# The Cost of Capital and the Innovative Efficiency of Public Firms

Oleg R. Gredil, Ryan H. Peters, Sheri Tice, Vinh Tran*

June 30, 2023

**Abstract**

We study the effects of the cost of capital on innovative efficiency and output. Using firm peer shocks to the discount-rate component of equity valuation, we show that costlier capital increases successful patent applications, future patent citations, and market valuation of future patents. An interquartile increase in the cost of capital increases the innovative efficiency per dollar of intangibles by 0.06 of the outcome's standard deviation or 11% of the sample average output per year. We show that in response to our proxy of adverse shocks to cost of capital, firms reduce capital and labor expenditures. They also tend to shrink their sales and fixed assets but maintain their R&D expenditures. This suggests that the high adjustment costs in R&D expenditures are consistent with firm value maximization.

**Keywords:** Innovation, Innovative efficiency, Cost of Capital, Discount-rate shocks, R&D adjustment cost, Investments, Patenting, ESG

**JEL:** G30,G32,G34,O3,O34

*All authors are with Tulane University Freeman School of Business. The emails are, respectively, ogredil@tulane.edu, rpeters4@tulane.edu, stice@tulane.edu, vtran6@tulane.edu.

# 1 Introduction

Innovation is a backbone of productivity growth (Solow, 1957; Romer, 1986) and, therefore, is crucial for economic development. It is also well established that a lack of access to capital inhibits innovation (see, e.g., Hall and Lerner, 2010; Kerr and Nanda, 2015; Howell, 2017). However, relatively little is known about whether the level of returns that the investors expect from innovative firms matters too. Is cheap capital (e.g., due to government subsidies, or "market manias") more conducive to high-impact innovation than expensive capital? Do firms and sectors that investors fall "out of favor" (or "in love") with for their ESG footprint become worse or better at innovation?[1]

This paper sheds light on answers to these questions by studying the effects of plausibly exogenous shocks to the cost of capital on the innovative efficiency and output in a large sample of firms that were public as of the shock arrival. We find that a one standard deviation increase in the cost of capital increases successful patent applications by 0.057 of the standard deviation cumulatively over the three years following the shock year, or about 10% of the sample average patent output per year. Over 90% of that increase cannot be explained by changes in the labor, capital, and R&D inputs and, therefore, is driven by a higher efficiency of innovation. We find no evidence that these additional patents are inferior—the response magnitudes are similar for the market valuation of the granted patents and are about 30% larger for patent lifetime citations.

We apply the standard decomposition of stock returns into discount rate and cash-flow news, as implemented in Lochstoer and Tetlock (2020), to distill the equity valuation component that is orthogonal to firms' profitability changes. To reduce the measurement error on the discount-rate news at the individual firm-year level, we follow Leary and Roberts (2014) in using peers' average stock returns to produce plausibly exogenous variation that the firms may respond to. We show that these discount-rate shocks do not revert over several years and are economically significant. To further reduce the scope for the spurious correlation with cash-flow news, we control for peers' cash-flow news in

[1] See, for example, "Carbonomics: The dual action of Capital Markets transforms the Net Zero cost curve" report by Goldman Sachs on 11/10/2021 for representative views on the "new era" in the cost of capital differences.

all our tests. Thus, our assumptions are that (i) peers' stock valuations are sufficiently correlated with those of the focal firms, (ii) firms respond to the seemingly unexplained but persistent changes in their stock valuations (e.g., because they perceive them as informative to the firm's own cost of capital). We verify assumption (i) and note that we should find no results if assumption (ii) fails.

We find that the efficiency increase is driven mostly by firm-years that receive adverse shocks and less so by the decrease of those that receive a favorable shock. The tercile of most adversely shocked firm-years exhibits a statistically significant increase in efficiency across all output metrics, and at 1- to 3-year horizons, while the tercile of firm-years that endured the largest decrease in the cost of capital exhibit a statistically significant decline in the innovative efficiency only at a 3-year horizon. The adversely-shocked firms dispose of assets and respond by reducing capital expenditures and employment levels faster than favorably-shocked firms respond with increases. Favorably-shocked firms increase net equity issuance more than adversely-shocked firms reduce it. However, consistent with prior evidence on high adjustment cost for such investments (Hall, Griliches, and Hausman, 1986; Hall and Lerner, 2010; Gulen, Li, Peters, and Zekhnini, 2021), neither group changes their R&D expenditures significantly. We also examine whether financial constraints can explain the responsiveness of the firms to the discount-rate news in the cross-section but find no consistent results with the established proxies.

We use three patent databases to ensure that the measurement error on our innovative output metrics is minimized: the extended database from Kogan, Papanikolaou, Seru, and Stoffman (2017), the Global Corporate Patent Database from Bena, Ferreira, Matos, and Pires (2017), and the DISCERN database from Arora, Belenzon, and Sheer (2021). Our sample includes 99,948 firm-years from 1989–2017 and 1.5 million patents granted from 1989–2020. We scale patents' output, market valuations, and citations by the firm's intangible and knowledge capital (Peters and Taylor, 2017) before the shock arrival to account for heterogeneity across firms. We take advantage of both the firms' self-proclaimed industry membership and the 10K text-based product proximity measures of Hoberg and Phillips (2016). Our inference is robust to auto- and cross-correlations at the industry level.

We subject our results to a battery of robustness tests that include changes to variable construction and econometric methods. In particular, we show that there is no effect before the shock arrival and after three years following the shock. We also show that results hold with alternative VAR specifications, different sample criteria for discount-rate shock computation, and different peer definitions. We show that results for innovative output and efficiency hold qualitatively with cost of capital shocks derived from the analyst forecasts (see, inter alia, Gebhardt, Lee, and Swaminathan, 2001). However, unlike with the variables in our main analyses, these earnings forecast-based proxies of discount-rate shocks (while being significantly correlated with our preferred proxy) do not significantly affect the employment and capital expenditures, which can be regarded as validation tests for the proxy strength.

We contribute to several strands of literature. The question of the determinants and drivers of innovation has been generating much interest from scholars, who examined the roles of firm characteristics, governance structures, and market environments in innovation at mature corporations, as well as early-stage startups (see, Kerr and Nanda, 2015; Lerner and Nanda, 2020; He and Tian, 2018; He and Tian, 2020, for recent reviews). We relax the implicit assumption in these studies that "capital availability equals the cost of capital," and document a causal effect of plausibly pure discount-rate shocks on the production of innovation at public firms. Related to us are studies measuring intangible capital, its role and cross-sectional variation over time.[2] We recognize the importance of these trends in our variable construction.

Our results have implications for the fast-growing literature on corporate ESG matters (see, e.g., Berg, Koelbel, and Rigobon, 2022; Edmans, 2022) and, especially, the cost of capital implications thereof (see, e.g., Pástor, Stambaugh, and Taylor, 2021, 2022). In particular, our estimates suggest that in the long-term "green" firms' marginal output may lag that of "brown" ones (i.e., firms with an adverse environmental impact), thus

[2]See, for example, Eisfeldt and Papanikolaou (2013), Peters and Taylor (2017), Eisfeldt, Kim, and Papanikolaou (2020), Ewens, Peters, and Wang (2020), Falato, Kadyrzhanova, Sim, and Steri, 2022, Belo, Gala, Salomao, and Vitorino (2022).

reducing the relative valuation gap between the two types (a.k.a., the "greenium").

Our findings also relate to those in a recent study by Almeida et al. (2022), who show that short-term incentives (i.e., a risk of the EPS-forecast miss) lead to increases in the firms' innovative efficiency. The authors show that the relationship is present amongst highly innovative firms only. Our settings are different in that we look at long-term incentives unrelated to the earnings news of the firm, and we find results on both the intensive and extensive margins. We show that, upon adverse discount-rate arrival, not only does the patent count increase, but so does the probability of obtaining at least one patent.

Finally, the challenges with measuring patent output at the firm-year level (see Lerner and Seru, 2022 for details) that we address through independent validation across multiple databases also represents a contribution to the extant literature. We show that the pairwise concordance in positive patent counts by firm-years is less than 70%, with discrepancies being particularly large in years before 2002. Applying our criteria of the patent-firm-year presence in at least two databases likely eliminates false positives (and negatives) across the databases and results in a comparable (or better) firm-year coverage than that in any single database.

In the next section, we describe our data and the research design it commands. The following two sections report the results and robustness tests.

# 2 Data and Research Design

In this section, we describe our data and key variables of interest. These variables are feasible proxies of innovative output and plausibly exogenous shocks to the firms' cost of capital. The strengths and limitations of the feasible proxies determine our research design, which we also introduce in this section.

Table 1 reports summary statistics for the panel of 99,948 COMPUSTAT firm-years during 1988–2017, for which we can construct our cost of capital shock variable. These are the firms that were themselves public in the year of the shock measurement. Most of the variables in Panel A are standard and defined in Appendix B.. All continuous variables are winsorized at 1% and 99%, and all dollar variables are adjusted for inflation. Following the extant literature, we drop firms whose industry classification is regulated (SIC 4900 to 4999), financial (SIC 6000 to 6999), or public service (SIC above 9000). We also drop firms with missing or non-positive book values of assets or sales. Finally, we drop firms that have less than 5 million dollars (in 1990 constant dollars) in fixed assets.

## 2.1 Cost of capital shocks

We rely on the standard decomposition of stock return decomposition (Campbell and Vuolteenaho, 2004; Campbell, Polk, and Vuolteenaho, 2010) to construct our main proxy of cost of capital shocks. We use the code from Lochstoer and Tetlock (2020) (LT) to estimate a panel VAR model of expected return, and construct the firm-year level estimates of discount-rate news (DR) and cash-flow news (CF):

$$r_{i,t+1} - E_t[r_{i,t+1}] = CF_{i,t+1} - DR_{i,t+1} \tag{1}$$

, whereby $r_{i,t+1}$ and $E_t[r_{i,t+1}]$ are, respectively, the realized and the expected log returns of stock $i$. We seek to examine the relation between DR and the future innovative output of the firm.

While the LT methodology allows for predictive coefficients to vary across firms and over time, the resulting estimates have several limitations that are important for our research question. First, they are subject to measurement errors insofar the VAR coefficient estimates are subject to uncertainty, the model can be misspecified, and, thus, a portion of CF can be attributed to DR for some firm-years. Second, for data availability and continuity reasons, the shock estimates are not available for many firms, especially young and with a short record of being public. To address these limitations, we follow Leary and Roberts (2014) in using peers' stock returns (in our case, the DR- and CF-components thereof) to produce plausibly exogenous variation that the firms may respond to.

We define firm peers using the best possible estimate of relatedness. We utilize both the self-reported SIC industry definitions from CRSP and the 10K-based product similarity metrics from the text-based industry classification database (TNIC) of Hoberg and Phillips (2016). To identify the most similar peers, we require all peers to have their TNIC scores greater than the median score (0.0367) in the TNIC database or to have the same SIC 2-digit industry or the same FIC 2-digit industry as the focal firm.[3] If a firm-year does not have at least 3 TNIC-peers, we use other peers that have the same SIC-4digit industry as the focal firm with the smallest differences in sales. All firm-years in our main tests have at least three peers and at most ten peers with LT shocks. Furthermore, following the main analysis in LT, we exclude the bottom NYSE decile from the VAR estimation, which implies that only relatively large firms will be considered as salient-enough peers.

The first two rows of Panel A of Table 1 report those peer-average DR and CF shocks.[4] For brevity, we will omit the 'peer-average'-prefix through the remainder of the text. Of interest here are the measures of shock dispersion. The standard deviation and interquartile range of DR at 0.09 and 0.11 are less than half of those of CF (0.21 and 0.22). We note that, unlike CF, DR shocks are rather symmetric at the 1st- and 99th-percentiles, representing and change in the peers' average valuation of about 22%. Importantly, per equation (1), positive values of CF correspond to higher stock returns, while positive values of DR correspond to lower stock returns.

Figure 1 plots the average DR and CF shocks across the firms in the bottom, top, and middle two deciles as of the year of the decile cut, and the ten adjacent years. Panel A plot DRs for DR-based cuts and reveals neither meaningful pre-trend in the DR shocks nor autocorrelation (see Table A1 for details). Thus, these shocks tend not to reverse quickly but represent a lasting change in the valuation of peers. However, panel B shows that the average DR shock value varies notably (albeit the magnitudes are about one-third of those from the "DR-native cut" in Panel A) across the CF-deciles. Panels C and D show that these correlations are symmetric. This is consistent with the strong negative

[3]FIC industry classification is the fixed-industry version of TNIC and is also available on the Hoberg-Phillips Data Library website.

[4]Before computing the averages, we exponentiate the values across the peers and subtract one.

correlation between the firm-level discount rate and cash-flow shocks documented in LT and underscores the need to control for CF in the analysis of the effects of DR. Given this pattern, we decide against a binary definition of treated firm-years in favor of modeling DR as a continuous treatment that is non-separable from that from CF (see, e.g., Su, Ura, and Zhang, 2019).

We are agnostic about the precise nature of the DR shocks. In our regression analysis, we control for CF shocks, year fixed-effects, and firm fixed-effects, as well as a host of firm- and peer-level time-varying characteristics related to risk exposure and growth. Therefore, the residual measurement error in DR, as well as pure time- and cross-sectional variation in DR, will be absorbed. The leftover variation is within the industry clusters and is eclipsing the behavioral- and the (unspanned) risk factors. One such potential factor is changing investors' attitudes towards ESG-impact of the business. An increase in the "greenium" (Pástor, Stambaugh, and Taylor, 2021) will appear as positive DR shocks for "brown" firms and negative DR shocks for "green" firms, all else equal.

In summary, our DR variable is capturing the, on average, "depressed stock price" that future- and past changes in profitability of its most salient peers cannot explain. As in Leary and Roberts (2014), we assume that the management of the focal firm likely observes, and has incentives to act upon, this information. Should this assumption fail in our settings, we will find no results. At this point, we note that for 46,075 firm-years with observable 'own DR' (i.e., less than half of our sample), the correlation with DR used in our analysis is 61%, which is consistent with the shock being on average relevant even if the management does not track peers' stock valuation. In robustness tests, we examine several alternative measures of DR and CF, including those that exhibit a close to zero correlation with CF shocks and that are based on analyst forecasts.

## 2.2 Innovative output

Our primary measure of innovative output is the number of patents that the firm produces in the aftermath of the DR shock.

We use the June 2021 version of Kogan, Papanikolaou, Seru, and Stoffman (2017)

(KPSS) database as our main source of patenting data, which contains patent data through 2020. Our focus is on patent development that results in the application filing, as opposed to the market's price response at the patent granting date. One potential concern is that relying solely on the KPSS database may result in a significant measurement error in patent applications (that are eventually granted) since the firm may not have publicly traded stock at the grant date and the firm may change names between the patent filing and granting date, and filing can occur in jurisdictions other than the U.S. We, therefore, augment and verify the patent data in KPSS with the other two major databases of patents: the Global Corporate Patent Database (GCPD) featured in Bena, Ferreira, Matos, and Pires (2017) (BFMP), the Duke Innovation and Scientific Enterprises Research Network (DISCERN) database featured in Arora, Belenzon, and Sheer (2021) (ABS). The GCPD and DISCERN databases cover patent assignments through, respectively, the first half of 2017 and 2015.

For years through 2015, we include a patent number observation in our final data set if at least two of the three databases report this patent number as matching the gvkey-permno as of the patent assignment date. This approach allows us to increase the coverage to 23,517 firm-years with positive patent count from 15,205, whereby patent counts coincide between KPSS and BFMP (see appendix Table A3 for details). For patents granted in 2016 and 2017 that are present in GCPD but missing from KPSS, we manually verify a close match between the CRSP name and the patent assignee name. We use the standard CRSP-Compustat linking table and CRSP names table to establish the time-specific mapping between gvkey, permno, and patent assignee names. Our final data set includes 1,500,017 unique patents assigned to 4,247 gvkey (4,132 permno) between 1989 and 2020. Of these, 521 patents were assigned to more than one gvkey or permno.

To measure the patent output X years after DR shock, we count the number of unique patents that have (A) application date between $1 + (X - 1) \cdot 12$ and $X \cdot 12$ months after June 30th of the shock year, and (B) that have been assigned to the same gvkey as the shocked firm on on the patent grant date, or (ii) the shock date.

We normalize firm-year patent counts by the value of firm knowledge capital and intangible capital as of the year preceding the shock year. The intangible capital is the COMPUSTAT variable INTANO (set to zero if missing). Knowledge capital estimates are from Peters and Taylor (2017), obtained from the WRDS repository as of June 2022. The rationale for this normalization is two-fold. First, we reduce the heterogeneity in the outcome variable across our panel, since the level of innovation varies greatly across firms and is expected to be proportional to the investments in knowledge and intangible capital. Second, recent work by Cohn, Liu, and Wardlaw (2022) shows that, unlike the common in the prior literature logs of one plus patent counts, linear models of ratios of counts to the relevant stock variables are not prone to spurious results.[5]

In addition to patent counts, we examine the market value ('KPSS value') and the patent lifetime citations count ('Total citations'), both obtained from the KPSS database and scaled by the sum of INTANO and knowledge capital of Peters and Taylor (2017). The summary statistics for our three output variables are reported in Panel B of Table 1 for 46,037 firms with at least one patent between 1989 and 2020. The panel shows that the average (standard deviation) patent count is 0.022 (0.044) patents per \$million of intangible capital. The respective statistics for KPSS value and Total citations are 0.289 (0.682) \$million per \$million of intangible capital and 0.44 (1.218) citations per \$million of intangible capital.

To estimate the effect of DR on patent output, we run the following linear regression for several horizons $k > 0$, that index year since the shock value in year $t$:

$$\text{Patent count}_{i,t+k} = b\text{DR}_{i,t} + c\text{CF}_{i,t} + d'\text{Controls}_{i,t-1} + t + i + \epsilon_{i,t} \tag{2}$$

where $i$ and $t$ indicate the firm and year fixed effects, while $\epsilon_{i,t}$ is the unobserved error term, correlated across time and industries. The vector of 'Controls' include the one-year lagged Sales, market-to-book, return on assets, PP&E, leverage, and age of the firm itself and the average across its peers used to construct DR and CF. The main coefficient of interest is $b$.

[5] We address the Welch (2020) critique of regressions featuring the ratios with lagged variables in our robustness tests.

### 2.3 Innovative efficiency

We model the innovative efficiency of the firm analogously to the standard definition of productivity, as the change in output that cannot be explained by changes in the inputs:

$$\text{InnovOutput} = f(\text{Labor}, \text{Employment}, \text{R\&D}, \text{InnovEfficiency})$$

Assuming that the innovation production function $f(\cdot)$ is log-linear in all inputs and that firm- and year-fixed effect address the heterogeneity in the fractions of the firm's capital and labor utilization in the production of innovation (as opposed to other output), we estimate the effects of DR on the innovative efficiency by augmenting equation (2) with changes in the inputs over the respective horizon $k$:

$$\begin{aligned} \text{Patent count}_{i,t+k} =& b\text{DR}_{i,t} + c\text{CF}_{i,t} + \lambda' \sum_{\tau=1}^{k} \text{Inputs}_{i,t+\tau} \\ & + d'\text{Controls}_{i,t-1} + t + i + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $\text{Inputs}_{i,t+\tau}$ is a vector of changes in the natural logs of real 1+R&D, 1+CAPEX, and the employees count from period $t + \tau - 1$ to $t + \tau$.

The summary statistics for the Inputs are reported in Panel A of Table 1. The standard deviation fn the R&D continuously compounded change is 0.218; for CAPEX, it is 0.574; for Employment, it is 0.234. The bottom quartile and the median change in R&D are zero, as many firms do not report R&D separately.

We also examine whether the shocks to the cost of capital affect $\text{Input(j)}_{t+\tau}$ by changing the outcome variable in equation (2):

$$\text{Input(j)}_{i,t+k} = b\text{DR}_{i,t} + c\text{CF}_{i,t} + d'\text{Controls}_{i,t-1} + t + i + \epsilon_{i,t} \quad . \tag{4}$$

Economic theory predicts that increases in the cost of capital should reduce the investments by the firm, as fewer projects will appear to have positive expected net present value. The effects may be different across Inputs, representing various trade-offs the management faces. For example, prior work shows that managers are reluctant to cut R&D (REFERENCE NEEDED).

Finally, to test for asymmetry in response to positive and negative DR shocks, we augment the models per equations (2), (3), and (4) with the interactions of DR with 'BadDR' and 'GoodDR' dummies. 'BadDR' indicates DR shocks in the top tercile, with the average value of DR shock of 0.05 across the tercile, corresponding to 5% *decrease* in peer's valuations that cannot be traced to peers' earnings news. Meanwhile, 'GoodDR' indicate DR shocks in the bottom tercile. For these, the discount-rate driven *increase* in peer valuations was 13%.

# 3 Results

In this section, we report the results of the tests of the effects of DR on innovative output and efficiency using the empirical models described in the previous section. In addition, we examine the effects of DR on capital, labor, and R&D inputs, as well as the operational performance of the firm, its balance sheet, and capital raising activities.

## 3.1 Innovative output

In Panel A of Table 2, we examine the relationship between firms' discount rate shocks and innovation output. The columns report estimates of equation (2). Columns (1) to (3) report regression results for patent count, columns (4) to (6) for KPSS value, and columns (7) to (9) for total citations. The coefficient estimates on DR are positive and statistically significant in years 1, 2, and 3 after the shock year and for all measures of innovation output (patent count, KPSS value, and total citations), suggesting that an increase in the cost of capital leads to higher innovation output (per $M of intangible capital) for up to at least three years after firms experience DR shock. We also standardize all outcome variables by their respective standard deviations, so coefficient estimates on DR represent one standard deviation change in innovative output per unit change in the cost of capital. For example, the coefficient on DR in column (1) is 0.164, which indicates that increasing the value of DR from its 25th percentile (-0.11) to its 75th percentile (0.00) is associated with a 0.036 standard deviation increase in the number of patents applied (and eventually granted) per $M of intangible capital.

Cumulatively over three years after an interquartile shock, the change in the patent output corresponds to 10% of the average patent output per dollar of intangible and knowledge capital. The corresponding magnitudes for the patents market values and total citations are, respectively, 12% and 18%.

To rule out the possibility that our results are driven by firm-years with zero patents (hence, zero KPSS value and citations), we re-estimate equation (2) on a sub-sample of firms that have at least one patent in the pooled sample. As a result of this restriction, the sample reduces by about half. Results for this sub-sample analysis are reported in Panel B of Table 2. Similar to Panel A, all outcome variables are standardized by their corresponding standard deviations. The coefficient estimates on DR continue to be positive and statistically significant for most of the specifications, consistent with innovative firms increasing their innovative output after an increase in the cost of capital. We also observe that the magnitudes of the coefficients are very similar to those in panel B and are about one standard error higher for the 3-year horizon. For subsequent tables, we focus on the full sample to avoid using hindsight with regard to future positive patent output.

In Panel C of Table 2, we estimate a linear probability model that is similar to Equation (2), but the dependent variable is a dummy equal to 1 if firm $i$ has at least one patent applied (and eventually granted) in year t+k and 0 otherwise. Columns (1) through (5) report regression results when we examine the probability of firms having at least one patent for only one-year ahead (i.e., year 1,2,3,4, or 5 after the DR shock year). All coefficient estimates on DR are positive and statistically significant, suggesting that firms are more likely to have a patent after they experience an increase in their cost of capital. Columns (6) to (9) of this panel report regression results for multiyear probability (i.e., year 1 to 2, 1 to 3, 1 to 4, or 1 to 5), and all coefficients are also positively significant at the 1% level.

These results suggest positive (negative) shocks to the cost of capital tend to increase (decrease) the innovative output across all three measures, and the effects monotonically strengthen as we go from one to a three-year horizon. In the robustness section, we show that results are robust to including additional leads and lags of DR shocks.

## 3.2 Inputs

We now examine the effects of DR on inputs relevant to the output of innovation by estimating the empirical model per Equation (4). Panel A of Table 3 reports the results. Coefficient estimates on DR for columns (1) to (3) are not significant, suggesting that firms do not reduce their investment in R&D following an increase in the cost of capital. In contrast, coefficients on DR for columns (4), (5), (7), and (8) are all negative and statistically significant, indicating that firms decrease their investment in physical and human capital in the two years after an increase in the cost of capital.

Next, we examine whether the reduction in physical and human capital expenditures identified above is driven by firm-years experiencing the highest increases in the cost of capital. As discussed in section 2.3, we sort firm-years into terciles based on their DR shocks. The average value of DR for the 3rd, 2nd, and 1st tercile is 0.05, -0.055, and -0.13, respectively. We create two dummy variables, BadDR and GoodDR, which take the value of one if the corresponding firm-year is sorted into the 3rd and 1st tercile, respectively, and zero otherwise. We then interact the continuous DR variable with dummies BadDR and GoodDR.

Panel B of Table 3 reports the results for this estimation. The two bottom rows of this panel report the p-value of the hypothesis test that the sum of the coefficient estimates on the baseline DR and on its interaction term with dummy BadDR (or GoodDR) is equal to 0. In column (4), the coefficient estimate on the interaction term with BadDR is negative and statistically significant. This indicates that firms that experience an increasing cost of capital reduce investment in CAPX one year after the shock, whereas firms with a decreasing cost of capital do not (interaction with GoodDR is insignificant). In column (5), the coefficient on the interaction term with BadDR is not significant, but when taking the baseline DR and interaction with BadDR together, the point estimate suggests that firms with an increase in cost of capital continue to reduce CAPX in year 2 relative to DR shock year. In column (6), the interaction term with BadDR is positively significant; however, the joint test with baseline DR indicates that firms with bad DR shocks do not increase their CAPX. In column (7), the interaction term with BadDR is not significant, but taking baseline DR and interaction with BadDR together indicates that firms with an increase in the cost of capital decrease human capital in their firms one year after the shock year.

### 3.3 Innovative efficiency

To explore the effects of cost of capital on innovative efficiency, we regress measures of innovative output on DR, controlling for ex-post changes in innovative inputs (i.e., the change in innovative efficiency is the change in innovative output that cannot be explained by changes in inputs). Panel A of Table 4 reports the results of this regression - equation (3). Coefficient estimates on DR are positive and statistically significant across all columns, consistent with firms increasing their innovative efficiency (for up to at least 3 years) after experiencing an increase in cost of capital, where innovative efficiency is measured in terms of the number of patents (patent count), economic value (KPSS value), and scientific value (total citations) of patents. Consistent with previous tables, we also scale all dependent variables by their respective standard deviations, so coefficient estimates on DR represent one standard deviation's worth of change in innovative efficiency per unit change in cost of capital. For example, in column (1), we can interpret the coefficient estimate on DR as one unit increase in cost of capital leading to a 0.154 standard deviation increase in the number of patents per $M of intangible capital, and this increase in patent output is due to improved efficiency.

Panel B of Table 4 also reports results for innovative efficiency, but we interact the continuous variable DR with dummies BadDR and GoodDR (similar to Panel B of Table 3) to explore if firms respond differently to an increase (BadDR) or decrease (GoodDR) in cost of capital when it comes to innovative efficiency. Controls for ex-post changes in inputs are included in all regressions but not reported on this panel for brevity. The interaction on BadDR is statistically and positively significant only for patent count in year 2 and KPSS value in year 1, but p-values of joint test with baseline DR suggest that firms increase their innovative efficiency (measured with patent count, KPSS value, and total citations) for at least up to 3 years after they experience an increase in cost of capital, with the exception of KPSS value in year 3 (column (6)). In contrast, most of the p-values of the joint test of baseline DR and interaction with GoodDR are not statistically significant, indicating that the effect of cost of capital on innovative efficiency is more pronounced when firms experience a bad DR shock.

## 3.4 Operational performance

We next explore the relationship between the cost of capital and firms' operating performance (measured by the change in total sales, assets, and EBITDA margin and the percentage change in EBITDA). We run a fixed-effects model that is similar to equation (2), but the dependent variables are those previously listed measures of operating performance. Table 5 reports the results of this regression. Panel A looks at the effect of cost of capital on sales growth and assets growth. The coefficient estimate on DR is negative and statistically significant for columns (1),(2), (5), and (7), consistent with firms decreasing their total sales and assets following an increase in cost of capital, and these effects last up to two years for sales and three years for assets. Panel B explores the relationship between cost of capital and the change in EBITDA margin or percentage change in EBITDA. The coefficient estimate on DR is negative and statistically significant for columns (1) and (5), suggesting that firms have a lower EBITDA margin and a lower EBITDA one year after an increase in cost of capital.

## 3.5 Asset disposal and capital raising

We next examine the relationship between the cost of capital and the composition of firms' assets. We run a regression that is similar to equation (2) where the dependent variables are cash, non-cash current assets, net PP&E, other assets, the sum of net PP&E

and other assets, and asset turnover. Table 6 reports the results of this regression. In Panel A, the coefficient on DR is negative and statistically significant for columns (1) and (5), indicating that firms reduce their cash holdings and non-cash current assets one year after experiencing an increase in cost of capital. However, firms reverse course and increase their cash holdings in year 2, as indicated by the positive and statistically significant coefficient on DR in column (2). In Panel B, the coefficient on DR is negative and statistically significant in columns (1), (2), and (5), suggesting that firms reduce PP&E in years 1 & 2 and other assets in year 1 after having an increase in cost of capital. Panel C reinforces the results of panel B. That is, firms cut PP&E and other assets in the two years after an increase in cost of capital, as indicated by the negative and statistically significant coefficient on DR in columns (1) and (2). Despite a reduction in all major components of assets, firms' asset turnover increases in years 1 and 3 following an increase in cost of capital, as suggested by the positive and statistically significant coefficient on DR in columns (5) and (7) of Panel C. These results are consistent with firms increasing not only innovative efficiency (documented in previous sections) but also asset efficiency more broadly.

We also explore the relationship between firms' cost of capital and capital raising. We do this by running a regression that is similar to equation (2), but the dependent variables are net equity issuance and net debt issuance. Panel A of Table 7 reports results for this regression, and the coefficient estimate on DR is positive and statistically significant for columns (2) and (3), suggesting that firms issue more equity in years 2 and 3 after an increase in cost capital. In contrast, the coefficient estimate on DR is negative and statistically significant for columns (1) to (3), indicating that firms issue less debt in the three years after an increase in cost of capital. In Panel B, we interact the continuous variable DR with dummies BadDR and GoodDR (similar to Panel B of Table 3). In column (1) of panel B, the coefficient estimate is significantly negative on DR but positive on interaction with BadDR. This is suggestive evidence that firms that experience the highest increase in cost of capital are less likely to issue less equity. In column (5), the interaction on BadDR is negative but not statistically significant.

However, when taking the interaction with BadDR and the baseline DR together, the point estimate suggests that firms with the highest increase in the cost of capital issue less debt (p-value of joint test equals 0.04).

# 4 Robustness

For robustness checks, we first investigate the relationships between cost of capital and one-year-ahead innovative output and efficiency with the inclusion of additional leads and lags of DR and CF shocks. Specifically, we estimate two models that are similar to equations (2) and (3), but we also include four lag and three lead values of DR and CF as independent variables in all regressions. Table 8 reports the regression results of this estimation. The outcome variables are patent count in columns (1) and (3) and KPSS value in columns (2) and (4). Columns (1) and (2) examine the innovative output, while columns (3) and (4) explore innovative efficiency with the inclusion of one-year-ahead changes in inputs (R&D, CAPX, and employment). The coefficient estimates on one- and two-year-lagged values of DR are positive and statistically significant across all four columns, which can be partly explained by the positive autocorrelation embedded in DR shocks. However, none of the coefficients on lead values of DR are statistically significant at the 10% level. More importantly, the coefficient estimates on contemporaneous DR ($\text{DR}_t$) remain positive and statistically significant across four columns, consistent with firms increasing both innovative output and efficiency (measured by patent count and KPSS value) following an increase in cost of capital.

Next, we re-examine cost of capital and innovative efficiency on the full sample, but with additional controls. Table 9 reports the regression results of equation (3), but we also control for one-year lagged levels of innovative inputs (R&D, CAPEX, and employment) in Panel A or ratio of 1 over intangible capital in Panel B (to address the concern that our main results on innovative efficiency are driven by the persistent scaling variable - lagged intangible capital). In both Panels A and B, the coefficient estimates on DR remain positive and statistically significant across all columns, consistent with firms increasing their innovative efficiency in the three years after an increase in cost capital.

Table 10 reports the regression results of equation (3) on a subsample that includes only peers whose TNIC scores are greater than the median (0.0367) in the TNIC database. That is, in contrast to the sample used in the main analysis, in this subsample we do not use SIC peers that are closest in sales with the focal firm as peers for firm-years that do not have at least three TNIC peers with above median TNIC scores. The difference between Panels A & B is the inclusion of peers that are in the bottom NYSE decile. As a result of the exclusion of SIC peers, our number of observations drops by about 29% in Panel A and 23% in Panel B (compared with the full sample used in Panel A of Table 4). In Panel A, the coefficient estimates on DR remain positive and statistically significant across all columns, with the exception of total citations in year 1 (column (7).) In Panel B, the coefficients on DR are still positive and statistically significant for patent count and total citations in years 2 & 3 and KPSS value in year 3. We attribute the reduced statistical power in Panel B to the inclusion of small firms in the NYSE decile that are not salient-enough peers. Qualitatively, the results in this table reinforce that firms increase their innovative efficiency following an increase in the cost of capital.

Finally, we examine a different methodology to construct DR shocks. This methodology follows the implied cost of capital estimation procedure described in Gebhardt, Lee, and Swaminathan (2001), which has been used extensively in the accounting literature. The autocorrelation of this accounting-based DR shock (aDR) and its correlation with DR and CF used in the main analysis are reported in the appendix Table A1. We observe that, unlike DR, aDR exhibits no persistence, a notably positive (albeit moderate) correlation with contemporaneous DR but about as strong but negative correlation with the two lags of DR.

Table A2 in the appendix explores the relationship between the accounting-based DR shock and innovative output, inputs, the probability of getting a patent, innovative efficiency, fixed assets, and asset turnover. We use the contemporaneous stock returns as an alternative measure of cash flow shocks. Panel A of this table reports regression results for equation 2 (with accounting-based DR shock), and the coefficient estimates on

DR are positive for most specifications except column (2). However, those estimates are only statistically significant for KPSS value in columns (4) to (6) and for total citations in columns (7) and (9). This suggests that firms' economic and scientific values of patents increase after an increase in accounting-based cost of capital. In Panel B, the coefficient estimate on DR is only positive and statistically significant in column (9) at the 5% level, indicating that firms are more likely to obtain a patent during a period of five years after a DR shock. Panel C reports the regression results of equation 4, and although some of the coefficient estimates on DR are negative, none is statistically significant. The results of this panel suggest that firms do not cut their investment in R&D and in physical and human capital even when their cost of capital increases, which is not consistent with standard corporate finance theory and can be partly explained by the measurement errors introduced by analyst forecasts used in the accounting-based-DR estimation procedure. However, even with reduced statistical power due to measurement errors, the positive and statistically significant coefficients on DR in most specifications of Panel D still indicate that firms increase their innovative efficiency after an increase in cost of capital. In Panel E, we rerun equation 4, but the dependent variables are $\Delta$ Net PP&E and Other Assets and Asset Turnover. In contrast with results using LT-based measures of shocks, the coefficient estimates on DR are not statistically significant in columns (1) and (2), suggesting that firms do not decrease PP&E and Other Assets following an increase in cost of capital. However, the positive and statistically significant coefficient on DR in column (5) indicates that firms increase their asset efficiency one year after an increase in cost of capital, consistent with results using LT shocks.

# 5 Conclusion

This paper studies the effect of firms' perceived cost of capital on the production of innovations and the efficiency thereof. Our proxy of changes in the cost of capital is based on the equity return component that is orthogonal to the cash-flow news of the firm. Contrary to the notion that subsidies spur innovations, we find that adverse shocks to the cost of capital drive higher innovative output and efficiency.

Also—in contrast to scaling back capital expenditures, employment, and fixed assets—firms seem to be reluctant to cut R&D expenditure in response to adverse shocks to the cost of capital. In light of our results on the innovative output, this reluctance seems to be concordant with the shareholder value maximization rather than reflecting higher information asymmetry (and, hence, higher agency costs) of R&D expenditures.

One way to reconcile our results with the extant literature on the importance of subsidization for innovation is that the cost of capital is not tantamount to its availability. While the availability of capital is a necessary condition for financing the innovation, a low expected return on that capital is conducive to neither innovative efficiency nor higher output. This result has important policy implications.

Our results are consistent with venture capital-backed being responsible for a disproportionately large fraction of the production of innovation (Lerner and Nanda, 2020) despite the cost of capital being high for the venture capitalists (Ewens, Jones, and Rhodes-Kropf, 2013) and, hence, for the startups in which they invest.

## References


Almeida, Heitor, Fos, Vyacheslav, Hsu, Po-Hsuan, Kronlund, Mathias, and Tseng, Kevin (2022) Do short-term incentives hurt innovation?, *University of Illinois Urbana-Champaign Working Paper.*

Arora, Ashish, Belenzon, Sharon, and Sheer, Lia (2021) Knowledge Spillovers and Corporate Investment in Scientific Research, *American Economic Review* 111, 871–898.

Belo, Frederico, Gala, Vito D, Salomao, Juliana, and Vitorino, Maria Ana (2022) Decomposing firm value, *Journal of Financial Economics* 143, 619–639.

Bena, Jan, Ferreira, Miguel A., Matos, Pedro, and Pires, Pedro (2017) Are foreign investors locusts? The long-term effects of foreign institutional ownership, *Journal of Financial Economics* 126, 122–146.

Berg, Florian, Koelbel, Julian F, and Rigobon, Roberto (2022) Aggregate confusion: the divergence of esg ratings, *Review of Finance* 26, 1315–1344.

Campbell, John Y, Polk, Christopher, and Vuolteenaho, Tuomo (2010) Growth or glamour? fundamentals and systematic risk in stock returns, *Review of Financial Studies* 23, 305–344.

Campbell, John Y and Vuolteenaho, Tuomo (2004) Bad beta, good beta, *American Economic Review* 94, 1249–1275.

Cohn, Jonathan B, Liu, Zack, and Wardlaw, Malcolm I (2022) Count (and count-like) data in finance, *Journal of Financial Economics* 146, 529–551.

Edmans, Alex (2022) The end of ESG, *European Corporate Governance Institute–Finance Working Paper.*

Eisfeldt, Andrea L, Kim, Edward, and Papanikolaou, Dimitris (2020) Intangible value, *National Bureau of Economic Research Working Paper.*

Eisfeldt, Andrea L and Papanikolaou, Dimitris (2013) Organization capital and the cross-section of expected returns, *The Journal of Finance* 68, 1365–1406.

Ewens, Michael, Jones, Charles M, and Rhodes-Kropf, Matthew (2013) The price of diversifiable risk in venture capital and private equity, *Review of Financial Studies* 26, 1854–1889.

Ewens, Michael, Peters, Ryan H, and Wang, Sean (2020) Measuring intangible capital with market prices, *National Bureau of Economic Research Working Paper*.

Falato, Antonio, Kadyrzhanova, Dalida, Sim, Jae, and Steri, Roberto (2022) Rising intangible capital, shrinking debt capacity, and the us corporate savings glut, *The Journal of Finance* 77, 2799–2852.

Gebhardt, William R., Lee, Charles M. C., and Swaminathan, Bhaskaran (2001) Toward an Implied Cost of Capital, *Journal of Accounting Research* 39, 135–176.

Gulen, Huseyin, Li, Dongmei, Peters, Ryan H, and Zekhnini, Morad (2021) Intangible capital in factor models, *Purdue University Working Paper*.

Hall, Bronwyn H and Lerner, Josh (2010) The financing of r&d and innovation. In: *Handbook of the economics of innovation*. Vol. 1. Elsevier, 609–639.

Hall, Bronwyn H., Griliches, Zvi, and Hausman, Jerry A. (1986) Patents and r and d: is there a lag?, *International Economic Review* 27, 265–283.

He, Jie and Tian, Xuan (2018) Finance and Corporate Innovation: A Survey, *Asia-Pacific Journal of Financial Studies* 47, 165–212.

He, Jie and Tian, Xuan (2020) Institutions and Innovation: A Review of Recent Literature, *Annual Review of Financial Economics, forthcoming*.

Hoberg, Gerard and Phillips, Gordon (2010) Product market synergies and competition in mergers and acquisitions: A text-based analysis, *Review of Financial Studies* 23, 3773–3811.

Hoberg, Gerard and Phillips, Gordon (2016) Text-based network industries and endogenous product differentiation, *Journal of Political Economy* 124, 1423–1465.

Howell, Sabrina T (2017) Financing innovation: evidence from r&d grants, *American economic review* 107, 1136–64.

Kerr, William R and Nanda, Ramana (2015) Financing innovation, *Annual Review of Financial Economics* 7, 445–462.

Kogan, Leonid, Papanikolaou, Dimitris, Seru, Amit, and Stoffman, Noah (2017) Technological innovation, resource allocation, and growth, *The Quarterly Journal of Economics*, 665–712.

Leary, Mark T. and Roberts, Michael R. (2014) Do Peer Firms Affect Corporate Financial Policy?, *Journal of Finance* 69, 139–178.

Lerner, Josh and Nanda, Ramana (2020) Venture capital's role in financing innovation: what we know and how much we still need to learn, *Journal of Economic Perspectives* 34, 237–61.

Lerner, Josh and Seru, Amit (2022) The use and misuse of patent data: issues for finance and beyond, *Review of Financial Studies* 35, 2667–2704.

Lochstoer, Lars A. and Tetlock, Paul C. (2020) What Drives Anomaly Returns?, *Journal of Finance* 75, 1417–1455.

Pástor, L'uboš, Stambaugh, Robert F, and Taylor, Lucian A (2021) Sustainable investing in equilibrium, *Journal of Financial Economics* 142, 550–571.

Pástor, L'uboš, Stambaugh, Robert F, and Taylor, Lucian A (2022) Dissecting green returns, *Journal of Financial Economics* 146, 403–424.

Peters, Ryan H and Taylor, Lucian A (2017) Intangible capital and the investment-q relation, *Journal of Financial Economics* 123, 251–272.

Romer, Paul M (1986) Increasing returns and long-run growth, *Journal of political economy* 94, 1002–1037.

Solow, Robert M (1957) Technical change and the aggregate production function, *The review of Economics and Statistics*, 312–320.

Su, Liangjun, Ura, Takuya, and Zhang, Yichong (2019) Non-separable models with high-dimensional data, *Journal of Econometrics* 212, 646–677.

Welch, Ivo (2020) Ratio of changes: how real estate shocks did not affect corporate investment, *University of California Los Angeles Working Paper*.

**Table 1:** Summary Statistics

This table reports the summary statistics of all variables constructed using a sample of US public firms from 1988 to 2017. Refer to Appendix B for variable definitions. Panel A reports summary statistics for variables of all firms in the sample. Panel B reports summary statistics for innovative efficiency measures of firms with at least one patent applied (and eventually granted) in the sample.

Panel A: All firm-years

| | count | mean | stdev | p1 | p25 | median | p75 | p99 |
|---|---|---|---|---|---|---|---|---|
| DR | 99,949 | −0.045 | 0.088 | −0.22 | −0.11 | −0.06 | 0.00 | 0.23 |
| CF | 99,949 | 0.047 | 0.212 | −0.42 | −0.08 | 0.02 | 0.14 | 0.87 |
| Sales_p | 99,949 | 6.813 | 1.315 | 2.53 | 6.10 | 6.95 | 7.69 | 9.54 |
| MTB_p | 99,876 | 2.008 | 1.260 | 0.66 | 1.18 | 1.62 | 2.40 | 7.58 |
| ROA_p | 99,948 | 0.113 | 0.101 | −0.33 | 0.09 | 0.13 | 0.17 | 0.26 |
| PPE_p | 99,949 | 0.301 | 0.205 | 0.04 | 0.14 | 0.25 | 0.42 | 0.84 |
| LEV_p | 99,949 | 0.210 | 0.116 | 0.01 | 0.12 | 0.20 | 0.29 | 0.51 |
| Age_p | 99,949 | 2.306 | 0.462 | 1.28 | 1.97 | 2.31 | 2.64 | 3.30 |
| Sales_f | 94,799 | 6.181 | 2.007 | 1.20 | 4.80 | 6.10 | 7.51 | 11.11 |
| MTB_f | 85,671 | 1.594 | 1.326 | 0.31 | 0.80 | 1.16 | 1.86 | 8.04 |
| ROA_f | 94,690 | 0.098 | 0.151 | −0.58 | 0.06 | 0.12 | 0.18 | 0.42 |
| PPE_f | 94,799 | 0.313 | 0.238 | 0.02 | 0.12 | 0.24 | 0.46 | 0.91 |
| LEV_f | 94,449 | 0.247 | 0.226 | 0.00 | 0.05 | 0.21 | 0.37 | 1.00 |
| Age_f | 93,183 | 2.196 | 0.823 | 0.00 | 1.61 | 2.30 | 2.83 | 3.56 |
| Δ ln(1+XRD) | 92,195 | 0.028 | 0.218 | −0.80 | 0.00 | 0.00 | 0.04 | 1.02 |
| Δ ln(1+CAPX) | 92,195 | 0.015 | 0.574 | −1.79 | −0.27 | 0.03 | 0.32 | 1.71 |
| Δ ln(EMP) | 88,325 | 0.044 | 0.234 | −0.77 | −0.05 | 0.03 | 0.13 | 0.92 |
| Δ ln(Sales) | 92,195 | 0.068 | 0.251 | −0.54 | −0.05 | 0.05 | 0.17 | 0.82 |
| Δ ln(Assets) | 92,195 | 0.057 | 0.278 | −0.74 | −0.07 | 0.03 | 0.15 | 1.13 |
| Δ EBITDA/Sales | 92,027 | 0.011 | 0.342 | −1.66 | −0.02 | 0.00 | 0.02 | 2.21 |
| % Change EBITDA | 92,026 | 0.018 | 0.990 | −3.21 | −0.23 | 0.04 | 0.29 | 3.17 |
| Δ Cash | 87,149 | 0.012 | 0.104 | −0.24 | −0.02 | 0.00 | 0.03 | 0.38 |
| Δ Non-cash Current Assets | 85,341 | 0.045 | 0.150 | −0.23 | −0.02 | 0.02 | 0.08 | 0.59 |
| Δ Net PP&E | 88,252 | 0.041 | 0.120 | −0.14 | −0.01 | 0.01 | 0.05 | 0.54 |
| Δ Other Assets | 86,228 | 0.040 | 0.141 | −0.18 | −0.01 | 0.00 | 0.04 | 0.63 |
| Δ Net PP&E & Other Assets | 86,228 | 0.087 | 0.244 | −0.25 | −0.02 | 0.02 | 0.11 | 1.10 |
| Asset Turnover | 92,195 | 1.123 | 0.852 | 0.05 | 0.57 | 0.95 | 1.45 | 4.07 |
| Net Equity Issuance | 80,726 | 0.029 | 0.182 | −0.24 | −0.01 | 0.00 | 0.01 | 1.20 |
| Net Debt Issuance | 87,793 | 0.048 | 0.217 | −0.36 | −0.03 | 0.00 | 0.05 | 1.32 |
| N_peers | 99,949 | 8.986 | 2.080 | 3.00 | 10.00 | 10.00 | 10.00 | 10.00 |
| avg_score | 84,488 | 0.080 | 0.052 | 0.01 | 0.04 | 0.07 | 0.11 | 0.23 |
| 1/intan17 | 94,799 | 0.030 | 0.079 | 0.00 | 0.00 | 0.01 | 0.02 | 0.52 |
| Beta*Mkt Return | 99,949 | 0.156 | 0.212 | −0.34 | 0.03 | 0.16 | 0.28 | 0.74 |

Panel B: Firms with a patent

| | count | mean | stdev | p1 | p25 | median | p75 | p99 |
|---|---|---|---|---|---|---|---|---|
| Patent count | 46,037 | 0.022 | 0.044 | 0.00 | 0.00 | 0.00 | 0.02 | 0.21 |
| KPSS value | 45,034 | 0.289 | 0.682 | 0.00 | 0.00 | 0.01 | 0.20 | 3.44 |
| Total citations | 45,999 | 0.438 | 1.218 | 0.00 | 0.00 | 0.00 | 0.18 | 6.41 |

**Table 2:** Innovative Output

Panel A and B report OLS regression results of the model Patent count$_{i,t+k}$ (or KPSS value$_{i,t+k}$ or Total citations$_{i,t+k}$ ) $= b\,\text{DR}_{i,t} + c\,\text{CF}_{i,t} + d'\text{Controls}_{i,t-1} + t + i + \text{error}_{i,t}$. Panel C reports OLS regression results of the model I(Patent)$_{i,t+k} = b\,\text{DR}_{i,t} + c\,\text{CF}_{i,t} + d'\text{Controls}_{i,t-1} + t + i + \text{error}_{i,t}$. I(Patent)$_{i,t+k}$ is a dummy equal to 1 if firm i has at least one patent applied (and eventually granted) in year t+k and 0 otherwise. Controls include Sales_p, MTB_p, ROA_p, PPE_p, LEV_p, Age_p, Sales_f, MTB_f, ROA_f, PPE_f, LEV_f, and Age_f. Refer to Appendix B for variable definitions. Year fixed effects, $t$, and firm fixed effects, $i$, are included in all regressions. Higher value of DR reflects negative returns and higher cost of capital. Higher value of CF reflects higher returns. All dependent variables are scaled by their respective standard deviation. Coefficient estimates are shown, and their standard errors are clustered by industry and displayed in parentheses below. ***(**)(*) denotes significance at the 1% (5%) (10%) two-tailed level.

Panel A: All firms

| | Patent count | | | KPSS value | | | Total citations | | |
|---|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| DR | 0.123** | 0.133** | 0.233*** | 0.061 | 0.098* | 0.191*** | 0.148 | 0.203** | 0.261** |
| | (2.14) | (2.29) | (2.83) | (1.13) | (1.67) | (2.78) | (1.60) | (2.50) | (2.60) |
| CF | 0.048* | 0.085** | 0.134*** | 0.132*** | 0.116*** | 0.134*** | 0.123** | 0.131** | 0.172*** |
| | (1.70) | (2.30) | (2.67) | (3.58) | (2.92) | (2.91) | (2.24) | (2.43) | (2.99) |
| betaXmkt | 0.147** | 0.205*** | 0.269*** | 0.313*** | 0.286*** | 0.227*** | 0.296*** | 0.332*** | 0.310*** |
| | (2.41) | (3.44) | (4.50) | (4.37) | (3.61) | (2.78) | (3.24) | (3.27) | (2.89) |
| Observations | 85,250 | 85,250 | 85,250 | 84,488 | 84,509 | 84,531 | 85,227 | 85,226 | 85,227 |
| R-squared | 0.063 | 0.075 | 0.087 | 0.064 | 0.068 | 0.077 | 0.095 | 0.106 | 0.114 |

Panel B: Firms with at least one patent

| | Patent count | | | KPSS value | | | Total citations | | |
|---|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| DR | 0.095 | 0.076 | 0.309* | 0.069 | 0.096 | 0.261** | 0.139 | 0.234 | 0.372* |
| | (0.88) | (0.72) | (1.99) | (0.61) | (0.81) | (2.17) | (0.75) | (1.57) | (1.96) |
| CF | 0.040 | 0.112** | 0.218*** | 0.220*** | 0.190*** | 0.222*** | 0.172** | 0.201** | 0.285*** |
| | (0.81) | (2.13) | (3.06) | (3.88) | (3.25) | (3.38) | (2.04) | (2.57) | (3.51) |
| Observations | 41,333 | 41,333 | 41,333 | 40,571 | 40,592 | 40,614 | 41,310 | 41,309 | 41,310 |
| R-squared | 0.112 | 0.135 | 0.156 | 0.106 | 0.118 | 0.135 | 0.163 | 0.182 | 0.197 |

Panel C: Probability of getting a patent.

| | Single year | | | | | Multiyear | | | |
|---|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+4 | t+5 | t+1:2 | t+1:3 | t+1:4 | t+1:5 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| DR | 0.063*** | 0.066*** | 0.062*** | 0.064** | 0.055 | 0.063*** | 0.084*** | 0.092*** | 0.084*** |
| | (2.96) | (3.01) | (2.70) | (2.15) | (1.66) | (3.62) | (4.05) | (4.70) | (4.13) |
| CF | 0.012** | 0.018*** | 0.034*** | 0.021*** | 0.012 | 0.015*** | 0.025*** | 0.026*** | 0.024*** |
| | (2.58) | (3.37) | (4.18) | (2.91) | (1.36) | (3.26) | (5.15) | (7.23) | (7.46) |
| Observations | 85,250 | 85,250 | 85,250 | 85,250 | 85,250 | 85,250 | 85,250 | 85,250 | 85,250 |
| R-squared | 0.015 | 0.023 | 0.047 | 0.080 | 0.109 | 0.022 | 0.028 | 0.035 | 0.041 |

**Table 3:** Innovative Inputs

Panel A reports OLS regression results of the model $\Delta$ ln(1+XRD)$_{i,t+k}$ (or $\Delta$ ln(1+CAPX)$_{i,t+k}$ or $\Delta$ ln(EMP)$_{i,t+k}$ ) = $b\,$DR$_{i,t}$ + $c\,$CF$_{i,t}$ + $d'$Controls$_{i,t-1}$ + $t$ + $i$ + error$_{i,t}$. Panel B is similar to Panel A, but all observations are sorted into terciles based on their DR. The average DR for the 3rd(2nd)(1st) tercile is 0.054(-0.055)(-0.132). BadDR$_{i,t}$ (GoodDR$_{i,t}$) is a dummy equal to 1 if firm$_i$-year$_t$ observation is sorted into the 3rd (1st) DR tercile and 0 otherwise. We interact BadDR and GoodDR dummies with the continuous variable DR. Controls include Sales_p, MTB_p, ROA_p, PPE_p, LEV_p, Age_p, Sales_f, MTB_f, ROA_f, PPE_f, LEV_f, and Age_f. Refer to Appendix B for variable definitions. Year fixed effects, $t$, and firm fixed effects, $i$, are included in all regressions. Higher value of DR reflects negative returns and higher cost of capital. Higher value of CF reflects higher returns. All dependent variables are scaled by their respective standard deviation. Coefficient estimates are shown, and their standard errors are clustered by industry and displayed in parentheses below. ***(**)(*) denotes significance at the 1% (5%) (10%) two-tailed level.

Panel A: No interaction with BadDR and GoodDR

| | $\Delta$ ln(1+XRD) | | | $\Delta$ ln(1+CAPX) | | | $\Delta$ ln(EMP) | | |
|---|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| DR | −0.038 | −0.006 | 0.103 | −0.432*** | −0.826*** | −0.052 | −0.689*** | −0.212* | −0.030 |
| | (−0.34) | (−0.08) | (1.14) | (−3.27) | (−2.97) | (−0.39) | (−6.23) | (−1.78) | (−0.38) |
| CF | 0.189*** | 0.268*** | −0.003 | 0.394*** | 0.280*** | −0.183** | 0.344*** | 0.179*** | −0.092** |
| | (5.39) | (5.15) | (−0.10) | (5.26) | (3.98) | (−2.15) | (8.93) | (3.82) | (−2.12) |
| Observations | 78,690 | 73,146 | 68,027 | 78,690 | 73,146 | 68,027 | 76,294 | 70,977 | 66,112 |
| R-squared | 0.026 | 0.018 | 0.014 | 0.061 | 0.054 | 0.049 | 0.097 | 0.070 | 0.062 |

Panel B: Interaction with BadDR and GoodDR

| | $\Delta$ ln(1+XRD) | | | $\Delta$ ln(1+CAPX) | | | $\Delta$ ln(EMP) | | |
|---|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| BadDR=1 x DR | −0.020 | 0.305 | −0.028 | −0.916*** | 0.378 | 0.836* | −0.408 | 0.804** | 0.506 |
| | (−0.08) | (0.77) | (−0.11) | (−3.41) | (0.93) | (1.84) | (−1.66) | (2.26) | (1.41) |
| GoodDR=1 x DR | 0.143 | 0.052 | 0.132 | 0.221 | 0.104 | 0.248 | 0.052 | 0.424** | 0.350 |
| | (1.48) | (0.47) | (0.78) | (1.41) | (0.66) | (1.37) | (0.39) | (2.52) | (1.57) |
| DR | −0.099 | −0.170 | 0.052 | −0.124 | −1.048** | −0.555* | −0.530** | −0.785*** | −0.431 |
| | (−0.74) | (−0.96) | (0.31) | (−0.65) | (−2.30) | (−1.73) | (−2.45) | (−2.85) | (−1.38) |
| CF | 0.194*** | 0.264*** | 0.001 | 0.416*** | 0.276*** | −0.190** | 0.352*** | 0.178*** | −0.090** |
| | (5.05) | (5.30) | (0.04) | (5.90) | (3.73) | (−2.28) | (9.51) | (4.12) | (−2.17) |
| Observations | 78,690 | 73,146 | 68,027 | 78,690 | 73,146 | 68,027 | 76,294 | 70,977 | 66,112 |
| R-squared | 0.026 | 0.018 | 0.014 | 0.062 | 0.054 | 0.050 | 0.097 | 0.070 | 0.062 |
| Pr{DR×(1+BadDR)}=0 | 0.573 | 0.577 | 0.863 | 0.000 | 0.000 | 0.223 | 0.000 | 0.919 | 0.560 |
| Pr{DR×(1+GoodDR)}=0 | 0.671 | 0.326 | 0.297 | 0.566 | 0.032 | 0.221 | 0.001 | 0.048 | 0.491 |

**Table 4:** Innovative Efficiency

Panel A reports OLS regression results of the model Patent $\text{count}_{i,t+k}$ (or KPSS $\text{value}_{i,t+k}$ or Total $\text{citations}_{i,t+k}$ ) $= b\,\text{DR}_{i,t} + c\,\text{CF}_{i,t} + d'\text{Controls}_{i,t-1} + e' \sum_{\tau=1}^{k} \text{Inputs}_{i,t+\tau} + t + i + \text{error}_{i,t}$. Panel B is similar to Panel A, but all observations are sorted into terciles based on their DR. The average DR for the 3rd(2nd)(1st) tercile is 0.054(-0.055)(-0.132). $\text{BadDR}_{i,t}$ ($\text{GoodDR}_{i,t}$) is a dummy equal to 1 if $\text{firm}_i$-$\text{year}_t$ observation is sorted into the 3rd (1st) DR tercile and 0 otherwise. We interact BadDR and GoodDR dummies with the continuous variable DR. Inputs are Δ ln(1+XRD), Δ ln(1+CAPX), and Δ ln(EMP). Controls include Sales_p, MTB_p, ROA_p, PPE_p, LEV_p, Age_p, Sales_f, MTB_f, ROA_f, PPE_f, LEV_f, and Age_f. Refer to Appendix B for variable definitions. Year fixed effects, $t$, and firm fixed effects, $i$, are included in all regressions. Higher value of DR reflects negative returns and higher cost of capital. Higher value of CF reflects higher returns. All dependent variables and Inputs are scaled by their respective standard deviation. Coefficient estimates are shown, and their standard errors are clustered by industry and displayed in parentheses below. ***(**)(*) denotes significance at the 1% (5%) (10%) two-tailed level.

Panel A: No interaction with BadDR and GoodDR

| | Patent count | | | KPSS value | | | Total citations | | |
|---|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| DR | 0.114** | 0.121* | 0.233*** | 0.053 | 0.098* | 0.213*** | 0.140 | 0.224** | 0.256** |
| | (2.06) | (1.82) | (2.69) | (1.01) | (1.77) | (2.89) | (1.39) | (2.36) | (2.34) |
| CF | 0.029 | 0.055 | 0.118** | 0.111*** | 0.081** | 0.123*** | 0.117** | 0.113* | 0.168*** |
| | (1.11) | (1.47) | (2.37) | (3.00) | (2.01) | (2.73) | (2.06) | (1.90) | (2.76) |
| Δ ln(1+XRD): | | | | | | | | | |
| t + 1 | 0.050*** | 0.067*** | 0.077*** | 0.047*** | 0.061*** | 0.067*** | 0.049*** | 0.062*** | 0.075*** |
| | (4.53) | (5.56) | (5.79) | (4.19) | (4.48) | (4.79) | (4.08) | (4.53) | (5.01) |
| t + 2 | | 0.049*** | 0.069*** | | 0.052*** | 0.067*** | | 0.054*** | 0.065*** |
| | | (4.56) | (5.66) | | (4.11) | (4.66) | | (4.73) | (4.66) |
| t + 3 | | | 0.054*** | | | 0.059*** | | | 0.054*** |
| | | | (3.90) | | | (3.87) | | | (3.73) |
| Δ ln(1+CAPX): | | | | | | | | | |
| t + 1 | −0.006 | 0.000 | 0.001 | 0.005 | 0.009* | 0.010** | −0.004 | 0.002 | −0.001 |
| | (−1.39) | (0.09) | (0.32) | (1.66) | (1.73) | (2.16) | (−0.94) | (0.56) | (−0.16) |
| t + 2 | | −0.000 | 0.005 | | 0.012*** | 0.016*** | | 0.002 | 0.007** |
| | | (−0.11) | (0.84) | | (4.77) | (2.71) | | (0.62) | (2.02) |
| t + 3 | | | 0.003 | | | 0.014*** | | | 0.005* |
| | | | (0.66) | | | (3.28) | | | (1.81) |
| Δ ln(EMP): | | | | | | | | | |
| t + 1 | 0.019*** | 0.013** | 0.003 | 0.022*** | 0.006** | 0.002 | 0.007 | −0.002 | −0.006 |
| | (3.28) | (2.59) | (0.69) | (4.40) | (2.07) | (0.58) | (1.47) | (−0.33) | (−0.93) |
| t + 2 | | 0.016*** | 0.006 | | 0.020*** | 0.000 | | 0.004 | −0.007 |
| | | (2.68) | (1.09) | | (4.26) | (0.03) | | (0.76) | (−1.14) |
| t + 3 | | | 0.009* | | | 0.013** | | | −0.001 |
| | | | (1.73) | | | (2.62) | | | (−0.15) |
| Observations | 76,294 | 70,144 | 64,671 | 75,572 | 69,459 | 64,013 | 76,275 | 70,125 | 64,653 |
| R-squared | 0.067 | 0.085 | 0.105 | 0.072 | 0.085 | 0.103 | 0.101 | 0.116 | 0.131 |

Panel B: Interaction with BadDR and GoodDR

| | Patent count | | | KPSS value | | | Total citations | | |
|---|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| BadDR=1 x DR | 0.164 | 0.326* | 0.165 | 0.423*** | 0.315* | −0.113 | 0.477 | 0.377 | 0.134 |
| | (1.14) | (1.86) | (0.90) | (3.31) | (1.68) | (−0.91) | (1.60) | (0.95) | (0.43) |
| GoodDR=1 x DR | 0.019 | 0.255* | 0.109 | 0.159 | 0.256* | 0.053 | 0.113 | 0.158 | 0.029 |
| | (0.16) | (1.84) | (0.69) | (1.64) | (1.81) | (0.53) | (0.64) | (0.72) | (0.12) |
| DR | 0.031 | −0.151 | 0.105 | −0.216** | −0.169 | 0.240* | −0.131 | −0.025 | 0.181 |
| | (0.29) | (−1.04) | (0.80) | (−2.58) | (−1.07) | (1.87) | (−0.56) | (−0.08) | (0.60) |
| CF | 0.027 | 0.057 | 0.118** | 0.108*** | 0.084** | 0.127*** | 0.112* | 0.112* | 0.167*** |
| | (0.99) | (1.54) | (2.41) | (2.86) | (2.09) | (2.82) | (1.98) | (1.86) | (2.85) |
| Observations | 76,294 | 70,144 | 64,671 | 75,572 | 69,459 | 64,013 | 76,275 | 70,125 | 64,653 |
| R-squared | 0.067 | 0.085 | 0.105 | 0.072 | 0.085 | 0.103 | 0.101 | 0.116 | 0.131 |
| Pr{DR×(1+BadDR)}=0 | 0.018 | 0.041 | 0.022 | 0.015 | 0.025 | 0.168 | 0.004 | 0.010 | 0.019 |
| Pr{DR×(1+GoodDR)}=0 | 0.608 | 0.336 | 0.054 | 0.589 | 0.408 | 0.002 | 0.900 | 0.380 | 0.162 |

**Table 5:** Cost of Capital and Operational Performance

This table reports OLS regression results of the model $Y_{i,t+k} = b\,DR_{i,t} + c\,CF_{i,t} + d'Controls_{i,t-1} + t + i + error_{i,t}$. Y is $\Delta$ln(Sales) or $\Delta$ln(Assets) in Panel A and $\Delta$EBITDA/Sales or % Change EBITDA in Panel B. Controls include Sales_p, MTB_p, ROA_p, PPE_p, LEV_p, Age_p, Sales_f, MTB_f, ROA_f, PPE_f, LEV_f, and Age_f. Refer to Appendix B for variable definitions. Year fixed effects, $t$, and firm fixed effects, $i$, are included in all regressions. Higher value of DR reflects negative returns and higher cost of capital. Higher value of CF reflects higher returns. All dependent variables are scaled by their respective standard deviation. Coefficient estimates are shown, and their standard errors are clustered by industry and displayed in parentheses below. ***(**)(*) denotes significance at the 1% (5%) (10%) two-tailed level.

Panel A: Sales Growth and Assets Growth

| | Δ ln(Sales) | | | | Δ ln(Assets) | | | |
|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+4 | t+1 | t+2 | t+3 | t+4 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| DR | −1.127*** | −0.923* | −0.002 | 0.148 | −0.803*** | −0.168 | −0.201* | 0.126 |
| | (−8.81) | (−1.77) | (−0.02) | (0.42) | (−5.13) | (−1.26) | (−1.74) | (0.58) |
| CF | 0.429*** | −0.015 | −0.220** | 0.101 | 0.514*** | 0.262*** | −0.097** | 0.085 |
| | (3.51) | (−0.10) | (−2.23) | (0.78) | (9.10) | (5.34) | (−2.12) | (1.04) |
| Observations | 78,690 | 73,146 | 68,027 | 63,190 | 78,690 | 73,146 | 68,027 | 63,190 |
| R-squared | 0.170 | 0.117 | 0.110 | 0.105 | 0.120 | 0.079 | 0.068 | 0.062 |

Panel B: Growth in EBITDA Margin and EBITDA

| | Δ EBITDA/Sales | | | | % Change EBITDA | | | |
|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+4 | t+1 | t+2 | t+3 | t+4 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| DR | −1.423 | −0.033 | 0.141 | 0.366 | −0.489*** | −0.382 | −0.211 | −0.051 |
| | (−1.66) | (−0.41) | (0.72) | (1.59) | (−6.48) | (−1.39) | (−1.49) | (−0.21) |
| CF | −0.178 | −0.275** | −0.093* | 0.204 | 0.286*** | −0.020 | −0.169*** | −0.004 |
| | (−1.26) | (−2.12) | (−1.83) | (1.59) | (4.02) | (−0.30) | (−2.93) | (−0.05) |
| Observations | 78,607 | 73,059 | 67,941 | 63,112 | 78,606 | 73,058 | 67,940 | 63,111 |
| R-squared | 0.030 | 0.011 | 0.008 | 0.009 | 0.021 | 0.013 | 0.015 | 0.014 |

**Table 6:** Cost of Capital and Asset Utilization

This table reports OLS regression results of the model $Y_{i,t+k} = b\,DR_{i,t} + c\,CF_{i,t} + d'Controls_{i,t-1} + t + i + error_{i,t}$. Y is ΔCash or ΔNon-cash Current Assets in Panel A, ΔNet PP&E or ΔOther Assets in Panel B, and ΔNet PP&E and Other Assets or Asset Turnover in Panel C. Controls include Sales_p, MTB_p, ROA_p, PPE_p, LEV_p, Age_p, Sales_f, MTB_f, ROA_f, PPE_f, LEV_f, and Age_f. Refer to Appendix B for variable definitions. Year fixed effects, $t$, and firm fixed effects, $i$, are included in all regressions. Higher value of DR reflects negative returns and higher cost of capital. Higher value of CF reflects higher returns. All dependent variables are scaled by their respective standard deviation. Coefficient estimates are shown, and their standard errors are clustered by industry and displayed in parentheses below. ***(**)(*) denotes significance at the 1% (5%) (10%) two-tailed level.

Panel A: Current assets

| | Δ Cash | | | | Δ Non-cash Current Assets | | | |
|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+4 | t+1 | t+2 | t+3 | t+4 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| DR | −0.279** | 0.197*** | −0.056 | 0.127 | −0.488*** | −0.014 | −0.049 | 0.222* |
| | (−2.13) | (2.79) | (−0.61) | (1.50) | (−4.43) | (−0.10) | (−0.77) | (1.87) |
| CF | 0.282*** | 0.073** | −0.021 | 0.049 | 0.474*** | 0.223*** | −0.045 | 0.072 |
| | (4.63) | (2.11) | (−0.56) | (1.17) | (8.36) | (3.50) | (−1.26) | (1.43) |
| Observations | 77,715 | 72,341 | 67,275 | 62,458 | 76,210 | 70,982 | 66,047 | 61,350 |
| R-squared | 0.020 | 0.012 | 0.017 | 0.017 | 0.097 | 0.083 | 0.082 | 0.085 |

Panel B: Non-current assets by type

| | Δ Net PP&E | | | | Δ Other Assets | | | |
|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+4 | t+1 | t+2 | t+3 | t+4 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| DR | −0.351*** | −0.382*** | −0.295 | −0.020 | −0.390** | −0.104 | −0.030 | 0.010 |
| | (−3.87) | (−2.98) | (−1.59) | (−0.09) | (−2.35) | (−1.12) | (−0.39) | (0.09) |
| CF | 0.278*** | 0.290*** | 0.086 | 0.106 | 0.220*** | 0.225*** | 0.073** | 0.060 |
| | (2.87) | (9.81) | (1.44) | (1.31) | (5.83) | (6.17) | (2.14) | (1.43) |
| Observations | 78,690 | 73,146 | 68,027 | 63,190 | 77,007 | 71,627 | 66,653 | 61,948 |
| R-squared | 0.134 | 0.113 | 0.105 | 0.105 | 0.051 | 0.040 | 0.037 | 0.034 |

Panel C: Fixed assets and turnover

| | Δ Net PP&E and Other Assets | | | | Asset Turnover | | | |
|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+4 | t+1 | t+2 | t+3 | t+4 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| DR | −0.473*** | −0.275*** | −0.137 | 0.035 | 0.154*** | 0.006 | 0.015 | 0.023 |
| | (−3.46) | (−2.73) | (−1.12) | (0.18) | (2.92) | (0.12) | (0.23) | (0.44) |
| CF | 0.302*** | 0.299*** | 0.090* | 0.103 | 0.085*** | 0.022 | −0.012 | −0.003 |
| | (4.75) | (9.57) | (1.97) | (1.62) | (3.69) | (1.11) | (−0.54) | (−0.17) |
| Observations | 77,007 | 71,627 | 66,653 | 61,948 | 78,690 | 73,146 | 68,027 | 63,190 |
| R-squared | 0.104 | 0.084 | 0.080 | 0.078 | 0.034 | 0.038 | 0.054 | 0.064 |

**Table 7:** Cost of Capital and External Financing

Panel A reports OLS regression results of the model Net Equity Issuance$_{i,t+k}$ (or Net Debt Issuance$_{i,t+k}$ ) $= b\,\mathrm{DR}_{i,t} + c\,\mathrm{CF}_{i,t} + d'\mathrm{Controls}_{i,t-1} + t + i + \mathrm{error}_{i,t}$. Panel B is similar to Panel A, but all observations are sorted into terciles based on their DR. The average DR for the 3rd(2nd)(1st) tercile is 0.054(-0.055)(-0.132). BadDR$_{i,t}$ (GoodDR$_{i,t}$) is a dummy equal to 1 if firm$_i$-year$_t$ observation is sorted into the 3rd (1st) DR tercile and 0 otherwise. We interact BadDR and GoodDR dummies with the continuous variable DR. Controls include Sales_p, MTB_p, ROA_p, PPE_p, LEV_p, Age_p, Sales_f, MTB_f, ROA_f, PPE_f, LEV_f, and Age_f. Refer to Appendix B for variable definitions. Year fixed effects, $t$, and firm fixed effects, $i$, are included in all regressions. Higher value of DR reflects negative returns and higher cost of capital. Higher value of CF reflects higher returns. All dependent variables are scaled by their respective standard deviation. Coefficient estimates are shown, and their standard errors are clustered by industry and displayed in parentheses below. ***(**)(*) denotes significance at the 1% (5%) (10%) two-tailed level.

Panel A: No interaction with BadDR and GoodDR

| | Net Equity Issuance | | | | Net Debt Issuance | | | |
|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+4 | t+1 | t+2 | t+3 | t+4 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| DR | −0.204 | 0.108 | 0.116* | 0.156 | −0.188 | −0.197** | −0.160* | 0.046 |
| | (−1.16) | (1.49) | (1.77) | (1.36) | (−1.37) | (−2.10) | (−1.69) | (0.34) |
| CF | 0.295*** | 0.170*** | −0.014 | −0.009 | 0.092* | 0.163*** | 0.034 | 0.046 |
| | (4.04) | (3.17) | (−0.73) | (−0.30) | (1.91) | (4.35) | (0.81) | (1.06) |
| Observations | 72,031 | 67,166 | 62,644 | 58,312 | 78,477 | 72,897 | 67,766 | 62,922 |
| R-squared | 0.063 | 0.052 | 0.046 | 0.037 | 0.073 | 0.054 | 0.045 | 0.042 |

Panel B: Interaction with BadDR and GoodDR

| | Net Equity Issuance | | | | Net Debt Issuance | | | |
|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+4 | t+1 | t+2 | t+3 | t+4 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| BadDR=1 x DR | 1.021*** | 0.573** | −0.426 | −0.117 | −0.105 | 0.126 | 0.505 | 0.047 |
| | (3.56) | (2.02) | (−1.63) | (−0.58) | (−0.31) | (0.64) | (1.60) | (0.20) |
| GoodDR=1 x DR | −0.262** | 0.067 | −0.204* | −0.011 | −0.019 | −0.333*** | 0.284* | 0.249* |
| | (−2.19) | (0.60) | (−1.83) | (−0.08) | (−0.16) | (−2.73) | (1.78) | (1.89) |
| DR | −0.539** | −0.186 | 0.410** | 0.216 | −0.131 | −0.093 | −0.528** | −0.095 |
| | (−2.23) | (−0.96) | (2.52) | (1.40) | (−0.45) | (−0.47) | (−2.01) | (−0.51) |
| CF | 0.270*** | 0.163*** | −0.013 | −0.007 | 0.094* | 0.150*** | 0.034 | 0.053 |
| | (3.93) | (3.08) | (−0.71) | (−0.25) | (1.82) | (3.73) | (0.81) | (1.28) |
| Observations | 72,031 | 67,166 | 62,644 | 58,312 | 78,477 | 72,897 | 67,766 | 62,922 |
| R-squared | 0.064 | 0.052 | 0.046 | 0.037 | 0.073 | 0.055 | 0.045 | 0.042 |
| Pr{DR×(1+BadDR)}=0 | 0.010 | 0.002 | 0.914 | 0.455 | 0.086 | 0.746 | 0.849 | 0.790 |
| Pr{DR×(1+GoodDR)}=0 | 0.002 | 0.359 | 0.030 | 0.175 | 0.538 | 0.004 | 0.148 | 0.229 |

**Table 8:** Innovative Output and Efficiency with Leads and Lags

Column 1(2) reports OLS regression results of the model Patent count$_{i,t+1}$ (KPSS value$_{i,t+1}$) = $\sum_{k=-4}^{k=3} b'\text{DR}_{i,t+k} + \sum_{k=-4}^{k=3} c'\text{CF}_{i,t+k} + d'\text{Controls}_{i,t-1} + t + i + \text{error}_{i,t}$. Columns (3) and (4) are similar to columns (1) and (2), but we also controls for Δln(1+XRD), Δln(1+CAPX), and Δln(EMP) in year t+1. Controls include Sales_p, MTB_p, ROA_p, PPE_p, LEV_p, Age_p, Sales_f, MTB_f, ROA_f, PPE_f, LEV_f, and Age_f. Refer to Appendix B for variable definitions. Year fixed effects, $t$, and firm fixed effects, $i$, are included in all regressions. Higher value of DR reflects negative returns and higher cost of capital. Higher value of CF reflects higher returns. All dependent variables are scaled by their respective standard deviation. Coefficient estimates are shown, and their standard errors are clustered by industry and displayed in parentheses below. ***(**)(*) denotes significance at the 1% (5%) (10%) two-tailed level.

| | Innovative Output $_{t+1}$ | | | | Innovative Efficiency $_{t+1}$ | | | |
|---|---|---|---|---|---|---|---|---|
| | Patent count (1) | | KPSS value (2) | | Patent count (3) | | KPSS value (4) | |
| DR shocks: | | | | | | | | |
| t - 4 | 0.040 | (0.39) | 0.065 | (0.80) | −0.021 | (-0.19) | 0.018 | (0.18) |
| t - 3 | 0.066 | (0.66) | 0.041 | (0.39) | 0.069 | (0.67) | 0.045 | (0.39) |
| t - 2 | 0.379*** | (3.03) | 0.238*** | (3.14) | 0.386*** | (3.00) | 0.277*** | (2.99) |
| t - 1 | 0.364*** | (2.97) | 0.240*** | (3.23) | 0.361** | (2.63) | 0.268*** | (3.01) |
| t | 0.265*** | (2.67) | 0.229** | (2.35) | 0.246** | (2.49) | 0.224** | (2.26) |
| t + 1 | 0.109 | (0.95) | 0.159 | (1.21) | 0.064 | (0.52) | 0.120 | (0.92) |
| t + 2 | 0.089 | (1.05) | 0.055 | (0.55) | 0.064 | (0.70) | 0.024 | (0.23) |
| t + 3 | 0.063 | (0.73) | 0.077 | (0.77) | 0.063 | (0.72) | 0.077 | (0.75) |
| CF shocks: | | | | | | | | |
| t - 4 | 0.028 | (0.98) | 0.055 | (1.54) | 0.021 | (0.69) | 0.055 | (1.40) |
| t - 3 | 0.062 | (1.66) | 0.085** | (2.11) | 0.063 | (1.62) | 0.090** | (2.13) |
| t - 2 | 0.139*** | (3.58) | 0.115*** | (3.19) | 0.148*** | (3.61) | 0.129*** | (3.31) |
| t - 1 | 0.160*** | (4.47) | 0.161*** | (3.70) | 0.154*** | (3.99) | 0.157*** | (3.26) |
| t | 0.118*** | (3.56) | 0.231*** | (3.95) | 0.097*** | (3.34) | 0.215*** | (3.56) |
| t + 1 | 0.068*** | (3.05) | 0.219*** | (4.60) | 0.066** | (2.49) | 0.231*** | (4.35) |
| t + 2 | 0.033** | (2.38) | 0.154*** | (4.55) | 0.022 | (1.66) | 0.159*** | (5.16) |
| t + 3 | −0.005 | (-0.22) | 0.052*** | (3.01) | −0.017 | (-0.79) | 0.046*** | (2.85) |
| Input Changes $_{t+1}$: | | | | | | | | |
| Δ ln(1+XRD) | | | | | 0.213*** | (4.30) | 0.204*** | (4.20) |
| Δ ln(1+CAPX) | | | | | −0.006 | (-0.98) | 0.010* | (2.00) |
| Δ ln(EMP) | | | | | 0.091*** | (3.57) | 0.092*** | (3.97) |
| betaXmkt | 0.151** | (2.31) | 0.288*** | (4.13) | 0.146** | (2.18) | 0.306*** | (4.42) |
| Observations | 77,313 | | 76,587 | | 69,187 | | 68,496 | |
| R-squared | 0.062 | | 0.074 | | 0.066 | | 0.083 | |

$t$ statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 9:** Innovative Efficiency with additional controls

Panel A and B report OLS regression results of the model Patent $\text{count}_{i,t+k}$ (or KPSS $\text{value}_{i,t+k}$ or Total $\text{citations}_{i,t+k}$ ) $= b\,\text{DR}_{i,t} + c\,\text{CF}_{i,t} + d'\text{Controls}_{i,t-1} + e'\sum_{\tau=1}^{k}\text{Inputs}_{i,t+\tau} + f'\text{Extra}_{i,t-1} + t + i + \text{error}_{i,t}$. Extra includes levels of XRD, CAPX, and EMP in Panel A or 1/intan17 in Panel B. Inputs are $\Delta$ ln(1+XRD), $\Delta$ ln(1+CAPX), and $\Delta$ ln(EMP). Controls include Sales_p, MTB_p, ROA_p, PPE_p, LEV_p, Age_p, Sales_f, MTB_f, ROA_f, PPE_f, LEV_f, and Age_f. Refer to Appendix B for variable definitions. Year fixed effects, $t$, and firm fixed effects, $i$, are included in all regressions. Higher value of DR reflects negative returns and higher cost of capital. Higher value of CF reflects higher returns. All dependent variables and Extra are scaled by their respective standard deviation. Coefficient estimates are shown, and their standard errors are clustered by industry and displayed in parentheses below. ***(**)(*) denotes significance at the 1% (5%) (10%) two-tailed level.

Panel A: Control for 1/intangibles

| | Patent count | | | KPSS value | | | Total citations | | |
|---|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| DR | 0.152** | 0.172** | 0.306*** | 0.140** | 0.175*** | 0.269*** | 0.216* | 0.317*** | 0.346*** |
| | (2.43) | (2.42) | (3.25) | (2.44) | (3.29) | (3.47) | (1.92) | (2.89) | (3.08) |
| CF | 0.036 | 0.065* | 0.133** | 0.128*** | 0.097** | 0.135*** | 0.132** | 0.133** | 0.187*** |
| | (1.37) | (1.74) | (2.62) | (3.14) | (2.27) | (2.91) | (2.24) | (2.19) | (2.99) |
| 1/intan17 | −0.024 | −0.038 | −0.053* | −0.051** | −0.068** | −0.096** | −0.075** | −0.093** | −0.107** |
| | (−1.08) | (−1.45) | (−1.81) | (−2.07) | (−2.14) | (−2.66) | (−2.24) | (−2.35) | (−2.65) |
| Observations | 76,293 | 70,143 | 64,670 | 75,571 | 69,458 | 64,012 | 76,274 | 70,124 | 64,652 |
| R-squared | 0.066 | 0.085 | 0.104 | 0.071 | 0.085 | 0.105 | 0.101 | 0.116 | 0.131 |

Panel B: Control for lagged levels of Inputs

| | Patent count | | | KPSS value | | | Total citations | | |
|---|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| DR | 0.147** | 0.162** | 0.303*** | 0.129** | 0.158*** | 0.254*** | 0.212* | 0.303*** | 0.340*** |
| | (2.45) | (2.28) | (3.27) | (2.35) | (3.15) | (3.33) | (1.99) | (2.90) | (3.22) |
| CF | 0.036 | 0.065* | 0.135** | 0.126*** | 0.095** | 0.132*** | 0.132** | 0.132** | 0.188*** |
| | (1.40) | (1.74) | (2.62) | (3.02) | (2.17) | (2.75) | (2.25) | (2.15) | (3.03) |
| $\text{XRD}_{t-1}$ | −0.031** | −0.054** | −0.076** | −0.175*** | −0.208*** | −0.232*** | −0.094* | −0.114* | −0.132** |
| | (−2.07) | (−2.13) | (−2.09) | (−5.85) | (−5.83) | (−5.67) | (−1.89) | (−2.00) | (−2.06) |
| $\text{CAPX}_{t-1}$ | 0.021** | 0.027** | 0.033** | 0.035 | 0.031 | 0.027 | 0.039** | 0.044** | 0.047** |
| | (2.00) | (2.20) | (2.38) | (1.61) | (1.20) | (0.94) | (2.35) | (2.35) | (2.35) |
| $\text{EMP}_{t-1}$ | 0.043 | 0.047 | 0.052 | 0.029* | 0.031* | 0.034* | 0.050 | 0.052 | 0.055 |
| | (1.65) | (1.62) | (1.59) | (1.81) | (1.74) | (1.68) | (1.61) | (1.56) | (1.55) |
| Observations | 75,758 | 69,675 | 64,250 | 75,045 | 68,996 | 63,599 | 75,739 | 69,656 | 64,232 |
| R-squared | 0.068 | 0.088 | 0.108 | 0.087 | 0.107 | 0.130 | 0.104 | 0.121 | 0.137 |

**Table 10:** Sub-sample analysis for Innovative Efficiency

This table uses a subsample which only has peers whose TNIC scores are greater than the median, and reports OLS regression results of the model Patent count$_{i,t+k}$ (or KPSS value$_{i,t+k}$ or Total citations$_{i,t+k}$ ) = $b\,\mathrm{DR}_{i,t}$ + $c\,\mathrm{CF}_{i,t}$ + $d'\mathrm{Controls}_{i,t-1}$ + $e' \sum_{\tau=1}^{k} \mathrm{Inputs}_{i,t+\tau}$ + t + i + error$_{i,t}$. Inputs are Δ ln(1+XRD), Δ ln(1+CAPX), and Δ ln(EMP). Controls include Sales_p, MTB_p, ROA_p, PPE_p, LEV_p, Age_p, Sales_f, MTB_f, ROA_f, PPE_f, LEV_f, and Age_f. Refer to Appendix B for variable definitions. Year fixed effects, $t$, and firm fixed effects, $i$, are included in all regressions. In Panel A, we exclude peers that are in the bottom NYSE decile. In Panel B, we include those peers in the analysis. Higher value of DR reflects negative returns and higher cost of capital. Higher value of CF reflects higher returns. All dependent variables are scaled by their respective standard deviation. Coefficient estimates are shown, and their standard errors are clustered by industry and displayed in parentheses below. $^{***}(^{**})(^{*})$ denotes significance at the 1% (5%) (10%) two-tailed level.

Panel A: Peers are above median TNIC score

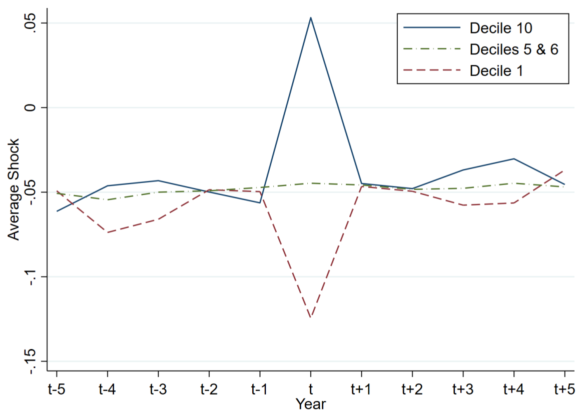
| | Patent count | | | KPSS value | | | Total citations | | |
|---|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| DR | 0.202* | 0.210* | 0.370*** | 0.186** | 0.219** | 0.351*** | 0.256 | 0.318* | 0.345** |
| | (1.87) | (1.75) | (2.78) | (2.00) | (2.15) | (2.68) | (1.64) | (1.88) | (2.40) |
| CF | 0.059* | 0.074* | 0.136** | 0.146*** | 0.105* | 0.140** | 0.151** | 0.127* | 0.171*** |
| | (1.74) | (1.82) | (2.51) | (2.69) | (1.85) | (2.43) | (2.22) | (1.93) | (2.69) |
| Observations | 54,070 | 49,542 | 45,552 | 53,527 | 49,027 | 45,066 | 54,058 | 49,529 | 45,539 |
| R-squared | 0.090 | 0.113 | 0.136 | 0.092 | 0.109 | 0.130 | 0.116 | 0.135 | 0.154 |

Panel B: Peers are above median TNIC score and inclusive of bottom NYSE size decile

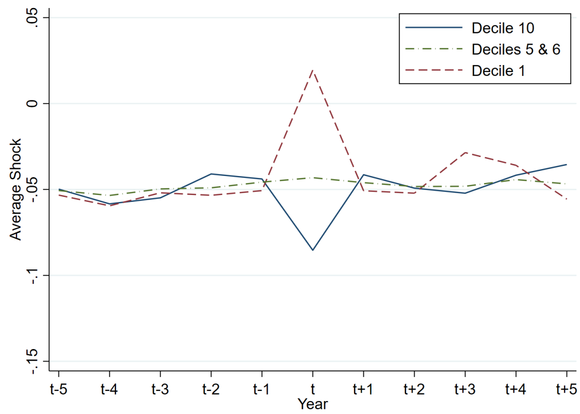
| | Patent count | | | KPSS value | | | Total citations | | |
|---|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| DR | 0.111 | 0.172** | 0.187*** | −0.015 | 0.098 | 0.126* | 0.076 | 0.177** | 0.230** |
| | (1.41) | (2.34) | (2.84) | (−0.36) | (1.59) | (1.92) | (0.61) | (2.09) | (2.22) |
| CF | 0.027 | 0.036* | 0.055** | 0.068** | 0.048 | 0.054* | 0.077** | 0.064** | 0.088** |
| | (1.41) | (1.79) | (2.36) | (2.19) | (1.49) | (1.97) | (2.26) | (2.05) | (2.62) |
| Observations | 58,961 | 54,035 | 49,676 | 58,395 | 53,495 | 49,162 | 58,949 | 54,022 | 49,663 |
| R-squared | 0.084 | 0.107 | 0.129 | 0.087 | 0.103 | 0.123 | 0.110 | 0.128 | 0.146 |

**Figure 1:** Time series properties of DR and CF shocks

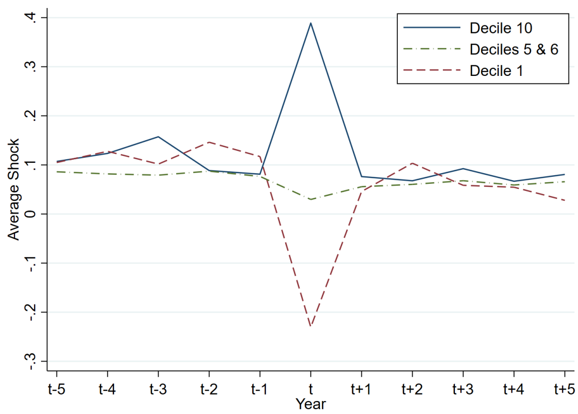
Panel A (B) plots the average DR shocks for deciles 1, 5&6, and 10 of DR (CF). Panel C (D) plots the average CF shocks for deciles 1, 5&6, and 10 of CF (DR). Decile 10 of DR (CF) corresponds to a bad (good) shock experienced by firms. Higher value of DR reflects negative returns and higher cost of capital. Higher value of CF reflects higher returns.



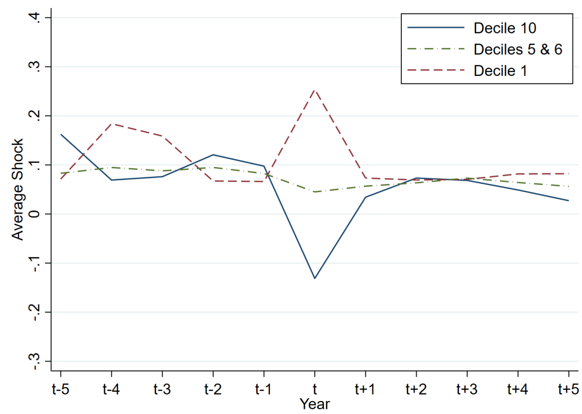

Panel A: DR shocks for DR deciles




Panel B: DR shocks for CF deciles




Panel C: CF shocks for CF deciles




Panel D: CF shocks for DR deciles

# Appendices

## Appendix A. Additional results

**Table A1:** Correlations among DR and CF shocks

This table reports the Pearson correlation coefficients among contemporaneous DR (CF), $\text{DR}_{t-1}$ ($\text{CF}_{t-1}$), and $\text{DR}_{t+1}$ ($\text{CF}_{t+1}$). These DR and CF shocks follow Lochstoer and Tetlock (2020). We also report correlation coefficients among those shocks and alternative measures of discount rate shocks (denoted aDR and $\text{aDR}_{t+1}$) that follow Gebhardt, Lee, and Swaminathan (2001).

| | $\text{DR}_{t-1}$ | $\text{DR}_t$ | $\text{DR}_{t+1}$ | $\text{CF}_{t-1}$ | $\text{CF}_t$ | $\text{CF}_{t+1}$ | $\text{aDR}_t$ | $\text{aDR}_{t+1}$ |
|---|---|---|---|---|---|---|---|---|
| $\text{DR}_{t-1}$ | 1.000 | | | | | | | |
| $\text{DR}_t$ | 0.298 | 1.000 | | | | | | |
| $\text{DR}_{t+1}$ | 0.050 | 0.315 | 1.000 | | | | | |
| $\text{CF}_{t-1}$ | -0.443 | 0.095 | 0.144 | 1.000 | | | | |
| $\text{CF}_t$ | -0.088 | -0.478 | 0.086 | -0.001 | 1.000 | | | |
| $\text{CF}_{t+1}$ | 0.015 | -0.133 | -0.456 | -0.133 | 0.060 | 1.000 | | |
| $\text{aDR}_t$ | -0.173 | 0.189 | -0.021 | 0.116 | -0.244 | 0.046 | 1.000 | |
| $\text{aDR}_{t+1}$ | -0.166 | -0.111 | 0.179 | 0.058 | 0.087 | -0.192 | 0.015 | 1.000 |

**Table A2:** Results with alternative definition of shocks

This table uses alternative measures of discount rate and cash flow shocks that follow Gebhardt, Lee, and Swaminathan (2001), and it reports pooled OLS regression results of the model $\text{Y}_{i,t+k} = b\,\text{DR}_{i,t} + c\,\text{CF}_{i,t} + d'\text{Controls}_{i,t-1} + t + i + \text{error}_{i,t}$. In Panels A & D, Y is Patent count, KPSS value, or Total citations. In Panel B, Y is I(Patent), and I(Patent) is a dummy equal to 1 if firm i has at least one patent applied (and eventually granted) in year t+k and 0 otherwise. In Panel C, Y is Δ ln(1+XRD), Δ ln(1+CAPX), or Δ ln(EMP). In Panel E, Y is Δ Net PP&E and Other Assets and Asset Turnover. Controls include Sales_p, MTB_p, ROA_p, PPE_p, LEV_p, Age_p, Sales_f, MTB_f, ROA_f, PPE_f, LEV_f, and Age_f. In Panel D, Controls also include ex-post log changes in innovative inputs (similar to Panel A of Table 4). Refer to Appendix B for variable definitions. Year fixed effects, t, and firm fixed effects, i, are included in all regressions. Higher value of DR reflects negative returns and higher cost of capital. Higher value of CF reflects positive returns. All dependent variables are scaled by their respective standard deviation. Coefficient estimates are shown, and their standard errors are clustered by industry and displayed in parentheses below. ***(**)(*) denotes significance at the 1% (5%) (10%) two-tailed level.

Panel A: Innovative Output

| | Patent count | | | KPSS value | | | Total citations | | |
|---|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| DR | 0.038 | −0.004 | 0.022 | 0.078* | 0.064** | 0.073** | 0.057** | 0.025 | 0.049** |
| | (1.58) | (−0.32) | (1.55) | (1.70) | (2.59) | (2.36) | (2.48) | (1.49) | (2.52) |
| CF | 0.036** | 0.049** | 0.062** | 0.114*** | 0.084*** | 0.073*** | 0.099*** | 0.098*** | 0.108*** |
| | (2.36) | (2.36) | (2.34) | (3.37) | (2.81) | (2.72) | (4.09) | (3.42) | (3.69) |
| Observations | 82,240 | 82,240 | 82,240 | 81,505 | 81,525 | 81,552 | 82,217 | 82,217 | 82,216 |
| R-squared | 0.064 | 0.076 | 0.087 | 0.064 | 0.069 | 0.079 | 0.096 | 0.106 | 0.116 |

**Table A2:** continued.

Panel B: Probability of getting a patent

| | Single year | | | | | Multiyear | | | |
|---|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+4 | t+5 | t+1:2 | t+1:3 | t+1:4 | t+1:5 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| DR | 0.004 | −0.002 | −0.000 | 0.003 | −0.008 | 0.005 | 0.006 | 0.007 | 0.010** |
| | (1.03) | (−0.48) | (−0.01) | (0.31) | (−0.91) | (1.32) | (1.12) | (1.32) | (2.15) |
| CF | −0.005 | −0.003 | 0.010** | 0.002 | −0.001 | −0.002 | 0.001 | −0.001 | 0.000 |
| | (−1.10) | (−0.78) | (2.06) | (0.53) | (−0.26) | (−0.51) | (0.37) | (−0.30) | (0.12) |
| Observations | 82,240 | 82,240 | 82,240 | 82,240 | 82,240 | 82,240 | 82,240 | 82,240 | 82,240 |
| R-squared | 0.015 | 0.023 | 0.046 | 0.079 | 0.110 | 0.022 | 0.028 | 0.034 | 0.041 |

Panel C: Changes in innovative input

| | Δ ln(1+XRD) | | | Δ ln(1+CAPX) | | | Δ ln(EMP) | | |
|---|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| DR | 0.021 | −0.023 | 0.017 | 0.082 | −0.033 | −0.017 | −0.025 | 0.025 | 0.042 |
| | (0.63) | (−1.18) | (1.00) | (1.47) | (−0.97) | (−0.87) | (−0.97) | (0.95) | (1.50) |
| CF | 0.067** | 0.190*** | 0.038 | 0.209*** | 0.388*** | 0.065 | 0.192*** | 0.244*** | 0.017 |
| | (2.47) | (6.25) | (1.01) | (6.90) | (5.56) | (1.35) | (8.09) | (5.93) | (0.55) |
| Observations | 75,965 | 70,600 | 65,674 | 75,965 | 70,600 | 65,674 | 73,598 | 68,464 | 63,788 |
| R-squared | 0.024 | 0.018 | 0.015 | 0.056 | 0.056 | 0.049 | 0.091 | 0.073 | 0.062 |

Panel D: Innovative Efficiency

| | Patent count | | | KPSS value | | | Total citations | | |
|---|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| DR | 0.036 | −0.006 | 0.024 | 0.086* | 0.073** | 0.088** | 0.052** | 0.020 | 0.051** |
| | (1.36) | (−0.40) | (1.36) | (1.70) | (2.42) | (2.12) | (2.26) | (1.09) | (2.57) |
| CF | 0.037** | 0.048* | 0.058* | 0.115*** | 0.073** | 0.063* | 0.105*** | 0.098*** | 0.112*** |
| | (2.19) | (1.89) | (1.99) | (3.05) | (2.09) | (1.99) | (4.08) | (2.86) | (3.38) |
| Observations | 73,598 | 67,677 | 62,416 | 72,902 | 67,016 | 61,789 | 73,579 | 67,658 | 62,397 |
| R-squared | 0.069 | 0.088 | 0.106 | 0.074 | 0.087 | 0.106 | 0.102 | 0.119 | 0.133 |

Panel E: Fixed assets and turnover

| | Δ Net PP&E and Other Assets | | | | Asset Turnover | | | |
|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+4 | t+1 | t+2 | t+3 | t+4 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| DR | −0.004 | 0.012 | 0.057*** | 0.005 | 0.028*** | 0.008 | 0.011 | 0.016 |
| | (−0.08) | (0.25) | (4.32) | (0.27) | (3.43) | (0.89) | (0.81) | (1.26) |
| CF | 0.136*** | 0.302*** | 0.161*** | 0.078* | 0.030** | 0.024** | 0.003 | 0.001 |
| | (5.16) | (4.82) | (3.46) | (1.87) | (2.61) | (2.14) | (0.21) | (0.10) |
| Observations | 74,393 | 69,183 | 64,380 | 59,872 | 75,965 | 70,600 | 65,674 | 61,041 |
| R-squared | 0.099 | 0.086 | 0.083 | 0.080 | 0.041 | 0.048 | 0.067 | 0.076 |

**Table A3:** Public firm patents information across different databases

This table compares patent counts by firm-year across three databases: (i) Kogan, Papanikolaou, Seru, and Stoffman (2017) (KPSS) accessed in June 2022, (ii) the Global Corporate Patent Database featured in Bena, Ferreira, Matos, and Pires (2017) (BFMP), (iii) and the DISCERN database of Arora, Belenzon, and Sheer (2021) (ABS) over the years of overlapping coverage. Column (1) contains firm-year counts whereby the positive number of patents is the same in KPSS and BFMP. Column (2) contains firm-years with positive count in KPSS but zero in BFMP. Columns (3) and (4) contain firm-years with positive counts in KPSS ($N_k$) and BFMP ($N_b$), such that, respectively, $2 \geq N_k - N_b \geq 1$ and $N_k - N_b > 2$. Column (5) contains firm-years with positive count in BFMP but zero in KPSS. Columns (6) and (7) contain firm-years with positive counts in KPSS and BFMP, such that, respectively, $2 \geq N_b - N_k \geq 1$ and $N_b - N_k > 2$. Column (8) contains firm-counts with patents, in which the individual patent information coincides in at least two databases out of three. Relative to the counts in column (8), KPSS database has 5,827 firm-years with different patent count and 3,017 with missing patents, BFMP database has 3,539 firm-years with different and 5,038 with missing, whereas the ABS database has 6,694 firm-years with different patent count relatively to those that match exactly in KPSS and BFMP.

| Grant | KPSS ∩ BFMP | KPSS surplus | | | BFMP surplus | | | 2+ DBs |
|---|---|---|---|---|---|---|---|---|
| year | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| 1989 | 202 | 251 | 78 | 79 | 26 | 48 | 27 | 525 |
| 1990 | 286 | 284 | 69 | 76 | 26 | 44 | 30 | 612 |
| 1991 | 315 | 294 | 67 | 82 | 36 | 47 | 36 | 670 |
| 1992 | 384 | 289 | 95 | 93 | 40 | 23 | 31 | 722 |
| 1993 | 397 | 283 | 97 | 87 | 42 | 29 | 42 | 718 |
| 1994 | 476 | 314 | 94 | 86 | 56 | 44 | 43 | 826 |
| 1995 | 476 | 298 | 88 | 69 | 66 | 88 | 78 | 877 |
| 1996 | 618 | 274 | 118 | 85 | 68 | 40 | 72 | 960 |
| 1997 | 651 | 273 | 125 | 81 | 64 | 59 | 77 | 1,005 |
| 1998 | 717 | 261 | 157 | 86 | 79 | 52 | 106 | 1,077 |
| 1999 | 690 | 209 | 146 | 77 | 80 | 64 | 121 | 1,032 |
| 2000 | 722 | 152 | 46 | 54 | 115 | 184 | 173 | 1,097 |
| 2001 | 714 | 127 | 55 | 50 | 116 | 187 | 175 | 1,123 |
| 2002 | 784 | 106 | 40 | 55 | 88 | 139 | 145 | 1,069 |
| 2003 | 809 | 109 | 51 | 56 | 95 | 77 | 150 | 1,050 |
| 2004 | 763 | 103 | 52 | 55 | 107 | 102 | 141 | 1,007 |
| 2005 | 728 | 78 | 40 | 59 | 104 | 111 | 128 | 942 |
| 2006 | 628 | 77 | 29 | 57 | 120 | 190 | 180 | 992 |
| 2007 | 573 | 64 | 25 | 45 | 122 | 192 | 200 | 939 |
| 2008 | 578 | 61 | 29 | 48 | 116 | 147 | 164 | 838 |
| 2009 | 622 | 69 | 32 | 52 | 119 | 97 | 119 | 797 |
| 2010 | 571 | 59 | 34 | 66 | 123 | 117 | 151 | 756 |
| 2011 | 550 | 57 | 32 | 44 | 167 | 112 | 163 | 734 |
| 2012 | 432 | 60 | 21 | 30 | 163 | 190 | 258 | 833 |
| 2013 | 469 | 53 | 23 | 37 | 201 | 158 | 243 | 812 |
| 2014 | 536 | 49 | 29 | 43 | 224 | 140 | 170 | 755 |
| 2015 | 513 | 37 | 27 | 50 | 244 | 142 | 167 | 749 |
| Total | 15,204 | 4,291 | 1,699 | 1,702 | 2,807 | 2,823 | 3,390 | 23,517 |

# Appendix B. Variable definitions

| Variables Name | Variable Definitions |
|---|---|
| DR | Average of peers' discount rate shocks. |
| CF | Average of peers' cash flow shocks. |
| Sales_p | Average of peers' ln(SALE). |
| MTB_p | Average of peers' market-to-book (MTB) ratios, with MTB defined as (PRCC_F*CSHPRI + DLC + DLTT + PSTKL - TXDITC)/AT. |
| ROA_p | Average of peers' ratios of OIBDP to AT. |
| PPE_p | Average of peers' ratios of PPENT to AT. |
| LEV_p | Average of peers' ratios of (DLC+DLTT) to AT. |
| Age_p | Average of peers' ln(age), with age equal the number of years since IPO. |
| Sales_f | Firm's ln(SALE). |
| MTB_f | Firm's MTB ratio. |
| ROA_f | Firm's ratio of OIBDP to AT. |
| PPE_f | Firm's ratio of PPENT to AT. |
| LEV_f | Firm's ratio of (DLC+DLTT) to AT. |
| Age_f | Firm's ln(age), with age equal the number of years since IPO. |
| $\Delta$ ln(1+XRD) | $\ln(1+\text{XRD}_{t+k}) - \ln(1+\text{XRD}_{\text{t+k}-1})$, adjusted for inflation. |
| $\Delta$ ln(1+CAPX) | $\ln(1+\text{CAPX}_{\text{t+k}}) - \ln(1+\text{CAPX}_{\text{t+k}-1})$, adjusted for inflation. |
| $\Delta$ ln(EMP) | $\ln(\text{EMP}_{\text{t+k}}) - \ln(\text{EMP}_{\text{t+k}-1})$ |
| $\Delta$ ln(Sales) | $\ln(\text{SALE}_{\text{t+k}}) - \ln(\text{SALE}_{\text{t+k}-1})$, adjusted for inflation. |
| $\Delta$ ln(Assets) | $\ln(\text{AT}_{\text{t+k}}) - \ln(\text{AT}_{\text{t+k}-1})$, adjusted for inflation. |
| $\Delta$ EBITDA/Sales | Change in ratio of EBITDA to SALE from year t+k-1 to t+k. |
| % Change EBITDA | Change in EBITDA from year t+k-1 to t+k, scaled by $\text{EBITDA}_{\text{t+k}-1}$. |
| $\Delta$ Cash | Change in CH from year t+k-1 to t+k, scaled by $\text{AT}_{\text{t}-1}$. |
| $\Delta$ Non-cash Current Assets | Change in (ACT - CH) from year t+k-1 to t+k, scaled by $\text{AT}_{\text{t}-1}$. |
| $\Delta$ Net PP&E | Change in PPENT from year t+k-1 to t+k, scaled by $\text{AT}_{\text{t}-1}$. |
| $\Delta$ Other Assets | Change in (AT - ACT - PPENT ) from year t+k-1 to t+k, scaled by $\text{AT}_{\text{t}-1}$. |
| $\Delta$ Net PP&E & Other Assets | Change in (AT - ACT) from year t+k-1 to t+k, scaled by $\text{AT}_{\text{t}-1}$. |
| Asset Turnover | Ratio of SALE to AT in year t+k. |
| Net Equity Issuance | SSTK - PRSTKC in year t+k, scaled by $\text{AT}_{\text{t}-1}$. |
| Net Debt Issuance | Change in (DLTT + DLC) from year t+k-1 to t+k, scaled by $\text{AT}_{\text{t}-1}$. |
| N_peers | Average number of peers of each firm-year. |
| avg_score | Average TNIC score of peers of each firm-year. TNIC scores are from Hoberg and Phillips (2010). |
| intan17 | The sum of knowledge capital, organizational capital, and INTANO, adjusted for inflation. Knowledge and organizational capital are from Peters and Taylor (2017). |
| Patent count | The number of all patents applied (and eventually granted) in year t+k, scaled by $\text{intan17}_{\text{t}-1}$. |
| KPSS value | The sum of KPSS values of all patents applied (and eventually granted) in year t+k, scaled by $\text{intan17}_{\text{t}-1}$. |
| Total citations | The sum of forward citations received by all patents applied (and eventually granted) in year t+k, scaled by $\text{intan17}_{\text{t}-1}$. |