries (SIC codes 3660, 3690-3692, and 3699) are identified as high-technology. In robustness checks, I use Loughran and Ritter's (2004) high-technology firm classification, which is similar to Qian et al. (2012) but results in a more restrictive sample of high-technology issuers. I find that my results are not sensitive to different high-technology classifications.

⁹ The sample period from 1975 to 2005 includes the years in which the internet bubble burst. Therefore, in robustness checks, I exclude offerings made over the period from 1999 to 2001 and find that the results are not affected by the internet bubble burst.

¹⁰ The patent data can be obtained from the website provided by Kogan et al. (2016) at https://iu.app.box.com/v/patents. Another commonly used patent data source is the NBER patent database, which is developed by Hall, Jaffe, and Trajtenberg (2001). However, it covers a shorter time period from 1976 to 2006. Moreover, Kogan et al. (2016) provide additions and corrections to the NBER patent data for the overlapping period (i.e., 1976-2006).

period from 1976 to 2010, and the data prior to 1976 are created based on sophisticated textual analysis algorithms and suffer from lower quality. Therefore, the SEO sample begins in 1975 as R&D productivity is measured starting the year immediately following the seasoned offering.

Another limitation is the truncation problem, which arises as the patent data approaches its end of coverage (i.e., the year of 2010). Specifically, a patent obtains its official record and enters into the constructed dataset only when its application to the USPTO is ultimately granted. On average, it takes two years for a patent application to go through the USPTO review process and eventually become a patent. With an average two-year lag between application and grant, one would observe a sharp decrease in the number of patent applications that are ultimately granted as the dataset approaches 2009 and 2010. Hence, the SEO sample ends in 2005 to address this truncation problem in the patent data as suggested by prior research (e.g., Hall, Jaffe, and Trajtenberg, 2001).

To measure the output of R&D expenditures, this paper uses the cumulative number of patent applications (which are ultimately granted) filed to the USPTO over the three years following the offering. As suggested by Lerner and Seru (2015), firms, eager to protect their intellectual property, tend to file patent applications soon after the development stage, whereas the grant of patents is subject to many other factors, such as the contemporaneous state of the patent office at the time of application. Therefore, patent application measures the output of R&D expenditures in a timelier and more reasonable manner.

Table 1, Panel B presents the distributions over the sample period. The number of seasoned issues ranges over time from a minimum of 81 for the period 1986-1990 to a maximum of 193 for the period 1996-2000. Table 1, Panel C, which reports the distributions across nine high-technology industries, indicates that issuers in electronic equipment and pharmaceutical products represent more than half of the final sample. On average, a high-technology issuer has total assets of \$490 million and sales of \$340 million, and invests \$26 million in R&D projects during the year immediately prior to the offering.

3.2 Research design

3.2.1 Measurement of pre-SEO R&D expenditures

Appendix 1 provides a comprehensive description of variable definitions, and Appendix 2 illustrates the time line for seasoned offerings and the measurement of key variables. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year t+1 is the fiscal year immediately following the SEO issue day.¹¹ For an average seasoned issuer, the fiscal year immediately prior to the offering ends six months preceding the SEO filing day, and the issuance of shares takes place three weeks following the

¹¹ The SEO filing day is the day when a seasoned issuer files the prospectus with the SEC after its security registration, typically a Form S-3, is declared effective by the SEC. The prospectus is identified as a 424B filing in the EDGAR database.

SEO filing day. I measure the intensity of R&D as of the fiscal year immediately prior to the SEO filing day, which is available in the prospectuses filed by issuers with the SEC. Following prior research (e.g., Cohen and Zarowin, 2010), R&D intensity ($R\&D_{it-1}$) is measured as R&D expenditures scaled by beginning total assets. Using beginning total assets as a scalar mitigates the concern that R&D intensity will be magnified as an increase in R&D expenditures lowers total assets mechanically.¹² In addition to the level of R&D intensity, I use the change in R&D expenditures from the previous year scaled by beginning total assets to measure R&D surprise ($\Delta R\&D_{it-1}$). Since it is not a routine for analysts to report detailed forecasts for R&D expenditures (e.g., Gunny, 2010). However, firm-specific effects might induce model misspecification and estimation error (e.g., Owens, Wu, and Zimmerman, 2016). In robustness checks, I estimate R&D surprise using the discretionary expense model from Cohen and Zarowin (2010), and find that the main inferences do not change.

On average, high-technology issuers invest 18 percent of total assets in R&D activities during the year immediately preceding the offering, and the increase in R&D expenditures accounts for around four percent of total assets. Tercile ranks of R&D intensity and R&D surprise are constructed to break down the annual cross-section of issuers into three groups. For the empirical analyses, Rank($R\&D_{it-1}$) and Rank($\Delta R\&D_{it-1}$) are standardized to range from zero to one, with zero indicating the bottom tercile with non-intensive or low surprise issuers and one indicating the top tercile with R&D intensive or high surprise issuers. An average R&D intensive (non-intensive) issuer has a R&D intensity of 36 percent (5 percent), while an average issuer with high (low) surprise has a R&D surprise of 11 percent (-2 percent).

3.2.2 Test of the prediction on R&D productivity

To test the prediction that high pre-SEO R&D expenditures are associated with lower productivity, I estimate the following regression model:

R&D Productivity =
$$\alpha + \beta_1 \cdot \operatorname{Rank}(R \& D_{it-1}) + \sum_{k=2}^{K} \beta_k \cdot C_{it-1}^k + \varepsilon_{it-1}.$$
 (1)

This model regresses R&D productivity on pre-SEO R&D expenditures along with a vector of control variables using pooled cross-sectional OLS regression. The primary explanatory variable is the rank of either R&D intensity or R&D surprise for the fiscal year immediately prior to the offering. The dependent variable is R&D productivity which is measured in terms of either innovative output or operating performance over the three years following the offering.

Patents capture the productivity of R&D expenditures, and are recognized as the most important measure of innovative output (e.g., Griliches, 1990). I obtain data on firms' patenting

¹² The inferences do not change using average total assets as an alternative scalar. Sales are not considered to be an appropriate scalar for seasoned issuers as they create a mechanical problem if firms manage pre-SEO sales upward (e.g., Cohen and Zarowin, 2010).

activities from the updated KPSS patent dataset constructed by Kogan et al. (2016), which covers all patents applied to and granted by the USPTO. The KPSS patent dataset provides detailed information on patent assignee names, assignee's Compustat-matched identifiers, patent application year and grant date, the number of citations received by each patent up to 2010, and patent technology class. Based on the information retrieved at a patent level from the KPSS patent dataset, I create a measure of innovative output (*PATENT_{it}*) at a firm-year level by aggregating each firm's total number of patent applications filed in each year that are ultimately granted.

Nevertheless, PATENT_{it} is a simple count of patents, which does not necessarily capture the quality of a firm's innovative output (e.g., Traitenberg, 1990). Indeed, patents vary widely in their technological influence and economic value, which is reflected in citation counts and the market response to patent grant news (e.g., Hall et al., 2005; Kogan et al., 2016). With these considerations, I further develop two measures to capture the quality of a firm's innovative output. The first measure, IPATENT_{it}, captures firm i's number of influential patents filed to the USPTO during year t. A patent is classified as influential if its citation count excluding selfcitations is above the average across all patents in the same technology class and granted in the same year. Note that patents of some technology classes have greater generality and thus are more heavily cited, and that patents granted closer to the end of the citation data collection period (i.e., the year of 2010) are mechanically less cited. Therefore, I compare citations across patents with the same technology class and the same grant year. The second measure, $VPATENT_{it}$, is firm i's number of valuable patents filed to the USPTO during year t. A patent is classified as valuable if the market response to patent grant news is above the average across all patents in the same technology class and granted in the same year. The market response is measured as a cumulative three-day stock return over the window from the grant day to two trading days after.¹³

It follows two steps to measure the productivity of an issuer's pre-SEO R&D activities. First, I cumulate the number of all patents ($\sum_{\tau=1}^{3} PATENT_{it+\tau}$), influential patents ($\sum_{\tau=1}^{3} IPATENT_{it+\tau}$), and valuable patents ($\sum_{\tau=1}^{3} VPATENT_{it+\tau}$), respectively, over the threeyear period starting the year immediately following the offering. Then, the cumulative sum of patents is divided by the R&D expenditures (*XRD*_{it-1}) made during the year immediately prior to the offering.

In addition to patent related output, R&D productivity is gauged by a firm's future operating performance. I take the average annual sales $(\sum_{\tau=1}^{3} SALE_{it+\tau}/3)$ over the three-year period starting the year immediately following the offering divided by the R&D expenditures (*XRD*_{*it*-1}) made during the year immediately prior to the offering. Appendix 2 illustrates the

¹³ As a robustness check for the measurement of innovation output, I find similar results with the following alternatives: (i) measure $PATENT_{it}$ by aggregating each firm's total number of patent grants received in each year, (ii) define $IPATENT_{it}$ based on a patent's total citation count including self-citations, (iii) define $VPATENT_{it}$ based on the one-day return at the grant date and the cumulative five-day return over the window from the grant day to four trading days after, and (iv) define $IPATENT_{it}$ and $VPATENT_{it}$ based on the median value of citations and stock market responses, respectively, across all patents in the same technology class and granted in the same year.

measurement window for pre-SEO R&D expenditures and their corresponding productivity. This three-year measurement window for R&D productivity raises horizon concerns. One concern is that it might take a longer period for R&D expenditures to translate into innovative output. To address this concern, I expand the measurement window to five years following the offering. Another concern, on the contrary, is that R&D expenditures might generate innovative output earlier. To mitigate the second horizon concern, I measure patents by aggregating each firm's total number of patent grants received during each year, and then cumulate patents over the three years following the offering. The main inferences do not change using alternative measurement windows for R&D productivity.

An average high-technology seasoned issuer generates 29 patents in total, 9 influential patents, and 14 valuable patents over the three years following the offering, and has annual sales of \$520 million over the same period. In terms of productivity, each million dollars spent on R&D activities deliver 1.48 patents in total, 0.40 influential patent, and 0.54 valuable patent over the three years following the offering, and translate into annual sales of \$50 million over the same period.

Following the existing literature (e.g., Hall and Ziedonis, 2001), the vector of control variables includes the scale effect of R&D investments ($SCALE_{it-1}$), firm size measured as the natural log of total assets (SIZE_{it-1}), sales growth (SG_{it-1}), return-on-assets (ROA_{it-1}), leverage (LEV_{it-1}) , Tobin's Q (TOBIN_{it-1}), capital intensity (CAP_{it-1}), capital expenditures (CAPEX_{it-1}), and cash holdings (CASH_{it-1}), along with industry and year fixed effects. All control variables are measured as of the fiscal year immediately prior to the offering and winsorized at the top and bottom one-percent levels of their distributions. In a recent study, Lerner and Seru (2015) identify three challenges from the impact of time, technology class, and region for the patent data. First, the establishment of the U.S. Court of Appeals for the Federal Circuit (CAFC) in 1982 provided a streamlined venue for treating patent cases, and therefore more patents were granted after 1982. Including year fixed effects addresses the first challenge from the impact of time. Second, patent activities may vary with industries and technology classes, which is addressed by including industry fixed effects in the model. Finally, Lerner and Seru (2015) suggest that firms operating in states with business friendly policy reforms, such as California and Massachusetts, are likely to produce more innovative output. Therefore, in robustness checks, I identify the state of each issuer's headquarters, and find that the main inferences do not change after controlling for state fixed effects.

3.2.3 Test of the prediction on price run-up

To test the second prediction that high pre-SEO R&D expenditures are associated with higher stock price run-ups before the offering, I estimate the following regression model:

$$RUNUP_{it} = \alpha + \beta_1 \cdot \operatorname{Rank}(R \& D_{it-1}) + \sum_{k=2}^{K} \beta_k \cdot C_{it-1}^k + \varepsilon_{it-1}.$$
 (2)

This model regresses stock price rise immediately prior to the offering on pre-SEO R&D expenditures along with a vector of control variables using pooled cross-sectional OLS regression. The primary explanatory variable is the rank of either R&D intensity or R&D

surprise for the fiscal year immediately prior to the offering. The dependent variable is price runup ($RUNUP_{it}$) which is measured as the cumulative 60-day stock return from 62 trading days before to three trading days before the SEO filing day.

The vector of control variables in equation (2) is similar to that of the model specified in equation (1), except that it excludes the scale effect of R&D investments ($SCALE_{it-1}$) and adds the contemporaneous price movement of the market ($MRUNUP_{it}$) to control for the market-wide effect prior to the offering. $MRUNUP_{it}$ is the cumulative 60-day CRSP value-weighted index return including distributions measured over the same window as $RUNUP_{it}$.

3.2.4 Test of the prediction on long-term stock return

To test the last prediction on long-term stock performance, I develop three measures of buy-and-hold adjusted stock return ($LTRET_{it+3}$) over the 36-month post-SEO period starting the first month of the fiscal year immediately following the offering. The first measure is market adjusted stock return based on the CRSP value-weighted index including distributions. The second measure, size adjusted long-term stock return, is calculated by deducting from the issuer's raw return the average value-weighted return for the CRSP decile portfolio with the same size, where size is measured as the market value of equity at the beginning of the return accumulation period.

The last measure is adjusted stock return based on Fama and French's (1993) three-factor model. Following Teoh, Welch, and Wong (1998), I estimate the factor loadings on the three Fama-French (1993) factors for each individual issuer by running a time series regression of the monthly return in excess of the risk free rate on the three Fama-French factors over the 24 months ending in the last month of the fiscal year immediately prior to the SEO filing day.

$$R_{im} - r_m^f = \gamma_1 \cdot (R_m^{mkt} - r_m^f) + \gamma_2 \cdot R_m^{smb} + \gamma_3 \cdot R_m^{hml} + \varepsilon_{im}.$$
 (3)

I estimate the factor loadings (γ) of the model specified in equation (3), where R_{im} is issuer *i*'s return for month *m*, r_m^f is the one-month Treasury bill rate for month *m*, R_m^{mkt} is the monthly return of the CRSP value-weighted index including distributions, R_m^{smb} is the average return on small firm portfolios minus the average return on big firm portfolios, and R_m^{hml} is the average return on value firm portfolios minus the average return on growth firm portfolios.¹⁴ A minimum of twelve available months is required to estimate the factor loadings for each issuer.

The individual issuer's expected return for each month is calculated for the 36 months starting the first month of the fiscal year immediately following the SEO issue day, using the estimated factor loadings ($\hat{\gamma}$), one-month Treasury bill rate and factor returns for the corresponding month:

¹⁴ Data on the factors and the Treasury bill rates are obtained from the website of Kenneth French at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

$$ER_{im} = r_m^f + \hat{\gamma}_1 \cdot (R_m^{mkt} - r_m^f) + \hat{\gamma}_2 \cdot R_m^{smb} + \hat{\gamma}_3 \cdot R_m^{hml}.$$
(4)

I obtain the monthly abnormal return for each issuer by deducting from the raw return the expected return estimated using Fama and French's (1993) three-factor model as specified in equation (4). Finally, I cumulate the abnormal returns over the 36 months following the offering.

Chapter 4

Empirical Results

4.1 Time series of R&D expenditures around SEOs

Table 3 presents the time series of R&D intensity around SEOs for partitions of hightechnology issuers based on R&D intensity (Panel A) and R&D surprise (Panel B) for the year immediately prior to the offering. In contrast to the finding of R&D curtailment around SEOs (e.g., Cohen and Zarowin, 2010; Kothari et al., 2016), I show that issuers in high-technology industries significantly increase R&D expenditures prior to the offering. In fact, R&D intensity of an average issuer increases from 16.66 percent to 17.84 percent during the year immediately prior to the offering, and falls to 14.61 percent during the year immediately following the offering. Paired t-tests suggest that the pre-SEO increase of 1.18 percent and the post-SEO decline of 3.46 percent are significant at the five percent level and the one percent level, respectively.

Table 3, Panel A, breaking down issuers into three groups on the basis of R&D intensity for the year immediately prior to the offering ($R \& D_{it-1}$), indicates that only issuers with high $R \& D_{it-1}$ (R&D intensive issuers) exhibit a time series pattern of rising prior to the offering and declining immediately thereafter, while other issuers maintain a relatively flat time series of R&D expenditures around the offering. On average, R&D intensive issuers have a significant increase of four percent in R&D intensity during the year immediately prior to the offering, but have a significant decrease of ten percent during the year immediately thereafter. This pattern among R&D intensive issuers appears anomalous, especially when compared to the flat R&D time series for non-intensive issuers (with low $R \& D_{it-1}$). Table 3, Panel B shows that the differential R&D time series patterns are more striking when issuers are grouped based on the pre-SEO R&D surprise ($\Delta R \& D_{it-1}$). Figure 1 plots the time series of the level of R&D expenditures as a percentage of beginning total assets for issuers in the top and bottom terciles of R&D intensity (Panel A) and R&D surprise (Panel B), visualizing the differential time series patterns between R&D intensive and non-intensive issuers.

To ensure that the decline in R&D intensity is not a mechanical consequence of an increased asset base following the offering, I measure R&D intensity as a percentage of SG&A expenses and find robust evidence that R&D intensive issuers significantly increase R&D expenditures during the year immediately prior to the offering and significantly decrease R&D immediately thereafter (untabulated). Figure 2 plots the time series of the level of R&D expenditures as a percentage of SG&A expenses for issuers in the top and bottom terciles of R&D intensity (Panel A) and R&D surprise (Panel B). Although the differential time series patterns between R&D intensive issuers exhibit the anomalous pattern of rising prior to the offering and declining immediately thereafter.

Taken together, the evidence suggests that the convention of R&D curtailment for earnings inflation is less relevant for seasoned issuers in high-technology industries where

investors' attention is shifted from bottom line numbers toward growth related metrics, especially R&D expenditures. Instead, the evidence confirms the relevance of the overinvestment prediction from prior analytical research (Bebchuk and Stole, 1993), and motivates the employment of pre-SEO R&D expenditures to identify seasoned issuers which might potentially strategically overinvest or invest in less profitable R&D projects to inflate market valuation.

4.2 R&D overinvestment manifested in lower productivity

Table 4 provides descriptive evidence that high-technology issuers with intensive pre-SEO R&D expenditures have significantly lower productivity, using partitions of issuers based on R&D intensity and R&D surprise for the year immediately prior to the offering, respectively. Specifically, Panel A reports that the number of patents generated by each million dollars of R&D expenditures decreases from 2.24 for non-intensive issuers to 0.99 for R&D intensive issuers, with a significant difference of more than one patents over the three years following the offering. R&D intensive issuers generate not only fewer patents but also patents of lower quality. Moving from an average non-intensive issuer to an average R&D intensive issuer, the number of patents with technological influence generated by each million dollars of R&D expenditures drops significantly from 0.61 to 0.30, and the number of patents with economic value generated by each million dollars of R&D expenditures drops significantly from 0.80 to 0.37. In addition to innovative output, high pre-SEO R&D intensity is associated with operating underperformance over the three years following the offering. Moving from an average non-intensive issuer to an average R&D intensive issuer, the annual sales generated by each million dollars of R&D expenditures drop from \$120 million to \$10 million, with a significant difference of \$110 million at the one percent level.

Table 4, Panel B indicates that the differences in productivity are smaller in magnitude whereas the inferences do not change using partitions of issuers based on R&D surprise. For example, the number of patents generated by each million dollars of R&D expenditures decreases from 1.96 for issuers with low surprise to 1.07 for issuers with high surprise, with a significant difference of 0.89 at the one percent level. With respect to sales, moving from an average issuer with low surprise to an average issuer with high surprise, the annual sales generated by each million dollars of R&D expenditures drop from over \$90 million to below \$20 million, with a significant difference of around \$80 million at the one percent level.

Table 5 provides the results of the regressions of R&D productivity on pre-SEO R&D expenditures after controlling for a wide array of relevant predictors for R&D productivity including the scale effect of R&D investments. Panel A explores the variation across issuers based on R&D intensity, and Panel B explores the variation across issuers based on R&D surprise, both indicating that high pre-SEO R&D expenditures are associated with lower productivity following the offering.

The estimated coefficients on $\text{Rank}(R\&D_{it-1})$ are significantly negative at the one percent level based on standard errors clustered by firm and year using two-tailed tests. In terms of economic significance, moving from a non-intensive issuer to a R&D intensive issuer, each million dollar investment in R&D generates 1.34 fewer patents, 0.27 fewer influential patent,

0.41 fewer valuable patent, and \$63 million lower annual sales over the three years following the offering. Consistent with the descriptive results, the estimated coefficients on Rank($\Delta R \& D_{it-1}$) are smaller in magnitude and slightly weaker in terms of statistical significance. The main inferences, nevertheless, do not change using R&D surprise for sample partitioning.

Table 6 provides the results of the regressions of R&D productivity on pre-SEO R&D expenditures after controlling for state fixed effects. Lerner and Seru (2015) suggest that firms operating in states with business friendly policy reforms, such as California and Massachusetts, are likely to produce more innovative output. Therefore, I identify the state of each issuer's headquarters and include state fixed effects in the regression model. Panel A and Panel B show robust evidence of compromised R&D productivity for R&D intensive issuers after controlling for state fixed effects.

To address the concern that it is due to certain firm characteristics that issuers with high pre-SEO R&D expenditures have systematically lower productivity, I conduct a difference-indifferences analysis of R&D productivity between R&D intensive and non-intensive issuers, before and after the offering. For the pre-SEO period, I measure the productivity of the earlier R&D investments made during the year that is six years prior to the offering. For the post-SEO period, I measure the productivity of R&D expenditures made during the year immediately before the offering. Note that the measurement windows for pre- and post-SEO productivity do not have overlap.

This analysis requires earlier R&D data to be available and positive, which results in a restricted sample of 465 SEOs (i.e., 52 percent of the final sample). I focus on the number of patents for this analysis. Table 7, Panel A shows that, although R&D intensive issuers have significantly lower productivity over the years following the offering, the productivity of their earlier R&D expenditures is no different from that of non-intensive issuers. Following the offering, R&D intensive issuers have an average decline of 1.51 in the number of patents generated by each million dollars of R&D expenditures while this number is only 0.89 for non-intensive issuers, leading to a significant difference-in-differences of -0.63. Using partitions of issuers based on R&D surprise, Panel B provides evidence that issuers with high R&D surprise even have slightly higher productivity for issuers in the top and bottom terciles of R&D intensity (Panel A) and R&D surprise (Panel B).

Taken together, the evidence supports the first prediction that seasoned issuers with high pre-SEO R&D expenditures have lower productivity, as indicated by lower innovative output and poorer operating performance. This lower productivity following the offering, which is a primary manifestation of overinvestment or investment in less profitable projects, is consistent with the theoretical prediction from Bebchuk and Stole (1993).

4.3 Pre-SEO R&D expenditures and SEO pricing

The evidence thus far suggests that managers facing short-term valuation pressure tend to invest in less productive R&D projects prior to SEOs. In this section, I examine the effect of pre-SEO R&D investments on SEO valuation at the time of offerings. Table 8 provides descriptive

evidence that high-technology issuers with high pre-SEO R&D expenditures have favorable valuation around SEOs, using partitions of issuers based on R&D intensity (Panel A) and R&D surprise (Panel B) for the year immediately prior to the offering.

Table 8, Panel A shows that R&D intensive issuers have an average stock price run-up (*RUNUP_{it}*) of 42 percent over a 60-day window from 62 trading days preceding to three trading days preceding the SEO filing day, whereas the price run-up is much smaller (29 percent) for non-intensive issuers. This difference in price run-up (13 percent) is significant at the one percent level and equivalent to 37 percent of the average price run-up for all issuers in the sample.¹⁵ Panel B shows that the difference in price run-up (10 percent) between issuers in the top and bottom terciles of R&D surprise is of a smaller magnitude but still significant at the one percent level.

Another commonly used valuation indicator is the short-window return around the SEO filing day. It is a stylized fact that seasoned issuers experience price drops around the announcement of offerings (e.g., Asquith and Mullins, 1986). Consistent with prior research, I find that issuers in all three terciles of R&D intensity have a negative five-day return (*DROP*_{*it*}) around the SEO filing day. R&D intensive issuers have an average price drop of 0.68 percent from two trading days preceding to two trading days following the SEO filing day, which is significantly smaller than the drop for non-intensive issuers (2.37 percent). However, the difference in price drops around the SEO filing day between issuers in the top and bottom terciles of R&D surprise is insignificant.

Figure 4 plots the average stock returns cumulated from 62 trading days before to 62 trading days after the SEO filing day for issuers in the top and bottom terciles of R&D intensity (Panel A) and R&D surprise (Panel B), providing additional evidence of the impact of pre-SEO R&D expenditures on issuers' SEO valuation. The vertical line indicates the SEO filing day. Both issuers with high R&D intensity and issuers with high R&D surprise (solid red lines) have higher price run-ups prior to the SEO filing day compared to issuers with low R&D intensity and issuers with low R&D surprise (dashed black lines), respectively. All the issuers experience price drops within a short window around the SEO filing day, which are followed by a slow price recovery. Figure 5 plots the average market adjusted stock returns cumulated over the same window as Figure 4, confirming that price run-ups after market adjustment are higher for issuers with more intensive R&D expenditures.

Turning to seasoned issuers' valuation multiples prior to the offering, Table 8, Panel A demonstrates that R&D intensive issuers have lower book-to-market ratios (BTM_{it}). In particular, they have an average book-to-market ratio of 26 percent while this number is 391 percent for non-intensive issuers, suggesting that R&D intensive issuers obtain a favorable valuation at the time of offerings. Panel B provides similar result for issuers with high R&D surprise.

¹⁵ Nevertheless, an average price run-up of 36 percent across the high-technology issuers is consistent with the notion that managers, when issuing seasoned equities, time the market to achieve a high valuation (e.g., Baker and Wurgler, 2002; DeAngelo, DeAngelo, and Stulz, 2010).

Table 9 provides the results of the regressions of price run-up prior to offerings on pre-SEO R&D expenditures after controlling for a wide array of relevant factors for SEO pricing including the contemporaneous movement of the stock market. Column (1) explores the variation across issuers based on R&D intensity, and Column (2) explores the variation across issuers based on R&D surprise, both indicating that high pre-SEO R&D expenditures are associated with higher price run-ups. The estimated coefficient on Rank($R \& D_{it-1}$) is significantly positive at the one percent level based on standard errors clustered by firm and year using twotailed tests. The estimated coefficient on Rank($\Delta R \& D_{it-1}$) is of a smaller magnitude and significantly positive at the five percent level, suggesting that investors are less sensitive to R&D surprise than to R&D level at the time of offerings.

In terms of economic significance, moving from a non-intensive issuer to a R&D intensive issuer, stock price run-up increases by nine percent over the 60-day window prior to the offering. Again, moving from an issuer with low R&D surprise to an issuer with high surprise, stock price run-up increases by nine percent over the same window. Together, evidence in Table 8 and Table 9 supports the second prediction that issuers with high pre-SEO R&D expenditures have higher price run-ups prior to the offering, suggesting that investors respond positively to R&D expenditures for high-technology issuers at the time of SEOs.

4.4 Pre-SEO R&D expenditures and long-term stock returns

I next investigate the association between pre-SEO R&D expenditures and long-term stock performance. Table 10 provides evidence that high-technology issuers with high pre-SEO R&D expenditures have inferior long-term stock performance following the offering, using partitions of issuers based on R&D intensity (Panel A) and R&D surprise (Panel B) for the year immediately prior to the offering. Three alternative measures are employed to adjust for risks associated with the market, firm size, and growth, including (i) market adjusted stock returns using the CRSP value-weighted index including distributions, (ii) size adjusted stock returns using the CRSP cap-based portfolio index, and (iii) Fama-French three-factor adjusted stock returns.

Long-term stock performance ($LTRET_{it+3}$), measured over the same window as R&D productivity, is the buy-and-hold adjusted stock return over the 36-month post-SEO period starting the first month of the fiscal year immediately following the SEO issue day. Consistent with the finding of stock underperformance of seasoned issuers (e.g., Spiess and Affleck-Graves, 1995; Loughran and Ritter, 1995), an average high-technology issuer experiences a market adjusted return of -21 percent and a size adjusted return of -20 percent over the three years following the offering, respectively. The Fama-French three-factor adjusted return is minus one percent for an average issuer, which is least negative after adjusting for risks associated with the market, firm size and growth.

Breaking down issuers into three groups on the basis of R&D intensity for the year immediately prior to the offering, Table 10, Panel A indicates that all three measures of long-term stock performance are monotonically decreasing with the rank of R&D intensity. For example, R&D intensive issuers have an average Fama-French three-factor adjusted return of minus ten percent over the three years following the offering, whereas non-intensive issuers have

an average return of four percent, with a significant difference of 15 percent at the one percent level. This difference in long-term performance is most pronounced when return is adjusted by firm size, with a mean value of 18 percent.

Breaking down issuers into three groups on the basis of R&D surprise for the year immediately prior to the offering, Table 10, Panel B shows a similar monotonic negative relation between R&D surprise and long-term stock performance. However, results become weaker in terms of statistical significance, indicating that investors are less responsive to R&D surprise than to R&D level. This echoes the finding on SEO pricing in Section 4.3.

Figure 6 and Figure 7 plot the average market adjusted and size adjusted stock returns cumulated over the 36-month period starting the first month of the fiscal year immediately following the offering for issuers in the top and bottom terciles of R&D intensity (Panel A) and R&D surprise (Panel B), respectively. The vertical lines indicate the fiscal year end of the years following the offering. It is evident that the stock underperformance of issuers with high pre-SEO R&D expenditures is more pronounced when R&D intensity is used for sample partitioning.

Taken together, this section highlights the new finding of a monotonic negative relation between pre-SEO R&D expenditures and long-term stock returns, supporting the last prediction that issuers with high pre-SEO R&D expenditures experience lower long-term stock returns following the offering. Prior research documents that current R&D expenditures positively predict future returns, suggesting that investors underreact to R&D information (e.g., Lev and Sougiannis, 1996; Chan et al., 2001). However, the evidence of higher price run-ups prior to the offering and inferior long-term stock performance thereafter for issuers with high pre-SEO R&D expenditures indicates that investors appear to initially overestimate the future benefits of these R&D expenditures, but are subsequently disappointed by their low productivity over the ensuing years.

Chapter 5

Additional Analyses

5.1 Managerial opportunism or overconfidence

Evidence so far suggests that overinvestment or investment in less productive R&D projects serves to inflate SEO valuation, and eventually results in value destruction following the offering. Managers' R&D overinvestment decision, however, might be driven by their optimistic bias rather than opportunistic intent. As suggested by Malmendier and Tate (2005), optimistic judgments often lead to managerial overconfidence, which in turn affects corporate investment decisions. Also, overconfidence often goes hand in hand with managerial opportunism.¹⁶

In additional analyses, I examine whether issuers with high pre-SEO R&D expenditures are more likely to have overconfident managers. Table 11 reports the frequency of issuers with overconfident managers, using partitions of issuers based on R&D intensity (Panel A) and R&D surprise (Panel B) for the year immediately prior to the offering. I identify overconfident managers based either on their option holdings or on their corporate decisions on acquisition, financing, and distribution that prior research has found to be related with overconfidence. The first measure based on option holdings employs ExecuComp data. Due to missing data and a limited coverage starting from 1992, I obtain a restricted sample of 101 SEOs out of 496 SEOs over the period from 1992 to 2005. The second measure, only requiring Compustat data, covers the full sample of 902 SEOs over the period from 1975 to 2005.

Table 11, Panel A shows that using the overconfidence measure based on option holdings, R&D intensive issuers are more likely to have overconfident mangers, but the difference from non-intensive issuers is insignificant. In addition, the frequency of overconfidence does not monotonically increase with R&D intensity. Turning to the second measure, R&D intensive issuers even show a significantly lower frequency of overconfidence compared to non-intensive issuers. The evidence based on R&D surprise for sample partitioning in Panel B is consistent with that in Panel A. Together, there is no evidence that overconfidence is significantly more prevalent among issuers with high pre-SEO R&D expenditures, which indicates that managers' R&D overinvestment is more likely to be associated with their opportunistic intent to elevate investors' growth expectations.

¹⁶ For example, Schrand and Zechman (2012) argue that managerial overconfidence tends to be followed by opportunistic behavior. Schrand and Zechman (2012) analyze 49 firms subject to AAERs and find that around three quarters of these financial misstatements start from managers' optimistic bias, not necessarily an opportunistic intent to mislead investors. However, optimistic managers, in subsequent periods, are more likely to be in a position where they are compelled to intentionally misstate earnings.

5.2 Managerial opportunism: comparison between SEO firms and non-SEO firms

This section provides further evidence of managerial opportunism around SEOs by comparing SEO firms to a matched sample of non-SEO firms. Specifically, I match each SEO firm to a non-SEO firm using coarsened exact matching based on firm size, sales growth, R&D intensity, and Tobin's Q for the year that is two years prior to the offering. I further match exactly on industry membership and year.

Table 12 shows that issuers and non-issuers have no significant difference in these fundamental characteristics after the matching procedure which generates non-SEO matches for 656 SEO firms. Using partitions of issuers based on R&D intensity, I compare R&D surprise for the year immediately prior to the offering across R&D intensive issuers and R&D intensive non-issuers. I find that R&D intensive issuers have significantly higher R&D surprises prior to the offering than their matched non-issuers. Such issuers also have significantly lower R&D productivity measured by the number of patents and significantly lower size adjusted long-term stock returns over the three years following the offering, suggesting that managers strategically overinvest or invest in less productive R&D projects to boost SEO valuation.¹⁷

5.3 Analysts' forecasts and the frequency of misses

This section provides more direct evidence that high pre-SEO R&D expenditures serve to elevate growth expectations while fail to deliver the expected benefits. Table 13 explores the variation in analysts' long-term growth forecasts (LTG_{it}) and the subsequent frequency of missing analysts' sales forecasts ($MISS_{it+k}$) over the three years following the offering, using partitions of issuers based on R&D intensity (Panel A) and R&D surprise (Panel B) for the year immediately prior to the offering. I use the latest consensus forecasts made preceding the SEO filing day with a long-term horizon for 529 SEOs with analysts' coverage from I/B/E/S. I/B/E/S provides analysts' long-term growth forecasts which represent an expected annual increase in operating earnings over the next three to five years. I/B/E/S, however, does not provide data on realized long-term growth rates. I use analysts' sales forecasts for two reasons. First, unlike long-term growth rates and actual values of sales are available from I/B/E/S. Second, sales are a better growth related metric than earnings for high-technology firms which are characterized by frequent loss reporting.

Table 13, Panel A shows that analysts' long-term growth forecasts are monotonically increasing with the rank of R&D intensity. R&D intensive issuers have an average forecasted long-term growth rate of 31 percent, which is significantly higher than that of non-intensive issuers (24 percent). The last three columns of Table 13, Panel A report the proportions of issuers that miss analysts' sales forecasts (made prior to the offering) for each year over the three years following the offering. I find that 70 percent of R&D intensive issuers fall short of analysts' sales

¹⁷ The comparison between R&D non-intensive issuers and their matched non-issuers finds no significant difference in R&D surprise, R&D productivity, or long-term stock returns (untabulated). This is consistent with my previous finding that R&D intensive issuers, with an anomalous R&D pattern of rising prior to the offering and declining immediately thereafter, are more likely to overinvest in R&D projects.

forecasts for the fiscal year immediately after the offering, whereas this number is 39 percent for non-intensive issuers. For the following two years, R&D intensive issuers continue to miss with significantly higher likelihoods than non-intensive issuers. Panel B confirms that issuers with higher pre-SEO R&D surprise benefit from higher analysts' long-term growth forecasts but are more likely to miss sales expectations subsequently. This evidence suggests that analysts indeed pay attention to R&D expenditures when making growth forecasts for high-technology companies. Analysts, however, fare no better than investors in correctly anticipating the future benefits of pre-SEO R&D expenditures.

5.4 Managers' disclosure of the intended use of proceeds

The evidence thus far indicates that managers strategically overinvest or invest in less productive R&D projects prior to seasoned offerings to elevate investors' growth expectations. In this section, I investigate whether managers voluntarily disclose more information about the intended use of proceeds to complement pre-SEO R&D numbers and thereby reinforce investors' growth expectations.

Seasoned issuers are obliged to discuss the intended use of proceeds in their security registration filings with the SEC, typically Form S-3, while the disclosure level is at the discretion of managers. I manually collect this information from the latest amended S-filings in EDGAR for 328 SEOs between 1997 and 2005 since SEC filings are not publicly available through EDGAR until June 1996. Prior research identifies three main categories of intended use: investment, debt repayment, and general corporate purposes (e.g., Walker and Yost, 2008; Autore, Bray, and Peterson, 2009). I further break down the category of investment into R&D plan and acquisition to provide more detailed analyses of managers' disclosure of intended use. An issuer is classified as having an "R&D plan" if it mentions planned spending on R&D projects. Within issuers having an "R&D plan", the discussion of intended use varies greatly in terms of concreteness. Therefore, I further classify an issuer as having a "specific R&D plan" if it provides information on the specific product lines or research programs related to the R&D plan, or gives quantitative information on the portion of proceeds used for the R&D plan. An issuer falls into the category of general corporate purposes if it does not mention any use of proceeds for R&D, acquisition, or debt repayment.

Table 14 reports the proportions of SEO issuers for each category of intended use of proceeds, using partitions of issuers based on R&D intensity (Panel A) and R&D surprise (Panel B) for the year immediately prior to the offering. Specifically, Panel A shows that the proportion of issuers with intended use of proceeds for R&D purposes increases significantly from 12 percent for non-intensive issuers to 72 percent for R&D intensive issuers. Furthermore, R&D intensive issuers are significantly more likely to have specific plans for future R&D spending and acquisition plans for complementary technologies, products, and businesses. In addition, these issuers tend to state the use of proceeds for debt repayment and general corporate purposes less frequently, which is in line with prior evidence that these two purposes are perceived by investors as negative signals about future growth (e.g., Walker and Yost, 2008). Panel B confirms that a significantly higher proportion of issuers with high R&D surprise fall into the categories of "R&D plan" and "specific R&D plan".

These findings suggest that managers not only overinvest in R&D projects to elevate investors' expectations for future growth, but also voluntarily disclose more nonfinancial information on future R&D plans to reinforce investors' growth expectations.

Chapter 6

Robustness Checks

6.1 Expanded measurement window of five years for R&D productivity

The three-year measurement window for R&D productivity used in the main analyses raises a horizon concern that it might take a longer period for R&D expenditures to translate into innovative output. To address this concern, I expand the measurement window to five years following the offering and find consistent evidence of lower productivity for issuers with high pre-SEO R&D expenditures.

Table 15, Panel A reports that for an average non-intensive issuer, each million dollars of R&D expenditures generate 9 patents in total, 3.76 influential patents, and 4.94 valuable patents over the five years following the offering, and has annual sales of \$400 million over the same period. For an average R&D intensive issuer, however, each million dollars of R&D expenditures generate 2 patents in total, 0.66 influential patents, and 0.75 valuable patents over the five years following the offering, and has annual sales of \$10 million over the same period. Panel B indicates that the differences in productivity are smaller in magnitude whereas the inferences do not change using partitions of issuers based on R&D surprise.

6.2 **R&D** productivity without scaling

To alleviate the concern that the lower productivity of R&D intensive issuers is mainly attributable to the denominator effect, I revise the productivity measures by taking out the scalar, R&D expenditures (XRD_{it-1}), and find consistent evidence of lower innovative output for issuers with high pre-SEO R&D expenditures.

Table 16, Panel A shows that an average R&D intensive issuer generates 22 patents in total, 7 influential patents, and 9 valuable patents over the three years following the offering, and has annual sales of \$180 million over the same period. By contrast, an average non-intensive issuer generates 43 patents in total, 13 influential patents, and 22 valuable patents over the three years following the offering, and has annual sales of \$1 billion over the same period. Panel B confirms that issuers with higher R&D surprise have lower innovative output and sales over the three years following the offering.

6.3 Alternative measure of R&D surprise estimated from discretionary expense model

To check the sensitivity of the results to R&D surprise proxy, I estimate R&D surprise ($ABR\&D_{it-1}$) using discretionary expense model from Cohen and Zarowin (2010) and revisit the main analyses using partitions of issuers based on R&D surprise for the year immediately prior to the offering.

Table 17 presents the descriptive evidence that issuers with higher R&D surprise have significantly lower productivity, in terms of patent counts, patent quality, and operating performance. Table 18 provides the results of the regressions of R&D productivity on R&D surprise. The estimated coefficients on Rank($ABR\&D_{it-1}$) are significantly negative at the one percent level based on standard errors clustered by firm and year using two-tailed tests.

Table 19 and Table 20 illustrate that issuers with higher R&D surprise have higher price run-ups before the SEO announcement and smaller price drops around the announcement. The magnitude of valuation benefit relative to issuers with lower R&D surprise is even greater using model-estimated R&D surprise. Table 21 shows that the more pronounced long-term stock underperformance for issuers with higher R&D surprise is robust to model-estimated surprise. All three measures of long-term stock performance are monotonically decreasing with the rank of model-estimated R&D surprise.

In sum, the main results hold using an alternative measure of R&D surprise estimated from discretionary expense model.

6.4 Exclusion of SEOs affected by internet bubble bursting

The full sample period from 1975 to 2005 includes the years in which the internet bubble burst. This might affect the main results, especially the finding of long-term stock underperformance. Therefore, in this robustness check, I exclude seasoned offerings made over the period from 1999 to 2001, which results in a restricted sample of 787 offerings. I then revisit the main analyses. The results stay substantially the same.

Table 22 and Table 23 provide robust evidence that after excluding SEOs affected by Internet bubble bursting, issuers with high pre-SEO R&D expenditures generate fewer patents, patents of lower quality, and lower sales over the three years following the offering. Table 24 and Table 25 document that issuers with high pre-SEO R&D expenditures have higher price run-ups prior to the offering. The higher price run-ups, however, are followed by lower long-term stock returns over the three years subsequent to the offering, as shown in Table 26.

6.5 Exclusion of software companies

Although most R&D expenditures are not allowed to be capitalized under U.S. GAAP, costs associated with software development can be capitalized when the commercial software achieves technological feasibility or when the software for internal use enters into its application development or implementation stage. The main results therefore might be sensitive to the different accounting treatments for R&D expenditures between software and non-software companies. Thus, I exclude the 111 software companies from the full sample and revisit the main analyses using the remaining 791 non-software seasoned offerings.

Table 27 and Table 28 provide consistent evidence that after excluding software companies, issuers with high pre-SEO R&D expenditures generate fewer patents, patents of lower quality, and lower sales over the three years following the offering. Table 29 and Table 30

present consistent evidence that such issuers have higher price run-ups prior to the offering. The higher price run-ups, however, are followed by lower long-term stock returns over the three years subsequent to the offering, as shown in Table 31. This result becomes even stronger using the sample of non-software offerings.

6.6 Alternative classification of high-technology companies

Pharmaceutical firms are known for their intensive R&D investment and relatively slow conversion from R&D investment to innovative output and sales, which raises a concern that the main results might be largely driven by pharmaceutical firms. Following Loughran and Ritter's (2004) classification which excludes pharmaceutical firms, I obtain a restrictive sample of 564 high-technology issuers. I then revisit the main analyses and find that the main results hold using this alternative classification of high-technology industries.

Table 32 describes the sample distribution by industry. Table 33 and Table 34 provide consistent evidence that issuers with high pre-SEO R&D expenditures generate fewer patents, patents of lower quality, and lower sales over the three years following the offering. Table 35 and Table 36 present consistent evidence that such issuers have higher price run-ups prior to the offering. The higher price run-ups, however, are followed by lower long-term stock returns over the three years subsequent to the offering, as shown in Table 37.

Chapter 7

Conclusion

Focusing on high-technology issuers, this study offers new insights into managers' R&D investment decisions at the time of SEOs. Consistent with prior analytical research (Bebchuk and Stole, 1993), I find that R&D intensive issuers faced with short-term valuation pressure strategically overinvest in R&D projects prior to the offering to elevate investors' growth expectations. Pre-SEO R&D overinvestment, however, manifests itself in lower innovative output and poorer operating performance over the years following the offering. Investors, in turn, appear to be initially optimistic about the future benefits of R&D investments, but are subsequently disappointed by their low productivity. This is evident in higher price run-ups prior to the offering and lower long-term stock returns thereafter for R&D intensive issuers. Such issuers also have higher analysts' long-term growth forecasts made prior to the offering while they are more likely to fall short of analysts' sales forecasts subsequently, suggesting that analysts fare no better than investors in correctly anticipating the future benefits of pre-SEO R&D expenditures. I further document that R&D intensive issuers tend to disclose more nonfinancial R&D information to complement pre-SEO R&D numbers, thereby reinforcing investors' growth expectations. One major takeaway for investors is that, in order to better assess firms' future operating and stock performance, they should not take at face value high R&D expenditures occurring shortly prior to SEOs as overinvestment in R&D destroys value.

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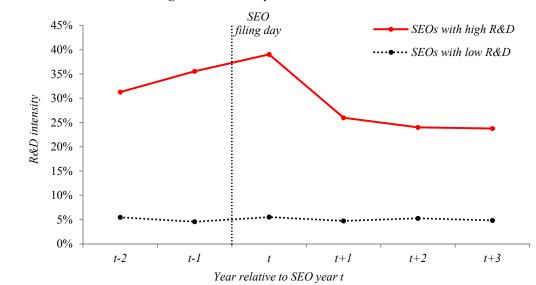
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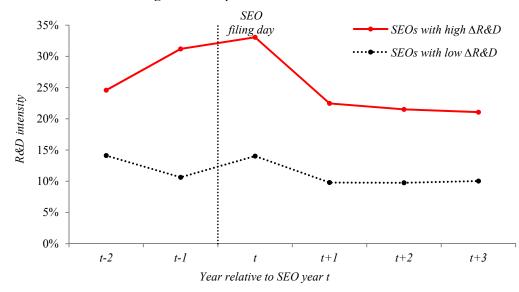
Figures

FIGURE 1 *Time Series of R&D Intensity around SEOs*



Panel A: SEOs with low versus high R&D intensity

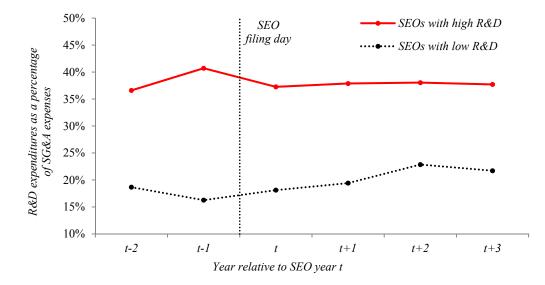
Panel B: SEOs with low versus high R&D surprise



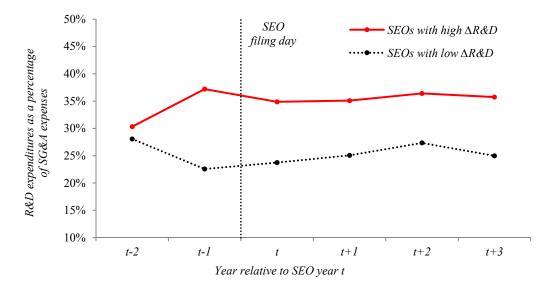
This figure presents the time series of R&D expenditures as a percentage of beginning total assets from two years prior to the SEO year to three years after. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year t+1 is the fiscal year immediately following the SEO issue day. Panel A plots the time series for SEOs in the top (high) and bottom (low) terciles of R&D intensity for fiscal year *t*-1. Panel B plots the time series for SEOs in the top (high) and bottom (low) terciles of R&D surprise for fiscal year *t*-1. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

FIGURE 2 *Time Series of R&D Expenditures as a Percentage of SG&A Expenses*

Panel A: SEOs with low versus high R&D intensity

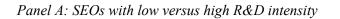


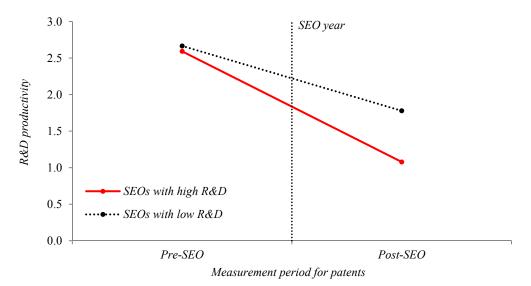
Panel B: SEOs with low versus high R&D surprise



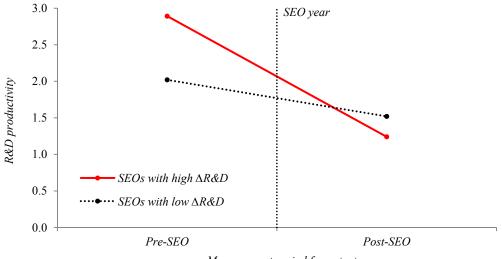
This figure presents the time series of R&D expenditures as a percentage of SG&A expenses from two years prior to the SEO year to three years after. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year t+1 is the fiscal year immediately following the SEO issue day. Panel A plots the time series for SEOs in the top (high) and bottom (low) terciles of R&D intensity for fiscal year *t*-1. Panel B plots the time series for SEOs in the top (high) and bottom (low) terciles of R&D surprise for fiscal year *t*-1. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

FIGURE 3 *The Difference-in-Differences of R&D Productivity*





Panel B: SEOs with low versus high R&D surprise



Measurement period for patents

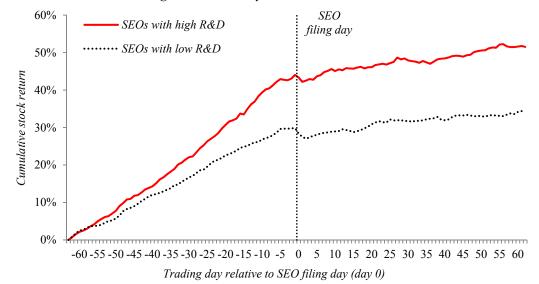
FIGURE 3

(continued)

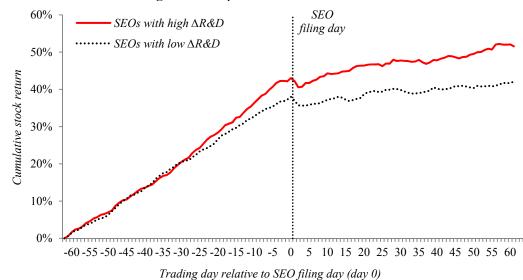
This figure presents the difference-in-differences of R&D productivity between SEO issuers with high and low pre-SEO R&D expenditures. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. For the post-SEO period, R&D productivity is measured as the cumulative number of applications of patents (which are ultimately granted) from fiscal year *t*+1 to *t*+3 divided by the R&D expenditures for fiscal year *t*-1. For the pre-SEO period, R&D productivity is measured as the cumulative number of applications of patents (which are ultimately granted) from fiscal year *t*-4 to *t*-2 divided by the R&D expenditures for fiscal year *t*-6. This analysis employs a restricted sample of 465 SEOs with R&D data available for fiscal year *t*-6. Panel A plots mean R&D productivity for SEOs in the top (high) and bottom (low) terciles of R&D intensity for fiscal year *t*-1. Panel B plots mean R&D productivity for SEOs in the top (high) and bottom (low) terciles of R&D intensity for fiscal year *t*-1. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

FIGURE 4 Pre-SEO R&D Expenditures and Stock Returns around SEOs

Panel A: SEOs with low versus high R&D intensity

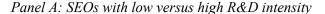


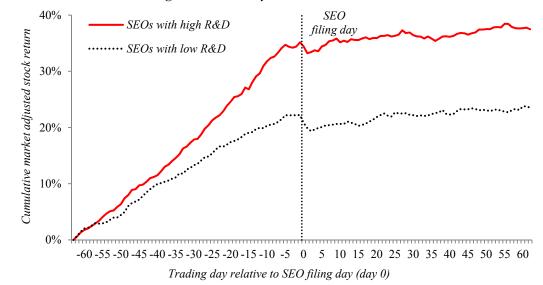
Panel B: SEOs with low versus high R&D surprise



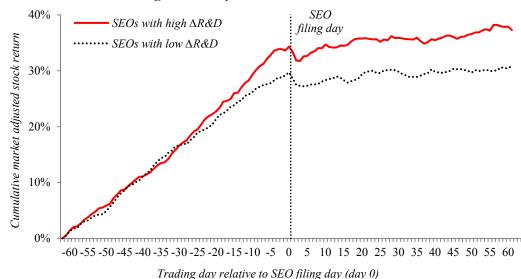
This figure presents the mean cumulative stock returns from 62 trading days before the SEO filing day (day 0) to 62 trading days after. Panel A plots the mean cumulative stock returns for SEOs in the top (high) and bottom (low) terciles of R&D intensity for the fiscal year immediately prior to the SEO filing day. Panel B plots the mean cumulative stock returns for SEOs in the top (high) and bottom (low) terciles of R&D surprise for the fiscal year immediately prior to the SEO filing day. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

FIGURE 5 *Pre-SEO R&D Expenditures and Market Adjusted Stock Returns around SEOs*





Panel B: SEOs with low versus high R&D surprise

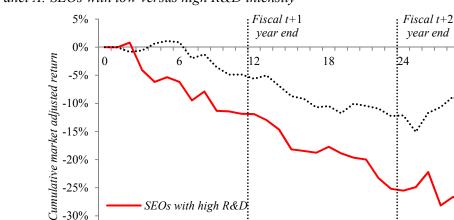


This figure presents the mean cumulative market adjusted stock returns from 62 trading days before the SEO filing day (day 0) to 62 trading days after. Panel A plots the mean cumulative market adjusted stock returns for SEOs in the top (high) and bottom (low) terciles of R&D intensity for the fiscal year immediately prior to the SEO filing day. Panel B plots the mean cumulative market adjusted stock returns for SEOs in the top (high) and bottom (low) terciles of R&D surprise for the fiscal year immediately prior to the SEO filing day. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

FIGURE 6 Pre-SEO R&D Expenditures and Post-SEO Market Adjusted Long-Term Stock Returns

30

36



SEOs with high R&D

••••••• SEOs with low R&D

Panel A: SEOs with low versus high R&D intensity

-15%

-20%

-25%

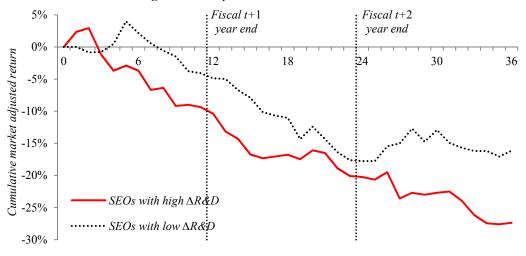
-30%

-35%

Month relative to fiscal end of SEO year t

÷

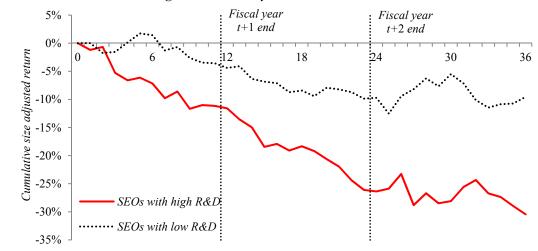
Panel B: SEOs with low versus high R&D surprise



Month relative to fiscal end of SEO year t

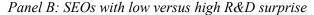
This figure presents the mean cumulative market adjusted stock returns over the 36-month post-SEO period starting the first month of the fiscal year immediately following the SEO issue day. The vertical lines indicate the end of fiscal year t+1 and t+2 following SEO year t, respectively. Panel A plots the mean cumulative market adjusted stock returns for SEOs in the top (high) and bottom (low) terciles of R&D intensity for the fiscal year immediately prior to the SEO filing day. Panel B plots the mean cumulative market adjusted stock returns for SEOs in the top (high) and bottom (low) terciles of R&D surprise for the fiscal year immediately prior to the SEO filing day. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

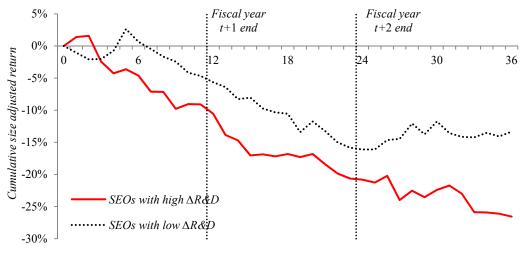
FIGURE 7 Pre-SEO R&D Expenditures and Post-SEO Size Adjusted Long-Term Stock Returns



Panel A: SEOs with low versus high R&D intensity

Month relative to the end of SEO year t





Month relative to the end of SEO year t

This figure presents the mean cumulative size adjusted stock returns over the 36-month post-SEO period starting the first month of the fiscal year immediately following the SEO issue day. The vertical lines indicate the end of fiscal year t+1 and t+2 following SEO year t, respectively. Panel A plots the mean cumulative size adjusted stock returns for SEOs in the top (high) and bottom (low) terciles of R&D intensity for the fiscal year immediately prior to the SEO filing day. Panel B plots the mean cumulative size adjusted stock returns for SEOs in the top (high) and bottom (low) terciles of R&D surprise for the fiscal year immediately prior to the SEO filing day. Panel B plots the mean cumulative size adjusted stock returns for SEOs in the top (high) and bottom (low) terciles of R&D surprise for the fiscal year immediately prior to the SEO filing day. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

Tables

TABLE 1Sample Selection

Panel A: Sample selection

| Sample selection | # of SEOs |
|--|--------------|
| High-technology SEOs on NYSE/NASDAQ/AMEX from 1975 to 2005 with offering price above \$5, excluding spin-offs, reverse LBOs, closed-end funds, unit investment trusts, REITs, limited partnerships, rights issues, unit offerings, nondomestic and simultaneous domestic-international offers | 2,223 |
| Exclude SEOs with missing link to Compustat or CRSP | (609) |
| Exclude SEOs with missing R&D expenditures for the two years prior to the SEO filing day | (658) |
| Exclude SEOs with missing financial data for the year prior to the SEO filing day | (54) |
| Final sample | 902 |

Panel B: Sample distribution across years

| Offer years | # of SEOs | % of Sample |
|-------------|-----------|-------------|
| 1975 - 1980 | 85 | 9.42 |
| 1981 - 1985 | 174 | 19.29 |
| 1986 - 1990 | 81 | 8.98 |
| 1991 - 1995 | 190 | 21.06 |
| 1996 - 2000 | 193 | 21.40 |
| 2001 - 2005 | 179 | 19.84 |
| Total | 902 | 100.00 |

Panel C: Sample distribution across industries

| Industry | # of SEOs | % of Sample |
|--|-----------|-------------|
| Business services (computer and R&D related) | 17 | 1.88 |
| Computers | 96 | 10.64 |
| Computer software | 111 | 12.31 |
| Electrical equipment (tech related) | 9 | 1.00 |
| Electronic equipment | 239 | 26.50 |
| Measuring and control equipment | 86 | 9.53 |
| Medical equipment | 101 | 11.20 |
| Pharmaceutical products | 225 | 24.94 |
| Telecommunication | 18 | 2.00 |
| Total | 902 | 100.00 |

(continued)

This table describes the sample selection process (Panel A) and presents the distributions and descriptive statistics of the final sample. Panel B breaks down the sample by year. Panel C breaks down the sample based on the nine high-technology industries identified by Fama and French's (1997) 49-industry classification. The final sample includes 902 SEOs from 1975 to 2005.

| |) I | | 0.1 D | Percentiles | | |
|----------------------------|-----|---------|-----------|-------------|--------|---------|
| Variable | Ν | Mean | Std. Dev. | 25th | 50th | 75th |
| ASSET _{it-1} (BN) | 902 | \$0.49 | \$2.43 | \$0.03 | \$0.07 | \$0.18 |
| $SALE_{it-1}$ (BN) | 902 | \$0.34 | \$1.36 | \$0.02 | \$0.05 | \$0.15 |
| $XRD_{it-1}(MN)$ | 902 | \$26.47 | \$72.56 | \$2.79 | \$7.00 | \$20.39 |
| $SIZE_{it-1}$ | 902 | 4.40 | 1.49 | 3.40 | 4.20 | 5.17 |
| $R\&D_{it-1}$ | 902 | 0.18 | 0.19 | 0.06 | 0.12 | 0.22 |
| $\Delta R \& D_{it-1}$ | 902 | 0.04 | 0.09 | 0.00 | 0.02 | 0.05 |
| $SCALE_{it-1}$ | 902 | 0.52 | 1.26 | 0.05 | 0.14 | 0.36 |
| SG_{it-1} | 902 | 0.51 | 1.22 | 0.08 | 0.27 | 0.55 |
| ROA_{it-1} | 902 | 0.03 | 0.31 | -0.11 | 0.11 | 0.22 |
| LEV _{it-1} | 902 | 0.18 | 0.20 | 0.01 | 0.13 | 0.29 |
| $CASH_{it-1}$ | 902 | 0.28 | 0.27 | 0.05 | 0.19 | 0.46 |
| CAP_{it-1} | 902 | 0.21 | 0.14 | 0.10 | 0.19 | 0.30 |
| CAPEX _{it-1} | 902 | 0.10 | 0.11 | 0.03 | 0.07 | 0.13 |
| TOBIN _{it-1} | 902 | 3.00 | 2.45 | 1.34 | 2.16 | 3.69 |
| RUNUP _{it} | 902 | 0.36 | 0.44 | 0.07 | 0.27 | 0.51 |
| MRUNUP _{it} | 902 | 0.06 | 0.06 | 0.02 | 0.06 | 0.10 |
| $DROP_{it}$ | 902 | -0.01 | 0.08 | -0.06 | -0.02 | 0.03 |
| BTM_{it} | 902 | 0.34 | 0.24 | 0.17 | 0.28 | 0.45 |

TABLE 2Descriptive Statistics

This table reports the empirical distributions of main variables used in the analysis. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| | # of | | | | | Paired t- | tests | |
|---|--------------|---------------------------------------|---------------|---------------|-------------------------------|-----------|-------------------------------|--------|
| $\operatorname{Rank}(R\&D_{it-1})$ | SEOs | <i>R&D</i> _{<i>it</i>-2} | $R\&D_{it-1}$ | $R\&D_{it+1}$ | $R\&D_{it-1}$ - $R\&D_{it-2}$ | t-stat | $R\&D_{it+1}$ - $R\&D_{it-1}$ | t-stat |
| All SEOs | 902 | 16.66% | 17.84% | 14.61% | 1.18%** | 2.43 | -3.46%*** | -6.26 |
| Low | 293 | 5.47% | 4.56% | 4.73% | -0.91%** | -2.42 | 0.14% | 0.85 |
| Medium | 310 | 13.14% | 13.31% | 12.46% | 0.17% | 0.37 | -0.76% | -1.39 |
| High | 299 | 31.27% | 35.55% | 25.98% | 4.28%*** | 3.25 | -9.53%*** | -6.55 |
| Panel B: SEOs | with low | versus hig | gh R&D sı | ırprise | | | | |
| | # of | | | | | Paired | t-tests | |
| $\operatorname{Rank}(\Delta R \& D_{it-1})$ | # 01 SEOs | $R\&D_{it-2}$ | $R\&D_{it}$ | $R\&D_{it}$ | +1 $R\&D_{it-1}$ - | tatat | $R\&D_{it+1}$ - | t atat |

TABLE 3Time Series of R&D Expenditures around SEOs

Panel A: SEOs with low versus high R&D intensity

| | # of | of | | | Paired t-tests | | | |
|---|--------------|---------------|---------------|---------------|--|--------|-------------------------------|--------|
| $\operatorname{Rank}(\Delta R \& D_{it-1})$ | # of SEOs | $R\&D_{it-2}$ | $R\&D_{it-1}$ | $R\&D_{it+1}$ | <i>R&D_{it-1} -</i> <i>R&D_{it-2}</i> | t-stat | $R\&D_{it+1}$ - $R\&D_{it-1}$ | t-stat |
| All SEOs | 902 | 16.66% | 17.84% | 14.61% | 1.18%** | 2.43 | -3.46%*** | -6.26 |
| Low | 293 | 14.11% | 10.63% | 9.79% | -3.48%*** | -3.5 | -1.01%* | -1.79 |
| Medium | 310 | 11.42% | 11.77% | 11.18% | 0.35% | 0.93 | -0.67% | -0.83 |
| High | 299 | 24.58% | 31.20% | 22.47% | 6.62%*** | 7.04 | -8.49*** | -6.78 |

This table reports the mean R&D intensity for the two fiscal years immediately prior to the SEO year and the fiscal year immediately following the SEO year, and examines the time series of R&D intensity using paired t-tests. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issuers day. Panel A sorts SEO issuers into terciles of R&D intensity for fiscal year *t*-1. Panel B sorts SEO issuers into terciles of R&D intensity for fiscal year *t*-1. Panel B sorts SEO issuers into terciles of R&D intensity for fiscal year *t*-1. Panel B sorts SEO issuers into terciles of R&D surprise for fiscal year *t*-1. ***, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| | | Productivity measures | | | | |
|------------------------------------|--------------|---|--|--|---|--|
| $\operatorname{Rank}(R\&D_{it-1})$ | # of SEOs | $\frac{\sum_{\tau=1}^{3} PATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} IPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} VPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} SALE_{it+\tau} / 3}{XRD_{it-1}}$ | |
| All SEOs | 902 | 1.48 | 0.40 | 0.54 | 0.05 | |
| Low | 293 | 2.24 | 0.61 | 0.80 | 0.12 | |
| Medium | 310 | 1.24 | 0.31 | 0.46 | 0.02 | |
| High | 299 | 0.99 | 0.30 | 0.37 | 0.01 | |
| High - Low | | -1.25*** | -0.31*** | -0.43*** | -0.11*** | |
| t-statistic | | -4.74 | -3.22 | -3.83 | -8.92 | |

 TABLE 4

 Productivity of Pre-SEO R&D Expenditures

Panel B: SEOs with low versus high R&D surprise

Panel A: SEOs with low versus high R&D intensity

| | | Productivity measures | | | | |
|-------------------------------|--------------|---|--|--|---|--|
| Rank $(\Delta R \& D_{it-1})$ | # of SEOs | $\frac{\sum_{\tau=1}^{3} PATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} IPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} VPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{r=1}^{3} SALE_{it+r} / 3}{XRD_{it-1}}$ | |
| All SEOs | 902 | 1.48 | 0.40 | 0.54 | 0.05 | |
| Low | 293 | 1.96 | 0.54 | 0.64 | 0.09 | |
| Medium | 310 | 1.43 | 0.36 | 0.59 | 0.04 | |
| High | 299 | 1.07 | 0.32 | 0.40 | 0.02 | |
| High - Low | | -0.89*** | -0.22** | -0.24** | -0.08**** | |
| t-statistic | | -3.40 | -2.26 | -2.19 | -6.61 | |

This table reports evidence of variation in R&D productivity on pre-SEO R&D expenditures. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. R&D productivity is measured as the cumulative number of applications of patents, influential patents, and valuable patents (which are ultimately granted), and average sales over the three-year period from fiscal year *t*+1 to *t*+3 scaled by the R&D expenditures for fiscal year *t*-1. Panel A (Panel B) reports the mean productivity of pre-SEO R&D expenditures based on the standardized tercile rank of R&D intensity (R&D surprise) for fiscal year *t*-1. Note that in Panel B the average productivity in terms of sales for issuers with low surprise (high surprise) before rounding is 0.094 (0.017), with a difference of 0.077 which is rounded up to 0.08. ***, **, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| | R&D productivity | | | | | |
|----------------------------|--------------------------------------|---------------------------------------|--|--|--|--|
| | (1) | (2) | (3) | (4) | | |
| | $\sum_{\tau=1}^{3} PATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} IPATENT_{it+\tau}$ | $\sum\nolimits_{\tau=1}^{3} VPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} SALE_{it+\tau} / 3$ | | |
| | XRD _{it-1} | XRD _{it-1} | $\overline{XRD_{it-1}}$ | XRD _{it-1} | | |
| INTERCEPT | 3.532*** | 0.692*** | 1.301*** | 0.070^{***} | | |
| | (4.17) | (3.11) | (3.75) | (3.34) | | |
| Rank(R&D _{it-1}) | -1.335*** | -0.270*** | -0.405*** | -0.063*** | | |
| | (-3.40) | (-2.53) | (-2.76) | (-5.32) | | |
| SCALE _{it-1} | 0.120 | 0.051 | 0.051 | 0.021*** | | |
| | (1.18) | (1.11) | (1.08) | (10.66) | | |
| SIZE _{it-1} | -0.158* | 0.001 | 0.040 | 0.004 | | |
| | (-1.70) | (0.03) | (1.05) | (1.29) | | |
| SG_{it-1} | 0.067 | -0.005 | -0.005 | 0.002 | | |
| | (1.04) | (-0.34) | (-0.26) | (0.85) | | |
| ROA_{it-1} | 0.022 | -0.056 | 0.030 | -0.001 | | |
| | (0.08) | (-0.57) | (0.24) | (-0.11) | | |
| LEV _{it-1} | 0.113 | 0.048 | -0.057 | 0.044^{*} | | |
| | (0.33) | (0.38) | (-0.34) | (1.76) | | |
| TOBIN _{it-1} | 0.042 | 0.007 | 0.035 | 0.000 | | |
| | (0.63) | (0.32) | (1.01) | (0.41) | | |
| CAP_{it-1} | 2.458*** | 0.959*** | 1.131*** | -0.142*** | | |
| | (2.89) | (3.13) | (2.76) | (-4.24) | | |
| CAPEX _{it-1} | 0.708 | 0.630 | 0.606 | 0.102*** | | |
| | (0.45) | (1.00) | (1.00) | (2.88) | | |
| CASH _{it-1} | 1.318*** | 0.566*** | 0.630*** | -0.051** | | |
| | (3.32) | (3.47) | (2.80) | (-2.41) | | |
| Industry fixed effects | Yes | Yes | Yes | Yes | | |
| Year fixed effects | Yes | Yes | Yes | Yes | | |
| Number of SEOs | 902 | 902 | 902 | 902 | | |
| Adj. R ² | 25.93% | 24.78% | 21.90% | 44.02% | | |

TABLE 5Regressions of R&D Productivity on Pre-SEO R&D Expenditures

| TABLE 5 |
|-------------|
| (continued) |

| | R&D productivity | | | | | | |
|---------------------------------------|--------------------------------------|---------------------------------------|--|--|--|--|--|
| | (1) | (2) | (3) | (4) | | | |
| | $\sum_{\tau=1}^{3} PATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} IPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} VPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} SALE_{it+\tau} / 3$ | | | |
| | $\frac{1}{XRD_{it-1}}$ | XRD_{it-1} | $\underline{\qquad}$ XRD _{it-1} | $\frac{2}{XRD_{it-1}}$ 0.042*** | | | |
| INTERCEPT | 2.947*** | 0.592*** | 1.084*** | 0.042*** | | | |
| | (3.58) | (2.66) | (3.02) | (2.48) | | | |
| $\mathbf{Rank}(\Delta R \& D_{it-1})$ | -0.893*** | -0.205* | -0.218** | -0.041*** | | | |
| | (-2.54) | (-1.83) | (-1.94) | (-3.41) | | | |
| $SCALE_{it-1}$ | 0.132 | 0.053 | 0.056 | 0.022*** | | | |
| | (1.31) | (1.16) | (1.19) | (10.50) | | | |
| $SIZE_{it-1}$ | -0.129 | 0.006 | 0.050 | 0.006^{*} | | | |
| | (-1.36) | (0.23) | (1.24) | (1.75) | | | |
| SG_{it-1} | 0.080 | -0.002 | -0.002 | 0.003 | | | |
| | (1.22) | (-0.14) | (-0.12) | (0.98) | | | |
| ROA_{it-1} | 0.485^{*} | 0.037 | 0.172 | 0.021* | | | |
| | (1.82) | (0.38) | (1.52) | (1.87) | | | |
| LEV_{it-1} | 0.150 | 0.050 | -0.034 | 0.046^{*} | | | |
| | (0.43) | (0.38) | (-0.20) | (1.80) | | | |
| TOBIN _{it-1} | 0.029 | 0.005 | 0.030 | -0.000 | | | |
| | (0.43) | (0.22) | (0.87) | (-0.16) | | | |
| CAP_{it-1} | 2.619*** | 0.980*** | 1.204*** | -0.134*** | | | |
| | (3.11) | (3.23) | (2.89) | (-4.12) | | | |
| CAPEX _{it-1} | 0.746 | 0.664 | 0.559 | 0.102*** | | | |
| | (0.43) | (0.98) | (0.85) | (2.53) | | | |
| CASH _{it-1} | 1.180**** | 0.543*** | 0.578^{**} | -0.058*** | | | |
| | (2.63) | (3.13) | (2.40) | (-2.75) | | | |
| Industry fixed effects | Yes | Yes | Yes | Yes | | | |
| Year fixed effects | Yes | Yes | Yes | Yes | | | |
| Number of SEOs | 902 | 902 | 902 | 902 | | | |
| Adj. R ² | 24.87% | 24.55% | 21.15% | 42.78% | | | |

Panel B: Regressions of R&D productivity on R&D surprise

(continued)

This table reports evidence of variation in R&D productivity on pre-SEO R&D expenditures. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. R&D productivity is measured as the cumulative number of applications of patents, influential patents, and valuable patents (which are ultimately granted), and average sales over the three-year period from fiscal year *t*+1 to *t*+3 scaled by the R&D expenditures for fiscal year *t*-1. Panel A (Panel B) reports results from pooled OLS regressions of R&D productivity on the rank of R&D intensity (R&D surprise) along with a vector of control variables. Industry fixed effects are based on Fama and French's (1997) 49-industry classification. The reported t-statistics in parentheses are based on standard errors clustered by firm and year. ***, **, * represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| TABLE 6 |
|--|
| Regressions of R&D Productivity on Pre-SEO R&D Expenditures: Controlling for State Fixed Effects |

| | R&D productivity | | | | | |
|----------------------------|---|--|---|--|--|--|
| - | (1) | (2) | (3) | (4) | | |
| | $\sum_{\tau=1}^{3} PATENT_{it+\tau}$ | $\sum\nolimits_{\tau=1}^{3} IPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} VPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} SALE_{it+\tau} / 3$ | | |
| | <i>XRD</i> _{<i>it-1</i>} 5.459 ^{***} | $\frac{2}{XRD_{it-1}}$ 1.182*** | <i>XRD</i> _{<i>it-1</i>} 2.328 ^{***} | XRD _{it-1} | | |
| INTERCEPT | 5.459*** | 1.182*** | 2.328*** | 0.103* | | |
| | (3.95) | (3.29) | (3.44) | (1.77) | | |
| Rank(R&D _{it-1}) | -1.345*** | -0.275*** | -0.414*** | -0.065*** | | |
| | (-3.36) | (-2.59) | (-2.75) | (-4.91) | | |
| SCALE _{it-1} | 0.131 | 0.057 | 0.055 | 0.020^{***} | | |
| | (1.31) | (1.25) | (1.17) | (9.89) | | |
| SIZE _{it-1} | -0.191** | -0.013 | 0.023 | 0.004 | | |
| | (-1.99) | (-0.43) | (0.61) | (1.34) | | |
| SG_{it-1} | 0.075 | -0.004 | -0.002 | 0.002 | | |
| | (1.13) | (-0.30) | (-0.10) | (0.74) | | |
| ROA_{it-1} | 0.057 | -0.015 | 0.072 | -0.004 | | |
| | (0.17) | (-0.14) | (0.48) | (-0.38) | | |
| LEV_{it-1} | 0.061 | 0.003 | -0.103 | 0.036 | | |
| | (0.16) | (0.02) | (-0.57) | (1.46) | | |
| TOBIN _{it-1} | 0.026 | 0.004 | 0.029 | 0.001 | | |
| | (0.41) | (0.21) | (0.94) | (0.63) | | |
| CAP_{it-1} | 1.986** | 0.830*** | 0.968** | -0.135*** | | |
| | (2.14) | (2.46) | (2.20) | (-3.79) | | |
| $CAPEX_{it-1}$ | 0.687 | 0.650 | 0.521 | 0.082^{**} | | |
| | (0.45) | (1.12) | (0.91) | (2.42) | | |
| $CASH_{it-1}$ | 1.028*** | 0.473*** | 0.529** | -0.052*** | | |
| | (2.45) | (2.89) | (2.26) | (-2.45) | | |
| Industry fixed effects | Yes | Yes | Yes | Yes | | |
| Year fixed effects | Yes | Yes | Yes | Yes | | |
| State fixed effects | Yes | Yes | Yes | Yes | | |
| Number of SEOs | 902 | 902 | 902 | 902 | | |
| Adj. R ² | 29.83% | 28.28% | 26.61% | 48.06% | | |

Panel A: Regressions of R&D productivity on R&D intensity

(continued)

| | R&D productivity | | | | |
|---------------------------|---|---------------------------------------|---------------------------------------|--|--|
| | (1) | (2) | (3) | (4) | |
| | $\sum_{\tau=1}^{3} PATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} IPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} VPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} SALE_{it+\tau} / 3$ | |
| | <u>XRD_{it-1}</u> 4.881 ^{***} | XRD_{it-1} | XRD_{it-1} | XRD _{it-1} | |
| INTERCEPT | 4.881*** | 1.095*** | 2.125*** | 0.072 | |
| | (3.44) | (2.94) | (3.06) | (1.22) | |
| Rank(\alpha R & D_{it-1}) | -0.884*** | -0.219** | -0.241*** | -0.039*** | |
| | (-2.53) | (-1.99) | (-2.27) | (-3.44) | |
| SCALE _{it-1} | 0.141 | 0.058 | 0.059 | 0.021*** | |
| | (1.43) | (1.30) | (1.27) | (9.66) | |
| SIZE _{it-1} | -0.169* | -0.009 | 0.030 | 0.005^{*} | |
| | (-1.75) | (-0.29) | (0.79) | (1.78) | |
| SG_{it-1} | 0.084 | -0.001 | 0.000 | 0.002 | |
| | (1.31) | (-0.10) | (0.02) | (0.85) | |
| ROA_{it-1} | 0.527 | 0.081 | 0.217 | 0.018 | |
| | (1.55) | (0.73) | (1.51) | (1.58) | |
| LEV_{it-1} | 0.106 | 0.004 | -0.083 | 0.039 | |
| | (0.28) | (0.03) | (-0.44) | (1.55) | |
| TOBIN _{it-1} | 0.016 | 0.003 | 0.025 | 0.000 | |
| | (0.25) | (0.15) | (0.84) | (0.01) | |
| CAP_{it-1} | 2.152** | 0.849*** | 1.031** | -0.125*** | |
| | (2.37) | (2.55) | (2.33) | (-3.69) | |
| $CAPEX_{it-1}$ | 0.815 | 0.717 | 0.528 | 0.084^{**} | |
| | (0.49) | (1.14) | (0.87) | (2.28) | |
| CASH _{it-1} | 0.970^{**} | 0.468*** | 0.505** | -0.055*** | |
| | (1.99) | (2.64) | (1.98) | (-2.62) | |
| Industry fixed effects | Yes | Yes | Yes | Yes | |
| Year fixed effects | Yes | Yes | Yes | Yes | |
| State fixed effects | Yes | Yes | Yes | Yes | |
| Number of SEOs | 902 | 902 | 902 | 902 | |
| Adj. R ² | 28.93% | 28.16% | 26.03% | 46.80% | |

Panel B: Regressions of R&D productivity on R&D surprise

(continued)

This table reports evidence of variation in R&D productivity on pre-SEO R&D expenditures controlling for state fixed effects. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. R&D productivity is measured as the cumulative number of applications of patents, influential patents, and valuable patents (which are ultimately granted), and average sales over the three-year period from fiscal year *t*+1 to *t*+3 scaled by the R&D expenditures for fiscal year *t*-1. Panel A (Panel B) reports results from pooled OLS regressions of R&D productivity on the rank of R&D intensity (R&D surprise) along with a vector of control variables. Industry fixed effects are based on Fama and French's (1997) 49industry classification. The reported t-statistics in parentheses are based on standard errors clustered by firm and year. ***, **, * represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| | | R& | R&D productivity | | |
|---|-----------|---|---|-------------------------------------|--|
| Rank(<i>R&D</i> _{<i>it</i>-1}) | # of SEOs | Pre-SEO $\frac{\sum_{r=2}^{4} PATENT_{it-r}}{XRD_{it-6}}$ | $\frac{\text{Post-SEO}}{\sum_{\tau=1}^{3} PATENT_{it+\tau}} XRD_{it-1}$ | Diff: Post- SEO minus Pre-SEO | |
| All SEOs | 465 | 2.51 | 1.42 | -1.09 | |
| Low | 175 | 2.67 | 1.78 | -0.89 | |
| Medium | 172 | 2.29 | 1.29 | -1.00 | |
| High | 118 | 2.59 | 1.08 | -1.51 | |
| High - Low | | -0.07 | -0.70**** | -0.63*** | |
| t-statistic | | -0.14 | -2.59 | -2.92 | |

TABLE 7 Difference-in-Differences Analysis of R&D Productivity

Panel B: SEOs with low versus high R&D surprise

Panel A: SEOs with low versus high R&D intensity

| | | R&D productivity | | | | |
|---|-----------|---|--|-------------------------------------|--|--|
| $\operatorname{Rank}(\Delta R \& D_{it-1})$ | # of SEOs | Pre-SEO $\frac{\sum_{r=2}^{4} PATENT_{it-r}}{XRD_{it-6}}$ | Post-SEO $\frac{\sum_{r=1}^{3} PATENT_{it+r}}{XRD_{it-1}}$ | Diff: Post- SEO minus Pre-SEO | | |
| All SEOs | 465 | 2.51 | 1.42 | -1.09 | | |
| Low | 176 | 2.02 | 1.52 | -0.50 | | |
| Medium | 178 | 2.75 | 1.43 | -1.32 | | |
| High | 111 | 2.89 | 1.24 | -1.65 | | |
| High - Low | | 0.87^{*} | -0.28 | -1.15*** | | |
| t-statistic | | 1.68 | -1.03 | -2.24 | | |

This table reports the mean R&D productivity for pre- and post-SEO period respectively, and presents the results of a difference-in-differences analysis of R&D productivity between SEO issuers with high and low pre-SEO R&D expenditures using t-tests. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. For the post-SEO period, R&D productivity is measured as the cumulative number of applications of patents (which are ultimately granted) from fiscal year *t*+1 to *t*+3 divided by the R&D expenditures for fiscal year *t*-1. For the pre-SEO period, R&D productivity is measured as the cumulative number of applications of patents (which are ultimately granted) from fiscal year *t*-4 to *t*-2 divided by the R&D expenditures for fiscal year *t*-6. This analysis employs a restricted sample of 465 SEOs with R&D data available for fiscal year *t*-6. Panel A sorts SEO issuers into terciles of R&D intensity for fiscal year *t*-1. Panel B sorts SEO issuers into terciles of R&D surprise for fiscal year *t*-1. ***, * represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| Panel A: SEOs with low versus high R&D intensity | | | | | | |
|--|-----------|---------------------|-------------|------------|--|--|
| $\operatorname{Rank}(R\&D_{it-1})$ | # of SEOs | RUNUP _{it} | $DROP_{it}$ | BTM_{it} | | |
| All SEOs | 902 | 35.54% | -1.22% | 33.53% | | |
| Low | 293 | 28.79% | -2.37% | 39.11% | | |
| Medium | 310 | 35.83% | -0.66% | 35.64% | | |
| High | 299 | 41.87% | -0.68% | 25.87% | | |
| High - Low | | 13.08%*** | 1.69%** | -13.24%*** | | |
| t-statistic | | 3.71 | 2.54 | -7.04 | | |

TABLE 8Pre-SEO R&D Expenditures and SEO Pricing

Panel B: SEOs with low versus high R&D surprise

| Rank($\Delta R \& D_{it-1}$) | # of SEOs | RUNUP _{it} | DROP _{it} | BTM_{it} |
|--------------------------------|-----------|---------------------|--------------------|------------|
| All SEOs | 902 | 35.54% | -1.22% | 33.53% |
| Low | 293 | 33.14% | -1.22% | 39.68% |
| Medium | 310 | 30.77% | -0.77% | 34.68% |
| High | 299 | 42.85% | -1.68% | 26.31% |
| High - Low | | 9.71%*** | -0.46% | -13.37%*** |
| t-statistic | | 2.58 | -0.66 | -6.82 |

This table reports evidence of variation in SEO pricing on pre-SEO R&D expenditures. Year *t* is the year in which an issuer files SEO, and year *t*-1 is the fiscal year immediately prior to the SEO filing day. Panel A (Panel B) reports the mean values of valuation measures around SEOs based on the standardized tercile rank of R&D intensity (R&D surprise) for fiscal year *t*-1. ***, ** , * represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| | Price run-ups prior to SEOs | |
|--|-----------------------------|----------------------------|
| | (1) | (2) |
| | <i>RUNUP</i> _{it} | <i>RUNUP</i> _{it} |
| INTERCEPT | 0.252*** | 0.269*** |
| | (3.39) | (3.64) |
| $\mathbf{Rank}(\mathbf{R}\&\mathbf{D}_{it-1})$ | 0.093*** | |
| | (2.80) | |
| Rank($\Delta R \& D_{it-1}$) | | 0.089** |
| | | (2.04) |
| MRUNUP _{it} | 1.989*** | 2.014*** |
| | (8.53) | (8.33) |
| SIZE _{it-1} | -0.036*** | -0.037*** |
| | (-4.60) | (-4.67) |
| SG_{it-1} | 0.003 | 0.002 |
| | (0.31) | (0.20) |
| ROA_{it-1} | -0.064 | -0.096*** |
| | (-1.47) | (-2.71) |
| LEV _{it-1} | 0.037 | 0.039 |
| | (0.50) | (0.51) |
| TOBIN _{it-1} | -0.009 | -0.009 |
| | (-0.68) | (-0.66) |
| CAP_{it-1} | 0.168 | 0.168 |
| | (1.18) | (1.20) |
| CAPEX _{it-1} | -0.154 | -0.186 |
| | (-0.97) | (-1.14) |
| CASH _{it-1} | 0.070 | 0.074 |
| | (0.57) | (0.62) |
| Industry fixed effects | Yes | Yes |
| Year fixed effects | Yes | Yes |
| Number of SEOs | 902 | 902 |
| Adj. R ² | 28.89% | 28.93% |

 TABLE 9

 Regressions of Price Run-ups on Pre-SEO R&D Expenditures

(continued)

This table reports evidence of variation in SEO pricing on pre-SEO R&D expenditures. Year *t* is the year in which an issuer files SEO, and year *t*-1 is the fiscal year immediately prior to the SEO filing day. It reports results from pooled OLS regressions of issuers' stock price run-up prior to the SEO filing day on the rank of pre-SEO R&D expenditures along with a vector of control variables. Stock price run-up is measured as the cumulative 60-day stock return from 62 trading days before to three trading days before the SEO filing day. Industry fixed effects are based on Fama and French's (1997) 49-industry classification. The reported t-statistics in parentheses are based on standard errors clustered by firm and year. ***, **, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| TABLE 10 |
|---|
| Pre-SEO R&D Expenditures and Post-SEO Long-Term Stock Returns |

| $\operatorname{Rank}(R \& D_{it-1})$ | | $LTRET_{it+3}$ | | |
|--------------------------------------|-----------|-----------------|---------------|-----------------------------------|
| | # of SEOs | Market adjusted | Size adjusted | Fama-French 3- factor adjusted |
| All SEOs | 902 | -21.30% | -19.96% | -1.14% |
| Low | 293 | -13.04% | -11.64% | 4.38% |
| Medium | 310 | -19.80% | -18.28% | 2.63% |
| High | 299 | -30.97% | -29.75% | -10.45% |
| High - Low | | -17.93%*** | -18.11%** | -14.83%*** |
| t-statistic | | -2.71 | -2.31 | -2.72 |

Panel A: SEOs with low versus high R&D intensity

Panel B: SEOs with low versus high R&D surprise

| | | | LTRET _{it+3} | |
|---|-----------|----------------------|-----------------------|-----------------------------------|
| $\operatorname{Rank}(\Delta R \& D_{it-1})$ | # of SEOs | Market adjusted | Size adjusted | Fama-French 3- factor adjusted |
| All SEOs | 902 | -21.30% | -19.96% | -1.14% |
| Low | 293 | -15.40% | -14.21% | 0.62% |
| Medium | 310 | -20.54% | -19.78% | 3.58% |
| High | 299 | -27.88% | -25.76% | -7.75% |
| High - Low | | -12.48% [*] | -11.55%* | -8.38% |
| t-statistic | | -1.72 | -1.77 | -1.40 |

This table reports the mean long-term stock returns over the three years following the SEO year. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. Long-term stock returns are measured as buy-and-hold adjusted stock returns, inclusive of dividends, for the 36-month post-SEO period starting the first month of fiscal year *t*+1. Stock returns are adjusted using (i) the *CRSP* value-weighted index including distributions, (ii) the *CRSP* cap-based portfolio index, or (iii) expected returns estimated from Fama and French's (1993) three-factor model. Panel A sorts SEO issuers into terciles of R&D intensity for fiscal year *t*-1. Panel B sorts SEO issuers into terciles of R&D surprise for fiscal year *t*-1. ***, ** * represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| | Measuring Managerial overconfidence | | | |
|------------------------------------|-------------------------------------|-------------------------------|---|-------------------------------|
| $\operatorname{Rank}(R\&D_{it-1})$ | Based o | n option holdings | Based on acquisition, financing and distribution activities | |
| | # of SEOs | OVERCONFIDENT _{it-1} | # of SEOs | OVERCONFIDENT _{it-1} |
| All SEOs | 101 | 45.54% | 902 | 53.88% |
| Low | 43 | 37.21% | 293 | 65.87% |
| Medium | 35 | 54.29% | 310 | 51.61% |
| High | 23 | 47.83% | 299 | 44.48% |
| High - Low | | 10.62% | | -21.39%**** |
| t-statistic | | 0.82 | | -5.35 |

TABLE 11 Pre-SEO R&D Expenditures and Managerial Overconfidence

Panel A: SEOs with low versus high R&D intensity

Panel B: SEOs with low versus high R&D surprise

| | Measuring Managerial overconfidence | | | |
|---|-------------------------------------|-------------------------------|---|-------------------------------|
| $\operatorname{Rank}(\Delta R \& D_{it-1})$ | Based on option holdings | | Based on acquisition, financing and distribution activities | |
| | # of SEOs | OVERCONFIDENT _{it-1} | # of SEOs | OVERCONFIDENT _{it-1} |
| All SEOs | 101 | 45.54% | 902 | 53.88% |
| Low | 28 | 42.86% | 293 | 58.36% |
| Medium | 43 | 46.51% | 310 | 58.06% |
| High | 30 | 46.67% | 299 | 45.15% |
| High - Low | | 3.81% | | -13.21%*** |
| t-statistic | | 0.29 | | -3.24 |

This table reports the proportions of SEO issuers with overconfident managers, and compares the proportions between issuers with high and low per-SEO R&D expenditures using t-tests. Year *t* is the year in which an issuer files SEO, and year *t*-1 is the fiscal year immediately prior to the SEO filing day. Two measures of overconfidence are employed. The first measure is based on CEOs' option holdings using ExecuComp data. Due to missing data and a limited coverage starting from 1992, this overconfidence measure is only available for 101 SEOs out of 496 SEOs over the period from 1992 to 2005. The second measure is constructed based on mangers' acquisition, financing, and distribution activities that prior research has found to be related with managerial overconfidence. The second measure employs Compustat data which allows full coverage of the 902 SEOs over the period from 1975 to 2005. Panel A sorts SEO issuers into terciles of R&D intensity for fiscal year *t*-1. Panel B sorts SEO issuers into terciles of R&D intensity for fiscal year *t*-1. Panel B sorts SEO issuers into terciles of R&D surprise for fiscal year *t*-1. ***, ** * represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| | SEOs with Rank(<i>R&D</i> _{it-1}) | | | | Matched non-SEOs with Rank(<i>R&D</i> _{<i>it</i>-1}) | | | SEO high - Non- SEO high | |
|---|--|--------|-------|------|---|-------|---------|-----------------------------|--|
| | Low | Medium | High | Low | Medium | High | Diff | t- statistic | |
| Ν | 209 | 230 | 217 | 209 | 230 | 217 | | | |
| Matching variables | | | | | | | | | |
| $R\&D_{it-2}$ | 0.04 | 0.10 | 0.19 | 0.02 | 0.09 | 0.19 | 0.00 | 0.21 | |
| $SIZE_{it-2}$ | 4.86 | 4.35 | 3.97 | 4.77 | 4.45 | 3.98 | -0.01 | -0.08 | |
| SG _{it-2} | 0.25 | 0.23 | 0.34 | 0.20 | 0.21 | 0.31 | 0.03 | 0.52 | |
| TOBIN _{it-2} | 1.80 | 1.83 | 2.83 | 1.64 | 2.06 | 3.01 | -0.18 | -0.73 | |
| Comparison after ma | atching | | | | | | | | |
| $\Delta R \& D_{it-1}$ | 0.00 | 0.01 | 0.07 | 0.00 | 0.01 | 0.04 | 0.03*** | 4.11 | |
| $\frac{\sum_{\tau=1}^{3} PATENT_{it+\tau}}{XRD_{it-1}}$ | 2.50 | 1.45 | 0.72 | 2.29 | 1.81 | 1.54 | -0.82* | -1.71 | |
| Size adjusted LTRET _{it+3} | -0.09 | -0.15 | -0.36 | 0.08 | -0.08 | -0.15 | -0.21** | -2.31 | |

 TABLE 12

 Comparison of SEO Firms with Matched Non-SEO Firms

This table reports the comparison between SEO firms and a matched sample of non-SEO firms. Each SEO firm is matched to a non-SEO firm using coarsened exact matching based on firm size, sales growth, R&D intensity and Tobin's Q for the year that is two years prior to the offering. I further match exactly on industry membership and year. The matching procedure generates non-SEO matches for 656 SEO firms over the period from 1975 to 2005. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. ***, ** * represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| $\operatorname{Rank}(R \& D_{it-1})$ | # - 6850- | LTC | Percentage of SEOs missing sales forecasts | | | |
|--------------------------------------|-----------|------------|--|---------------|----------------------|--|
| | # of SEOs | LTG_{it} | $MISS_{it+1}$ | $MISS_{it+2}$ | MISS _{it+3} | |
| All SEOs | 529 | 27.20% | 56.17% | 65.77% | 73.81% | |
| Low | 197 | 24.00% | 38.89% | 37.93% | 52.63% | |
| Medium | 197 | 27.95% | 57.50% | 75.86% | 84.21% | |
| High | 135 | 30.74% | 69.88% | 75.47% | 78.26% | |
| High - Low | | 6.74%*** | 30.99%*** | 37.54%*** | 25.63%** | |
| t-statistic | | 4.88 | 4.05 | 3.56 | 2.10 | |

TABLE 13 Pre-SEO R&D Expenditures and Analysts' Forecasts

| $\operatorname{Rank}(\Delta R \& D_{it-1})$ | # - 6850- | LTC | Percentage of SEOs missing sales forecasts | | | |
|---|-----------|------------|--|----------------------|---------------|--|
| | # of SEOs | LTG_{it} | $MISS_{it+1}$ | $MISS_{it+2}$ | $MISS_{it+3}$ | |
| All SEOs | 529 | 27.20% | 56.17% | 65.77% | 73.81% | |
| Low | 182 | 23.62% | 45.95% | 52.78% | 60.71% | |
| Medium | 201 | 27.54% | 53.25% | 65.38% | 81.25% | |
| High | 146 | 31.18% | 67.86% | 75.51% | 80.00% | |
| High - Low | | 7.56%*** | 21.91%*** | 22.73% ^{**} | 19.29%* | |
| t-statistic | | 5.73 | 2.83 | 2.22 | 1.76 | |

This table reports the mean values of analysts' long-term growth forecasts made preceding the SEO filing day, and the proportions of SEO issuers that miss analysts' sales forecasts for each fiscal year over the three years following the offering. It compares issuers with high and low pre-SEO R&D expenditures using t-tests within a restricted sample of 529 SEOs with analysts' coverage from I/B/E/S. Year t is the year in which an issuer files SEO, year t-1 is the fiscal year immediately prior to the SEO filing day, and year t+1 is the fiscal year immediately following the SEO issue day. Panel A sorts SEO issuers into terciles of R&D intensity for fiscal year t-1. Panel B sorts SEO issuers into terciles of R&D surprise for fiscal year t-1. ***, **, * represent significance at the 1, 5, 10 percent level, respectively, based on twotailed tests. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

 TABLE 14

 Pre-SEO R&D Expenditures and Disclosure of the Intended Use of Proceeds

| | | $PROCEEDUSE_{it}$ | | | | |
|------------------------------------|--------------|-------------------|----------------------|-------------|-------------------|----------------------------------|
| $\operatorname{Rank}(R\&D_{it-1})$ | # of SEOs | R&D plan | Specific R&D plan | Acquisition | Debt repayment | General corporate purposes |
| All SEOs | 328 | 42.07% | 11.59% | 73.17% | 30.49% | 11.59% |
| Low | 104 | 11.54% | 3.85% | 64.42% | 53.85% | 16.35% |
| Medium | 112 | 40.18% | 8.04% | 71.43% | 25.89% | 12.50% |
| High | 112 | 72.32% | 22.32% | 83.04% | 13.39% | 6.25% |
| High - Low | | 60.78%*** | 18.48%*** | 18.61%*** | -40.45%*** | -10.10%** |
| t-statistic | | 11.50 | 4.22 | 3.15 | -6.88 | -2.34 |

Panel A: SEOs with low versus high R&D intensity

| | | PROCEEDUSE _{it} | | | | |
|---|--------------|--------------------------|----------------------|-------------|-------------------|----------------------------------|
| $\operatorname{Rank}(\Delta R \& D_{it-1})$ | # of SEOs | R&D plan | Specific R&D plan | Acquisition | Debt repayment | General corporate purposes |
| All SEOs | 328 | 42.07% | 11.59% | 73.17% | 30.49% | 11.59% |
| Low | 105 | 31.43% | 8.57% | 74.29% | 41.90% | 10.48% |
| Medium | 111 | 28.83% | 8.11% | 71.17% | 37.84% | 14.41% |
| High | 112 | 65.18% | 17.86% | 74.11% | 12.50% | 9.82% |
| High - Low | | 33.75%*** | 9.29%** | -0.18% | -29.40%*** | -0.65% |
| t-statistic | | 5.26 | 2.04 | -0.03 | -5.10 | -0.16 |

(continued)

This table reports the proportions of SEO issuers for each category of intended use of proceeds as stated in the latest amended Form S-3 which is filed with the SEC through EDGAR, and compares the sample distribution between issuers with high and low pre-SEO R&D expenditures using t-tests. This analysis employs a restricted sample of 328 SEOs from 1997 to 2005 since SEC filings are not publicly available through EDGAR until June 1996. Year t is the year in which an issuer files SEO, and year t-1 is the fiscal year immediately prior to the SEO filing day. There are four main categories of intended use of proceeds: R&D plan, acquisition, debt repayment, and general corporate purposes. An issuer is classified as having an "R&D plan" if it mentions planned spending on R&D activities. Within this category, an issuer is further classified as having a "specific R&D plan" if it provides information on the specific product lines or research programs related to the R&D plan, or gives quantitative information on the portion of proceeds used for the R&D plan. An issuer is classified as having an intended use for "acquisition" if it mentions planned acquisition of complementary technologies, products, or other businesses. An issuer is classified as having an intended use for "debt repayment" if it mentions planned repayment or reduction of any outstanding debt. Note that an issuer can be classified into more than one category including R&D plan, specific R&D plan, acquisition, and debt repayment. An issuer falls into the category of "general corporate purposes" if it does not mention any use of proceeds for R&D, acquisition, or debt repayment. Panel A sorts SEO issuers into terciles of R&D intensity for fiscal year t-1. Panel B sorts SEO issuers into terciles of R&D surprise for fiscal year t-1. ***, **, * represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

TABLE 15

 Productivity of Pre-SEO R&D Expenditures: Using Expanded Measurement Window of Five Years

| | | Productivity measures | | | | |
|------------------------------------|--------------|---|--|--|---|--|
| $\operatorname{Rank}(R\&D_{it-1})$ | # of SEOs | $\frac{\sum_{\tau=1}^{5} PATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{r=1}^{5} IPATENT_{it+r}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{5} VPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{5} SALE_{it+\tau} / 5}{XRD_{it-1}}$ | |
| All SEOs | 902 | 4.74 | 1.72 | 2.22 | 0.14 | |
| Low | 293 | 9.39 | 3.76 | 4.94 | 0.40 | |
| Medium | 310 | 2.96 | 0.81 | 1.06 | 0.03 | |
| High | 299 | 2.03 | 0.66 | 0.75 | 0.01 | |
| High - Low | | -7.36** | -3.10 [*] | -4.20** | -0.38* | |
| t-statistic | | -2.43 | -1.93 | -2.37 | -1.71 | |

Panel A: SEOs with low versus high R&D intensity

| | | Productivity measures | | | |
|-------------------------------|--------------|--|---|---|--|
| Rank $(\Delta R \& D_{it-1})$ | # of SEOs | $\frac{\sum_{\tau=1}^{5} PATENT_{it+\tau}}{VDD}$ | $\frac{\sum_{\tau=1}^{5} IPATENT_{it+\tau}}{VPD}$ | $\frac{\sum_{\tau=1}^{5} VPATENT_{it+\tau}}{VPD}$ | $\frac{\sum_{\tau=1}^{5} SALE_{it+\tau} / 5}{VRD}$ |
| | | XRD_{it-1} | XRD_{it-1} | XRD_{it-1} | XRD_{it-1} |
| All SEOs | 902 | 4.74 | 1.72 | 2.22 | 0.14 |
| Low | 293 | 7.39 | 2.80 | 3.73 | 0.37 |
| Medium | 310 | 4.26 | 1.57 | 2.03 | 0.05 |
| High | 299 | 2.64 | 0.82 | 0.93 | 0.02 |
| High - Low | | -4.76 | -1.98 | -2.80** | -0.35 |
| t-statistic | | -1.60 | -1.25 | -1.63 | -1.56 |

This table reports evidence of variation in R&D productivity on pre-SEO R&D expenditures using an expanded measurement window of five years. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. R&D productivity is measured as the cumulative number of applications of patents, influential patents, and valuable patents (which are ultimately granted), and average sales over the five-year period from fiscal year *t*+1 to *t*+5 scaled by the R&D expenditures for fiscal year *t*-1. Panel A (Panel B) reports the mean productivity of pre-SEO R&D expenditures based on the standardized tercile rank of R&D intensity (R&D surprise) for fiscal year *t*-1. ****, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| $\operatorname{Rank}(R\&D_{it-1})$ | # of SEOs | Output measures | | | |
|------------------------------------|--------------|--------------------------------------|--|--|---|
| | | $\sum_{\tau=1}^{3} PATENT_{it+\tau}$ | $\sum\nolimits_{\tau=1}^{3} IPATENT_{it+\tau}$ | $\sum\nolimits_{\tau=1}^{3} VPATENT_{it+\tau}$ | $\sum\nolimits_{\tau=1}^{3} SALE_{it+\tau} / 3$ |
| All SEOs | 902 | 28.73 | 9.30 | 13.94 | 0.52 |
| Low | 293 | 42.75 | 12.61 | 21.93 | 1.01 |
| Medium | 310 | 22.25 | 8.75 | 10.86 | 0.38 |
| High | 299 | 21.70 | 6.64 | 9.30 | 0.18 |
| High - Low | | -21.05** | -5.97* | -12.63** | -0.83*** |
| t-statistic | | -1.99 | -1.90 | -2.07 | -5.00 |

TABLE 16Outputs of Pre-SEO R&D Expenditures

Panel A: SEOs with low versus high R&D intensity

| Rank | # of | Output measures | | | |
|--------------------------|------|---|--|--|--|
| $(\Delta R \& D_{it-1})$ | SEOs | $\sum\nolimits_{\tau=1}^{3} PATENT_{it+\tau}$ | $\sum\nolimits_{\tau=1}^{3} IPATENT_{it+\tau}$ | $\sum\nolimits_{\tau=1}^{3} VPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} SALE_{it+\tau} / 3$ |
| All SEOs | 902 | 21.70 | 6.64 | 9.30 | 0.18 |
| Low | 293 | 40.57 | 10.65 | 18.31 | 0.88 |
| Medium | 310 | 27.76 | 11.06 | 15.41 | 0.51 |
| High | 299 | 18.12 | 6.16 | 8.13 | 0.17 |
| High - Low | | -22.45** | -4.48 | -10.18 [*] | -0.71*** |
| t-statistic | | -2.32 | -1.47 | -1.93 | -4.45 |

This table reports evidence of variation in R&D output of pre-SEO R&D expenditures. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year t+1 is the fiscal year immediately following the SEO issue day. R&D output is measured as the cumulative number of applications of patents, influential patents, and valuable patents (which are ultimately granted), and average sales over the three-year period from fiscal year t+1 to t+3. Panel A (Panel B) reports the mean output of pre-SEO R&D expenditures based on the standardized tercile rank of R&D intensity (R&D surprise) for fiscal year t-1. ***, ***, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| | | Productivity measures | | | | |
|--|--------------|---|--|--|---|--|
| Rank (<i>ABR&D</i> _{it-1}) | # of SEOs | $\frac{\sum_{\tau=1}^{3} PATENT_{ii+\tau}}{XRD_{ii-1}}$ | $\frac{\sum_{\tau=1}^{3} IPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} VPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} SALE_{it+\tau}/3}{XRD_{it-1}}$ | |
| All SEOs | 902 | 1.48 | 0.40 | 0.54 | 0.05 | |
| Low | 293 | 2.23 | 0.60 | 0.80 | 0.11 | |
| Medium | 310 | 1.29 | 0.32 | 0.47 | 0.03 | |
| High | 299 | 0.96 | 0.29 | 0.36 | 0.01 | |
| High - Low | | -1.27*** | -0.31*** | -0.44*** | -0.09*** | |
| t-statistic | | -4.89 | -3.16 | -3.93 | -8.13 | |

 TABLE 17

 Productivity of Pre-SEO R&D Expenditures: Using Alternative Measure of R&D Surprise Estimated from Discretionary Expense Model

This table reports evidence of variation in R&D productivity on pre-SEO R&D expenditures using alternative measure of R&D surprise estimated from discretionary expense model in Cohen and Zarowin (2010). Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. R&D productivity is measured as the cumulative number of applications of patents, influential patents, and valuable patents (which are ultimately granted), and average sales over the three-year period from fiscal year *t*+1 to *t*+3 scaled by the R&D expenditures for fiscal year *t*-1. ***, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| | R&D productivity | | | | |
|------------------------------|--------------------------------------|---------------------------------------|--|--|--|
| | (1) | (2) | (3) | (4) | |
| | $\sum_{\tau=1}^{3} PATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} IPATENT_{it+\tau}$ | $\sum\nolimits_{\tau=1}^{3} VPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} SALE_{it+\tau} / 3$ | |
| | XRD _{it-1} | XRD_{it-1} | XRD _{it-1} | XRD _{it-1} | |
| INTERCEPT | 3.216*** | 0.622*** | 1.223*** | 0.052^{***} | |
| | (4.11) | (2.96) | (3.59) | (2.49) | |
| Rank(ABR&D _{it-1}) | -1.206*** | -0.237** | -0.389*** | -0.053*** | |
| | (-3.61) | (-2.32) | (-2.85) | (-5.07) | |
| SCALE _{it-1} | 0.121 | 0.051 | 0.051 | 0.021*** | |
| | (1.19) | (1.11) | (1.06) | (10.91) | |
| SIZE _{it-1} | -0.137 | 0.005 | 0.046 | 0.005 | |
| | (-1.53) | (0.19) | (1.18) | (1.57) | |
| SG_{it-1} | 0.062 | -0.006 | -0.006 | 0.002 | |
| | (0.88) | (-0.39) | (-0.32) | (0.74) | |
| ROA_{it-1} | 0.046 | -0.048 | 0.029 | 0.001 | |
| | (0.16) | (-0.53) | (0.24) | (0.10) | |
| LEV _{it-1} | -0.009 | 0.025 | -0.100 | 0.039 | |
| | (-0.03) | (0.19) | (-0.58) | (1.56) | |
| TOBIN _{it-1} | 0.043 | 0.007 | 0.035 | 0.000 | |
| | (0.62) | (0.31) | (1.01) | (0.36) | |
| CAP_{it-1} | 2.480*** | 0.967^{***} | 1.127*** | -0.140*** | |
| | (3.01) | (3.26) | (2.81) | (-4.11) | |
| CAPEX _{it-1} | 0.489 | 0.581 | 0.553 | 0.089^{***} | |
| | (0.32) | (0.93) | (0.91) | (2.56) | |
| $CASH_{it-1}$ | 1.051*** | 0.512*** | 0.550** | -0.063*** | |
| | (2.63) | (3.21) | (2.38) | (-2.94) | |
| Industry fixed effects | Yes | Yes | Yes | Yes | |
| Year fixed effects | Yes | Yes | Yes | Yes | |
| Number of SEOs | 902 | 902 | 902 | 902 | |
| Adj. R ² | 25.93% | 24.73% | 22.05% | 43.70% | |

 TABLE 18

 Regressions of R&D Productivity on Pre-SEO R&D Expenditures: Using Alternative Measure of R&D

 Surprise Estimated from Discretionary Expense Model

(continued)

This table reports evidence of variation in R&D productivity on pre-SEO R&D surprise estimated from discretionary expense model in Cohen and Zarowin (2010). Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. R&D productivity is measured as the cumulative number of applications of patents, influential patents, and valuable patents (which are ultimately granted), and average sales over the three-year period from fiscal year *t*+1 to *t*+3 scaled by the R&D expenditures for fiscal year *t*-1. Industry fixed effects are based on Fama and French's (1997) 49-industry classification. The reported t-statistics in parentheses are based on standard errors clustered by firm and year. ***, **, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| Rank(ABR&D _{it-1}) | # of SEOs | <i>RUNUP</i> _{it} | DROP _{it} | BTM_{it} |
|------------------------------|-----------|----------------------------|--------------------|------------|
| All SEOs | 902 | 35.54% | -1.22% | 33.53% |
| Low | 293 | 31.14% | -1.86% | 36.99% |
| Medium | 310 | 32.87% | -1.24% | 37.47% |
| High | 299 | 42.62% | -0.57% | 26.08% |
| High - Low | | 11.48%*** | 1.29%** | -10.91%*** |
| t-statistic | | 3.11 | 1.92 | -5.97 |

 TABLE 19

 Pre-SEO R&D Expenditures and SEO Pricing: Using Alternative Measure of R&D Surprise Estimated from Discretionary Expense Model

This table reports evidence of variation in SEO pricing on pre-SEO R&D surprise estimated from discretionary expense model in Cohen and Zarowin (2010). Year *t* is the year in which an issuer files SEO, and year *t*-1 is the fiscal year immediately prior to the SEO filing day. ^{***}, ^{**}, ^{**} represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| | Price run-ups prior to SEOs |
|------------------------------|-----------------------------|
| | RUNUP _{it} |
| INTERCEPT | 0.273*** |
| | (3.73) |
| Rank(ABR&D _{it-1}) | 0.085*** |
| | (2.90) |
| MRUNUP _{it} | 1.981*** |
| | (8.55) |
| SIZE _{it-1} | -0.037*** |
| | (-4.90) |
| SG_{it-1} | 0.004 |
| | (0.34) |
| ROA _{it-1} | -0.065 |
| | (-1.50) |
| LEV _{it-1} | 0.046 |
| | (0.63) |
| TOBIN _{it-1} | -0.010 |
| | (-0.71) |
| CAP_{it-1} | 0.167 |
| | (1.18) |
| CAPEX _{it-1} | -0.139 |
| | (-0.88) |
| CASH _{it-1} | 0.089 |
| | (0.73) |
| Industry fixed effects | Yes |
| Year fixed effects | Yes |
| Number of SEOs | 902 |
| Adj. R ² | 28.90% |

TABLE 20 Regressions of Price Run-ups on Pre-SEO R&D Expenditures: Using Alternative Measure of R&D Surprise Estimated from Discretionary Expense Model

(continued)

This table reports evidence of variation in SEO pricing on pre-SEO R&D surprise estimated from discretionary expense model in Cohen and Zarowin (2010). Year *t* is the year in which an issuer files SEO, and year *t*-1 is the fiscal year immediately prior to the SEO filing day. It reports results from pooled OLS regressions of issuers' stock price run-up prior to the SEO filing day on the rank of R&D surprise along with a vector of control variables. Stock price run-up is measured as the cumulative 60-day stock return from 62 trading days before to three trading days before the SEO filing day. Industry fixed effects are based on Fama and French's (1997) 49-industry classification. The reported t-statistics in parentheses are based on standard errors clustered by firm and year. ***, ** , ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| | | $LTRET_{it+3}$ | | | |
|--------------------------------------|-----------|-----------------|---------------|-----------------------------------|--|
| $\operatorname{Rank}(ABR\&D_{it-1})$ | # of SEOs | Market adjusted | Size adjusted | Fama-French 3- factor adjusted | |
| All SEOs | 902 | -21.30% | -19.96% | -1.14% | |
| Low | 293 | -15.78% | -12.34% | 3.52% | |
| Medium | 310 | -18.98% | -19.42% | 1.29% | |
| High | 299 | -29.12% | -27.97% | -8.22% | |
| High - Low | | -13.33%* | -15.63%** | -11.74%*** | |
| t-statistic | | -1.72 | -2.10 | -2.87 | |

 TABLE 21

 Pre-SEO R&D Expenditures and Post-SEO Long-Term Stock Returns: Using Alternative Measure of R&D Surprise Estimated from Discretionary Expense Model

This table reports the mean long-term stock returns over the three years following the SEO year using alternative measure of R&D surprise estimated from discretionary expense model in Cohen and Zarowin (2010). Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. Long-term stock returns are measured as buy-and-hold adjusted stock returns, inclusive of dividends, for the 36-month post-SEO period starting the first month of fiscal year *t*+1. Stock returns are adjusted using (i) the *CRSP* value-weighted index including distributions, (ii) the *CRSP* cap-based portfolio index, or (iii) expected returns estimated from Fama and French's (1993) three-factor model. ***, **, *** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. The final sample includes 902 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

 TABLE 22

 Productivity of Pre-SEO R&D Expenditures: Excluding SEOs Affected by Internet Bubble Bursting

| | | Productivity measures | | | | |
|------------------------------------|--------------|---|--|--|---|--|
| $\operatorname{Rank}(R\&D_{it-1})$ | # of SEOs | $\frac{\sum_{\tau=1}^{3} PATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} IPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} VPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} SALE_{it+\tau} / 3}{XRD_{it-1}}$ | |
| All SEOs | 787 | 1.51 | 0.41 | 0.53 | 0.05 | |
| Low | 256 | 2.30 | 0.63 | 0.78 | 0.12 | |
| Medium | 271 | 1.25 | 0.31 | 0.44 | 0.02 | |
| High | 260 | 1.01 | 0.31 | 0.38 | 0.01 | |
| High - Low | | -1.29*** | -0.32*** | -0.40*** | -0.11*** | |
| t-statistic | | -4.46 | -2.97 | -3.39 | -8.39 | |

Panel A: SEOs with low versus high R&D intensity

| | | Productivity measures | | | | |
|-------------------------------|--------------|---|--|--|---|--|
| Rank $(\Delta R \& D_{it-1})$ | # of SEOs | $\frac{\sum_{\tau=1}^{3} PATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} IPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{r=1}^{3} VPATENT_{it+r}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} SALE_{it+\tau}/3}{XRD_{it-1}}$ | |
| All SEOs | 787 | 1.51 | 0.41 | 0.53 | 0.05 | |
| Low | 256 | 2.05 | 0.57 | 0.64 | 0.10 | |
| Medium | 272 | 1.43 | 0.35 | 0.57 | 0.05 | |
| High | 259 | 1.05 | 0.32 | 0.39 | 0.02 | |
| High - Low | | -1.00**** | -0.25** | -0.26** | -0.08*** | |
| t-statistic | | -3.45 | -2.30 | -2.20 | -6.26 | |

This table reports evidence of variation in R&D productivity on pre-SEO R&D expenditures excluding SEOs issued from 1999 to 2001 so that the internet bubble burst does not affect their future performance. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. R&D productivity is measured as the cumulative number of applications of patents, influential patents, and valuable patents (which are ultimately granted), and average sales over the three-year period from fiscal year *t*+1 to *t*+3 scaled by the R&D expenditures for fiscal year *t*-1. Panel A (Panel B) reports the mean productivity of pre-SEO R&D expenditures based on the standardized tercile rank of R&D intensity (R&D surprise) for fiscal year *t*-1. ***, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. This restricted sample includes 787 SEOs from 1975 to 1998 and from 2002 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

Regressions of R&D Productivity on Pre-SEO R&D Expenditures: Excluding SEOs Affected by Internet Bubble Bursting

| | | R&D pr | oductivity | |
|---|--------------------------------------|---------------------------------------|---------------------------------------|--|
| | (1) | (2) | (3) | (4) |
| | $\sum_{\tau=1}^{3} PATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} IPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} VPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} SALE_{it+\tau} / 3$ |
| | $\frac{1}{XRD_{it-1}}$ | XRD _{it-1} | XRD_{it-1} | $\frac{2.11}{XRD_{it-1}}$ 0.073*** |
| INTERCEPT | 4.209*** | 0.835*** | 1.609*** | 0.073*** |
| | (5.00) | (3.60) | (5.11) | (2.95) |
| Rank(<i>R&D</i> _{<i>it</i>-1}) | -1.340*** | -0.279** | -0.375*** | -0.063*** |
| | (-3.14) | (-2.34) | (-2.38) | (-4.76) |
| $SCALE_{it-1}$ | 0.117 | 0.050 | 0.051 | 0.021*** |
| | (1.19) | (1.10) | (1.10) | (10.67) |
| $SIZE_{it-1}$ | -0.245*** | -0.021 | 0.000 | 0.003 |
| | (-2.99) | (-0.84) | (0.00) | (0.91) |
| SG_{it-1} | 0.051 | -0.008 | -0.011 | -0.001 |
| | (0.75) | (-0.49) | (-0.52) | (-0.46) |
| ROA_{it-1} | -0.004 | -0.064 | 0.039 | -0.006 |
| | (-0.01) | (-0.54) | (0.25) | (-0.50) |
| LEV _{it-1} | 0.176 | 0.035 | -0.013 | 0.050^{*} |
| | (0.47) | (0.23) | (-0.07) | (1.65) |
| TOBIN _{it-1} | -0.029 | -0.014 | -0.004 | -0.000 |
| | (-0.44) | (-0.62) | (-0.17) | (-0.13) |
| CAP_{it-1} | 1.991** | 0.927^{***} | 0.886** | -0.145*** |
| | (2.12) | (2.60) | (2.08) | (-3.76) |
| CAPEX _{it-1} | 0.552 | 0.669 | 0.567 | 0.098*** |
| | (0.32) | (0.97) | (0.87) | (3.27) |
| CASH _{it-1} | 1.454*** | 0.659*** | 0.735*** | -0.042* |
| | (3.03) | (3.41) | (2.77) | (-1.71) |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Number of SEOs | 787 | 787 | 787 | 787 |
| Adj. R ² | 28.16% | 25.81% | 23.89% | 46.97% |

Panel A: Regressions of R&D productivity on R&D intensity

(continued)

| | | R&D p | oroductivity | |
|---------------------------------------|---|---|--|--|
| | (1) | (2) | (3) | (4) |
| | $\sum_{\tau=1}^{3} PATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} IPATENT_{it+\tau}$ | $\sum\nolimits_{\tau=1}^{3} VPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} SALE_{it+\tau} / 3$ |
| | <i>XRD</i> _{<i>it-1</i>} 3.817 ^{***} | <i>XRD</i> _{<i>it-1</i>} 0.774 ^{***} | $\overline{XRD_{it-1}}$ | <i>XRD</i> _{<i>it-1</i>} 0.048 ^{**} |
| INTERCEPT | 3.817*** | 0.774 ^{***} | 1.466*** | 0.048^{**} |
| | (4.89) | (3.38) | (4.74) | (2.34) |
| $\mathbf{Rank}(\Delta R \& D_{it-1})$ | -1.005*** | -0.236* | -0.238* | -0.039*** |
| | (-2.54) | (-1.87) | (-1.88) | (-3.09) |
| SCALE _{it-1} | 0.125 | 0.051 | 0.054 | 0.021*** |
| | (1.30) | (1.15) | (1.19) | (10.58) |
| SIZE _{it-1} | -0.225*** | -0.017 | 0.006 | 0.004 |
| | (-2.69) | (-0.68) | (0.23) | (1.30) |
| SG_{it-1} | 0.059 | -0.006 | -0.010 | -0.001 |
| | (0.89) | (-0.40) | (-0.49) | (-0.34) |
| ROA_{it-1} | 0.498 | 0.040 | 0.180 | 0.017 |
| | (1.59) | (0.33) | (1.33) | (1.40) |
| LEV _{it-1} | 0.180 | 0.030 | -0.003 | 0.052^* |
| | (0.47) | (0.19) | (-0.01) | (1.68) |
| TOBIN _{it-1} | -0.047 | -0.017 | -0.010 | -0.001 |
| | (-0.69) | (-0.77) | (-0.41) | (-0.70) |
| CAP_{it-1} | 2.033** | 0.920*** | 0.923** | -0.138*** |
| | (2.27) | (2.63) | (2.16) | (-3.68) |
| CAPEX _{it-1} | 0.599 | 0.709 | 0.531 | 0.091*** |
| | (0.32) | (0.96) | (0.75) | (2.84) |
| CASH _{it-1} | 1.303** | 0.632*** | 0.686** | -0.050** |
| | (2.34) | (3.08) | (2.42) | (-2.07) |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Number of SEOs | 787 | 787 | 787 | 787 |
| Adj. R ² | 27.44% | 25.71% | 23.37% | 45.62% |

Panel B: Regressions of R&D productivity on R&D surprise

(continued)

This table reports evidence of variation in R&D productivity on pre-SEO R&D expenditures excluding SEOs issued from 1999 to 2001 so that the internet bubble burst does not affect their future performance. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. R&D productivity is measured as the cumulative number of applications of patents, influential patents, and valuable patents (which are ultimately granted), and average sales over the three-year period from fiscal year *t*+1 to *t*+3 scaled by the R&D expenditures for fiscal year *t*-1. Panel A (Panel B) reports results from pooled OLS regressions of R&D productivity on the rank of R&D intensity (R&D surprise) along with a vector of control variables. Industry fixed effects are based on Fama and French's (1997) 49-industry classification. The reported t-statistics in parentheses are based on standard errors clustered by firm and year. ***, ***, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. This restricted sample includes 787 SEOs from 1975 to 1998 and from 2002 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

TABLE 24 Pre-SEO R&D Expenditures and SEO Pricing: Excluding SEOs Affected by Internet Bubble Bursting

| $\operatorname{Rank}(R\&D_{it-1})$ | # of SEOs | RUNUP _{it} | $DROP_{it}$ | BTM_{it} |
|------------------------------------|-----------|---------------------|-------------|------------|
| All SEOs | 787 | 30.83% | -1.53% | 34.59% |
| Low | 256 | 24.16% | -2.44% | 40.21% |
| Medium | 271 | 30.53% | -1.14% | 36.38% |
| High | 260 | 37.70% | -1.04% | 27.17% |
| High - Low | | 13.53%*** | 1.40%** | -13.04%*** |
| t-statistic | | 4.52 | 2.22 | -6.44 |

Panal A: SEAs with low varsus high R&D intensity

Panel B: SEOs with low versus high R&D surprise

| Rank($\Delta R \& D_{it-1}$) | # of SEOs | RUNUP _{it} | DROP _{it} | BTM_{it} |
|--------------------------------|-----------|---------------------|--------------------|------------|
| All SEOs | 787 | 30.83% | -1.53% | 34.59% |
| Low | 256 | 29.10% | -1.45% | 41.36% |
| Medium | 272 | 28.16% | -1.11% | 35.53% |
| High | 259 | 35.33% | -2.05% | 26.88% |
| High - Low | | 6.23%** | -0.61% | -14.49%*** |
| t-statistic | | 2.07 | -0.93 | -6.91 |

This table reports evidence of variation in SEO pricing on pre-SEO R&D expenditures excluding SEOs issued from 1999 to 2001 so that the internet bubble burst does not affect their future performance. Year t is the year in which an issuer files SEO, and year t-1 is the fiscal year immediately prior to the SEO filing day. Panel A (Panel B) reports the mean values of valuation measures around SEOs based on the standardized tercile rank of R&D intensity (R&D surprise) for fiscal year t-1. ***, **, * represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. This restricted sample includes 787 SEOs from 1975 to 1998 and from 2002 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| | Price run-ups | prior to SEOs |
|------------------------------------|---------------|---------------------|
| | (1) | (2) |
| | $RUNUP_{it}$ | RUNUP _{it} |
| INTERCEPT | 0.210*** | 0.269*** |
| | (2.44) | (2.94) |
| $\operatorname{Rank}(R\&D_{it-1})$ | 0.128*** | |
| | (5.45) | |
| Rank($\Delta R \& D_{it-1}$) | | 0.059* |
| | | (1.70) |
| MRUNUP _{it} | 1.863*** | 1.903*** |
| | (8.29) | (8.13) |
| $SIZE_{it-1}$ | -0.040*** | -0.041*** |
| | (-4.88) | (-4.86) |
| SG_{it-1} | -0.007 | -0.006 |
| | (-1.09) | (-0.90) |
| ROA_{it-1} | -0.029 | -0.081* |
| | (-0.62) | (-1.90) |
| LEV _{it-1} | 0.019 | 0.009 |
| | (0.25) | (0.11) |
| TOBIN _{it-1} | -0.021*** | -0.019*** |
| | (-3.69) | (-3.31) |
| CAP_{it-1} | 0.280** | 0.249^{*} |
| | (2.02) | (1.68) |
| CAPEX _{it-1} | -0.164 | -0.127 |
| | (-1.15) | (-0.83) |
| CASH _{it-1} | 0.082 | 0.099 |
| | (1.10) | (1.28) |
| Industry fixed effects | Yes | Yes |
| Year fixed effects | Yes | Yes |
| Number of SEOs | 787 | 787 |
| Adj. R ² | 27.70% | 26.66% |

 TABLE 25

 Regressions of Price Run-ups on Pre-SEO R&D Expenditures: Excluding SEOs Affected by Internet Bubble Bursting

(continued)

This table reports evidence of variation in SEO pricing on pre-SEO R&D expenditures excluding SEOs issued from 1999 to 2001 so that the internet bubble burst does not affect their future performance. Year *t* is the year in which an issuer files SEO, and year *t*-1 is the fiscal year immediately prior to the SEO filing day. It reports results from pooled OLS regressions of issuers' stock price run-up prior to the SEO filing day on the rank of pre-SEO R&D expenditures along with a vector of control variables. Stock price run-up is measured as the cumulative 60-day stock return from 62 trading days before to three trading days before the SEO filing day. Industry fixed effects are based on Fama and French's (1997) 49-industry classification. The reported t-statistics in parentheses are based on standard errors clustered by firm and year. ***, **, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. This restricted sample includes 787 SEOs from 1975 to 1998 and from 2002 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

Pre-SEO R&D Expenditures and Post-SEO Long-Term Stock Returns: Excluding SEOs Affected by Internet Bubble Bursting

| | | $LTRET_{it+3}$ | | | |
|------------------------------------|-----------|-----------------|-----------------------|-----------------------------------|--|
| $\operatorname{Rank}(R\&D_{it-1})$ | # of SEOs | Market adjusted | Size adjusted | Fama-French 3- factor adjusted | |
| All SEOs | 787 | -24.17% | -17.19% | -6.08% | |
| Low | 256 | -13.97% | -7.44% | -2.18% | |
| Medium | 271 | -22.93% | -16.01% | -2.10% | |
| High | 260 | -35.49% | -27.96% | -14.07% | |
| High - Low | | -21.52%** | -20.52% ^{**} | -11.89%** | |
| t-statistic | | -2.22 | -2.13 | -2.21 | |

Panel A: SEOs with low versus high R&D intensity

Panel B: SEOs with low versus high R&D surprise

| | # of SEOs | $LTRET_{it+3}$ | | | | |
|---|-----------|----------------------|---------------|-----------------------------------|--|--|
| $\operatorname{Rank}(\Delta R \& D_{it-1})$ | | Market adjusted | Size adjusted | Fama-French 3- factor adjusted | | |
| All SEOs | 787 | -24.17% | -17.19% | -6.08% | | |
| Low | 256 | -18.58% | -11.18% | -7.15% | | |
| Medium | 272 | -22.88% | -16.94% | -3.06% | | |
| High | 259 | -31.05% | -23.40% | -8.19% | | |
| High - Low | | -12.47% [*] | -12.22%* | -1.04% | | |
| t-statistic | | -1.63 | -1.65 | -1.28 | | |

This table reports the mean long-term stock returns over the three years following the SEO year excluding SEOs issued from 1999 to 2001 so that the internet bubble burst does not affect their future performance. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. Long-term stock returns are measured as buy-and-hold adjusted stock returns, inclusive of dividends, for the 36-month post-SEO period starting the first month of fiscal year *t*+1. Stock returns are adjusted using (i) the *CRSP* value-weighted index including distributions, (ii) the *CRSP* cap-based portfolio index, or (iii) expected returns estimated from Fama and French's (1993) three-factor model. Panel A sorts SEO issuers into terciles of R&D intensity for fiscal year *t*-1. Panel B sorts SEO issuers into terciles of R&D surprise for fiscal year *t*-1. ***, ** * represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. This restricted sample includes 787 SEOs from 1975 to 1998 and from 2002 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

 TABLE 27

 Productivity of Pre-SEO R&D Expenditures: Excluding Software Companies

| | | Productivity measures | | | |
|------------------------------------|--------------|---|--|--|---|
| $\operatorname{Rank}(R\&D_{it-1})$ | # of SEOs | $\frac{\sum_{\tau=1}^{3} PATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{r=1}^{3} IPATENT_{it+r}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} VPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} SALE_{it+\tau} / 3}{XRD_{it-1}}$ |
| All SEOs | 791 | 1.65 | 0.45 | 0.61 | 0.05 |
| Low | 258 | 2.48 | 0.68 | 0.90 | 0.11 |
| Medium | 265 | 1.42 | 0.36 | 0.52 | 0.02 |
| High | 268 | 1.08 | 0.32 | 0.41 | 0.01 |
| High - Low | | -1.40*** | -0.35*** | -0.49*** | -0.10*** |
| t-statistic | | -4.78 | -3.25 | -3.93 | -8.56 |

Panel A: SEOs with low versus high R&D intensity

| | | Productivity measures | | | | |
|-------------------------------|--------------|---|--|--|---|--|
| Rank $(\Delta R \& D_{it-1})$ | # of SEOs | $\frac{\sum_{\tau=1}^{3} PATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} IPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} VPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} SALE_{it+\tau}/3}{XRD_{it-1}}$ | |
| All SEOs | 791 | 1.65 | 0.45 | 0.61 | 0.05 | |
| Low | 248 | 2.24 | 0.62 | 0.73 | 0.09 | |
| Medium | 285 | 1.54 | 0.39 | 0.64 | 0.04 | |
| High | 258 | 1.21 | 0.36 | 0.45 | 0.02 | |
| High - Low | | -1.03*** | -0.26** | -0.28** | -0.07*** | |
| t-statistic | | -3.37 | -2.26 | -2.19 | -6.20 | |

This table reports evidence of variation in R&D productivity on pre-SEO R&D expenditures excluding software companies (SIC 7370-7373 and 7375). Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. R&D productivity is measured as the cumulative number of applications of patents, influential patents, and valuable patents (which are ultimately granted), and average sales over the three-year period from fiscal year *t*+1 to *t*+3 scaled by the R&D expenditures for fiscal year *t*-1. Panel A (Panel B) reports the mean productivity of pre-SEO R&D expenditures based on the standardized tercile rank of R&D intensity (R&D surprise) for fiscal year *t*-1. ***, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. This restricted sample includes 791 non-software SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| TABLE 28 | |
|---|----|
| Regressions of R&D Productivity on Pre-SEO R&D Expenditures: Excluding Software Companies | 25 |

| | | R&D pro | oductivity | |
|----------------------------|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | $\sum_{\tau=1}^{3} PATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} IPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} VPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} SALE_{it+\tau} / 3$ |
| | XRD _{it-1} 3.504 ^{***} | <i>XRD</i> _{<i>it-1</i>} 0.643 ^{***} | XRD _{it-1} 1.218 ^{***} | <i>XRD</i> _{<i>it-1</i>} 0.059 ^{***} |
| INTERCEPT | 3.504*** | 0.643*** | 1.218*** | 0.059*** |
| | (3.86) | (2.70) | (3.34) | (3.11) |
| Rank(R&D _{it-1}) | -1.645*** | -0.340*** | -0.519*** | -0.060*** |
| | (-3.59) | (-2.75) | (-2.93) | (-5.04) |
| $SCALE_{it-1}$ | 0.121 | 0.052 | 0.051 | 0.020^{***} |
| | (1.12) | (1.06) | (1.01) | (15.66) |
| SIZE _{it-1} | -0.157 | 0.006 | 0.050 | 0.004 |
| | (-1.58) | (0.24) | (1.24) | (1.27) |
| SG_{it-1} | 0.092 | -0.000 | 0.002 | 0.000 |
| | (1.22) | (-0.02) | (0.10) | (0.31) |
| ROA_{it-1} | -0.045 | -0.074 | 0.035 | -0.000 |
| | (-0.11) | (-0.57) | (0.20) | (-0.01) |
| LEV _{it-1} | 0.195 | 0.086 | -0.025 | 0.055** |
| | (0.55) | (0.66) | (-0.13) | (2.21) |
| TOBIN _{it-1} | 0.074 | 0.016 | 0.054 | 0.000 |
| | (0.91) | (0.64) | (1.37) | (0.31) |
| CAP _{it-1} | 1.913** | 0.817^{***} | 0.913** | -0.114*** |
| | (2.18) | (2.55) | (2.20) | (-2.97) |
| CAPEX _{it-1} | 1.289 | 0.803 | 0.826 | 0.109*** |
| | (0.77) | (1.16) | (1.29) | (2.83) |
| CASH _{it-1} | 1.640*** | 0.658*** | 0.767*** | -0.034 |
| | (3.76) | (3.67) | (3.07) | (-1.53) |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Number of SEOs | 791 | 791 | 791 | 791 |
| Adj. R ² | 27.21% | 25.62% | 23.15% | 47.53% |

Panel A: Regressions of R&D productivity on R&D intensity

(continued)

| | R&D productivity | | | | | |
|---------------------------------------|--------------------------------------|---------------------------------------|--|--|--|--|
| | (1) | (2) | (3) | (4) | | |
| | $\sum_{\tau=1}^{3} PATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} IPATENT_{it+\tau}$ | $\sum\nolimits_{\tau=1}^{3} VPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} SALE_{it+\tau} / 3$ | | |
| | 2.766 ^{***} | XRD _{it-1} | <i>XRD</i> _{<i>it-1</i>} 0.927 ^{**} | <i>XRD</i> _{<i>it</i>-1} 0.031 ^{**} | | |
| INTERCEPT | 2.766*** | 0.505^{**} | 0.927^{**} | 0.031** | | |
| | (3.10) | (2.08) | (2.41) | (1.99) | | |
| $\mathbf{Rank}(\Delta R \& D_{it-1})$ | -1.029*** | -0.232* | -0.245** | -0.037*** | | |
| | (-2.68) | (-1.87) | (-1.99) | (-2.86) | | |
| $SCALE_{it-1}$ | 0.136 | 0.055 | 0.058 | 0.020^{***} | | |
| | (1.26) | (1.13) | (1.14) | (14.75) | | |
| $SIZE_{it-1}$ | -0.125 | 0.013 | 0.062 | 0.006^{*} | | |
| | (-1.20) | (0.44) | (1.44) | (1.65) | | |
| SG_{it-1} | 0.099 | 0.001 | 0.002 | 0.001 | | |
| | (1.30) | (0.10) | (0.13) | (0.39) | | |
| ROA_{it-1} | 0.610^{*} | 0.062 | 0.242 | 0.024** | | |
| | (1.77) | (0.49) | (1.60) | (2.08) | | |
| LEV _{it-1} | 0.245 | 0.094 | 0.004 | 0.057^{**} | | |
| | (0.66) | (0.68) | (0.02) | (2.29) | | |
| TOBIN _{it-1} | 0.055 | 0.012 | 0.047 | -0.000 | | |
| | (0.66) | (0.49) | (1.20) | (-0.20) | | |
| CAP_{it-1} | 2.154*** | 0.858*** | 1.021** | -0.105*** | | |
| | (2.49) | (2.71) | (2.41) | (-2.82) | | |
| CAPEX _{it-1} | 1.184 | 0.801 | 0.712 | 0.104** | | |
| | (0.65) | (1.08) | (1.02) | (2.44) | | |
| CASH _{it-1} | 1.461*** | 0.627*** | 0.689*** | -0.040* | | |
| | (2.89) | (3.19) | (2.53) | (-1.84) | | |
| Industry fixed effects | Yes | Yes | Yes | Yes | | |
| Year fixed effects | Yes | Yes | Yes | Yes | | |
| Number of SEOs | 791 | 791 | 791 | 791 | | |
| Adj. R ² | 25.62% | 25.19% | 21.97% | 46.26% | | |

Panel B: Regressions of R&D productivity on R&D surprise

(continued)

This table reports evidence of variation in R&D productivity on pre-SEO R&D expenditures excluding software companies (SIC 7370-7373 and 7375). Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. R&D productivity is measured as the cumulative number of applications of patents, influential patents, and valuable patents (which are ultimately granted), and average sales over the three-year period from fiscal year *t*+1 to *t*+3 scaled by the R&D expenditures for fiscal year *t*-1. Panel A (Panel B) reports results from pooled OLS regressions of R&D productivity on the rank of R&D intensity (R&D surprise) along with a vector of control variables. Industry fixed effects are based on standard errors clustered by firm and year. ***, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. This restricted sample includes 791 non-software SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| TABLE 29 |
|--|
| Pre-SEO R&D Expenditures and SEO Pricing: Excluding Software Companies |

| Medium High High - Low | 263 268 | 42.19% 12.61% *** | -0.49% 2.02%*** | 26.69% -13.47%*** |
|------------------------------------|------------|-----------------------------|--------------------|----------------------|
| | | | | |
| Medium | 203 | 55.0570 | -0.4570 | 57.0070 |
| N C 11 | 265 | 35.63% | -0.43% | 37.06% |
| Low | 258 | 29.57% | -2.51% | 40.16% |
| All SEOs | 791 | 35.88% | -1.13% | 34.57% |
| $\operatorname{Rank}(R\&D_{it-1})$ | # of SEOs | <i>RUNUP</i> _{it} | $DROP_{it}$ | BTM_{it} |

Panel A: SEOs with low versus high R&D intensity

| $\operatorname{Rank}(\Delta R \& D_{it-1})$ | # of SEOs | RUNUP _{it} | DROP _{it} | BTM_{it} |
|---|-----------|---------------------|--------------------|------------|
| All SEOs | 791 | 35.88% | -1.13% | 34.57% |
| Low | 248 | 33.91% | -0.73% | 41.41% |
| Medium | 285 | 31.18% | -0.90% | 35.30% |
| High | 258 | 42.95% | -1.78% | 27.16% |
| High - Low | | 9.03%** | -1.04% | -14.25%*** |
| t-statistic | | 2.18 | -1.37 | -6.60 |

This table reports evidence of variation in SEO pricing on pre-SEO R&D expenditures excluding software companies (SIC 7370-7373 and 7375). Year *t* is the year in which an issuer files SEO, and year *t*-1 is the fiscal year immediately prior to the SEO filing day. Panel A (Panel B) reports the mean values of valuation measures around SEOs based on the standardized tercile rank of R&D intensity (R&D surprise) for fiscal year *t*-1. ***, **, * represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. This restricted sample includes 791 non-software SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| | Price run-ups prior to SEOs | |
|---------------------------------------|-----------------------------|---------------------|
| | (1) | (2) |
| | $RUNUP_{it}$ | RUNUP _{it} |
| INTERCEPT | 0.277*** | 0.283*** |
| | (3.94) | (3.64) |
| $\operatorname{Rank}(R\&D_{it-1})$ | 0.077** | |
| | (2.23) | |
| $\mathbf{Rank}(\Delta R \& D_{it-1})$ | | 0.081 |
| | | (1.62) |
| MRUNUP _{it} | 1.875*** | 1.907*** |
| | (7.14) | (7.21) |
| $SIZE_{it-1}$ | -0.033*** | -0.034*** |
| | (-4.17) | (-4.02) |
| SG_{it-1} | -0.004 | -0.005 |
| | (-0.32) | (-0.39) |
| ROA_{it-1} | -0.059 | -0.090* |
| | (-0.99) | (-1.65) |
| LEV _{it-1} | 0.011 | 0.013 |
| | (0.13) | (0.15) |
| TOBIN _{it-1} | -0.007 | -0.007 |
| | (-0.41) | (-0.39) |
| CAP_{it-1} | 0.126 | 0.127 |
| | (0.79) | (0.85) |
| $CAPEX_{it-1}$ | -0.145 | -0.174 |
| | (-0.89) | (-1.05) |
| CASH _{it-1} | 0.051 | 0.050 |
| | (0.39) | (0.38) |
| Industry fixed effects | Yes | Yes |
| Year fixed effects | Yes | Yes |
| Number of SEOs | 791 | 791 |
| Adj. R ² | 29.62% | 29.73% |

 TABLE 30

 Regressions of Price Run-ups on Pre-SEO R&D Expenditures: Excluding Software Companies

(continued)

This table reports evidence of variation in SEO pricing on pre-SEO R&D expenditures excluding software companies (SIC 7370-7373 and 7375). Year *t* is the year in which an issuer files SEO, and year *t*-1 is the fiscal year immediately prior to the SEO filing day. It reports results from pooled OLS regressions of issuers' stock price run-up prior to the SEO filing day on the rank of pre-SEO R&D expenditures along with a vector of control variables. Stock price run-up is measured as the cumulative 60-day stock return from 62 trading days before to three trading days before the SEO filing day. Industry fixed effects are based on Fama and French's (1997) 49-industry classification. The reported t-statistics in parentheses are based on standard errors clustered by firm and year. ***, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. This restricted sample includes 791 non-software SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

 TABLE 31

 Pre-SEO R&D Expenditures and Post-SEO Long-Term Stock Returns: Excluding Software Companies

| | | | LTRET _{it+3} | |
|------------------------------------|-----------|-----------------|-----------------------|-----------------------------------|
| $\operatorname{Rank}(R\&D_{it-1})$ | # of SEOs | Market adjusted | Size adjusted | Fama-French 3- factor adjusted |
| All SEOs | 791 | -23.33% | -22.10% | -1.36% |
| Low | 258 | -13.33% | -11.39% | 4.33% |
| Medium | 265 | -24.56% | -23.73% | 2.90% |
| High | 268 | -31.75% | -30.64% | -11.05% |
| High - Low | | -18.42%** | -19.25%** | -15.38%* |
| t-statistic | | -1.98 | -2.06 | -1.86 |

Panel A: SEOs with low versus high R&D intensity

| | | | $LTRET_{it+3}$ | |
|---|-----------|-----------------|----------------|-----------------------------------|
| $\operatorname{Rank}(\Delta R \& D_{it-1})$ | # of SEOs | Market adjusted | Size adjusted | Fama-French 3- factor adjusted |
| All SEOs | 791 | -23.33% | -22.10% | -1.36% |
| Low | 248 | -11.22% | -11.12% | 2.77% |
| Medium | 285 | -24.58% | -23.29% | 2.59% |
| High | 258 | -33.59% | -31.26% | -9.70% |
| High - Low | | -22.37%** | -20.15%** | -12.47%** |
| t-statistic | | -2.29 | -2.07 | -2.13 |

This table reports the mean long-term stock returns over the three years following the SEO year excluding software companies (SIC 7370-7373 and 7375). Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. Long-term stock returns are measured as buy-and-hold adjusted stock returns, inclusive of dividends, for the 36-month post-SEO period starting the first month of fiscal year *t*+1. Stock returns are adjusted using (i) the *CRSP* value-weighted index including distributions, (ii) the *CRSP* cap-based portfolio index, or (iii) expected returns estimated from Fama and French's (1993) three-factor model. Panel A sorts SEO issuers into terciles of R&D intensity for fiscal year *t*-1. Panel B sorts SEO issuers into terciles of R&D surprise for fiscal year *t*-1. ***, **, * represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. This restricted sample includes 791 non-software SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| Industry | # of SEOs | % of Sample |
|-----------------------------------|-----------|-------------|
| Computer hardware | 67 | 11.88 |
| Communications equipment | 83 | 14.72 |
| Electronics | 123 | 21.81 |
| Navigation equipment | 23 | 4.08 |
| Measuring and controlling devices | 82 | 14.54 |
| Medical instruments | 69 | 12.23 |
| Telephone equipment | 9 | 1.60 |
| Communications services | 2 | 0.35 |
| Software | 106 | 18.79 |
| Total | 564 | 100.00 |

 TABLE 32
 Sample Distribution across Industries: Using Loughran and Ritter's (2004) High-Tech Classification

This table describes the sample distribution across industries using Loughran and Ritter's (2004) classification of high-technology companies. This sample includes 564 SEOs from 1975 to 2005.

Productivity of Pre-SEO R&D Expenditures: Using Loughran and Ritter's (2004) High-Tech Classification

| | | | Productivity measures | | |
|------------------------------------|--------------|---|--|--|---|
| $\operatorname{Rank}(R\&D_{it-1})$ | # of SEOs | $\frac{\sum_{\tau=1}^{3} PATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} IPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} VPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} SALE_{it+\tau} / 3}{XRD_{it-1}}$ |
| All SEOs | 564 | | 0.44 | | |
| All SEOS | 304 | 1.60 | 0.44 | 0.59 | 0.06 |
| Low | 176 | 2.53 | 0.71 | 0.91 | 0.12 |
| Medium | 197 | 1.39 | 0.35 | 0.51 | 0.03 |
| High | 191 | 0.97 | 0.30 | 0.38 | 0.02 |
| High - Low | | -1.56*** | -0.41*** | -0.53*** | -0.11**** |
| t-statistic | | -4.34 | -2.99 | -3.34 | -6.99 |

Panel A: SEOs with low versus high R&D intensity

Panel B: SEOs with low versus high R&D surprise

| | | Productivity measures | | | | |
|-------------------------------|--------------|---|--|--|---|--|
| Rank $(\Delta R \& D_{it-1})$ | # of SEOs | $\frac{\sum_{\tau=1}^{3} PATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} IPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} VPATENT_{it+\tau}}{XRD_{it-1}}$ | $\frac{\sum_{\tau=1}^{3} SALE_{it+\tau}/3}{XRD_{it-1}}$ | |
| All SEOs | 564 | 1.60 | 0.44 | 0.59 | 0.06 | |
| Low | 176 | 2.33 | 0.63 | 0.75 | 0.10 | |
| Medium | 196 | 1.35 | 0.38 | 0.58 | 0.05 | |
| High | 192 | 1.20 | 0.34 | 0.47 | 0.02 | |
| High - Low | | -1.14*** | -0.29** | -0.28* | -0.07*** | |
| t-statistic | | -3.14 | -2.08 | -1.82 | -5.00 | |

This table reports evidence of variation in R&D productivity on pre-SEO R&D expenditures using Loughran and Ritter's (2004) classification of high-technology companies. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. R&D productivity is measured as the cumulative number of applications of patents, influential patents, and valuable patents (which are ultimately granted), and average sales over the three-year period from fiscal year *t*+1 to *t*+3 scaled by the R&D expenditures based on the standardized tercile rank of R&D intensity (R&D surprise) for fiscal year *t*-1. ***, **, * represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. This sample includes 564 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

Regressions of R&D Productivity on Pre-SEO R&D Expenditures: Using Loughran and Ritter's (2004) High-Tech Classification

| | R&D productivity | | | | | |
|----------------------------|--------------------------------------|---------------------------------------|---------------------------------------|--|--|--|
| | (1) | (2) | (3) | (4) | | |
| | $\sum_{\tau=1}^{3} PATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} IPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} VPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} SALE_{it+\tau} / 3$ | | |
| | XRD_{it-1} | XRD_{it-1} | XRD_{it-1} | $\overline{XRD_{it-1}}$ | | |
| INTERCEPT | 0.390 | -0.362 | -0.208 | 0.290*** | | |
| | (0.27) | (-0.71) | (-0.32) | (3.02) | | |
| Rank(R&D _{it-1}) | -1.186*** | -0.266 | -0.373* | -0.073*** | | |
| | (-2.69) | (-1.59) | (-1.79) | (-4.36) | | |
| SCALE _{it-1} | 0.467^{*} | 0.145 | 0.166 | 0.026*** | | |
| | (1.76) | (1.26) | (1.49) | (3.50) | | |
| $SIZE_{it-1}$ | 0.012 | 0.043 | 0.104 | 0.006 | | |
| | (0.10) | (0.90) | (1.62) | (1.07) | | |
| SG_{it-1} | 0.106 | -0.019 | -0.010 | 0.007 | | |
| | (1.15) | (-0.75) | (-0.27) | (1.10) | | |
| ROA_{it-1} | 0.011 | -0.136 | -0.092 | -0.022 | | |
| | (0.02) | (-0.93) | (-0.42) | (-1.43) | | |
| LEV_{it-1} | -0.649 | -0.030 | -0.180 | 0.038 | | |
| | (-1.10) | (-0.12) | (-0.64) | (1.12) | | |
| TOBIN _{it-1} | 0.112 | 0.023 | 0.075 | 0.002 | | |
| | (1.15) | (0.69) | (1.31) | (1.22) | | |
| CAP_{it-1} | 4.123*** | 1.324*** | 1.790*** | -0.155*** | | |
| | (3.20) | (3.35) | (3.83) | (-2.76) | | |
| $CAPEX_{it-1}$ | -0.048 | 0.852 | 0.446 | 0.136** | | |
| | (-0.02) | (0.97) | (0.52) | (2.14) | | |
| $CASH_{it-1}$ | -0.032 | 0.343 | 0.259 | -0.048 | | |
| | (-0.05) | (1.61) | (0.70) | (-1.26) | | |
| Industry fixed effects | Yes | Yes | Yes | Yes | | |
| Year fixed effects | Yes | Yes | Yes | Yes | | |
| Number of SEOs | 564 | 564 | 564 | 564 | | |
| Adj. R ² | 32.28% | 26.03% | 25.69% | 35.25% | | |

Panel A: Regressions of R&D productivity on R&D intensity

(continued)

| | R&D productivity | | | | | |
|---------------------------------------|--------------------------------------|---------------------------------------|--|---|--|--|
| | (1) | (2) | (3) | (4) | | |
| | $\sum_{\tau=1}^{3} PATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} IPATENT_{it+\tau}$ | $\sum\nolimits_{\tau=1}^{3} VPATENT_{it+\tau}$ | $\sum_{\tau=1}^{3} SALE_{it+\tau} / 3$ | | |
| | XRD_{it-1} | XRD_{it-1} | XRD _{it-1} | XRD _{it-1} 0.250 ^{***} | | |
| INTERCEPT | -0.118 | -0.450 | -0.399 | 0.250*** | | |
| | (-0.09) | (-1.00) | (-0.64) | (2.68) | | |
| $\mathbf{Rank}(\Delta R \& D_{it-1})$ | -1.139*** | -0.299* | -0.305* | -0.054*** | | |
| | (-3.20) | (-1.87) | (-1.82) | (-3.84) | | |
| $SCALE_{it-1}$ | 0.490^{*} | 0.148 | 0.175 | 0.028^{***} | | |
| | (1.87) | (1.34) | (1.62) | (3.79) | | |
| SIZE _{it-1} | 0.062 | 0.054 | 0.119* | 0.009^{*} | | |
| | (0.54) | (1.23) | (1.89) | (1.72) | | |
| SG_{it-1} | 0.162* | -0.004 | 0.004 | 0.009 | | |
| | (1.89) | (-0.18) | (0.12) | (1.36) | | |
| ROA_{it-1} | 0.535 | -0.011 | 0.064 | 0.008 | | |
| | (0.99) | (-0.07) | (0.31) | (0.54) | | |
| LEV _{it-1} | -0.418 | 0.013 | -0.096 | 0.056 | | |
| | (-0.75) | (0.05) | (-0.35) | (1.60) | | |
| TOBIN _{it-1} | 0.108 | 0.024 | 0.072 | 0.001 | | |
| | (1.26) | (0.78) | (1.34) | (0.70) | | |
| CAP_{it-1} | 4.259*** | 1.337*** | 1.853*** | -0.141*** | | |
| | (3.23) | (3.42) | (3.91) | (-2.60) | | |
| CAPEX _{it-1} | 0.106 | 0.920 | 0.455 | 0.134** | | |
| | (0.05) | (1.00) | (0.50) | (2.07) | | |
| $CASH_{it-1}$ | 0.005 | 0.348* | 0.274 | -0.044 | | |
| | (0.01) | (1.65) | (0.76) | (-1.14) | | |
| Industry fixed effects | Yes | Yes | Yes | Yes | | |
| Year fixed effects | Yes | Yes | Yes | Yes | | |
| Number of SEOs | 564 | 564 | 564 | 564 | | |
| Adj. R ² | 32.34% | 26.32% | 25.45% | 33.71% | | |

Panel B: Regressions of R&D productivity on R&D surprise

(continued)

This table reports evidence of variation in R&D productivity on pre-SEO R&D expenditures using Loughran and Ritter's (2004) classification of high-technology companies. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. R&D productivity is measured as the cumulative number of applications of patents, influential patents, and valuable patents (which are ultimately granted), and average sales over the three-year period from fiscal year *t*+1 to *t*+3 scaled by the R&D expenditures for fiscal year *t*-1. Panel A (Panel B) reports results from pooled OLS regressions of R&D productivity on the rank of R&D intensity (R&D surprise) along with a vector of control variables. Industry fixed effects are based on Fama and French's (1997) 49-industry classification. The reported t-statistics in parentheses are based on standard errors clustered by firm and year. ***, **, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. This sample includes 564 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

Pre-SEO R&D Expenditures and SEO Pricing: Using Loughran and Ritter's (2004) High-Tech Classification

| Rank($R\&D_{it-1}$) | # of SEOs | RUNUP _{it} | $DROP_{it}$ | BTM_{it} |
|-----------------------|-----------|---------------------|-------------|------------|
| | | | | |
| All SEOs | 564 | 35.08% | -1.16% | 36.61% |
| Low | 176 | 29.11% | -2.42% | 40.59% |
| Medium | 197 | 35.35% | -1.27% | 40.46% |
| High | 191 | 40.31% | 0.13% | 28.94% |
| High - Low | | 11.20%**** | 2.55%**** | -11.65%*** |
| t-statistic | | 2.65 | 3.08 | -4.68 |

Panel A: SEOs with low versus high R&D intensity

Panel B: SEOs with low versus high R&D surprise

| $\operatorname{Rank}(\Delta R \& D_{it-1})$ | # of SEOs | RUNUP _{it} | $DROP_{it}$ | BTM_{it} |
|---|-----------|---------------------|-------------|------------|
| All SEOs | 564 | 35.08% | -1.16% | 36.61% |
| Low | 176 | 33.56% | -1.55% | 41.95% |
| Medium | 196 | 31.92% | -1.22% | 39.66% |
| High | 192 | 39.70% | -0.73% | 28.57% |
| High - Low | | 6.14% | 0.82% | -13.38%*** |
| t-statistic | | 1.35 | 0.96 | -5.47 |

This table reports evidence of variation in SEO pricing on pre-SEO R&D expenditures using Loughran and Ritter's (2004) classification of high-technology companies. Year *t* is the year in which an issuer files SEO, and year *t*-1 is the fiscal year immediately prior to the SEO filing day. Panel A (Panel B) reports the mean values of valuation measures around SEOs based on the standardized tercile rank of R&D intensity (R&D surprise) for fiscal year *t*-1. ***, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. This sample includes 564 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

| | Price run-ups prior to SEOs | |
|------------------------------------|-----------------------------|--------------|
| | (1) | (2) |
| | <i>RUNUP</i> _{it} | $RUNUP_{it}$ |
| INTERCEPT | 0.194* | 0.228** |
| | (1.83) | (1.93) |
| $\operatorname{Rank}(R\&D_{it-1})$ | 0.113*** | |
| | (3.58) | |
| Rank($\Delta R \& D_{it-1}$) | | 0.114*** |
| | | (3.00) |
| MRUNUP _{it} | 1.941*** | 1.997*** |
| | (5.93) | (6.31) |
| SIZE _{it-1} | -0.037*** | -0.040*** |
| | (-3.32) | (-3.42) |
| SG_{it-1} | -0.031*** | -0.036*** |
| | (-2.82) | (-3.22) |
| ROA_{it-1} | -0.162** | -0.216*** |
| | (-2.06) | (-2.97) |
| LEV _{it-1} | 0.175^{*} | 0.150 |
| | (1.74) | (1.41) |
| TOBIN _{it-1} | -0.015 | -0.015 |
| | (-1.37) | (-1.29) |
| CAP_{it-1} | 0.235 | 0.222 |
| | (1.14) | (1.09) |
| CAPEX _{it-1} | -0.002 | -0.018 |
| | (-0.01) | (-0.11) |
| CASH _{it-1} | 0.153 | 0.147 |
| | (1.21) | (1.13) |
| Industry fixed effects | Yes | Yes |
| Year fixed effects | Yes | Yes |
| Number of SEOs | 564 | 564 |
| Adj. R ² | 32.90% | 32.99% |

TABLE 36Regressions of Price Run-ups on Pre-SEO R&D Expenditures: Using Loughran and Ritter's (2004) High-
Tech Classification

(continued)

This table reports evidence of variation in SEO pricing on pre-SEO R&D expenditures Loughran and Ritter's (2004) classification of high-technology companies. Year *t* is the year in which an issuer files SEO, and year *t*-1 is the fiscal year immediately prior to the SEO filing day. It reports results from pooled OLS regressions of issuers' stock price run-up prior to the SEO filing day on the rank of pre-SEO R&D expenditures along with a vector of control variables. Stock price run-up is measured as the cumulative 60-day stock return from 62 trading days before to three trading days before the SEO filing day. Industry fixed effects are based on Fama and French's (1997) 49-industry classification. The reported t-statistics in parentheses are based on standard errors clustered by firm and year. ***, ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. This sample includes 564 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

Pre-SEO R&D Expenditures and Post-SEO Long-Term Stock Returns: Using Loughran and Ritter's (2004) High-Tech Classification

| $\operatorname{Rank}(R\&D_{it-1})$ | | $LTRET_{it+3}$ | | |
|------------------------------------|-----------|-----------------|---------------|-----------------------------------|
| | # of SEOs | Market adjusted | Size adjusted | Fama-French 3- factor adjusted |
| All SEOs | 564 | -21.82% | -21.78% | 1.30% |
| Low | 176 | -15.48% | -15.34% | 4.25% |
| Medium | 197 | -16.10% | -16.40% | 4.37% |
| High | 191 | -33.58% | -33.15% | -4.58% |
| High - Low | | -18.10%** | -17.81%** | -8.83% |
| t-statistic | | -2.22 | -2.13 | -1.54 |

Panel A: SEOs with low versus high R&D intensity

Panel B: SEOs with low versus high R&D surprise

| $\operatorname{Rank}(\Delta R \& D_{it-1})$ | | $LTRET_{it+3}$ | | | |
|---|-----------|-----------------|---------------|-----------------------------------|--|
| | # of SEOs | Market adjusted | Size adjusted | Fama-French 3- factor adjusted | |
| All SEOs | 564 | -21.82% | -21.78% | 1.30% | |
| Low | 176 | -7.57% | -7.95% | 8.26% | |
| Medium | 196 | -28.85% | -28.16% | 3.59% | |
| High | 192 | -27.71% | -27.92% | -7.41% | |
| High - Low | | -20.14%** | -19.97% | -15.68% | |
| t-statistic | | -1.68 | -1.38 | -1.28 | |

This table reports the mean long-term stock returns over the three years following the SEO year using Loughran and Ritter's (2004) classification of high-technology companies. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. Long-term stock returns are measured as buy-and-hold adjusted stock returns, inclusive of dividends, for the 36-month post-SEO period starting the first month of fiscal year *t*+1. Stock returns are adjusted using (i) the *CRSP* value-weighted index including distributions, (ii) the *CRSP* cap-based portfolio index, or (iii) expected returns estimated from Fama and French's (1993) three-factor model. Panel A sorts SEO issuers into terciles of R&D intensity for fiscal year *t*-1. Panel B sorts SEO issuers into terciles of R&D surprise for fiscal year *t*-1. ***, ** , ** represent significance at the 1, 5, 10 percent level, respectively, based on two-tailed tests. This sample includes 564 SEOs from 1975 to 2005. See Appendix 1 for variable definitions and Appendix 2 for the timeline highlighting the variable measurement.

Appendices

APPENDIX 1 Variable Definitions

| Variable | Definition | | |
|-----------------------------|---|--|--|
| ABR&D _{it} | R&D surprise estimated from the discretionary expense model in Cohen and Zarowin (2010). | | |
| $ASSET_{it}$ | Total assets (at_{it} / 1000) for fiscal year <i>t</i> . | | |
| BTM _{it} | Book-to-market ratio measured as book value of common equity (ceq_{it-1}) divided by market value of common equity $(prcc_f_{it-1} \cdot csho_{it-1})$ at the beginning of fiscal year t. | | |
| CAP_{it} | Capital intensity measured as PP&E ($ppent_{it}$) scaled by total assets at the end of fiscal year <i>t</i> . | | |
| CAPEX _{it} | Capital expenditures ($capx_{it}$) scaled by total assets at the beginning of fiscal year t. Missing values of $capx_{it}$ are set to zero. | | |
| CASH _{it} | Cash and its equivalents (che_{it}) scaled by total assets at the end of fiscal year t. | | |
| DROP _{it} | Cumulative five-day market adjusted return from two trading days before to two trading days after the SEO filing day. Market returns are based on the CRSP value-weighted index including distributions. | | |
| IPATENT _{it} | Number of applications of influential patents that are filed during year <i>t</i> and are ultimately granted. A patent is classified as influential if its non-self citation counts are above the average across all patents in the same technology class and granted in the same year. | | |
| LEV _{it} | Leverage measured as short-term debt (dlc_{it}) plus long-term debt $(dltt_{it})$ scaled by total assets at the end of fiscal year <i>t</i> . | | |
| LTG _{it} | Analysts' latest consensus long-term growth forecast made after the end of fisc year <i>t</i> -1 and before the SEO filing day with a long-term horizon (<i>FPI</i> =0) from <i>I/B/E/S</i> . | | |
| LTRET _{it+3} | Buy-and-hold adjusted stock returns, inclusive of dividends, over the 36-month post-SEO period starting the first month of the fiscal year immediately following the SEO issue day. Stock returns are adjusted using (i) the <i>CRSP</i> value-weighted index including distributions, (ii) the <i>CRSP</i> cap-based portfolio index, or (iii) expected returns estimated from the Fama-French three-factor model. Raw returns from <i>CRSP</i> are adjusted for delisting returns. | | |
| <i>MISS_{it+k}</i> | Indicator variable equals one if the issuer misses analysts' sales forecast for the fiscal year t +k following the SEO issue day (where k takes the value of one, two, and three), and equals zero otherwise. I use analysts' latest consensus sales forecast which is made after the end of fiscal year t -1 and before the SEO filing day with a long-term horizon from $I/B/E/S$. | | |
| MRUPUP _{it} | Cumulative 60-day CRSP value-weighted index return including distributions from 62 trading days before to three trading days before the SEO filing day. | | |
| OVERCONFIDENT _{it} | Indicator variable equals one if the issuer has an overconfident manager, and equals zero otherwise. Two measures of overconfidence are employed following Schrand and Zechman (2012). The first measure is based on CEOs' option holdings using ExecuComp data. If the log of in-the-money unexercised exercisable options held by the CEO (<i>opt_unex_exer_est_val</i> _{it} + 0.01) is greater than the industry median based on the three-digit SIC code, then the manager is classified as overconfident. The second measure is constructed using four signals based on mangers' acquisition, financing, and distribution activities that prior | | |

| | research has found to be related with managerial overconfidence. If at least two of the four signals are positive for the issuer, then it is classified as having an overconfident manager. The first signal of overconfidence is positive if the cash outflow for acquisitions (aqc_{it}) scaled by total assets at the end of fiscal year t is greater than the industry median. The second signal of overconfidence is positiv if the debt-to-equity ratio is greater than the industry median. Debt-to-equity ratio is measured as short-term debt (dlc_{it}) plus long-term debt ($dltt_{it}$) divided by common equity (ceq_{it}) at the end of fiscal year t. The third signal of overconfidence is positive if the issuer uses either convertible debt ($dcpstk_{it}$) or preferred stock ($pstk_{it}$) for financing. The last signal of overconfidence is positive if the dividend per share ($dvpsp_{it}$) equals to zero for the issuer. |
|---|--|
| PATENT _{it} | Number of patent applications that are filed during year <i>t</i> and are ultimately granted. |
| PROCEEDUSE _{it} | Categorical variable indicating the intended use of proceeds as stated in the late amended Form S-3 which is filed with the SEC through EDGAR. There are for main categories of intended use of proceeds: R&D plan, acquisition, debt repayment, and general corporate purposes. An issuer is classified as having an "R&D plan" if it mentions planned spending on R&D activities. Within this category, an issuer is further classified as having a "specific R&D plan" if it provides information on the specific product lines or research programs related the R&D plan, or gives quantitative information on the portion of proceeds use for the R&D plan. An issuer is classified as having an intended use for "acquisition" if it mentions planned acquisition of complementary technologies products, or other businesses. An issuer is classified as having an intended use for "debt repayment" if it mentions planned repayment or reduction of any outstanding debt. Note that an issuer can be classified into more than one category including R&D plan, specific R&D plan, acquisition, and debt repayment. An issuer falls into the category of general corporate purposes if it does not mention any use of proceeds for R&D, acquisition, or debt repayment |
| Rank(ABR&D _{it}) | Tercile rank of $ABR&D_{it}$ dividing the annual cross-section of seasoned issuers into three groups, standardized to range from zero to one. |
| Rank(<i>R&D</i> _{it}) | Tercile rank of $R\&D_{it}$ dividing the annual cross-section of seasoned issuers into three groups, standardized to range from zero to one. |
| $\operatorname{Rank}(\Delta R \& D_{it})$ | Tercile rank of $\Delta R \& D_{ii}$ dividing the annual cross-section of seasoned issuers in three groups, standardized to range from zero to one. |
| $R\&D_{it}$ | R&D intensity measured as R&D expenditures (xrd_{it}) scaled by total assets at the beginning of fiscal year <i>t</i> . |
| $\Delta R \& D_{it}$ | R&D surprise measured as change in R&D expenditures $(xrd_{it} - xrd_{it-1})$ scaled by total assets at the beginning of fiscal year <i>t</i> . |
| <i>ROA_{it}</i> | Return-on-assets measured as operating income after depreciation $(oiadp_{it})$ divided by total assets at the beginning of fiscal year <i>t</i> . |
| RUPUP _{it} | Cumulative 60-day stock return from 62 trading days before to three trading da before the SEO filing day. |
| SALE _{it} | Sales ($sale_{it}$ / 1000) for fiscal year <i>t</i> . |
| SCALE _{it} | Scale effect of R&D expenditures $(1 / xrd_{it})$ for fiscal year <i>t</i> . |
| SG_{it} | Percentage growth in sales $(sale_{it})$ for fiscal year t. |
| SIZE _{it} | Firm size measured as the natural log of total assets (at_{it}) at the end of fiscal years |

| TOBIN _{it} | Tobin's Q measured as the ratio of total market value over total assets at the end of fiscal year <i>t</i> . Total market value is measured as the sum of the market value of common equity $(csho_{it} \cdot prcc_f_{it})$, short-term debt (dlc_{it}) , and long-term debt (dlt_{it}) . | |
|-----------------------------|--|--|
| <i>VPATENT_{it}</i> | Number of applications of valuable patents that are filed during year <i>t</i> and are ultimately granted. A patent is classified as valuable if the stock market response to patent grant news is above the average across all patents in the same technology class and granted in the same year. The stock market response is measured over the window from the grant day to two trading days after the grant day. | |
| XRD _{it} | R&D expenditures (xrd_{it}) for fiscal year t. | |

This appendix presents definitions for all variables in the analyses. Data variables in lowercases and italics are from Compustat.

Pre-SEO Post-SEO Fiscal year SEO year t Fiscal year t+1*t*+2 *t*-1 end t+3 end ^a SEO filing day ^b SEO issue day Measurement of Measurement of R&D productivity R&D expenditures (i.e., the cumulative number of $(R\&D_{it-1} \text{ and }$ Measurement of patents and sales) and long-term $\Delta R \& D_{it-1}$) and other price run-up stock returns ($LTRET_{it+3}$) over the (RUPUP_{it}), analysts' financial variables as three-year period following the SEO of the fiscal year long-term growth year t. immediately prior to forecasts (LTG_{it}) , and the SEO filing day. sales forecasts before the SEO filing day.

APPENDIX 2 *R&D Expenditures and SEO Timeline*

This figure describes the research design timeline. Year *t* is the year in which an issuer files SEO, year *t*-1 is the fiscal year immediately prior to the SEO filing day, and year *t*+1 is the fiscal year immediately following the SEO issue day. The median distance between the SEO filing day and the end of fiscal year *t*-1 is six months. The median distance between the SEO filing day and the SEO issue day is three weeks. The median distance between the SEO issue day and the beginning of fiscal year *t*+1 is five months.