The Changing Nature of Firm R&D: Short-termism & Technological Influence of US Firms

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Abstract:
In this paper, we examine the relationship between rising short-termism and the nature of innovation in US public firms, 1980-2009. Breakthrough inventions, or those that significantly influence later innovation, require sub-technologies to be created that don't yet exist. We argue that these inventions typically require a longer-term time horizon. Combining a measure of invention influence that examines the dispersion and depth of forward patent citations with a measure of a firm's short-term orientation, we find that more short-term firms both patent less and have less influential patents (conditional on patenting). Further, we find several factors that alter the magnitude of this relationship. Firms using more complex technologies, with more government funded R&D, with a stronger scientific orientation, lower R&D productivity, more organizational centralization, and facing greater product market competition show a stronger negative relationship. We then instrument for short-termism using changes in institutional investor blockholder behavior to causally link increases in short-term orientation to the production of fewer influential inventions. Given earlier documentation on rising short-termism in firms in recent years, our results have significant implications not only for the changing nature of firm R&D and firm competitiveness, but also US economic growth.

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1. Introduction

In 1938, Dupont patented nylon, an enormously successful product that was the result of a purposeful, decade long basic research effort by Dupont's corporate R&D lab (Ndiaye 2007) in which scientists were expected to do "pioneering research (p. 92)". The discovery of Nylon, over time, led to a complete restructuring of Dupont's business. "[B]y the 1950s, in many respects, [Dupont was] a fibers company that had some other businesses on the side" (Hounshell and Smith 1988). Similarly, AT&T's patent for the transistor, a central building block of the Third Industrial Revolution, came from Bell Labs. Eight individuals earned Nobel Prizes for work they completed while at Bell Labs.[2] These corporate patents have been foundational in the fields of chemicals and electronics and helped fuel the US economy for several decades.

Despite these successes, Dupont and AT&T have discontinued the strategies that led to these discoveries. Rising pressures on firms to generate short over long-term profits is one possible explanation for such behavior. Sampson and Shi (2020) reveal a general trend: market short-termism, which captures contracting firm time horizons, has been increasing for public US firms. Short-termism appears to affect firm investment levels in particular circumstances (Asker, Farre-Mensa, and Ljungqvist 2015; Flammer and Bansal 2017; He and Tian 2013; DesJardine 2015; Davies et al. 2014). Notwithstanding this evidence that short-termism may influence corporate investment, the effects of rising short-termism on innovative output are not well understood. Firm R&D spending has increased significantly, from $30.93B in 1980 to $297.28B in 2013 (NSF 2016). However, as suggested by the Dupont and AT&T illustrations, the nature of R&D may be changing from more long-term, foundational investments that spur innovation to more short-term, incremental, exploitative efforts designed to harvest existing knowledge.

Knott (2017) measures a decline in RQ, a measure of R&D productivity among public firms, and documents changing strategies around how innovation is generated (Knott, 2015). Corredoira, Goldfarb & Shi (2018) find in a sample of patents granted between 2001 and 2004, that those funded by the government were more likely to spark follow-on innovation than those solely funded by firms and Bernstein (2015) documents that firms going public changed R&D strategies to focus on greater external acquisition of new technologies. These results, coupled with evidence that US

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[2] https://web.archive.org/web/20160308115624/https://www.bell-labs.com/our-people/recognition/ Viewed June 26, 2018.

firms develop less science (Arora, Belenzon, and Patacconi 2018), is suggestive evidence that a shift in the nature of firm R&D has been taking place among firms.

Thus, in this paper we focus on the potentially profound effect of short-termism on the *nature* of R&D investments. In our analyses below, we evaluate whether and how the nature of innovation in US public firms has changed over time and how any observed changes correlate with short-termism. Using patent-based measures of influential inventions (Corredoira and Banerjee, 2015), we map the relationship with short-termism. Patent influence indicates the richness of a forward patent citation tree over a finite period or, in other words, how diverse and extensive (among classes and assignees) a patent's forward citations are. We begin by mapping out whether patent influence is shifting over time and find that, while there is still a group of firms that produce highly innovative patents, this group is much more concentrated than in the past. Patent influence is declining for most firms from 1980 to 2010.

We also find that public firms that are more short-term oriented are less likely to produce progenerative, influential patents. The effect we observe has two central components. First, leveraging within-firm variation, we report broad evidence that public firms with a more short-term orientation are less likely to patent. Second, conditional on patenting, patents by more short-term public firms tend to be less influential. These results are robust to the inclusion of variables demonstrated by prior research to bear a relationship with impactful R&D, such as firm diversification (Seru 2014), degree of R&D (de)centralization (Argyres and Silverman 2004; Arora, Belenzon, and Rios 2014) and whether the firm is a leader or laggard in its business segment (Hashmi 2013; Aghion et al. 2002). We also find that this effect is more pronounced for firms in technological areas that are more complex (in the sense that individual elements of a technological solution are themselves discreetly patentable, Cohen, Nelson & Walsh (2000)), as well as those that experience higher product market competition.

We present our results using both a traditional as well as an epistemic mapping approach (King, Goldfarb, & Simcoe, 2020). The latter approach maps the relationship between short-termism and patenting across choices of patent-based innovation measures and combinations of sampling criteria, control variables and modeling choices. We thereby provide the reader with a comprehensive map to help understand the sensitivity of the estimates to plausible empirical assumptions.

Several robustness checks support these general findings. Alternative measures of influential innovations, such as text-based measures of novelty (Fleming et al 2019) and backward patent citations (Rosenkopf and Nerkar 2001), as well as varied sampling yield similar results.

To move beyond correlational relationships and evaluate whether there is a causal impact of rising short-termism on the nature of firm R&D, we employ an instrumental variables approach that captures rising short-termism via changes in the trading behavior of institutional investors holding large blocks of shares. These results show a strong negative effect of rising levels of our instrumented short-termism variable on influential patenting by firms.

The potential implications of these results are profound. If firms are changing the nature of their investments, away from more fundamental and potentially path breaking R&D projects, towards those that are more incremental, they are in effect choosing shorter term, more certain, but likely smaller gains, over longer term, less certain, but market creating gains. Depending on how this phenomenon compares to that in other countries and given how breakthrough inventions are a critical engine of economic growth, this may signal a shift of US competitiveness. Follow up analyses show similar patterns of declining influential inventions among US private firms as well, implying that our results are not just reflecting a shift of breakthrough inventions from public to private firms.

The paper proceeds as follows. We set out a conceptual discussion of what drives breakthrough inventions, what it means for a firm to be short-term and the implications for these breakthrough inventions in Section 2. Our data and key measures are described in Section 3, along with descriptive graphs that show trends in influential patents (our proxy for breakthrough inventions) over time. Section 4 sets out our focal empirical results, demonstrating the persistent negative correlation between short-termism and patent influence as well as an instrumental variables approach that suggests the relationship between short-termism and influence may be causal. We conclude with a discussion of implications, limitations and future directions in Section 5.

2. Conceptual background

2.1 The process of breakthrough inventions

To make a connection between breakthrough inventions and a firm's time horizons, with the management priorities that follow, we first examine the process of breakthrough inventions. Based on prior work that we presently describe, our prior is that breakthrough inventions are those where multiple additional technologies have to be created in order to solve the original problem that the invention seeks to address. In other words, while incremental inventions are those that build upon established technologies, breakthrough inventions require creation of sub-technologies that don't yet exist.

Rosenberg's (1963) seminal paper on the machine tool industry described how early technologies were invented, subsequently improved, and then applied to a variety of applications over time. Rosenberg (1969) then noted that technological innovation in itself defines problems for subsequent innovation. Arthur (2009), tidies these ideas into a structured framework that leverages the observation that technological innovation is recombinatory in nature (Fleming, 2001), and hierarchical in the sense that inventors leverage an existing concept or idea and this effort serves as a Rosenbergian focusing device as inventors work to solve a series of technological challenges needed to render the idea operational. Early efforts to convert an idea into a working technology, that is, an artifact that *does* something, usually lead to initial outcomes that are not particularly useful. However, such efforts are still fruitful because they clarify not only what problems still need to be solved, but also identify what the barriers to implementation are in the first place. That is, efforts to solve each problem reveal a set of sub-problems, where the solutions are embodied in technologies and sub-technologies, respectively. When ideas are novel, we expect that it will take more time to work out how sub-technologies fit together to create an overall solution. The more new sub-technological problems that need to be worked out, the longer a firm requires to work out these individual problems.

Arthur (2009) illustrates these ideas via the example of Gary Starkweather's invention of the laser printer at Xerox in late 1969. Starkweather came up with the fundamental idea while working in Xerox's Webster, New York, Lab. The Webster lab was organized with a sharp focus on incremental improvements that could be embedded in the next version of Xerox copiers. Starkweather's laser idea, which came out of his doctoral work, was fundamentally recombinatorial in that it used the (newly invented) laser to "`paint' an image on a xerographic drum." When Starkweather proposed using laser technology to produce a printer at Xerox's Webster, NY lab, it was quickly recognized that creating a working laser printer was not possible by simply assembling off-the-shelf components (Hiltzik 2000). Reflecting the strategic priorities of the Webster lab, Starkweather was ordered to refocus his efforts on marginal improvements to existing, diffuse-light, CRT machines. Unhappy with this directive, and with a bit of luck, Starkweather was transferred to the newly created Xerox Palo Alto Research Center (PARC). PARC was organized completely differently, akin to an academic department with a long-term focus. Within the organizational freedom at PARC, Starkweather had both time and resources to solve many of the sub-problems of laser printing. This led to the 1969 breakthrough patent. Thus, the laser printer was invented in a quasi-academic environment, with few restrictions on budgets and freedom to work on interesting projects. With less restrictive budgets and mandates surrounding project scope and outcome timing, these examples suggest how a firm's time horizons can impact the *nature* of technological investments.[3]

In contrast to the laser printer example, Arthur considers inventions incremental when the sub-technologies are well established. An example would be the case of marginal improvements to CRT copiers. To develop these more incremental innovations, short-term horizons may suffice. When an idea is more novel, it generally requires solutions to a host of new, unanticipated subtechnology problems. Novel ideas are not simply more time consuming, they are more risky because they require solutions to additional subtechnological problems; each could wind up being very difficult to solve. Moreover, these new problems are difficult to anticipate ex-ante, when the original idea is imagined. For successful development of very novel ideas, a longer-term orientation is needed. However, the more subtechnologies needed to realize an idea, the more likely some of these inventions will have broad applications, generating solutions to problems yet unimagined (i.e., breakthrough inventions). Because such exploration is by definition more time consuming with uncertain outcomes, it likely requires longer time horizons and greater patience for returns within the organization itself.

2.2 How does firm short-term orientation link to the nature of innovation?

Research in behavioral economics and finance demonstrates the link between time horizons and willingness to engage in riskier investments, such as more ambitious R&D projects. Further, this research links the evaluation or feedback period to investor time horizons. For example, in experiments, longer feedback periods lead to greater long-term investment (Fellner and Sutter 2009) and, when returns are aggregated over longer time periods, individuals make riskier investments (Thaler et al. 1997). Further, market prices of risky assets have been higher when feedback and decision making is less frequent (Gneezy, Kapteyn, and Potters 2003).

Firms facing pressures to deliver short-term returns (i.e., those with a shorter time orientation) may find it difficult to invest in more novel, recombinatory R&D projects because these typically require solutions to a larger set of subtechnological problems requiring more time and that

[3] While the long-term orientation of Xerox PARC has been controversial - the laser printer, eventually brought to market in 1978, earned over $2B in revenues for Xerox. The annual budget for PARC at that time was approximately $6M (Hiltzik 2000) - thus it is difficult to claim this was not a win for Xerox. However, the time between a conception to project was over a decade. Xerox has since scaled back the long-term orientation of its research center.

are characterized by greater uncertainty (as noted above). Instead, these firms may prefer simpler projects - that is, those that require more straightforward applications of current technological solutions, since these will more likely lead to near term, more certain payoffs. There are two mechanisms within the firm that make more novel recombinations less likely in short-term oriented firms.

First, researchers have greater difficulty conveying the value of more novel projects, since these projects are usually characterized by higher information asymmetry. The laser printer example above illustrates this challenge; Starkweather, who had recently graduated from a department on the technological frontier, struggled to convey the promise of the new LASER technology to his managers. Second, even if frontier ideas are well understood, the time horizons necessary for success are often beyond the timelines of managers. This was certainly the case for Starkweather and the laser technology as Starkweather's initial requests to spend time on laser printing possibilities was stymied by managers focused on incremental improvements to CRT copiers (Hiltzik 2000). More generally, projects that require search across many potential recombinations or those that require in-depth search may not only be curtailed, but eliminated. Since it is difficult to predict how different subtechnologies may come together to produce useful technologies, curtailing such efforts will lead to a lower likelihood of finding progenerative innovation paths that lead to breakthrough inventions.

These arguments lead us to the central prediction of the paper: *Short-term-oriented firms are less likely to produce progenerative, or influential, inventions.* A secondary prediction is that the variance of project outcomes should be *higher* for long-term oriented firms as compared to short-term oriented firms. Because of prior observations that short-termism appears to be rising for the majority of US publicly listed firms (Sampson and Shi 2020), implications extend beyond firm performance to the economy as a whole. We note, however, the extensive heterogeneity across firms in the level of observed short-termism means that some firms are still likely engaged in longer term, riskier projects.

Importantly, firms and investors may prefer to have a short-term orientation. Establishing that there is a relationship between short-termism and both the extent and quality of patenting output on average in public firms does not necessarily imply that we ought to be concerned. We return to this discussion and debate after we have presented our description of the impact of short-termism on innovative output.

2.3 Sources of firm heterogeneity in the relationship between short-termism and influential inventions

We expect that firm heterogeneity adds variance to the expected relationship between short-termism and influential inventions. The literature evaluating relationships among firm characteristics, such as size, incumbency and organizational form, industry competitive dynamics and innovation is vast, revealing significant nuance in these relationships across firms and industries (see, e.g., Cohen 2010 for a relatively recent review of this literature). From this literature, however, we identify three key characteristics that may explain any observed heterogeneity in the relationship between short-termism and influential inventions. These include the extent of diversification, the degree of centralization of a firm's R&D program, and whether a firm is a leader or laggard in an industry.

The extent of diversification within a firm has been argued to alter the incentives to invest in more innovative projects. (Porter 1992) argued that conglomerates may be ill suited to more innovative projects. This may be due to the informational distance between divisions, which are close to the research, and headquarters (HQ), where funding decisions are made. Scherer (1999) notes that researchers or managers closest to the actual R&D projects have access to more tacit (or 'soft') information as to the quality of the projects. Credibly communicating this information to the decision-making HQ is the source of the funding problem; HQ cannot be sure that researchers or division managers won't distort information to ensure support for division R&D activities. Seru (2014) argues that, because of this anticipated information manipulation, HQ may optimally decide not to embark on more novel projects characterized by more uncertain outcomes. Anticipating this, divisional managers may propose only more certain, but incremental, projects to HQ (Rotemberg and Saloner 1994). Over time, this phenomenon would be expected to change the nature of R&D within diversified firms toward these incremental projects. Thus, we expect that influential inventions are less likely for more diversified firms. Further, we expect that rising short-termism within such firms will exacerbate this move away from ambitious projects as diversification increases. In other words, the extent of diversification may explain why some firms have a more negative relationship between short-termism and influence. Investors may rationally anticipate lower long-term returns to R&D for more diversified firms.

Closely related to diversification is the extent of decentralization of a firm's R&D program. The degree of (de)centralization of R&D reflects both where R&D is conducted in the firm and where project funding decisions are made (i.e., HQ or divisions). Such decentralization has been proposed as a mechanism to commit resources to more novel R&D projects, since the decision making power over project continuation rests with the division manager (Seru 2014). More optimal tradeoffs are possible given the stronger incentives possible with assigning decision rights closer to the information source; the tendency to distort information is reduced and division managers are more likely to terminate underperforming projects (Aghion and Tirole 1997). These arguments suggest that more experimental projects would take place in firms with more decentralized R&D. In contrast, Arora et al., (2014) find that more basic research, which bears a stronger link with influential inventions since basic research is characterized by projects without clear applications and certain payoffs similar to the novel recombinations that facilitate influential inventions, is more likely in firms with centralized R&D programs. We expect this effect to persist only for diversified firms. Whether decentralization supports more novel projects, improving the likelihood of influential inventions, depends on whether the firm is a diversified, multi-business firm. If the firm is a single business firm, then the difference empirically between decentralized and centralized R&D collapses.

Overall, it appears that a cluster of firm characteristics make influential inventions less likely and that rising short-termism will exacerbate these effects. Further details are contained in our discussion of the measures that capture these constructs below.

3. Data description: Sample & Measures

To evaluate whether firms with a short-term time horizon produce less influential inventions, we combine firm level, patent citation data with a market-based measure of short-termism. Our sample for estimation consists of all firms publicly listed on major US stock exchanges (i.e., NYSE/AMEX and NASDAQ) for the period 1980-2009. The short-termism measure requires five consecutive years of stock market data for each listed firm; thus, we exclude public firms listed for fewer than five years.[4]

3.1 Dependent variables capturing breakthrough inventions

We create two primary measures to capture the impact of a firm's inventions on subsequent innovation, using patent grant and application information collected from PATSTAT Global and the NBER dataset. Our sample includes all the USPTO applications for utility patents with application dates between January 1, 1976 and December 31, 2016 and corresponding patents granted before July 31, 2018. With this data, we calculate the influence and impact for patents

[4] We also exclude over the counter stocks as well as firms that have undergone changes that trigger a change in CUSIP identifier in the past five years. These changes include name change, (reverse) stock split, and restructuring (FINRA, 2016).

granted during the period 1980-2009. These variables are calculated according to the following definitions and are aggregated annually at the firm portfolio level.

Patent Impact captures the technological impact of a focal patent by the citations received from subsequent patents granted within 7-years of the publication date of the focal patent (but no later than 2018). *Patent Influence* captures the direct and indirect impact of a patent over a defined time window (Corredoira and Banerjee 2015; Corredoira, Goldfarb, and Shi 2018). *Patent Influence* is defined as:

$$Patent\ \ Influence = \sum_{k=1}^{\infty} \quad (\alpha^k A^{Tk}),$$

where α is the attenuation factor (in this study $\alpha = 1$), k is the citation generation, A^T is the transpose of the adjacency matrix defined by patent citations. Intuitively, this measure captures how many generations of patent trees are built upon a focal patent. In other words, the influence of a patent is the column sum of the matrix $\alpha^k A^{Tk}$. The citation tree defining the adjacency matrix is composed of all direct and indirect citations received by the focal patent from patents granted before 2018 and with publication date in the 7-year window following the publication date of the focal patent, conditional on having an application date later than that of the focal patent. As a result, *Patent Influence* reflects how much the focal patent has contributed to subsequent inventions, with larger scores reflecting greater long-term utilization of the knowledge embedded in a focal patent.

Due to the incentive structure of incentives in the patent system, patents, unlike academic literature, cite only their immediate antecedents – creating a de facto barrier to assess the influence beyond the direct antecedents. Therefore, capturing indirect citations with patent data is particularly important to identify dead paths or expansion into new frontiers. (Figure 1 shows an example of a technology network and its adjacency matrix). *Patent Impact* and *patent Influence* have distributions with very long right tails. Following Corredoira and Banerjee (2015) and Corredoira, Goldfarb, and Shi (2018), we take the natural logs of *Patent Impact* and *Patent Influence.*

Over our period of observation there have been systemic changes in patenting regimes and an overhaul of the patenting system that, among other things, resulted in different rules for the attribution of priority, and the publication of documents with the consequent increase in citations to applications. The implementation of these processes resulted in an increase in the number of citations to patent applications. Citations to applications were negligible before 2000, but by the 2010s well above 50% of patent citations were to applications. In addition to this change, patents also show systematic differences in the average number of citations over time and across classes. For these reasons we standardized the variables of interest.

We standardize these measures using a z-score, constructed by dividing the focal patent's impact or influence by the standard deviation of all patents' impact or influence in the focal patent's primary class in a given year. We drop all patents assigned to main classes with fewer than 30 patent applications in that year. We chose not to subtract the average or median from the z-scores, since not doing so allows a more natural interpretation given that the citation measures are all bounded below by 0. That is, the z-score measures the number of standard deviations from 0 in a given year. In this way, we are anchoring all the values to the zero of each measure, a value with the same meaning for all the classes and years.

We note that the distributions of values for *Patent Impact* and *Patent Influence* show very long tails, and we are particularly interested in the top of the distribution, since those are the inventions presenting breakthrough characteristics. Thus, we estimate the effect of firm short-termism on the average and the 95th percentile of a firm's portfolio for *Patent Impact* and *Patent Influence*.

3.2 Focal independent variable: Firm short-termism

As a proxy for a firm's time horizons, we use a measure employed by Sampson and Shi (2020) that estimates an implied discount rate used in the valuation of firm assets. The measure is derived from an asset pricing model first proposed by Miles (1993) and Davies et al. (2014). Simply put, we estimate the rate at which investors discount the expected future cash flows of a firm above and beyond firm-specific risk premium. The basic rationale is that a shorter time horizon, or stronger short-termism pressure, leads firms to focus heavily on near-term returns and to place less emphasis on returns from the more distant future, thus resulting in a much steeper discount rate for cash flows in later periods. Conceptually, we use a dividend discount model and treat stock price of firm *j* at time *t* as the net present value of its future cash flows over the next N periods:[5]

$$P_{jt} = \frac{E_t[D_{jt+1}]x}{(1+r_t+\pi_{jt})} + \frac{E_t[D_{jt+2}]x^2}{(1+r_t+\pi_{jt})^2} + \cdots \frac{(E_t[D_{jt+N}]+E_t[P_{jt+N}])x^N}{(1+r_t+\pi_{jt})^N} + \varepsilon \tag{4}$$

where P is the stock price, $E_t[D_{jt+N}]$ is the expected value of firm j's dividends in future period $t+N$, r_t is the market risk free rate, π_{jt} is firm j's risk premium, and N is the number of time periods used in the estimation of the current stock price. $E_t[P_{jt+N}]$ is the expected value of the terminal stock price at the end of the time window, $t+N$. The firm specific risk premium is defined as:

$$\pi_{jt}=\alpha_1 \beta_{jt}+\alpha_2 Z_{jt} \tag{5}$$

[5] While we consider dividends and stock prices in the main model, Sampson and Shi (2020) further demonstrate the validity of the measure is not sensitive to dividend policies and alternative definitions of cash flows (such as expected earnings and stock repurchases).

where β_{jt} is firm *j*'s beta, which measures the volatility of the firm's stock price compared with the whole market in period *t*, and Z_{jt} is firm *j*'s gearing (i.e., debt/equity), which measures the firm's risk associated with financial leverage in the same period. a_1, a_2 are estimated coefficients associated with the firm-specific risk factors.

The firm-specific, time-varying parameter *x* is thus an implied discount rate that is not explained by the risk premium and captures how much the market values future cash flows. If there is no significant discounting (or overvaluing) above and beyond the sum of the risk-free rate and the firm-specific risk premium, then *x* should equal one in theory; this is the null hypothesis. Empirically, we observe that most estimates of *x* are close to one, but that they vary meaningfully within and between firms.

We use current dividends and stock price to proxy for the current expectation of future dividends and terminal stock price, the standard approach in the related finance literature.[6] We obtain the company beta from CRSP, which uses the method proposed by Scholes and Williams (1977) for beta calculation. A firm's debt and equity are obtained from COMPUSTAT. Substituting these proxies and equation (5) into equation (4), we obtain the following equation for non-linear empirical estimation:

$$P_0 = \frac{(D_0)x}{(1+r_0+\alpha_1\beta_0+\alpha_2 Z_0)} + \frac{(D_0)x^2}{(1+r_0+\alpha_1\beta_0+\alpha_2 Z_0)^2} + \cdots \frac{(D_0+P_0)x^N}{(1+r_0+\alpha_1\beta_0+\alpha_2 Z_0)^N} + \varepsilon \qquad (6)$$

Sampson and Shi (2020) estimate several alternative versions of equation (6) above, some of which change the calculation of the firm specific risk premium to include additional risk factors identified by Fama and French (1992).[7] Since results on these alternative specifications substantively match those used in this paper, but significantly reduce the sample size, we focus on the results from estimating equation (6) above. *Short-termism*, our independent variable of interest, is then 1 – *x*. We subtract *x* from one to ease interpretation of results. As *Short-termism* increases, firm time horizons contract and we expect that the firm's influential innovation declines.

We note that this measure does not necessarily assume irrationality, even though the concept implies a 'mispricing' of stocks in the finance nomenclature. Finance scholars with divergent beliefs on price efficiency and investor rationality have debated the behavioral and risk-based explanations

6 Lagged stock prices and lagged dividends are used as instruments for future dividends and stock prices, being correlated with the terminal stock price, but uncorrelated with firm specific forecast errors on this terminal stock price (Davies et al. 2014; Miles 1993).

7 For a full list of the validation tests, please refer to Appendix C in the online supplemental material at: https://onlinelibrary.wiley.com/doi/full/10.1002/smj.3158

of short-termism (e.g., Benartzi and Thaler 1995; Schleifer and Vishny 1997). Regardless of the underlying reasons for finding that x diverges from one, few would dispute that actual stock prices deviate from standard model predictions systematically. For our purposes, this mispricing phenomenon is accounted for by the varying discount rate, and by association, *Short-termism*. We are agnostic about whether the additional discounting of future returns is due to investors' preferences for near-term returns or undefined risks associated with longer-term cash flows, and thus do not seek to ascertain an optimal discount rate for firms. Instead, we test whether reduced or intensified short-termism pressure is associated with the changing nature of firm R&D.

3.3 Control variables

To control for relevant firm characteristics that may both directly explain *Patent Influence* and any relationship with *Short-termism*, we include several control variables. The data source for all control variables is Compustat, unless otherwise noted.

Financial Slack: To capture the ability of firms to invest in R&D as well as being a proxy for the financial health and future prospects of a firm, we include *Financial Slack*, which is the five year moving average of the difference between current assets and liabilities, divided by total firm assets.

R&D Intensity: We include a measure of *R&D Intensity* to proxy for firm investment in the innovation process. Our measure is a five-year moving average of R&D spending scaled by total firm assets.

Market Competition: To capture the competition that a firm currently faces, we use a score that measures the degree to which a firm's products are in competitive space. This measure, called the Text-based Network Industry Classifications, comes from the Hoberg-Phillips Data Library (https://hobergphillips.tuck.dartmouth.edu/). A firm's competitors are identified by how closely they reside in product space to the firm. This is a continuous measure, based on text analysis from firm 10K product descriptions (Hoberg & Phillips, 2010) and varies over time. We take the sum of the similarity score for all competitors of the firm in the same product market.

Multi-business Firm: To proxy for whether a firm is likely to have a decentralized R&D structure, we include a dummy that equals one if the firm has more than one business segment.

Size: We use *Log(Assets)* to proxy for firm size, to account for the fact that larger firms may have more significant R&D programs over time. We also expect that this variable may also capture the maturity of the firm, which may bear implications for the type of innovation that a firm engages in.

Firm Patent Portfolio Size: We use a running *Log(3-Yr Patent Stock)* to capture a firm's patent portfolio size. This measure captures both the firm's patenting propensity as well as recent innovative activity. This data comes from our patent data compiled from PATSTAT Global and the NBER patent dataset.

Descriptive statistics are set out in Tables 1a and 1b. Table 1a reports descriptive statistics for the full sample and then split by patenting and non-patenting firms, while Table 1b reports pairwise correlations.

[Tables 1a and 1b here.]

We note that the samples appear to be similar across most variables; *Short-termism*, *Financial Slack*, and *Multi-business firm* share similar values across patenting and non-patenting firms. However, we note that patenting firms tend to be larger, face stronger competition and have higher *R&D Intensity* than their non-patenting counterparts.

3.3 Research design and model estimation

We assign our dependent variables (i.e., *Patent Influence* and *Impact*) to the year of patent application, since this represents the earliest observation of the invention. Because patent applications are now published in advance of grant (since around 2000), it is possible for a patent to receive citations even before it is granted. While we only include patents that are later granted in our dataset, we utilize all citations received within a 7-year window of publication of the application or the grant, whichever is earliest.

To estimate the relationship with firm *Short-termism*, we run two-way fixed effects regressions to estimate the within firm relationship between *Short-termism* and the production of influential and impactful patent portfolios in the year $t+1$, Y_{it+1}. While our primary focus is on *Patent Influence*, we also report models for the traditional first-generation citation measure, *Impact*, as well as the propensity to patent. In these regressions, β is the coefficient of interest.

$$Y_{it+1} = \beta \cdot short\ termism_{it} + \gamma z_{it} + \eta_i + \epsilon_{it}$$

z_{it} are control variables. As discussed below, our results are only sensitive to the inclusion of period or year effects, which is not surprising given that we normalize our key dependent variable, *Patent Influence*, by class and year. We lag our independent variables since we expect that the impact of *Short-termism* and other controls on innovative outcomes will not be immediate.

We expect a negative relationship between *Short-termism* and *Patent Influence*; further, we anticipate that this relationship will be strongest for the most influential patents within a firm's portfolio. However, *Short-termism* may also negatively impact the propensity to patent, and patent *Impact* as well as mean and median firm patents as well, so we test these relationships as well.

Interpreting a particular coefficient estimate requires not only strict pre-specification requirements, but also an assumption that a particular model is the true model (Spanos 2014; King, Goldfarb, and Simcoe 2020, Forthcoming). Since pre-specification is not a realistic approach for this exercise, we use an alternative strategy of evaluating whether the relationships between short termism and innovative output as measured by patenting obtains across a wide variety of plausible specifications. This allows us to address model uncertainty and determine under which modeling assumptions in terms of controls and lag structures are consistent with a measurable relationship between short-termism and patenting as well as short-termism and patenting, *patent influence,* and *patent impact.* To address model uncertainty we employ an epistemic mapping approach that iterates over all combinations of lags and controls and then concisely graphs the resulting estimated coefficient of interest, in our case, β (King, Goldfarb, and Simcoe 2020, Forthcoming; Leamer 1985). The method is useful because while we have plausibly argued that specific controls might affect our estimation of β, but we are not certain which combinations of these controls most closely approximates the true model. Moreover, different readers may have different beliefs about which combination might be most appropriate. Thus, we report every combination and show the variation of results across them. This allows us to focus on the differences that matter. Our reporting follows recent work in this area (Goldfarb and Yan 2020; Berchicci and King 2020).[8] While epistemic mapping is a particularly expansive and comprehensive method of robustness checking, some caution is in order. First, it is incorrect to interpret a graph as a distribution. Each coefficient estimate is not necessarily independent. For example, showing robustness of a result to the inclusion of two highly correlated control variables will likely provide less additional information as compared to showing the robustness to two control variables that are orthogonal to each other. Thus, one should interpret patterns generally, which we do in our discussion below.

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[8] The choice of what to include in an epistemic map is itself a discretionary process. In their appendix, King et al. (2020, Forthcoming) break this process into 4 steps: selecting inputs, outputs, reporting, and credibility weights. The selection of inputs is contextual, and in our case refers not only to the choices of potential measures of innovative output and quality, but also to alternative ways to measure short-termism, the choice of controls, choices regarding sample construction, and choices of empirical estimation technique, and choice of identification strategies. Maps might be reported as a graph, or as a database of estimated equations. The former are easier to interpret, while the latter allows greater discretion for the reader to develop their own interpretations.

We also estimate several sample splits and an instrumental variable analysis to further explore the relationship between *Short-termism* and *Patent Influence*. These additional estimations are described in more detail below.

4. Empirical results

4.1 Relationship Trends over Time

Sampson and Shi (2020) extensively document the within firm, industry average and market average of the discounting-based short-termism measure that we rely upon in our analyses below. This prior work reveals the upward trend in market discounting on average across firms over time, albeit with significant variance between industries and between firms within an industry. Further, within firm graphs reported in that paper reveal that short-termism is increasing for the vast majority of public firms over time.

To show general trends over time, we graph *Patent Influence* for public and private firm patent portfolios from 1985-2008 in Figures 2a, 2b and 2c. These graphs only include sample firms that patent and the level of analysis is a firm's patent portfolio.

[Figures 2a, 2b, 2c here.]

Figure 2a shows the average *Patent Influence* for all firm patent portfolios over time by percentile, where the 95pct represents the top 5% of firm patent portfolios in terms of influence. We note that the dispersion of *Patent Influence* increases in the later years of the sample, particularly among the 90th and 95th percentile groups. This dispersion also exists in private firm portfolios when considering the 95th percentile of the patent influence within a firm's portfolio as shown in Figure 2b. However, this dispersion is vastly more significant for the 95th percentile of public firms' patent portfolios (Figure 2c). While only descriptive, this pattern is suggestive of strong self-selection by firms in terms of the type of R&D and patenting strategy that they follow.

4.2 Relationship between Short-termism, Propensity to Patent and Patent Influence

We depict epistemic maps of the estimated coefficients relating short-termism to patenting in Figures 3a and 3b. The estimates are all firm fixed-effect, linear probability models that predict the increase in the probability of *not* patenting with a 1 unit increase in *short-termism*. The graph depicts the coefficient estimates of 140 regressions that include all unique combinations of the controls: *Financial Slack, R&D Intensity, Market Competition, Multi-Business Firm, Log Assets, and Log(3-Yr Patent Stock),* and a set of year dummies. The estimates are ordered from the largest point estimate to the smallest. The line in the graph depicts the point estimates while the grey area is the 95% confidence interval for each estimate. The point estimates range from approximately 2.6 to .12, and *if* this is the universe of plausible models, we can be reasonably confident that this measure of short-termism is negatively associated with patenting for this sample. Note that the mean of *short-termism* is -0.03, with a standard deviation of 0.02. Thus, a coefficient estimate of 1, for example, implies that a standard deviation increase in *short-termism* is related to a 2% decrease in the predicted probability that a firm will patent in a given year, which is relative to the mean patenting rate of .53 is approximately a 4% decrease in likelihood of patenting.

We report a few illustrative model results in Table 2. Specifically, we estimate both a fixed effect OLS and logit models with a full set of controls and without any controls; these results are reported in Table 2. These models include firm and year fixed effects.

[Table 2 here.]

These results suggest that the results are not particularly sensitive to the inclusion of none or all the controls, nor to a logit or linear model. However, the controls are strong predictors of patenting in expected ways. Firms with less financial slack, that spend less on R&D, are smaller, and have smaller patent portfolios are less likely to patent in the current year. Multi-business firms are also more likely to patent, though we note that this effect is statistically significant only in model (2). The epistemic map in Figure 3b depicts the same regressions as in Figure 3a, this time stratified by the set of 70 regressions that include *Market Competition* and the 70 that do not. This is the only such bifurcation in which we examined models with and without a particular control that produced distinguishing patterns. It is fair to say that the models predicting a larger effect all include a market competition control. This, together with the negative correlation between *Market Competition* and *Short-termism* suggests that the effects of short-termism are more pronounced for firms experiencing high product market competition, a possibility we expect to investigate moving forward.

We then estimate our key relationship of interest between *Short-termism* and *Patent Influence*, using several different versions of our dependent variable. We created an epistemic map using the 3 potential dependent variables: mean patent influence, 95th percentile of patent influence, and mean patent impact. More precisely, for each patent class year, we calculate the mean and standard deviation of influence, and then the z-score of each firm patent:

$$Patent\ Influence\ z-score_i = \frac{(Patent\ Influence_i - Average\ Patent\ Influence_j)}{Std\ Dev\ Patent\ Influence_j}$$

Average Patent Influence$_j$ is the average patent influence of all patents filed per year within the focal patent's 4-digit patent class (CPC, or 'cooperative patent classification'). Similarly, *Std Dev Patent Influence*$_j$ is the standard deviation of the patent influence of all patents filed per year within the focal patent's 4-digit patent class. With each patent's influence thus normalized, we aggregate each firm's patent portfolio and calculate the mean and 95th percentile of these portfolios by year. One can think of the 95th percentile patent as telling us how breakthrough-y a firm's portfolio is, where the mean tells us a more general story. Note that since the bottom 10% of patents receive no citations at all, one can interpret the 95th percentile measure as a 95:10 ratio.[9] A parallel procedure is implemented for patent impact, which is a traditional measure of patents weighted by direct citations. The results do not appear to be particularly sensitive to the precise dependent variable choice. Figure 4a depicts the entire distribution of estimates relating patent quality to *short-termism,* while Figure 4b depicts the same distribution, stratified by the dependent variable. Across these 765 specifications, *short-termism* robustly predicts lower patent quality if measured in the short term, over several generations in the measure of patent influence, and in the patenting of breakthrough innovations as proxied by the 95th percentile measure.

We report illustrative regressions in Table 3.

[Table 3 here.]

Columns (1) and (2) use the average *Patent Influence* of a firm's patent portfolio in that year as the dependent variable. Column (3) uses the 95th percentile *Patent Influence* score for a firm's patent portfolio in a year. These linear models include firm and year fixed effects and illustrate the robust negative relationship between *Short-termism* and *Patent Influence* (as well as *Impact*). The epistemic maps generalize the result that the regressions illustrate. Regardless of the controls we use, firms in our sample that were more short-term oriented produced fewer influential patents and, as proxied by the 95th percentile measure, fewer breakthrough inventions.

Financial Slack is positively correlated with influential inventions, but this effect is not robust across specifications. Curiously, *R&D Intensity* is not significantly correlated with influential patents. We suspect that *R&D Intensity* may not capture differences between types of R&D programs in firms adequately; that is, some large R&D programs may be focused on more incremental development and thus not correlate well with influential inventions as we have defined them. Firms facing more significant *Market competition* appear to have less influential patents, suggesting that competitive pressures may mean fewer resources and/or less patience to invest in next generation technologies. Firms that are less centralized (i.e., multi-business firms) are less likely to generate influential inventions; *Multi-business firm* is negative and significant across specifications. This finding

[9] We note that our results are sensitive to normalizing within class. This is not surprising as citation patterns will vary by technological field, just as citation patterns will vary by academic discipline.

is consistent with previous findings that more applied R&D programs are found in firms with less centralized R&D, which in turn is more likely to be true for multi-business firms. Larger firms (*Log(Assets)*) appear to generate patents with less influence and impact, while the effect of the firm's patent portfolio (*Log(3-Yr Patent Stock)*) is ambiguous across specifications. For the standardized measures (i.e., the z-scores), larger patent portfolios are correlated with more influential, impactful patents. However, for the non-standardized measure in Column (2), we note that portfolio size is negatively correlated with *Patent Influence*. We explore this anomalous result in future drafts.

4.3 Does the relationship between Short-termism and Patent Influence depend on sampling?

To explore whether *Short-termism* and *Patent Influence* vary according to different samples, we estimate *Patent Influence* as a function of *Short-termism* and controls, splitting the samples according to variables hypothesized in past literature to control for factors that affect a firm's R&D focus. We conduct six sample splits: 1) *Decentralization ratio*; 2) *Market competition*; 3) *Proportion of Complex Technology*; 4) *Govt. Funded R&D*; 5) *Scientific references*; and 6) *RQ*. The five yet undefined variables are constructed as follows (*Market competition* is described above).

Decentralization ratio: To capture the extent to which a firm's R&D efforts are centralized or decentralized, we use the measure defined by Arora et al., (2014), where patents are classified by whether they are assigned to a parent firm or its subsidiary or affiliate. These classifications are aggregated to the firm portfolio level, generating a *Decentralization ratio* that signals how much of the firm's R&D is conducted outside of the parent firm.[10] This measure varies between zero (i.e., all research is conducted within the parent) and one (i.e., all research is conducted outside the parent). We split the sample according to whether any of a firm's R&D is conducted outside the parent firm (i.e., *Decentralization ratio* > 0). We expect that, following this earlier research, that basic research usually takes place in firms with more centralized R&D programs. As such, our prior is that *Short-termism* will bear a more negative relationship with *Patent Influence* when the firm's R&D is more centralized.

Proportion of Complex Technology: We also split our sample according to the extent of patents that are classified in fields involving 'complex technology'. Complex technology is identified by, "whether a new, commercializable product or process is comprised of numerous separately patentable elements versus relatively few." (Cohen, Nelson & Walsh, 2000) This is measured according to the proportion of a firm's patent portfolio that fall within the following technology areas: computers

[10] We thank Ashish Arora, Sharon Belenzon and Luis Rios for sharing this measure with us.

& communications, electrical & electronic, surgery & medical instruments, and biotechnology (Hall, Jaffe, Tratjenberg, 2005). We split our sample according to whether the majority (i.e., > 50%) of the firm's patent portfolio is classified as falling within one of or more of these complex technology areas.

Govt. Funded R&D: We capture whether a firm receives government funding for at least one patent in its portfolio. Government funding indicates that the firm has received government contracts or grants and at least some of this funding was allocated to the firm's R&D process. We conduct this split because government funding may target fields that are basic, risky, and/or nascent, and/or those projects with no clear near-term commercial value. In this sense, government funded R&D may proxy for more basic or long-term research and, as such, our prior is that firms receiving government funding will show a stronger negative correlation between *Short-termism* and *Patent Influence*.

Scientific references: Scientific references are as defined following Marx and Fuegi (2020). Specifically, they are non-patent literature that appears on the front pages of patents and matches to Microsoft's Academic Graphs (i.e., the reference must be a scientific article and cannot be a product brochure, etc.). We split our sample according to whether there is at least one scientific reference in the firm's patent portfolio that year. Since reference to scientific literature signals more basic research with likely a longer term time horizon for payoffs, we expect the relationship between *Short-termism* and *Patent Influence* to be more strongly negative for firms that cite scientific literature in their patents.

RQ: We also split our sample according to *RQ* or 'research quotient', a measure of R&D productivity estimated by Knott (2008). *RQ* is revenues-based R&D elasticity; that is, it is the percentage increase in firm revenues from a one percent increase in R&D spending (Ibid.). RQ bears a positive relationship with firm R&D investment, market value and future revenue (Knott and Vieregger, 2017) and is a measure of R&D effectiveness, instead of effort (R&D spending).[11] Sampson and Shi (2020) find that *RQ* correlates negatively with *Short-termism*, but we have no prior as to what *RQ* may signal about the nature of a firm's R&D program. We split our sample according to whether the firm's *RQ* is above or below the median *RQ* for the sample in that year.

Results from the six sample splits are reported in Table 4.

[Table 4 here.]

The results shown in these six sets of regressions are largely consistent with our priors. Specifically, *Short-termism* has a larger negative correlation with *Patent Influence* when 1) the firm's

[11] More details on RQ construction are available via WRDS: https://wrds-web.wharton.upenn.edu/wrds/query_forms/navigation.cfm?navId=379

R&D is more centralized; 2) the firm faces stronger market competition; 3) the firm's patent portfolio has a higher proportion of complex technologies; 4) the firm receives government funding for some of its R&D programs; 5) the firm's patents reference scientific literature; and 6) the firm has lower than median R&D productivity.

4.4 Is the relationship of *Short-termism* with *Patent Influence* causal? IV Analysis

Our analysis above, while informative, is correlational. We argue that S*hort-termism* leads to less influential inventions, but it is also plausible that firms with less influential inventions face more short-term pressures from investors or competitors. To examine the direction of causality, we employ an instrumental variables approach that evaluates how existing institutional owners' shifting horizons, which is arguably exogenous to the firm, may influence short-termism pressure on firms and in turn affect firm's R&D priorities and outcomes.

There are several compelling reasons to focus on the role of institutional ownership in explaining the relationship between capital market pressure and R&D outcomes. First, institutional ownership is increasingly influential in the market. Shareholdings of large financial institutions have grown from 8% to 68% in 1950 to 2006, while retail holdings have dropped from 92% to 32% in the same period (Bogle, 2006). By 2009, institutional owners held 73% of the equity of the top 1000 US companies (Gilson and Gordon, 2013; Barton and Wiseman, 2014). Second, institutional owners vary in their temporal orientation, with some owners displaying significantly shorter holding periods and higher turnover rates of portfolio companies than others (Bushee, 2001). This short-term-oriented approach of some owners contributes to the rising market pressure for myopic behavior and ultimately affects firm decisions on uncertain projects, such as R&D (Bushee, 1998; Aghion, Van Reenen, and Zingales 2013). Third, an existing institutional owner may become more short-term oriented over time, which may exogenously impact individual firms within its portfolio by increasing pressures for short-term returns.

We identify significant shifts in the overall investment approach of an institutional owner by tracking whether it is viewed as a patient, long-term driven investor in a given year. According to the data and studies by Bushee (1998; 2001), institutional ownership classifications may range from "transient," a category of impatient owners with low portfolio diversification and high turnover, to "dedicated," which indicates low portfolio turnover and longer-term holdings. Given the robust findings of a positive (negative) association between transient (dedicated) ownership and short-termism (Sampson and Shi, 2020), we analyze the changes associated with transient and dedicated ownership. To ensure that the influence over the focal firm is plausible, we focus on institutional blockholders, or those holding 5% or more of a firm's outstanding shares. To alleviate selection bias, we exclude new owners with no holding in the previous year and previous owners who have no holdings in the current year.

We use two instruments to isolate the influence of existing institutional owners' shifting temporal focus on *Short-termism*. *Loss of Dedicated Ownership Classification* is a dummy that equals one if at least one existing institutional blockholder of the focal firm loses the "dedicated" classification. This means that dedicated owners have significantly shortened holding periods and increased turnover, signaling a marked shift towards a short-term focus. Similarly, *Loss of Transient Ownership Classification* equals one if at least one of a firm's institutional blockholders is no longer classified as "transient," the most short-term oriented group of all institutional owners.

Given the strong influence of institutional ownership, particularly larger holdings, on firm behavior, we expect the overall market to revise the valuation of a firm's future returns when its owners' investment approach reflects a more short-term or long-term focus. Specifically, the loss of dedicated (transient) ownership classification likely leads to higher (lower) discount rate of future returns, or greater (less) short-termism pressure on the firm. Meanwhile, we assume that ownership classification changes are unrelated to the focal firm because they are made on the basis of that institution's behavior across all shareholdings. It is difficult to imagine a situation where the institution changes its investment pattern as the result of a single firm that the institution holds shares in, particularly considering that we have already excluded all cases in which classification changes are accompanied by the adding or dropping of the focal firm.

To use these instruments to evaluate the causal impact of *Short-termism* on *Patent Influence*, we estimate *Patent Influence* as a function of instrumented *Short-termism* via a two-stage least squares, fixed-effect regression. Results from our two-stage regression are set out in Table 5, with our first stage, IV estimation set out in column (1) and our second stage estimation in column (2).

[Table 5 here.]

To ensure temporal precedence, the instruments are measured in the year before *Short-termism* is measured. We first validate the choice of classification changes of institutional blockholders as instruments by conducting a series of diagnostic tests for the IV estimation. First, the Durbin-Wu-Hausman test ($p < 0.05$) indicates that an IV approach for *Short-termism* is warranted. Second, statistics from Anderson canonical correlation test (Chi-sq. = 79.27, $p < 0.001$) indicate that under-identification is not a salient issue in the estimation. Third, the Cragg-Donald Wald F-statistic (13.24) surpasses most critical values supplied by Stock and Yogo (2005) and rejects the null hypothesis of weak instruments.[12] We then test whether the instruments are correlated with the error term in the second stage equation. Results of these tests, specifically the Sargan test (p = 0.6398) and Anderson-Rubin Wald test (p = 0.1215) suggest that orthogonality conditions are not violated, as required for instrument validity (Baum, Schaffer & Stillman, 2007).

Our main coefficient of interest, *Short-termism*, remains negative and significantly different from zero (p = 0.000) in the main equation on *Patent Influence* (column 2, Table 5), thus offering solid support for our causal claims. In column 1, we report that *Loss of Dedicated Ownership Classification* leads to more market short-termism as expected. We do not find clear evidence of the impact of *Loss of Transient Ownership Classification*.[13] Overall, these results confirm the strong negative link between *Short-termism* and *Patent Influence* and suggest that this relationship is causal, with rising firm short-termism contributing to declining *Patent Influence*.

4.5 Robustness

We undertake several additional analyses to evaluate the robustness of our results. We first explore alternative mechanisms for capturing influential inventions, using patent data. Specifically, we re-estimate the results in Table 3, using *Average Lexical Novelty* and *Average Back Citations* as our dependent variables. These variables are defined as follows.

Average Lexical Novelty: We follow Fleming et al (2019) and capture a scaled measure of the novel words contained in a patent. Novel words in a patent are thought to identify patents that are the result of more exploratory R&D strategies (Balsmeier et al 2018), without reliance on patent citations. Highly cited patents may arise due to an exploitation strategy that focuses on using existing firm competences and, thus, be a less precise measure of influential inventions (Balsmeier, Fleming and Manso 2017). While our measure of *Patent Influence* is less sensitive to this general critique on the use of patent citations, we include this measure of novelty as a robustness test.

Fleming et al (2019) note the number of words in a patent that are new to the patent corpus (following efforts to remove special characters, such as hyphens, etc.). We calculate the z-score for the logged version of this novelty measure for each patent (i.e., the novelty measure less the average

12 The null hypothesis is that the instruments are irrelevant in the first stage (i.e., *Short-termism*) regression.

13 In additional analyses not reported here, we observe that many transient owners who reduce turnover also diversify portfolios and become "quasi-indexers." However, the current literature is inconclusive on quasi-indexers' implications for short-termism. Even though quasi-indexers hold stocks longer than transient owners, they track the overall market more closely in terms of expectations, but also lack substantial voice and influence (Porter, 1992; Bushee, 1998; Aghion, Van Reenen, and Zingales 2013).

novelty measure in that class and year, divided by the standard deviation of the novelty measure for that class and year). We then take the average patent z-score for the firm portfolio by year.

Average Back Citations (Same & Different Class): Backward citations (i.e., citations from a focal patent to prior art), are thought to capture the firm's knowledge search efforts (e.g., Rosenkopf and Nerkar 2001; Nemet and Johnson 2012). We capture the average of the logged number of back citations by firm portfolio by year to either the same or a different patent class as the focal portfolio.

Results using these alternative dependent variables are set out in Table 6.

[Table 6 here.]

For both the *Average Lexical Novelty* and *Average Back Citations* (same class), the correlations with *Short-termism* are negative and significant, providing some support as to the robustness of the results reported above. However, the correlation between *Short-termism* and *Average Back Citations* (different class) is not different from zero. This may suggest that back citations to different patent classes than the focal patent are qualitatively different than such citations to the prior art within the same class. It may be that citations to different classes are more indicative of self-citation than citations to patents within the same class, a question we take up in future work.

We also explore a number of different samples to rule out some alternative explanations and/or outlier events. *Short-termism* is constructed in part from firm dividends as expectations of future cash flows. While we can still calculate *Short-termism* for firms that don't issue dividends (the terminal stock price becomes the sole return on investment), as a robustness check, we split the sample into firms that do and don't issue dividends and re-estimate our main results. We also re-estimate the relationship between *Short-termism* and *Patent Influence* excluding data during outlier financial events, specifically, the dot-com bubble in 2000-01 and the financial crisis in 2008-09. Sampson and Shi (2020) observe that *Short-termism* increases significantly during these two periods. These additional tests are reported in Table 7.

[Table 7 here.]

We note across all specifications reported that *Short-termism* is significantly negatively correlated with *Patent Influence*. While the magnitude of this relationship varies according to the specification and is largest in the dividend issuing sample in column (1), these results provide further support to our main findings that *Short-termism* bears a significant negative relationship with the influential inventions of a firm.

5. Discussion and Conclusion

Prior research has shown that there has been a secular decline in US public corporations' share of breakthrough patents - even as the number of corporate patents has increased. We show that this effect is primarily concentrated in firms that have relatively more short-term outlooks - as measured by implied investor discount rates (our measure of *Short-termism*). Firms with shorter time horizons are less likely to patent generally, and these patents are less likely to garner citations. Moreover, these firms are less likely to have long-term sustained influence in their technological domain. We are engaging in efforts to analyze the generality of the citation tree, which captures the breadth of application of an invention. Consistent with the underlying logic of this paper, preliminary results suggest that this breadth diminishes when firms face more significant short-termism pressures.

Our analysis does not directly address whether smaller entrepreneurial firms are engaging in more long-term plays and thereby substituting declining public firm efforts. For example, there is an active debate about whether the current crop of entrepreneurs is focusing on introspective, unimportant problems (Lapowsky et al. 2018). Kaplan (2018) points out that several new technologies, such as fracking, the internet and biotechnology, have emerged in recent years, and if markets are efficient, venture capitalists may rationally fill the void left by public firms. This argument ignores the links between the private and public equity markets. Nanda and Rhodes-Kropf (2013) argue that if the public market is less munificent, venture firms will take fewer risks since they anticipate that it might be difficult to sell more risky projects to public market investors. Together, this suggests that short-termism casts a wide shadow, even over the private equity markets - at least during bear markets. On the other hand, there is a suggestion that even in munificent capital markets, attractive narratives that can be quickly sold in the public markets may divert investment dollars from fundamental innovation (Duhigg 2020). This is consistent with the similar patterns of influence found for public and private firms over our period of observation (not reported here). The behavior of public firms, due to these firms' saliency, may drive the mimetic behavior of private firms. Moreover, if short-termism levels today are similar to short-termism levels during recent bear markets, then this raises concerns over economy-wide technology development and long-term firm performance.

It is also possible that short-termism is a reasonable response to changes in investment opportunities of many public firms. Robert Gordon is perhaps the best-known proponent of this view (Gordon 2017). Consistent with this view, Jones (2009) documents that innovation appears to be getting harder, at least insofar as it requires bigger teams. The Arthurian lens would suggest that in many areas of innovation, firms have built out much of the sub-technological infrastructure, and therefore we should expect longer time horizons to re-form as new technological opportunities emerge. For example, there are areas in which the private sector appears to be engaged in quite fundamental inquiry, such as artificial intelligence, machine learning and their applications. Thus, while our evidence suggests that fewer companies are engaged in this fundamental activity, it is possible that those that are, are doing so in quite productive ways. We leave this question to future study.

While these critiques prevent us from providing strong policy recommendations, the lower innovative output of the typical public firm is concerning. Kaplan's claim that this is made up by the dynamism of entrepreneurial firms is not particularly comforting in light of the documentation of reduced entrepreneurial dynamism in the economy. We expect to expound further on this point in future drafts of this paper.

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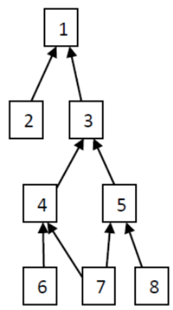
Figure 1: Technology Network and its Adjacency Matrix Illustration



	1	2	3	4	5	6	7	8
1	0	0	0	0	0	0	0	0
2	1	0	0	0	0	0	0	0
3	1	0	0	0	0	0	0	0
4	0	0	1	0	0	0	0	0
5	0	0	1	0	0	0	0	0
6	0	0	0	1	0	0	0	0
7	0	0	0	1	1	0	0	0
8	0	0	0	0	1	0	0	0

Adjacency Matrix.
On top and left of the matrix are the numbers identifying each patent (node) in the network on the left. A one in a cell represents a citation (network tie) from the patent on the left to the patent on top

Figure 2a: Average Patent Influence of Public & Private Firm Patent Portfolios, by percentile

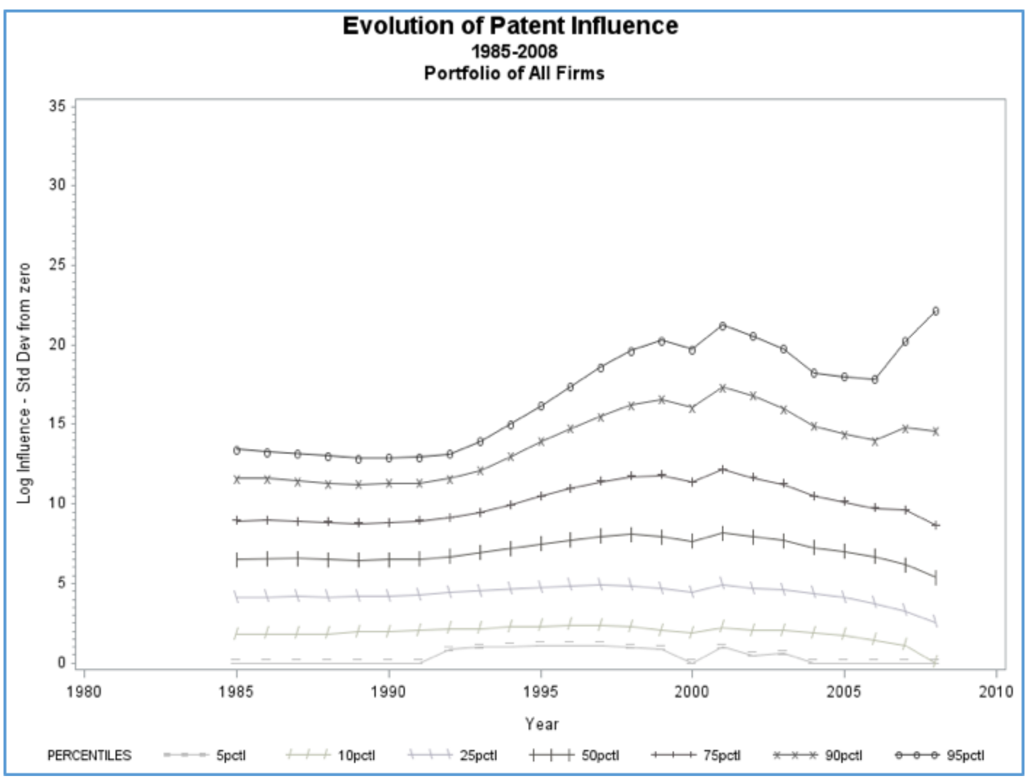


Figure 2b: 95th Percentile Patent Influence of Private Firm Patent Portfolios, by percentile

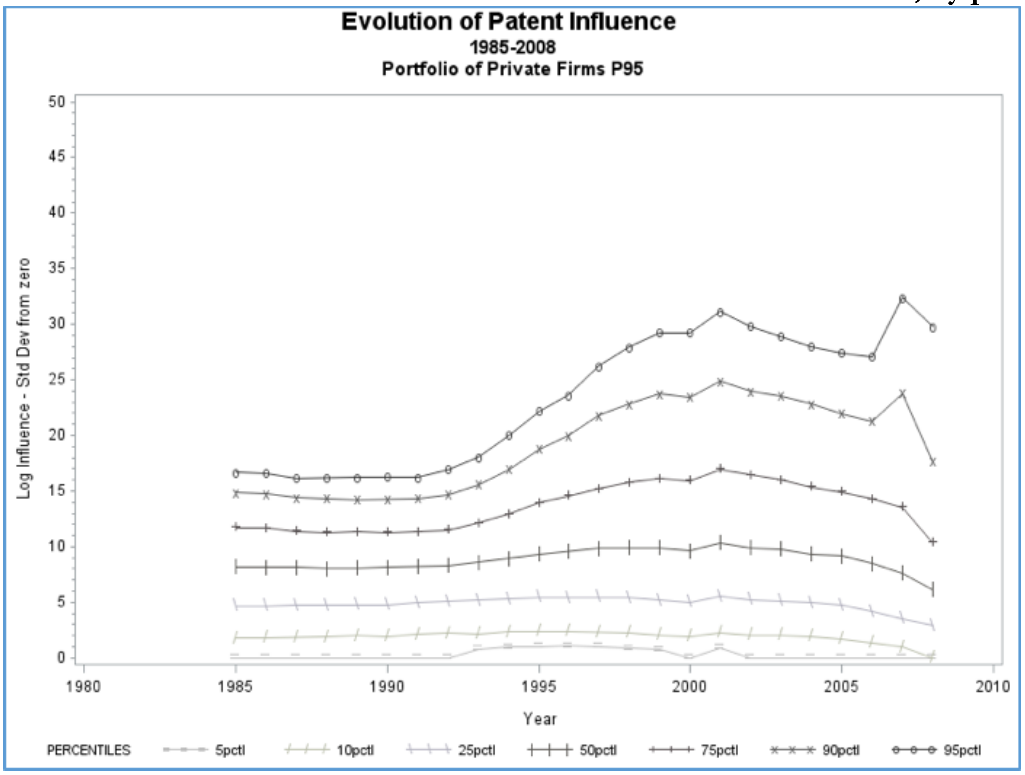


Figure 2c: 95th Percentile Patent Influence of Public Firm Patent Portfolios, by percentile

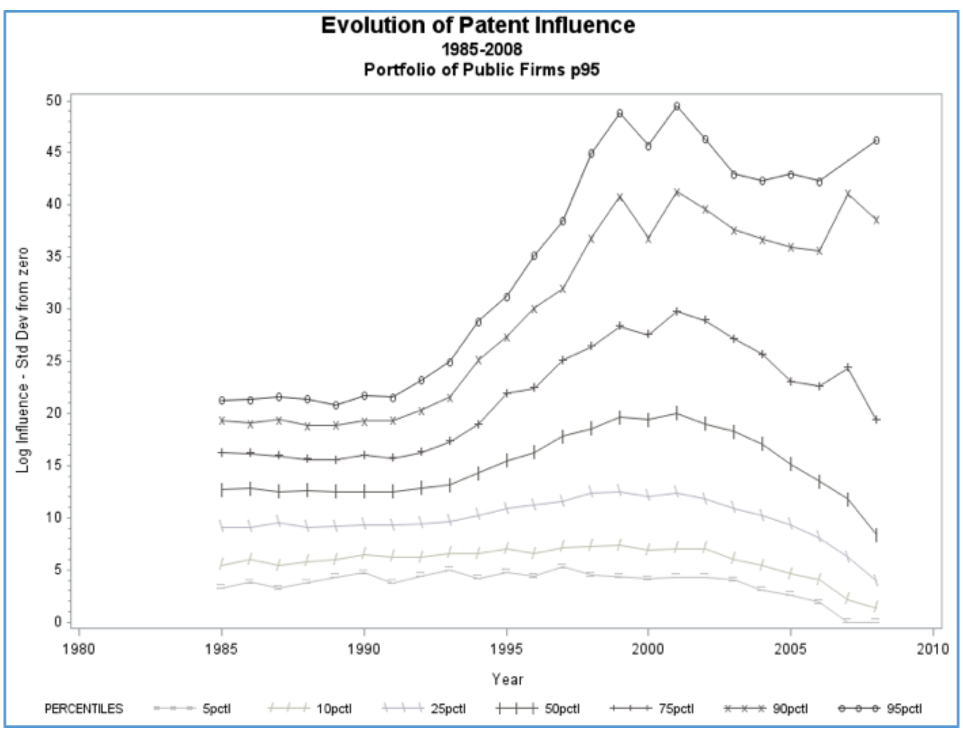


Figure 3a: Epistemic Map relating Short-termism to Pr(Patenting)

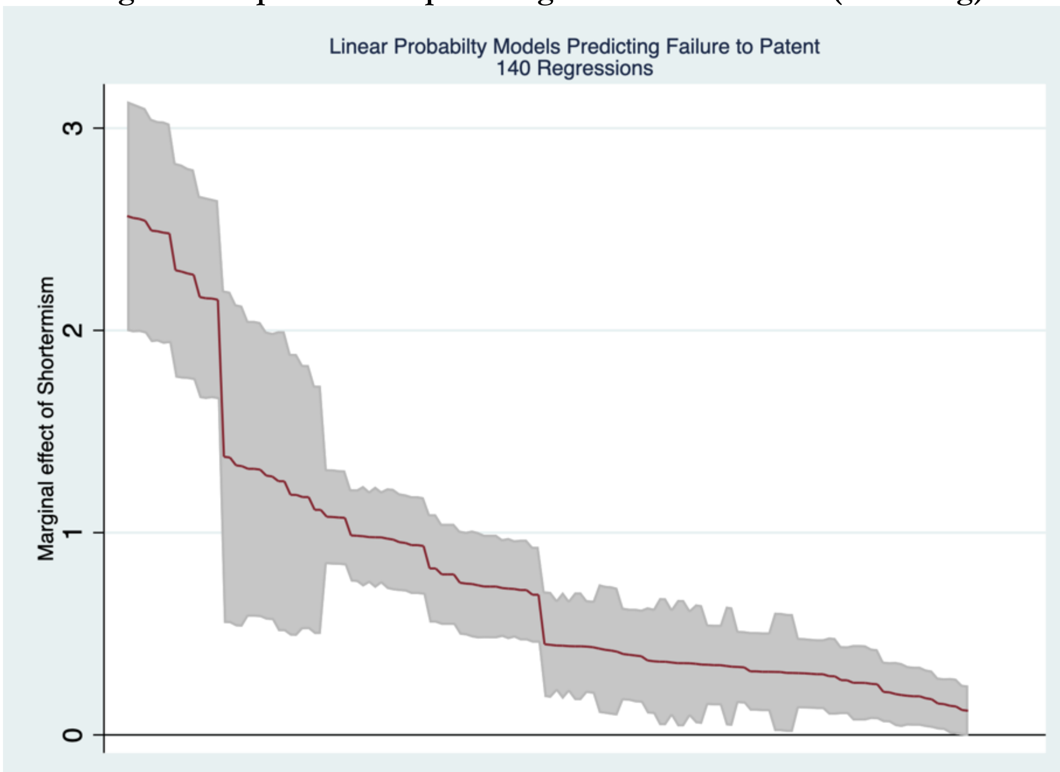


Figure 3b: Short-termism and Pr(Patenting), with and without competition control

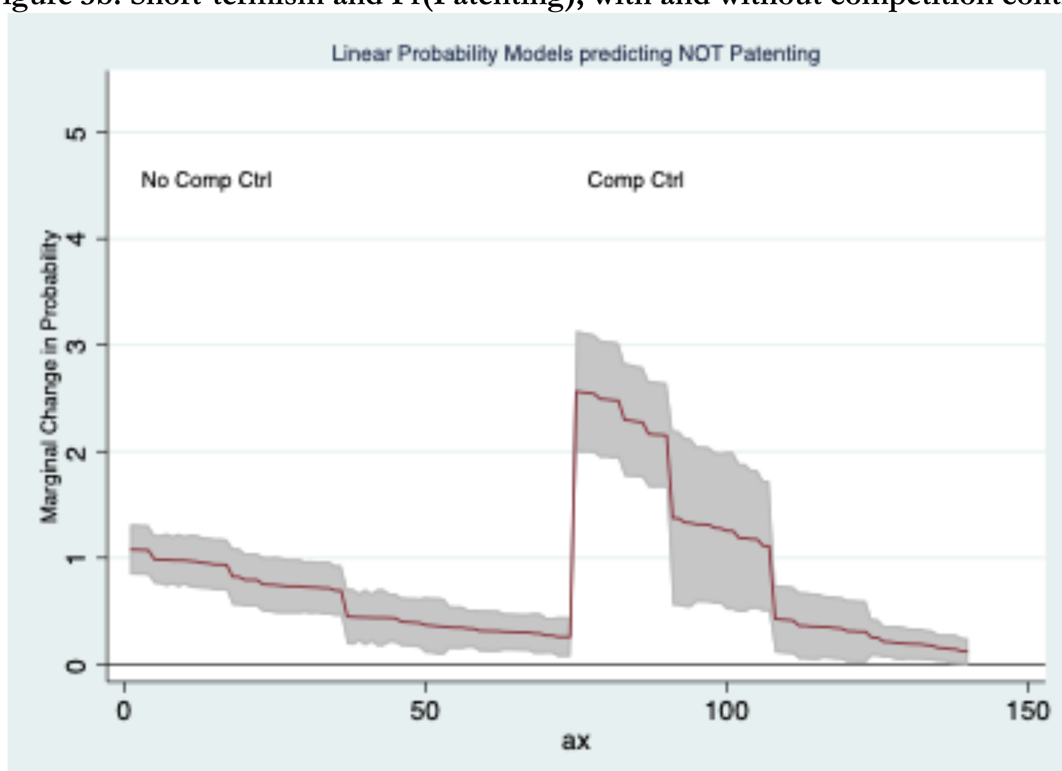


Figure 4a: All Models: Short-termism with Patent Influence and Impact

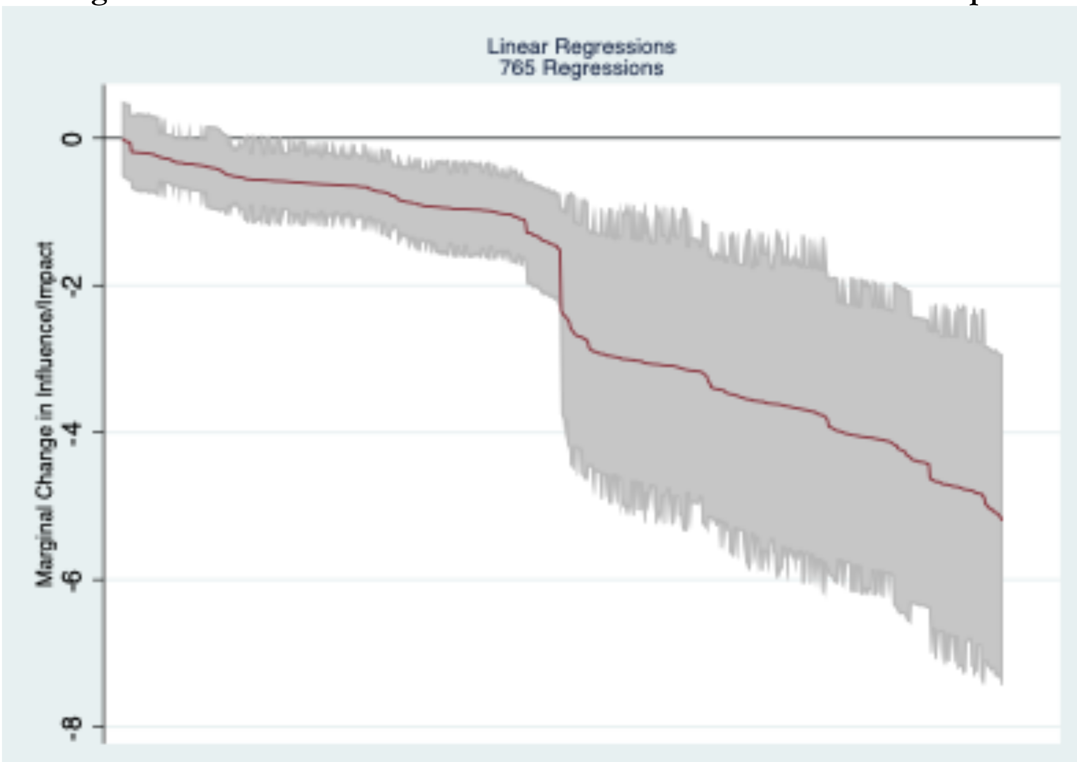


Figure 4b: All Models: Short-termism with Patent Influence and Impact by Dependent Variable

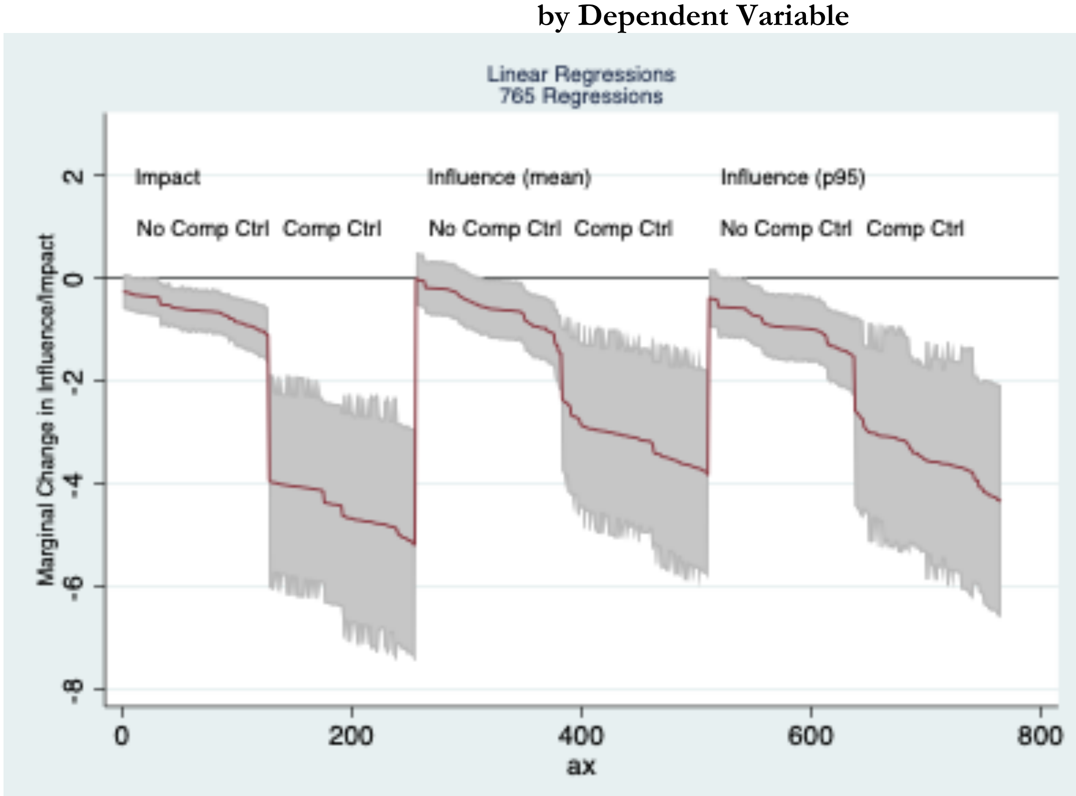


Table 1a: Descriptive statistics by sample

		Full sample (N = 12,142)	Patenting firms (N = 8,533)	Non-patenting firms (N = 6,487)
Firm patenting	Mean	0.5343		
(1 = no patenting)	Median	1.0000		
	Std Dev.	0.4988		
	Min	0.0000		
	Max	1.0000		
Patent Influence (Average)	Mean		1.0177	
	Median		0.9844	
	Std Dev.		0.5517	
	Min		0.0000	
	Max		4.0591	
Short-termism	Mean	-0.0304	-0.0329	-0.0279
	Median	-0.0323	-0.0343	-0.0308
	Std Dev.	0.0180	0.0174	0.0185
	Min	-0.0624	-0.0624	-0.0590
	Max	0.3882	0.3699	0.3882
Financial Slack	Mean	0.2677	0.2705	0.2573
	Median	0.2764	0.2728	0.2685
	Std Dev.	0.1850	0.1621	0.2003
	Min	-5.6827	-1.5463	-5.6827
	Max	0.6855	0.6669	0.6855
R&D Intensity	Mean	0.0765	0.0869	0.0669
	Median	0.0364	0.0547	0.0236
	Std Dev.	0.1090	0.1053	0.1084
	Min	0.0000	0.0000	0.0000
	Max	1.5250	1.1329	1.5250
Market competition	Mean	2.7451	3.2651	2.3807
	Median	0.4894	0.6860	0.3967
	Std Dev.	5.3230	5.7505	4.8832
	Min	0.0000	0.0000	0.0000
	Max	35.7957	33.6772	35.7957
Multi-business firm	Mean	0.4764	0.4927	0.4702
	Median	0.0000	0.0000	0.0000
	Std Dev.	0.4995	0.5000	0.4991
	Min	0.0000	0.0000	0.0000
	Max	1.0000	1.0000	1.0000
Log(Assets)	Mean	5.7645	6.2942	5.5928
	Median	5.6891	6.2212	5.4552
	Std Dev.	2.0143	2.1041	2.0452
	Min	0.5068	0.6780	0.5068
	Max	12.5269	12.5269	12.4884
Log(3-Yr Patent Stock)	Mean	1.1397	2.3253	
	Median	0.6931	1.9459	
	Std Dev.	1.2539	1.5377	
	Min	0.0000	0.6931	
	Max	7.5580	9.0985	

Table 1b: Pairwise correlations

	Firm Patenting	Patent Influence (average)	Short-termism	Financial Slack	R&D Intensity	Log(3-Yr Patent Stock)	Market competition	Multi-business firm	Log(Assets)
Firm Patenting	1								
Patent Influence (average)	0.6831	1							
Short-termism	0.1494	-0.1050	1						
Financial Slack	-0.0600	0.0231	-0.2534	1					
R&D Intensity	-0.0947	-0.0256	-0.2527	0.3110	1				
Log(3-Yr Patent Stock)	-0.6207	-0.1601	-0.0258	-0.0087	0.0736	1			
Market competition	-0.0733	-0.0531	-0.2084	0.3030	0.6010	0.0797	1		
Multi-business firm	-0.0133	-0.0557	0.1865	-0.2170	-0.2849	0.0542	-0.2563	1	
Log(Assets)	-0.0913	-0.1014	0.2946	-0.4583	-0.4294	0.3409	-0.1330	0.2809	1

Table 2: Predicting Firm Patenting

DV = Firm patenting (1 = no patents; 0 = patents)	**FE** (1)	(2)	**FE: logit** (3)	(4)
Short-termism	**0.31206**	**0.31148**	**4.67031**	**3.79360**
	(0.00000)	**(0.04018)**	**(0.00000)**	**(0.15368)**
Financial Slack		-0.09990		-1.06031
		(0.00000)		(0.00650)
R&D Intensity		-0.25621		-1.45058
		(0.00000)		(0.05743)
Market competition		0.00028		0.00839
		(0.78596)		(0.60930)
Multi-business firm		-0.00994		-0.14736
		(0.07552)		(0.10316)
Log(Assets)		-0.01654		-0.33123
		(0.00002)		(0.00000)
Log(3-Yr Patent Stock)		-0.07740		-0.43628
		(0.00000)		(0.00000)
Intercept	0.86783	0.91880		
	(0.00000)	(0.00000)		
N (observations)	78572	32770	27537	12142
R-squared	0.03845	0.09491		0.26459

p-values in parentheses
All models include firm and year fixed effects.
All independent variables lag the dependent variable by one year, except for R&D intensity & financial slack.

Table 3: Short-termism & Patent Influence

DV = Patent Influence	Average Patent Influence		P95 z-score	Avg. z-score	Impact: P95 z-score
	(1)	(2)	(3)	(4)	(5)
Short-termism	**-0.79737**	**-3.15775**	**-3.56848**	**-4.36563**	**-4.88935**
	(0.00694)	**(0.00060)**	**(0.00058)**	**(0.00001)**	**(0.00001)**
Financial Slack		0.18912	0.20766	0.19088	0.23136
		(0.14808)	(0.13251)	(0.03187)	(0.01870)
R&D Intensity		-0.01619	-0.11721	-0.04558	-0.12829
		(0.93853)	(0.59104)	(0.75636)	(0.41474)
Market competition		0.00737	0.00714	0.00804	0.00922
		(0.03416)	(0.03727)	(0.00056)	(0.00019)
Multi-business firm		-0.04584	-0.04264	-0.03188	-0.02562
		(0.02236)	(0.04582)	(0.02059)	(0.09238)
Log(Assets)		-0.07564	-0.09389	-0.09935	-0.11730
		(0.00001)	(0.00000)	(0.00000)	(0.00000)
Log(3-Yr Patent Stock)		-0.07250	0.06223	0.01138	0.13967
		(0.00000)	(0.00001)	(0.21575)	(0.00000)
Intercept	1.02024	1.50721	1.53652	1.36128	1.37543
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
N (observations)	17682	8533	8533	8602	8602
R-squared	0.00101	0.02980	0.02711	0.07899	0.11759

p-values in parentheses
All models include firm and year fixed effects.
All independent variables lag the dependent variable by one year, except for R&D intensity, financial slack and patent

Table 4: Short-termism & Patent Influence, Firm Variance by Sample

DV = Patent Influence	Decentralization ratio		Market Competition		Proportion of Complex Technology		Govt. Funded R&D		Patents have scientific references		RQ	
	= 0	> 0	<= median	> median	<= 50%	> 50%	= 0	> 0	= 0	= 1	<= median	> median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Short-termism	**-6.16375**	-2.98453	-1.45863	**-5.24409**	-0.35945	**-7.62152**	**-2.87763**	**-5.46624**	1.16355	**-4.49456**	**-4.88647**	**-2.55370**
	(0.00000)	(0.02946)	(0.13456)	**(0.00241)**	(0.50586)	**(0.00000)**	**(0.00182)**	**(0.00000)**	(0.41381)	**(0.00027)**	**(0.00001)**	**(0.04861)**
Financial Slack	0.53829	0.43632	0.42250	0.04211	0.08295	0.11818	0.21876	-0.14445	0.54290	0.06195	-0.18288	0.00675
	(0.03387)	(0.05183)	(0.04542)	(0.81487)	(0.70680)	(0.50985)	(0.11876)	(0.64965)	(0.21823)	(0.67618)	(0.55035)	(0.97456)
R&D Intensity	0.24523	-0.27932	-0.31751	0.12988	0.18721	-0.32301	-0.01469	-0.22962	0.89558	0.00304	-0.28809	0.16778
	(0.61748)	(0.51119)	(0.40186)	(0.59391)	(0.46521)	(0.41648)	(0.94810)	(0.72391)	(0.20793)	(0.98979)	(0.61201)	(0.68129)
Market competition	-0.02265	0.01134	-0.01946	0.00843	0.00689	0.00392	0.00786	0.00323	0.00055	0.00606	0.01174	0.00316
	(0.03448)	(0.01761)	(0.83195)	(0.02509)	(0.21668)	(0.44537)	(0.03989)	(0.60258)	(0.97646)	(0.08527)	(0.07197)	(0.57738)
Multi-business firm	0.01363	-0.05395	-0.05931	-0.03381	-0.03789	-0.05375	-0.04381	-0.04390	-0.01538	-0.06223	-0.04742	-0.05281
	(0.78060)	(0.03564)	(0.04346)	(0.23751)	(0.19927)	(0.07435)	(0.04307)	(0.34124)	(0.71170)	(0.00723)	(0.14590)	(0.07611)
Log(Assets)	-0.09249	-0.08665	-0.09302	-0.06634	-0.10194	-0.02038	-0.07437	-0.06348	-0.14165	-0.05559	-0.08346	-0.07850
	(0.01210)	(0.00132)	(0.00417)	(0.00120)	(0.00005)	(0.35606)	(0.00003)	(0.05018)	(0.00057)	(0.00286)	(0.02650)	(0.00249)
Log(3-Yr Patent Stock)	-0.10147	-0.03339	-0.09032	-0.05665	-0.05672	-0.09847	-0.08531	0.02905	-0.11697	-0.05379	-0.06164	-0.06449
	(0.00041)	(0.09320)	(0.00000)	(0.00175)	(0.00085)	(0.00000)	(0.00000)	(0.20911)	(0.00001)	(0.00068)	(0.00444)	(0.00275)
Intercept	1.45916	1.56857	1.72536	1.30574	1.71933	1.15213	1.51053	1.21393	1.93406	1.33455	1.59661	1.60967
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00015)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
N (observations)	1574	2955	4163	4370	3767	4766	7918	615	2531	6002	2808	3533
R-squared	0.05417	0.04219	0.02169	0.04404	0.02216	0.04624	0.02968	0.09327	0.02653	0.03667	0.03142	0.03020

p-values in parentheses
All models include firm and year fixed effects.
All independent variables lag the dependent variable by one year, except for R&D intensity, financial slack and patent stock.

Table 5: Short-termism & Patent Influence - IV Analysis

	Stage 1	**Stage 2**
DV =	Short-termism	Patent Influence
Short-termism		**-10.64476**
		(0.00000)
Financial Slack	-0.00541	0.12312
	(0.7060)	(0.53009)
R&D Intensity	0.04844	0.75178
	(0.3000)	(0.16828)
Market competition	-0.00044	0.00826
	(0.0120)	(0.01669)
Multi-business firm	0.00017	-0.05806
	(0.8930)	(0.00694)
Log(Assets)	0.00527	-0.04699
	(0.0000)	(0.04139)
Log(3-Yr Patent Stock)	0.00059	-0.00450
	(0.2390)	(0.69556)
Loss of Dedicated Ownership Classification	**0.011349**	
	(0.0000)	
Loss of Transient Ownership Classification	**0.0015438**	
	(0.2100)	
N (observations)		3357
R-squared		0.00184

p-values in parentheses
All models include firm and year fixed effects.
All independent variables lag the dependent variable by one year, except for R&D intensity, financial slack and patent stock.

Table 6: Alternative Measures of Influential Inventions

DV:	Average Lexical Novelty	Average Back Citations: Same class	Average Back Citations: Different class
	(1)	(2)	(3)
Short-termism	-1.24900	-1.24111	0.25196
	(0.00283)	(0.03375)	(0.66521)
Financial Slack	0.14797	-0.04307	0.07216
	(0.24081)	(0.83092)	(0.75433)
R&D Intensity	0.26136	-0.25436	0.08779
	(0.31800)	(0.45330)	(0.83060)
Market competition	0.00253	0.00036	0.00797
	(0.48253)	(0.93330)	(0.11721)
Multi-business firm	-0.02241	-0.03961	0.02919
	(0.36691)	(0.17291)	(0.32824)
Log(Assets)	-0.04662	0.04100	0.03812
	(0.00771)	(0.08946)	(0.14462)
Log(3-Yr Patent Stock)	-0.00941	0.01813	0.01744
	(0.37712)	(0.22024)	(0.23809)
Intercept	0.39911	1.35728	1.12417
	(0.00161)	(0.00000)	(0.00000)
N (observations)	7115	7151	7151
R-squared	0.00626	0.00306	0.00240

p-values in parentheses
All models include firm and year fixed effects.
All independent variables lag the dependent variable by one year, except for R&D intensity, financial slack and patent stock.

Table 7: Robustness Explorations

DV = Patent Influence	Only dividend issuing firms	Only non-dividend issuing firms	Excluding 2000-2001 bubble	Excluding 2008-2009 financial crisis
	(1)	(2)	(3)	(4)
Short-termism	-6.76873	-2.21986	-3.07541	-2.56004
	(0.00000)	(0.06011)	(0.00084)	(0.00233)
Financial Slack	0.19532	0.14897	0.30376	0.20498
	(0.20477)	(0.55260)	(0.02914)	(0.12289)
R&D Intensity	0.06423	1.55844	-0.22602	0.12491
	(0.77499)	(0.09355)	(0.34603)	(0.55568)
Market competition	0.00720	-0.00356	0.00607	0.00799
	(0.06624)	(0.58945)	(0.10542)	(0.01576)
Multi-business firm	-0.00867	-0.05683	-0.04821	-0.04556
	(0.75222)	(0.05488)	(0.02937)	(0.02621)
Log(Assets)	-0.03982	-0.11880	-0.11130	-0.05281
	(0.03272)	(0.00071)	(0.00000)	(0.00130)
Log(3-Yr Patent Stock)	-0.07837	-0.06473	-0.06346	-0.08773
	(0.00002)	(0.00111)	(0.00003)	(0.00000)
Intercept	1.05416	1.94896	1.70778	1.40866
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
N (observations)	5033	3500	6953	8159
R-squared	0.03452	0.02980	0.03998	0.02649

p-values in parentheses

All models include firm and year fixed effects.

All independent variables lag the dependent variable by one year, except for R&D intensity, financial slack and patent stock.