Taking the Road Less Traveled? Market Misreaction and Firm Innovation Directions

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Abstract

We propose that public investors react differently to patent issuance based on novelty, and these misreactions exert real impacts on the firms' future innovations. First, using textual measures of novelty, we find that investors underreact to the issuance of path-breaking innovations while overreact to trend-following ones. Novel patent issuance predicts lower risk but positive forecast errors, consistent with a non-risk-based novelty *mispricing* mechanism. A bounded-rationality model, where investors are unsure about the true novelty of a patent at issuance due to cognitive limits, explains the empirical patterns well. Second, using exogenous distraction shocks, such as sensational news, we present causal evidence that after disappointing returns, novel firms shift from creating and following up on novel innovations to copycatting. The findings highlight that investors' misreactions to patent novelty steer innovation directions away from higher-valued, groundbreaking research.

Keywords: stock market misvaluation, innovation novelty, behavioral finance, market efficiency, innovation direction

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1 Introduction

Technological development has been one of the critical drivers of economic growth in recent centuries. Not only is the amount of technological innovation important, but the direction of technology also matters (Acemoglu, 2023). The direction of technological advancements attracts more than just the attention of economists. Investors are also drawn to news about new technology. For example, during the COVID-19 outbreak, we saw large swings in stock prices when pharmaceutical companies released vaccines and for firms providing work-from-home technologies. We have also witnessed the recent excitement about blockchain technology (Cheng et al., 2019). In this paper, we study two related questions. First, how do investors react to news about technological innovation? Second, can investors' reactions to technological innovation affect future innovation directions?

To address these questions, we investigate stock price movements and firm innovation outputs after news of patent issuance. Using novelty measures constructed from patent text, we find that investors under-react to the issuance of novel technologies while overreacting to non-novel ones. We show that such mispricing can be explained by a model where investors have imprecise signals about patent novelty due to cognitive limits and, therefore, shrink their perception to an intermediate prior level. We further demonstrate that investor reactions to patent novelty change firms' decisions on the direction of future innovations. Firms that issue novel patents ("novel firms" thereafter) shift away from novel inventions, do not follow up on their original technology, and instead pursue overpriced, non-novel technologies. Using exogenous distracting events around patent issuance dates as an instrument, we provide causal evidence suggesting that firm managers are influenced by return reactions to patents when deciding on future innovation directions.

Our paper documents a new channel through which financial markets can influence technological change. Our key contribution is to document and reconcile the novel co-existence of under- and over-reaction to patent issuance based on its novelty, and to show that such investors' irrational behavior in turn changes firms' future innovation directions from novel to non-novel. To our knowledge, we are the first to show that investor biases can impact firms' future innovation strategy. We argue that investors underreact to novel patents, which creates an underpricing in novel firms' stock prices. If firm managers care about short-term fluctuations in firm market value, this creates a disincentive for them to continue pursuing novel R&D. On the other hand, investors get over-excited about non-novel technology and overprice the stock of non-novel firms, which then encourages managers to over-invest in

existing technologies.

The key challenge to studying the differential reactions to patent novelty is constructing a precise measure of patent novelty. We measure patent novelty using a comprehensive textual analysis of patent text following the methodology introduced by Kelly, Papanikolaou, Seru and Taddy (2021). They compute pairwise textual similarities between patents to quantify the commonality of each pair of patents. They identify breakthrough patents as patents that are distinct from previous innovations but that are strongly related to subsequent innovations. For our purposes, we are primarily interested in an *ex-ante* measure of novelty. Therefore, we modify the Kelly et al. (2021) definition as follows: we define a patent as novel if it has low aggregate textual similarities to all other patents filed five years before its filing year. At the same time, we identify non-novel inventions as those with high similarity to prior innovations. To quantitatively measure firms' future innovation directions, we create a patent-pairwise citation network so that for each patent, we observe every prior invention it builds on and all of its future citations.

With the data and measures in hand, we document two main findings. First, investors under-react to novel patents but over-react to non-novel patents. We run impulse response functions of firm-level subsequent returns on patent issuance of different novelty levels. Novel patent issuance positively predicts future returns in the next two years, suggesting that the initial reactions to novel patents are not sufficient, so future returns continue to drift, consistent with an underreaction to novelty. Conversely, non-novel patent issuance negatively predicts future returns, consistent with an initial overreaction as investors gradually correct for the overpricing, leading to a return reversal. (Non-)novel issuance predicts a return drift (reversal) of around 1% in the next two years. We back up this mispricing mechanism with several empirical tests. We argue against a risk-based story by showing that novel patent issuance predicts lower volatility than non-novel patents. We show direct evidence of incorrect beliefs where novel issuance predicts positive forecast errors in earnings expectations, suggesting investors are too pessimistic about future cash flows of high-novelty firms, hence underprice the stock. We also provide suggestive evidence that the effects are indeed driven by patent issuance events and come from a misperception of patent value, instead of a misperception of patent grant probability.

We propose a bounded-rationality model of investors to explain these mispricing patterns. When a patent is issued, since the novelty is defined only with *ex-ante* information, investors can, in principle, compute it. However, due to cognitive limits, it is likely that investors

are unsure about the true novelty of the patent at its issuance. Instead, they receive noisy but unbiased signals of patent novelty. Such signals shrink their posterior mean to an intermediate prior level, which leads them to underestimate the novelty of novel patents and overestimate the novelty of non-novel patents. Connecting perceived novelty to perceived value, the model predicts the following short-term and long-term response in the firm's stock price. In the short term, return responses are insignificantly different across novelty. However, in the long run, the model predicts significant return predictability as the firm value converges to the rational response of patent issuance. These model predictions match the empirical patterns of short-term and long-term average returns in the data. The model also predicts stronger misreactions and slower convergence with noisier signals. We verify this key model mechanism by empirically showing that firms with lower institutional holdings have stronger misreactions than those held primarily by institutional investors, as retail investors tend to receive noisier signals.

Second, we demonstrate that investors' misreactions to novelty in turn shift firms' innovation directions from novelty-seeking to copycatting. Using a patent citation network, we create several measures to assess firms' innovation directions. We examine whether firms' stock market reactions to patent issuance can predict future changes in their innovation directions. Ordinary least squares (OLS) estimates suggest that with disappointing 3-day returns after patent issuance, firms conduct fewer novelty-seeking innovations relative to copycatting (non-novel) ones and fewer follow-up innovations of current technology, in the following twenty quarters (five years). Since a firm's future innovations could correlate with unobserved determinants of its equity returns, to examine causal effects, we instrument for returns using sensational news (Peress and Schmidt, 2020) that are not economic or technological, as exogenous distractions to investors, and provide causal evidence that market reactions to patent issuance distort a firm's future innovation directions.

Specifically, we exploit within-firm time-series variations by comparing periods with varying distractions caused by sensational news. The period with more frequent sensational news in the 3-day window after patent issuance creates more distraction to investors, so they respond less strongly to the patent news, resulting in lower returns relative to the period without distractions. Following these lower returns, firms develop less on their current technology. They also pivot from new novel research to mimicking existing innovation trends, especially when most of the current innovations are novel. Following a 10% lower return on a quarterly basis, firms shift their shares of novel patent filings to non-novel by 1.1% in the next five years and this effect is concentrated when the majority of patents granted are

novel. Moreover, firms also decrease the share of follow-up filings in all patent filings by around 1% in the next five years. Such changes are important as they could induce lower economic value in innovating firms and decrease the positive externalities of novel patents. We discuss several channels through which firm managers consider their firms' short-term returns when making future innovation decisions (Stein, 1989) for future study.

Literature Review

Our paper contributes to three strands of literature.

First, we contribute to the literature on investor reactions to innovation news. We are most closely related to Hirshleifer et al. (2018) who document that firms' innovative originality positively predicts stock returns, but have important distinctions empirically and theoretically. Empirically, our measure, which is based on textual similarity, more directly measures how a patent is distinctive to previous patents than citing a wide set of technologies. We also find both positive predictability for novel patents and negative predictability for non-novel patents, which provides a new fact that investors overreact to existing technology. Theoretically, we provide a model that can jointly explain under and over-reaction, while an inattention model can only explain the under-reaction to originality. Inattention models also explain other underpricing of innovation, e.g. Hirshleifer et al. (2013) on innovation efficiency, Cohen et al. (2013) on R&D success, Fitzgerald et al. (2021) on innovation search strategy, Chemmanur et al. (2022) on grant news, etc. Despite the popularity of limited attention models, our paper offers a new framework to jointly understand both the under- and overpricing of technology, which we then verify in the data. Therefore, we also add to the recent studies trying to reconcile the co-existence of under- and over-reaction[1]. In a way that is new to the literature, we reconcile the co-existence of under- and over-reaction to the same type of news, patent issuance. Investors have an imprecise representation of patent novelty and thus form posterior beliefs close to an intermediate level.

Second, the paper suggests a novel and important channel by which financial markets exert real economic impact. There is a growing literature studying the effect of the secondary market on firm decisions through learning from prices. Chen, Goldstein and Jiang (2007)

[1]Bordalo, Gennaioli, Ma and Shleifer (2020) argue that individuals often overreact while the consensus opinion often underreacts. Wang (2021) proposes that investors underreact to persistent processes but overreact to random processes. Kwon and Tang (2021) demonstrate that investors underreact to less extreme events while overreacting to extreme news.

suggest that firm managers learn from private information in stock prices to make investment decisions. Price informativeness is also essential in other firm decisions, such as takeover activity (Edmans, Goldstein and Jiang, 2012) and R&D investments (Kang and Kim, 2017). Unlike the learning-from-prices channel, we propose that investors' behavioral biases, which lead to mispricing, can affect firms' future investment decisions. Moreover, the research on the effect of financial markets on firms' innovation strategies has focused primarily on the primary market. Bernstein (2015) studies the impact of going public on innovation quality, Lerner, Sorensen and Strömberg (2011) discuss the effects of LBO on innovation output, and Babina, Bernstein and Mezzanotti (2023) show the effect of local exposure to financial crises on local innovation players. These papers demonstrate the importance of financial frictions. We instead explore the possibility that behavioral forces in the secondary market also contribute to the shift in innovation behavior. On this front, Dong et al. (2021) document that stock overreactions affect innovative inventiveness and output with a positive sign. They focus on general overpricing, while we look at misreactions around patent issuance and closely tie reactions to patents to managers' decisions on future innovation strategies. Moreover, while they study the *amount* of future innovation, we are interested in the *direction* of innovation from novel to copycat innovations. Krieger et al. (2022) also look at the decision of novel vs. incremental innovations, focusing on the pharmaceutical firms. They argue that risk aversion and costly external financing lead them to underinvest in novel innovation. We look at this decision in all industries and tie it directly to investors' reactions to novelty.

Finally, we speak to the economic growth literature on heterogeneous innovation and innovation directions. In a 2023 AEA lecture, Acemoglu (2023) proposes two channels that can distort the direction of technology. The first one is differential externalities. If the negative externality is not priced in, technology will be directed towards the areas with negative externalities. Secondly, innovation is driven towards industries with a higher markup. For example, curative technologies usually have higher markup in healthcare, thus fostering more innovation. We study innovation direction at a more granular level. Instead of focusing on across industries, we study how firms choose their innovation directions. Acemoglu et al. (2022) argue that firms with an open-to-disruption culture are more likely to conduct radical innovations. We provide a new channel where the decision also depends on investors' perception, not just managers' own type. Akcigit and Kerr (2018) also study this question at the firm level. They are interested in whether firm managers choose internal (improving existing products) versus external innovations (acquiring a new product line). They find that large firms prefer internal innovation, and thus, major innovations tend to happen in

small firms. In their model, innovation direction shifts as the firm scales up, while in our paper, conditional on firm size, innovation direction can also shift due to investors' reactions.

The paper proceeds as follows. We describe our data sources and key measures in Section 2. In Section 3, we present results regarding investors' misreactions to patent novelty. We then develop a theoretical framework to explain the misreactions and verify its predictions in our data in Section 4. In Section 5, we show results on the future innovation directions and how misreactions slow novel technology advancements in novel firms. Section 6 concludes by discussing the implications of our results for future research.

2 Data and Measurement

We combine various data sources to establish the empirical results in the paper. Since we examine how investors react to patent issuance news and how investors' reactions to patents' novelty impact firms' future innovation directions, the key data construction is to combine information from patent data with firms' stock prices and financial statements.

2.1 Patent Data

Our study's first substantial data source is the patent records from the United States Patent and Trademark Office (USPTO). Over a period of nearly a century (from 1926 to 2022) , this extensive dataset provides valuable insights into technological advancements and innovation activity across various industries. The dataset includes information on a patent's filing and issuance date, inventors and assignees, classification codes, citation patterns, and the patent's full text, enabling us to construct different measures of innovation. We elaborate on the methodologies and definitions of these measures later in this section.

2.2 Firm-level Financial Data

For the main analyses, we obtain monthly stock returns and shares outstanding from the Center for Research in Security Prices (CRSP). Our sample includes all NYSE, AMEX, and NASDAQ (CRSP exchange code 1-3) common stocks (CRSP share code 10-12). To test the market reactions to the news of patent issuance, we match it with the patent data. Our focus is on the stock market reactions after the official USPTO announcement of patent issuances.

Following the methodology by Kogan et al. (2017), we link the patents to publicly-traded firms by using the assignee names as the key matching criterion. We drop patents that are matched to multiple firms to avoid double-counting. We end up with around 3.6 million patents that can be matched to a US public firm.

We also construct several control variables from CRSP. We calculate the market capitalization as $|prc| \times shrout$, and we use the market cap from December in the past year to calculate book-to-market ratio (Fama and French, 1992). Short-term reversal is the returns from month $t-1$ and the medium-term momentum is the cumulative returns from month $t-12$ to $t-2$. To study the short-term reactions, we also match CRSP daily returns to patents with issuance dates using the same mapping procedure. Using the daily returns, we also construct monthly realized volatility as the squared daily returns and the monthly beta by regressing daily returns in each firm-month on CRSP value-weighted index returns.

We extract an array of firm-specific accounting variables from Compustat, such as revenue, cost, book equity, employment, etc. Book equity is the shareholders' equity (`seq`) adjusted for tax credit (`txditc`) and preferred stocks (`pstkrv` or `pstkl` or `pstk`). We compute several profitability margins. Gross profit is revenue (`sales`) minus COGS (`cogs`), scaled by total asset (`at`), free cash flow is net income (`ni`) plus depreciation (`dp`) minus change in working capital (`wcapch`) and capital expenditure (`capx`) scaled by book equity (Novy-Marx, 2013), operating profit is revenue minus COGS, SG&A (`xsga`), and interest expenses (`xint`), scaled by book equity, investment is change in total assets (Fama and French, 2015), EPS is net income divided by adjusted share outstanding (`cshpr`) (Bordalo et al., 2019), and ROE is income before extraordinary items divided by lagged book equity (Hou et al., 2015). We also construct several firm input and output variables following Kogan et al. (2017). We use profits (`sales` minus `cogs`, deflated by CPI), output (`sales` plus change in inventories `invt`, deflated by CPI), employment (`emp`), and capital stock (`ppegt`, deflated by NIPA price of equipment).

2.3 Other Data

Institutional Holdings We obtain firm-quarter institutional ownership from FactSet. FactSet institutional ownership data mostly comes from the SEC 13F filings. All institutional investment managers with more than $100 million of AUM are required to file each quarter. We use the Ferreira and Matos (2008) construction of institutional holdings as our main measure of institutional shares. The data is available from 2000Q1 to 2021Q4.

Implied Volatility We obtain implied volatility measure from OptionMetrics. The implied volatility is from standardized at-the-money options. We construct a firm-month panel by averaging the implied volatility at the option level issued in each month. The data is available from January 1996 to December 2022.

Analyst Forecasts We use the sell-side analyst forecast data from I/B/E/S. We use analyst-level unadjusted forecasts of annual earnings from IBES and adjust earnings for stock splits using the CRSP cumulative adjustment factor. Directly using the adjusted file from IBES has rounding errors which may change the conclusion (Payne and Thomas (2003)). We use a potentially different adjustment factor at the forecast date and the earnings announcement date to make sure the adjusted earnings and forecasts are on the same basis. Following Bouchaud et al. (2019), we compute consensus earnings with the median of individual forecasts submitted at most 45 days after a total annual earnings announcement. If the analyst issues multiple forecasts during the 45-day period, we use the first forecast. We use the 1-year and 2-year future earnings forecasts from fiscal year 1982 to 2023.

Sensational news We identify sensational news using the news pressure measure of Eisensee and Strömberg (2007)[2]. The news pressure measure is the median number of minutes that are allocated to the news in the first three news segments. Following Peress and Schmidt (2020), we use the median news pressure from ABC, CBS, and NBC and define sensational news events as 10% of days with the highest news pressure in each year. Since economic and technology news may be correlated with firms' innovation decisions and bias our results, we exclude the sensational news days on which the headlines contain at least one word that is economic or related to technology[3].

[2]We thank David Strömberg for sharing an updated time series of daily news pressure from 1968 to June 2022. We directly download the data from his website https://davidstro.github.io/DataArchive/.

[3]The keywords are banking, bankruptcy, default, depression, economic, economy, election, employment, equity, federal reserve, fed reserve, fed rate, finance, financial, inflation, interest rate, recession, stock market, treasury, and war, technology, innovation and patent.

2.4 Innovation Novelty, Impact, and Direction

2.4.1 Measurement of Patent Novelty and Impact

The key variable of interest in our analyses is patent novelty, which is the degree to which an invention presents a unique, innovative idea compared to prior work. To quantify this feature, we opt for a text-based measure so that we can extract distinctive patterns, themes, and terminologies, allowing for a relatively objective assessment of a patent's novelty.

More specifically, our measure of patent novelty is inspired by Kelly et al. (2021)[4]. They define the importance of a patent by examining its similarity to both the patents filed before and after. Specifically, they propose an indicator of patent importance, denoted as q_j^{10} for patent j, as the ratio of its forward similarity FS_j^{10}, to its backward similarity BS_j^5:

$$q_j^{10} = \frac{FS_j^{10}}{BS_j^5}, \quad \text{where } \underbrace{BS_j^5}_{Novelty} = \sum_{i \in \mathcal{B}_{j,5}} \rho_{j,i}, \quad \underbrace{FS_j^{10}}_{Impact} = \sum_{i \in \mathcal{F}_{j,10}} \rho_{j,i}.$$

Delving deeper into each component, the backward similarity (BS_j^5) represents the ***novelty*** aspect of a patent. It sums up the pairwise similarities, $\rho_{j,i}$, of patent j to all patents filed in the five years preceding j's filing date. These preceding patents are captured in the set $\mathcal{B}_{j,5}$. This measure aims to understand how closely patent j resembles or diverges from previous innovations. On the other hand, the forward similarity (FS_j^{10}), capturing the ***impact*** dimension, is the summation of the pairwise similarities of patent j to all subsequent patents filed in the decade following j's filing date, represented as a set $\mathcal{F}_{j,10}$. This measure provides insight into the influence of patent j on subsequent innovations.

Our primary focus is the novelty aspect of each patent. As noted above, a patent with a lower similarity to preceding patents (lower BS_j^5) would indicate a higher degree of novelty. This metric is important and intuitive, as it helps us approximate *ex-ante* whether an invention is groundbreaking or merely a marginal improvement upon prior art. One should note that not all novel patents necessarily represent technological breakthroughs. Under such circumstances, we take advantage of the forward similarity metric FS_j^{10}, which captures the ex-post impact of a patent, to separate the patents with the same novelty levels further into high or low-impact groups.

[4]We thank the authors for sharing the dataset on https://github.com/KPSS2017/Measuring-Technological-Innovation-Over-the-Long-Run-Extended-Data.

2.4.2 Measurement of Innovation Direction and Diffusion

We construct a pairwise patent citation network to capture the breadth and depth of technological diffusion. This methodology is built on observing each patent's subsequent citations, ensuring a comprehensive mapping of the flow of knowledge and firms' innovation directions. Our data consists of 43 million patent citation pairs, specifically covering patents whose assignees are publicly traded firms available in the CRSP database. We employ it to explore the dynamics of firms' innovation directions. Specifically, we can infer whether firms are more willing to innovate further upon their original novel patents or opt to follow prevailing trends by referencing patents from other entities. Moreover, the citation network allows us to create proxies for evaluating a patent's social value. For example, we can employ the total citations a patent receives to indicate its influence and acceptance in the broader community. The metric gives us a reasonable estimate of a patent's social value.[5]

3 Market Reactions to Novelty

In this section, we study investors' differential responses to news of patent issuance by public firms, explicitly distinguishing between patents with high and low novelty. By integrating patent data with stock returns, we systematically estimate the short- and long-term firms' returns after the announcements of patent issuance, which seeks to illustrate whether investors under-react or overreact to such news. We then show robustness with alternative specifications and measurements. We also investigate the mechanism behind the difference in market reactions to novelty. Using expectations data, we show direct evidence of a mispricing-based explanation.

3.1 Impulse Response of Patent Issuance

In the empirical studies of investors' reactions to news, a prevalent methodology is to examine whether news predicts firms' future returns. Such an approach offers a framework for gauging the extent of market *mis*-reaction. Intuitively, if investors rationally respond to full information (FIRE), the firm's stock price should jump immediately to the correct level so that future long-term stock returns should be unpredictable. If, instead, the information

[5]Our proxies represent a lower bound on a patent's social value, given that a patent can bring significant value to society in ways not measured by the citation network.

revelation leads to positive predictability, we infer that investors do not take account of all the information when it is initially released, suggesting an underreaction to the news. Conversely, negative predictability can be seen as an indication of overreaction, where investors give an overly high valuation to the news upon its release.

Using this framework, we aim to compare investor reactions, or potential misreactions, to novel vs. nonnovel patents. In particular, we estimate the immediate response and the long-term predictability in returns to novel and non-novel patents, controlling for other determinants of returns.

We first classify each month's patents into novel versus non-novel types. For each firm, we collate all patents granted each month and categorize them into ten deciles based on their novelty levels. To prevent lookahead bias, we assign decile bins by comparing the novelty (patent backward similarity, BS_j^5) of the patents issued in each month with the decile cutoffs from the previous month. As such, patent novelty is constructed using only ex-ante information. We categorize novel patents as similarity deciles from 1 to 5 and non-novel as 6-10 so that results are not driven by extreme values.

Short-term return on patent issuance While our primary analysis focuses on the long-term predictability, we need to first explore the immediate return response to fully establish the empirical fact of investor misreaction. For example, if investors overreact to non-novel patents, we should see an immediate return jump followed by a negative predictability. To test this, we run a firm-day-level regression of 3-day returns on the patent issuance dummy, controlling for industry×date fixed effects (we use 3-digit SIC code throughout for industry) and an extensive list of return determinants, $X_{i,t}$: market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal (r_{t-1}), and medium-term momentum ($r_{t-12\to t-1}$).

$$R_{i,t,t+2} = \alpha_{ind,t} + \beta \mathbb{1}\{i \in \text{Patent}_t/\text{Novel}_t/\text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t,t+2}. \tag{1}$$

Second, we find that both novel and non-novel patent issuance predict sizable short-term returns. As shown in Table 1, the coefficients on novel and nonnovel issuance, when analyzed separately, are both positive and statistically significant. On average, returns increase by 0.074% (0.083%) 3 day after novel (non-novel) patent issuance, which is equal to an annualized return of 6.22% (6.97%). Second, we include both dummies together with a patent issuance dummy, only the coefficient on the patent issuance dummy is significant.

This suggests that patent issuance predicts positive three-day returns that do not differ by patent novelty.

Long-run impulse response to patent issuance Given that the short-term return response is positive and similar between novel and nonnovel patents, we investigate how the returns evolve in the long term. We compute local projections of future firm-month returns by innovation novelty indicators:

$$\begin{aligned} r_{i,t+\tau} = \alpha_{ind,t} &+ \beta_{\tau,novel} \mathbb{1}\{i \in \text{Novel}_t\} \\ &+ \beta_{\tau,non-novel} \mathbb{1}\{i \in \text{Non-novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}, \end{aligned} \tag{2}$$

where $r_{i,t+\tau}$ is the return of firm i in month $t+\tau$. $\alpha_{ind,t}$ are industry×month fixed effects (FEs) that control for industry-level drivers of returns. We also control for an extensive list of return determinants, $X_{i,t}$: market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal (r_{t-1}), and medium-term momentum ($r_{t-12\to t-1}$).

The main variables are the two indicator variables which are equal to 1 if firm i is granted at least one novel or non-novel patent in month t. The coefficients, $\beta_{\tau,novel}$ and $\beta_{\tau,non-novel}$, capture whether the issuance of (non-)novel patents predicts future returns, conditional on the fact that firms can issue the other type of patents simultaneously.

To study the dynamics of return predictability over time, we generate a cumulative impulse response function (IRF), $\sum_{\tau=1}^{T} \beta_{\tau,d}$, from $\tau = 1$ to 36 months. The cumulative IRF is a graphical representation of how a patent issuance shock predicts cumulative returns over three years. If we see a persistent increase in the cumulative IRF, this indicates that investors are gradually correcting their underreactions to positive news. If we see a persistent decrease, this suggests that investors are gradually correcting their initial overreactions to the news. When the function goes flat, the misreactions are fully corrected.

As shown in Figure 1, we see two distinct patterns. The solid black line represents the cumulative IRF of novel patent issuance, $\beta_{\tau,novel}$, while the red dashed line is the cumulative IRF of non-novel patent issuance, $\beta_{\tau,non-novel}$. The two lines represent the market's differential responses to groundbreaking versus incremental innovations. We see that novel patent issuance positively predicts returns in the next two years, which suggests that investors, in their assessment of novel patents, tend to exhibit under-reaction. The full value of ground-

breaking innovations is not immediately priced in, leading to a gradual adjustment in the firm's stock price. The issuance of novel patents leads to cumulative returns of 1%. Given the rarity of novel patents, this effect is economically significant.

By contrast, the red dashed line shows that non-novel issuance persistently predicts negative future returns. This negative predictability implies an overreaction to copycat innovations. After the initial overreaction, investors gradually correct for this bias, leading to a persistent negative effect on future returns.

Short-term return jumps combined with long-term return predictability give a comprehensive summary of misreactions to patent novelty. For a novel patent, although the stock price jumps up immediately following the patent news, the jump does not fully capture the value of the patent, so the price keeps going up subsequently, suggesting an under-reaction. On the other hand, for a non-novel patent, initially, we again see a positive jump, but part of it is due to investor over-excitement. Following the news, returns are gradually corrected downward, exhibiting negative predictability.

3.2 Cumulative Return Regressions

We next run an alternative specification in which we regress future cumulative returns on novel & non-novel patent issuance together with a host of known return predictors, same as in Section 3.1. We include industry×month fixed effects so that the specification resembles monthly Fama and MacBeth (1973) cross-sectional regressions with industry fixed effects. The dependent variables are future *cumulative* returns from 6 months to 36 months to capture the long-term price effects. We carefully eliminate the concern of survivorship bias created by cumulative returns. That is, for three-year cumulative returns, the observations will only include firms that exist at least three years after the patent issuance. However, we should also take into account investors' reactions to short-lived firms. For firms that do not exist for the full three-year period, we interpolate missing returns with their respective industry returns. The specification is thus

$$r_{t\to t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau} \quad (3)$$

As Table 2 shows, novel patent issuance positively predicts future long-term cumulative returns and non-novel patent issuance negatively predicts long-term returns. Novel issuance at most predicts 1.3% in the next three years, and non-novel issuance at most predicts -1%

in the next two years. These results confirm that investors under(over)-react to (non-)novel patent issuance.

To understand the difference in magnitude between cumulative return regressions and impulse response regressions, e.g., non-novel issuance predicts a larger effect (-2%) in the IRF plot, one could distinguish average cumulative returns and cumulative average returns. In impulse response, we compute average returns predictability in each horizon separately and accumulate the respective average effects. In cumulative return regressions, we compute the cumulative returns first and then regress out the average effects. The former takes the perspective of an investor rebalancing every period to get the average returns and the latter adopts a buy-and-hold strategy of an average firm for three years. We do not distinguish our preferred strategy but confirm the same conclusion with both strategies.

3.3 Robustness in Alternative Measures

To further support our main finding that investors underreact to novel innovations but overreact to non-novel innovations, we conduct several robustness checks with alternative measures and specifications in Online Appendix I.A.1.

First, to capture the intensive margin of misreactions, we use an alternative firm-level definition of innovation novelty. The measure is the fraction of novel patents among all patents granted each month, which is termed "novel intensity". This measure also addresses the common concern that different number of patents may lead to different responses that are not captured by the indicator variable in our main specification. We show that novel intensity positively predicts returns in the next two years, consistent with an underreaction to novelty. Second, we use the average similarity decile at the firm level as another continuous measure of firm novelty and show that this similarity measure negatively predicts future returns, consistent with an overreaction to non-novelty. We also investigate whether the misreaction to novelty is concentrated in novel patents with high or low quality. Do investors underreact only to novel patents with little impact or to impactful breakthroughs as well? Using 10-year *forward* similarity as a proxy for quality, we show a similar underreaction to both good- and bad-quality novel patents.

Finally, we investigate whether a trading strategy that longs novel firms and shorts non-novel firms generates superior performance. To capture the long-term effects, we use both a calendar-time portfolio approach and a low-frequency portfolio sort (similar to a buy-and-

hold strategy) both at three-year frequency. With both approaches, we show positive average alphas with common factor models.

3.4 Mechanism

In this section, we provide empirical evidence of the mechanism behind investor misreactions to patent novelty. We first provide suggestive evidence to rule out a rational risk-based explanation of return predictability, and then show direct evidence of mispricing in firms with novel versus nonnovel patent issuance. We also provide additional evidence that the mispricing is driven by a misperception of patent novelty. We argue against the notion that misperception of grant probability would drive our results, and in Online Appendix I.A.2, we provide a placebo test by reshuffling the novelty of the patents granted to the firm in each period. These discussions of the mechanism serve as guidance for a novelty misreaction model in Section 4.

Ruling out a risk-based explanation Return predictability does not always signify investor misreaction. A rational explanation for the positive predictability of patent novelty is that novel firms are riskier and, thus, investors demand a higher expected return as compensation. To test this hypothesis, we investigate the relationship between the issuance of (non-)novel patents and firms' future stock return volatility.

We do not find supporting evidence for a risk-based explanation using three different definitions of volatility. In Panel (a) of Figure 2, we run the following local projection regressions:

$$\sigma_{i,t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}, \quad (4)$$

where $\sigma_{i,t+\tau}$ is the standard deviation of realized daily returns in month $t+\tau$ and "Novel" equals 1 if the firm issues at least one patent with above-median novelty. We also control for firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal (r_{t-1}), and medium-term momentum ($r_{t-12\to t-1}$), and industry×month fixed effects.

We plot the impulse response for novel and non-novel issuance indicators. Firms issuing novel innovations even have significantly lower return volatility than firms issuing non-novel innovations, contrary to a risk-based story where novel firms have higher risks.

One may argue that realized total return volatility may not be the correct measure of risk since only systematic risk should be priced. We, therefore, test whether there is a significant difference in future market beta in response to the issuance of novel and non-novel patents. We run analogous regressions with future market beta as the dependent variable:

$$\beta_{i,t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}.$$

We estimate the monthly beta using daily returns in each month. Figure A.1 shows that non-novel patent issuance consistently predicts a higher beta than novel patents. If systematic risk is priced in returns, we should instead expect that novel patents predict higher returns. The fact that we see the converse pattern in the data suggests that the positive predictability of novel patents is unlikely to be driven by a risk-based story.

Another possible concern is that realized volatility is not the volatility that investors perceive at the time of issuance. To respond to this concern, we estimate the predictability of ex-ante implied volatility. We obtain the daily implied volatility of standardized 30-day at-the-money (ATM) options from OptionMetrics. Following Kelly et al. (2016), we exclude options with an implied volatility exceeding 100% per year. We construct a firm-month panel of implied volatility by averaging the implied volatility reported in each month. We run impulse response regressions with implied volatility as the dependent variable:

$$\text{Implied Vol}_{i,t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}. \tag{5}$$

Panel (b) of Figure 2 shows that non-novel patent issuance consistently predicts higher implied volatility than novel patents, implying that investors perceive higher volatility for firms with non-novel patents. If we believe that investors think novel patents are riskier, we should instead see a higher implied volatility for novel patents. On a side note, implied volatility decreases as we go further away from patent issuance. This is consistent with the idea that uncertainty around patent issuance gets resolved over time. We will explore more in our model of misreaction.

These disconnects between various definitions of risk and expected returns challenge the rational story and favor a behavioral story of investors' misreactions.

Earnings Forecast Errors, Mispricing, and Patent Novelty To establish a behavioral story of novelty misreaction, we show direct evidence of incorrect beliefs after novel vs.

non-novel patent issuance. Investors form overly pessimistic expectations about a firm's future profitability when it is granted novel versus non-novel patents. If investors trade based on these earnings expectations, the errors in earnings expectations would directly translate into return predictability. To test this mechanism, we study the subjective forecast errors after patent issuance, inspired by the setup in Ma (2023). The earnings expectations data come from IBES, which collects sell-side analyst forecasts of firm EPS. We extract the one-year and two-year earnings expectations, following the data construction process in Bouchaud et al. (2019). We measure consensus earnings forecasts by taking the median forecast from individual analyst-level forecasts issued within 45 days after the past announcement. We winsorize consensus expectations at the 1% level to remove anomalous forecasts. Denote the actual EPS in year $t+\tau$ as $\pi_{t+\tau}$ and the forecasts issued in year t as $F_t\pi_{t+\tau}$, and we regress earnings forecast error on patent issuance indicators in a firm-year panel:

$$\begin{aligned}\frac{\pi_{i,t+\tau} - F_t\pi_{i,t+\tau}}{P_{i,t-1}} = \alpha_\tau &+ \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_{t-1}\} \\ &+ \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_{t-1}\} + \gamma' X_{i,t-1} + \varepsilon_{i,t+\tau},\end{aligned} \tag{6}$$

where we scale EPS forecast errors by ex-ante stock price as in Bouchaud et al. (2019) and "(Non-)Novel" equals one if the firm issues at least one (non-)novel patent in year t. This specification captures the thought process in which an analyst in year t observes the novel vs. non-novel patents issued in year $t-1$ and needs to forecast the firm's profitability in the next two fiscal years. We use $t-1$ patent issuance to avoid lookahead bias, where patents are issued after the earnings forecasts are made.

A positive coefficient, $\beta_{\tau,d}, d \in \{novel, non-novel\}$, suggests an underreaction as investors form too pessimistic forecasts given a novel patent issuance. On the other hand, a negative coefficient suggests that investors are overly optimistic after the issuance event. In Table 3, we see positive coefficients for novel issuance and negative coefficients for non-novel issuance, suggesting that analysts give overly pessimistic forecasts after novel issuance and optimistic forecasts after non-novel issuance. This is consistent with the hypothesis that investors undervalue novel patents and overvalue non-novel patents. The coefficient for novel-patent issuance is statistically significant, while the one for non-novel issuance is only marginally insignificant due to a much smaller sample. As robustness, in Table I.A.1, we regress the same forecast errors on novel intensity, an intensive-margin measure of the firm's novelty. We see positive coefficients, which indicate that analysts are more pessimistic about

a firm's future profitability if it issues more novel patents. This is again consistent with an underpricing of firms with novel patents. Both results provide a belief-based mispricing explanation of the misreactions to patent novelty: investors form too pessimistic beliefs about firms with novel patents and hence underprice these stocks.

Patent Grant Probability versus Value The magnitude of return reaction to patent issuance is determined by the probability of a successful issuance multiplied by the unit value of the patent. This leads to two alternative interpretations of the results.

First, if investors perceive a lower grant probability of novel patents than the truth, this also results in an underreaction to novel patent issuance rather than an underestimation of patent value. First, we address this concern by arguing that, immediately after the patent issuance, there is no uncertainty to the investors about how long it took for the patent to be granted, so they should quickly correct their perception of the success probability of novel versus non-novel patents. This immediate correction of misperception is inconsistent with our results, as the mispricing takes two years to correct in our setting.

Second, if the patent office biases the approval rate of novel technologies to be lower than non-novel technologies, the magnitude of misreactions between novel and non-novel patents should adjust for different grant probabilities. The same 1% misreaction to novel versus non-novel patents would predict a stronger undervaluation of novel patents compared to the overvaluation of non-novel patents. To investigate the extent to which this creates large differences, we compare the average grant probability between novel and non-novel patents. In particular, we run the following patent-level regressions:

$$(\text{Grant - Filing Date})_i \times 12/365 = \alpha_m + \alpha_{cpc} + \alpha + \beta \mathbb{1}\{\text{Novel}_i\} + \varepsilon_i,$$

where we control the grant month fixed effects and indicators of the CPC technology class. Table 4 demonstrates the average grant length of novel versus non-novel patents. Non-novel patents, on average, take 32.3 months to get granted, and novel patents take 2.3 months longer. Using the properties of an exponential distribution, this translates into a grant probability of (non-)novel patent in a month of 2.9% (3.1%). The grant probabilities in an average month of novel versus non-novel innovation only differ by 0.2%, which is not economically significant.

4 A Model of Misreaction to Novelty

In this section, we present a framework to understand the return misreactions to patent novelty and the return dynamics after patent issuance. The model is consistent with a mispricing mechanism to patent novelty, as argued in Section 3.4 and also explains key empirical facts in Section 3.1, that is, a short-term jump that is indistinguishable across patent novelty, followed by a positive (negative) predictability for (non-)novel patents.

This is a bounded-rationality model where investors do not know the true novelty of a patent when it is first issued. Instead, they receive unbiased, noisy signals about patent novelty and are Bayesian learners of the true novelty. Since true patent novelty only depends on *ex-ante* information, it is therefore knowable to investors when patents come out. However, due to cognitive limits, investors are unsure about the patent's novelty, as new patents are hard to understand and process. This aside, investors are rational: they update from the signal in a Bayesian manner. The key prediction of the model is that at patent issuance, investors' perception of novelty is close to an intermediate prior; they, therefore, overestimate the novelty of non-novel patents and underestimate the novelty of novel patents.

Connecting perceived novelty to patent value, we show that the model makes predictions about expected returns after the issuance of patents with different levels of novelty, which is directly testable in the data. First, when patents are first issued, the return differences are not economically significant across novelty. Second, under- and over-reaction is monotonic: the more novel the patents are, the more strongly investors under-react to them. Second, the noisier the signals, the stronger the misreactions, and the longer it takes for the price to converge to the correct level.

4.1 Short-Term Reactions

We first derive the model predictions for the return reactions to patent issuance when a patent is issued. We denote the true novelty of a patent as $x \in [0, \infty)$. Investors have a prior distribution of the patent's true novelty, which we assume to be lognormally distributed:

$$\log x \sim N(\mu, \sigma^2).$$

We assume a lognormal prior to ensure that patent novelty is non-negative while maintaining tractability. Woodford (2020) also uses a lognormal prior in a model of cognitive

imprecision; he argues that lognormality is consistent with Fechner's explanation for Weber's law, where the subjective sensation of a stimulus is proportional to the logarithm of its intensity. Our model, however, differs from the Woodford (2020) model in a nuanced way. In a model with cognitive imprecision, agents see the true value but their perceptual system encodes it imprecisely; by contrast, in our model, agents do not observe the true value.

When a patent is first issued, a bounded-rational investor does not know the true novelty of the patent; instead, he receives an unbiased but noisy signal about the patent novelty:

$$r \sim N(\log x, \nu^2).$$

Then, she forms the posterior mean of patent novelty in a Bayesian matter:

$$\hat{x}(r) \equiv E[x|r] = \exp\left[\left(\frac{\nu^2}{\sigma^2+\nu^2}\right)\log\bar{x} + \left(\frac{\sigma^2}{\sigma^2+\nu^2}\right)r\right], \tag{7}$$

where $\bar{x} \equiv \exp[\mu + 1/2\sigma^2]$ is the prior mean.

Therefore, for a patent with true novelty x, the investor's estimate $\hat{x}$ follows a log-normal distribution with mean and variance

$$e(x) \equiv E[\hat{x}|x] = \exp\left(\beta^2\nu^2/2\right)\bar{x}^{1-\beta}x^{\beta} \quad var[\hat{x}|x] = (\exp(\beta^2\nu^2)-1)e(x)^2, \tag{8}$$

where $\beta \equiv \sigma^2/(\sigma^2+\nu^2) < 1$.

We see that the mean perception, $E[\hat{x}|x]$, shrinks to an intermediate level $\bar{x}$, and thus the investor underestimates novelty for novel patents, whereas for non-novel patents, she overestimates novelty.

Connecting Patent Novelty to Returns To generate a price effect from novelty misperception, we relate the investor's perceived novelty of the patent to the return reaction to patent issuance. In order to be consistent with our empirical findings, the true patent value must be positively correlated with novelty. However, the exact functional form of the relationship is unknown. Thus, we proceed as follows: we first decompose the return at issuance as

$$R_j = v_j + \varepsilon_j.$$

We also follow Kogan et al. (2017) in imposing that patent value is nonnegative and follows a normal distribution truncated at 0. We further assume that patent value is positively correlated with the perceived novelty of the patent in a log-linear way. That is,

$$v_j \sim trunc^{+}(\gamma_0 + \gamma_1 \log \hat{x}_j + \varepsilon_{x,j}).$$

Since the distribution of the sum of a truncated normal variable v_j and standard normal variable ε_j has no closed form, we simulate 1,000,000 independent draws of the two random variables and plot the mean of the simulated joint distribution, $E[R_j|x_j]$.

Figure 3 shows that novel patents have issuance returns lower than the rational benchmark, thus exhibiting under-reaction, while non-novel patents have issuance returns higher rational, thus exhibiting overreaction. Moreover, if investors receive very noisy signals, the returns differences across patent novelty will be economically insignificant. This matches our empirical findings that the firm's 3-day returns are positive for both novel and non-novel patent issuance, but they are not economically different, as presented in Table 1.

4.2 Long-Term Dynamics

In the previous section, we showed, in a static setting, that the short-term return reactions to novelty shrink to an intermediate level and are not economically different across levels of novelty. In the long term, as returns converge to the correct level, we shallobserve a more pronounced divergence in return responses. To capture this, we resort to a dynamic model.

We assume that, after patent issuance, investors receive a noisy signal *in each period*. The prior about patent novelty is again: $\log x \sim N(\mu, \sigma^2)$. In each period, investors receive an identical noisy signal:

$$r_t \sim N(\log x, \nu^2).$$

Model Solution Conditional on the series of signals, the posterior distribution in each period t is lognormal:

$$\log x|r_0, ..., r_t \sim N\left(\left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2}\right)^{-1}\left[\frac{t+1}{\nu^2}\left(\frac{1}{t+1}\sum_{i=1}^{t+1} r_i\right) + \frac{1}{\sigma^2}\mu\right], \left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2}\right)^{-1}\right). \tag{9}$$

Denote this conditional mean as μ_c and conditional variance as σ_c^2, and the posterior mean of novelty x at time t follows $\log E[x|r_1, ..., r_t] \equiv \log \hat{x}_t = \mu_c + \frac{1}{2}\sigma_c^2$. We are interested in the average novelty perception of a large sample of investors for each novelty level x.

$$\log e_t(x) \equiv \log E[\hat{x}_t|x] = E\left[\mu_c + \frac{1}{2}\sigma_c^2\right] + \frac{1}{2}var\left(\mu_c + \frac{1}{2}\sigma_c^2\right), \tag{10}$$

$$\text{where } E\left[\mu_c + \frac{1}{2}\sigma_c^2\right] = \left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2}\right)^{-1}\left[\frac{t+1}{\nu^2}\log x + \frac{1}{\sigma^2}\left(\mu + \frac{1}{2}\sigma^2\right)\right]$$

$$var\left(\mu_c + \frac{1}{2}\sigma_c^2\right) = \left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2}\right)^{-2}\left(\frac{t+1}{\nu^2}\right)^2\frac{\nu^2}{t+1}.$$

We see that the dynamic mean perceptions of novelty, $E[\hat{x}_t|x]$, are compressed toward the prior level at first, and gradually put more weight on the true novelty.

To capture the average reaction to novelty, same as the static case, we assume that the patent value is distributed as a truncated normal with a mean that is related to the logarithm of perceived novelty: $v_t \sim trunc^+(\gamma_0 + \gamma_1 \log \hat{x}_t + \varepsilon_{x,t})$. With this formulation, the distribution of patent value, v_t, in each period t is:

$$v_t \sim N^+\left(\gamma_0 + \gamma_1\left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2}\right)^{-1}\left[\frac{t+1}{\nu^2}\log x + \frac{1}{\sigma^2}\left(\mu + \frac{1}{2}\sigma^2\right)\right],\right.$$
$$\left.\gamma_1^2\left(\left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2}\right)^{-2}\left(\frac{t+1}{\nu^2}\right)^2\frac{\nu^2}{t+1}\right) + \sigma_x^2\right). \tag{11}$$

From Equation 11, we see two key predictions about the return reactions to novelty.

Prediction 1 (Perceived Patent Value)**.** *Average perceived patent value is a weighted combination of true value and prior value. Weights on the true value increase as t increases.*

At issuance, the weight on true novelty is small, and therefore, patent value is indistinguishable across novelty. As time passes, more weight is placed on true novelty, and thus, the model predicts a divergence in value as the posterior mean converges to the correct level.

Prediction 2 (Signal Noise)**.** *The weight on the true value is* inversely *correlated with signal noise. With noisier signals, the misreactions to novelty are stronger, and it takes longer to converge to the correct level.*

For illustration, we plot the average cumulative return to novelty, $E[R_t|x_t]$, where $R_t = v_t + \varepsilon_t, \varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. Since v_t is distributed as a truncated normal while ε_t is normally distributed, there is no closed form for the joint conditional distribution of $R_t|x_t$. We simulate 1,000,000 independent draws of the two random variables and plot the mean of the simulated joint distribution, $E[R_t|x_t]$.

In Figure 4, we plot the return reaction to ten novelty levels for 60 periods after the patent issuance. Simulations confirm key model predictions. First, investors underreact to the novel patents (large x) and overreact to non-novel ones but converge to the correct level of returns over time. In the short term, returns are compressed towards the prior, so they are not economically significantly different. However, we see a large divergence in return responses across different novelty levels as they converge to the correct level.

Simulations also align with key model comparative statics for the signal noise ν. A high ν indicates that investors receive very noisy signals. In reality, this approximates the case where the investors are primarily retail traders and do not have precise information on the novelty of firms' innovations. Conversely, a low ν corresponds to the case where firms have mostly institutional investors with professional knowledge. Institutional investors should better understand the technological advances and innovation strategies of the firms they invest in and thus receive less noisy signals about patent novelty.

Figure 5 plots the return dynamics after the patent issuance. We consider two levels of signal precision. High precision is the case where signal precision is the same as prior standard deviation ($\nu = \sigma$); low precision is the case where $\nu = 2\sigma$. With noisier signals, the initial reaction differs less across different novelty levels, suggesting stronger misreactions. We also see that investors take longer to converge to the correct level of reaction.

4.3 Empirical tests of the model

In this section, we empirically test three key model predictions. We start with the predictions for the short-term reactions; we then plot the long-term dynamics in the data. Finally, we test how misreactions vary with signal noise.

Short-Term Response The model predicts that the return reaction at issuance is indistinguishable between different novelty. To test this, we run firm-day-level regressions of 3-day returns at patent issuance on ten-decile indicators of patent novelty. Each indicator is

equal to 1 if patents with a given novelty level are granted to the firm on this day. If there is no patent issued, all indicators will be 0, which means that the counterfactual returns are the returns from the firms without patent issuance that are in the same industry and have similar firm observables:

$$R_{i,t,t+2} = \alpha_{ind,t} + \sum_{k=1}^{10} \beta_k \mathbb{1}\{i \in \text{Novelty Decile}_{k,t}\} + \gamma' X_{i,t} + \varepsilon_{i,t,t+2}, \tag{12}$$

where $\alpha_{ind,t}$ are industry×issuance-date FEs, and $X_{i,t}$ are market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum.

Figure 6 shows significant positive average returns in almost all ten deciles. We also see that the difference in response is not economically and statistically significant between novelty deciles. This is consistent with the model where, at issuance, since investors are unsure about patent novelty, they give an intermediate prior valuation to all patents.

Long-Term Response Despite similar short-term responses, the model predicts more significant differences in the long term, as investors receive more signals about patent novelty. We expect a positive return drift for novel innovations and a return reversal for non-novel innovations. Moreover, the more non-novel the patent is, the stronger reversal we shall see (the strongest negative predictability).

We test this directly by generalizing our result in Figure 1 to all ten deciles. We plot the cumulative impulse response of future 3-year monthly returns for ten deciles of patent novelty:

$$r_{i,t+\tau} = \alpha_{ind,t} + \sum_{d=1}^{10} \beta_{\tau,d} \mathbb{1}\{i \in \text{Novelty Decile}_{d,t}\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}. \tag{13}$$

This is the exact same specification as our main result with Equation 2, but instead of splitting novel versus non-novel by median, we explore all ten deciles. Figure 7 shows that, although in real data, the average reactions are noisier, we see that positive predictability decreases as we move down the novelty deciles, and we start to see negative predictability for non-novel deciles. The differences in impulse response are large and consistent with the model predictions.

Institutional Holdings and Signal Precision Finally, in the model, signal precision is a key parameter that drives the return response. If the signals are noisier, we expect stronger misreactions and slower convergence to the correct level. To test this mechanism in real data, we compare the return predictability of firms with high versus low institutional holdings. Institutional investors know better about the technology and shall receive less noisy signals about patent novelty, and thus exhibit weaker misreactions and faster convergence. We use institutional holdings data from FactSet, construct the institutional ownership (IO) as in Ferreira and Matos (2008), and split firms into high versus low IO by the monthly median. Figure 8 shows the results from the following regressions:

$$r_{i,t+\tau} = \alpha_{ind,t} + \sum_{d\in\{Novel,Non-Novel\}} \beta_{\tau,d,high} \mathbb{1}\{i \in d_t\} \times \mathbb{1}\{i \in \text{High Inst Hold}_t\}$$
$$+ \sum_{d\in\{Novel,Non-Novel\}} \beta_{\tau,d,low} \mathbb{1}\{i \in d_t\} \times \mathbb{1}\{i \in \text{Low Inst Hold}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}$$

We plot the cumulative impulse responses, $\beta_{\tau,d,high}$ and $\beta_{\tau,d,low}$, for $d =$ novel or non-novel issuance. We see exactly what the model predicts: firms with high institutional holdings have less positive predictability after novel issuance and less negative predictability after non-novel issuance, suggesting that the misreactions are weaker for firms with high institutional holdings. We also see that firms with high institutional holdings exhibit zero predictability earlier than firms with low institutional holdings, consistent with faster convergence.

5 Impact on Future Innovation

In previous sections, we documented a systematic difference in the equity market's response to patents with different novelty: underreaction to novel patents and overreaction to non-novel patents. The implications of this discrepancy are profound. It raises a pivotal question about the essence of innovation: could investors' reactions translate into real consequences for firms' future innovation directions?

In this section, we first examine whether firms' returns can predict future changes in their innovation directions. Ordinary least squares (OLS) estimates suggest that firms' disappointing three-day returns following patent issuance predict lower shares of sustaining innovation and lower shares of novelty-seeking innovations relative to "copycatting" (non-novel) ones in the future. To address the endogeneity issue, we instrument returns with

sensational news as exogenous distractions to investors and provide causal evidence for the same effects. This shift to copycat innovations implies that financial markets could push firms in sub-optimal innovation directions by exploiting existing technology with low remaining value and not trying the high-value novel directions.

5.1 Firm Innovation Directions and Dynamics

Firms' innovation directions are crucial for their long-term growth. A well-structured innovation strategy enables corporations to sustain customer value, create new markets, and even displace competitors from their established domains. However, firms' innovation strategies vary significantly based on their unique preferences and choice sets, making it challenging to systematically document their exact decision-making processes.

As an alternative, we infer a firm's innovation trajectory by analyzing its future patenting behavior.[6] Given the focus of our study on patent novelty, we classify firms' innovation directions into three categories, each closely tied to the novelty of their patenting activity. The first category is sustaining innovation, which involves incremental improvements that build on existing technologies, particularly those developed by the firm. For example, Apple's pioneering multi-touch technology[7] laid the groundwork for incremental innovations like pinch-to-zoom[8] and slide-between-user-interface[9], shaping the modern smartphone industry. Inspired by this, we construct the measure "number of follow-up patents" to quantify a firm's sustaining innovation using a patent pairwise citation network. Specifically, for firm i in year-quarter t, we count the number of patents filed by firm i in the subsequent four, twelve, or twenty quarters (i.e., one, three, or five years) that self-cite the firm's patents issued at time t. A higher value of this measure indicates that the firm generates more sustaining innovation to follow up on its recently issued technology.

The second type of innovation is "novelty-seeking." Beyond sustaining innovation built upon existing technologies, firms can actively pursue new ideas in their innovation process. Apple, for instance, has consistently created novel technologies, from the embedding of elec-

[6] One limitation of this approach is that it does not capture failed research projects, rejected patent applications, or ongoing long-term R&D investments. However, granted patents provide a valid measure of the realized changes in a firm's innovation direction.

[7] The US patent US20060097991A1, titled "Multipoint touchscreen".

[8] "Pinch-to-zoom": the US patent US9619132B2, titled "Device, method and graphical user interface for zooming in on a touch-screen display".

[9] "Slide between user interface": the US patent US9772751B2, titled "Using gestures to slide between user interfaces".

tronic devices in wearables - facilitating the Apple Watch launch - to the recent eye and hand tracking technologies behind Apple Vision Pro.[10] Conversely, the third type, "copycatting innovation", involves firms strategically replicating competitors' technologies, such as Apple's adoption of "folding device technology[11]," previously introduced by Samsung. To quantify these innovation types, we measure the number of novel and non-novel patents filed by firm i in the subsequent one, three, or five years following quarter t.When constructing these measures, we exclude firms' "self-citing" patents to prevent mechanical biases from these sustaining innovations and ensure an accurate representation of future innovation directions.[12]

Using these innovation measures, we address whether firms' short-term returns around patent issuance can predict changes in their future innovation directions. Specifically, we estimate a regression model at the firm-issuance-day level that relates firms' innovations in subsequent quarters to their three-day returns after patent issuance events within a given quarter[13]:

$$\text{Future Innovation}_{i,t+1\to t+\tau} = \beta r_{i,d\to d+2,t} + \gamma' Z_{i,t} + \alpha_i + \varepsilon_{i,d\to d+2,t}.$$

In this model, our main focus is on future innovation outcomes, $\text{Future Innovation}_{i,t+1\to t+\tau}$, representing the previously defined innovation directions (sustaining, novelty-seeking, or copycatting). To more precisely capture shifts in firms' future innovation strategies - particularly their choices between novelty-seeking and sustaining innovations following novel technology development - we construct two share-based measures rather than directly using patent counts as dependent variables.[14]

$$\text{Novelty-seeking Innovation}_{i,t+1\to t+\tau} = \frac{\text{No. of novel patents filed w/o self-citing}_{i,t+1\to t+\tau}}{\text{No. of patents filed w/o self-citing}_{i,t+1\to t+\tau}},$$

[10] "Embedding the electronic device to wearable": the US patent US8787006B2, titled as "Wrist-worn electronic device and methods therefor"; Technology in eye and hand tracking: For example, the US patent US10893801B2, titled as "Eye tracking system and method to detect the dominant eye".

[11] "folding device technology": the US patent application US20230011092A1, titled as "Hybrid coverlay/window structure for flexible display applications"

[12] Sustaining innovations are inherently less novel and thus more likely categorized as non-novel, potentially biasing measures if not excluded.

[13] We implement our model on a firm-quarter-issuance-day panel to better align with real-world practices. Firms typically reassess innovation strategies on a quarterly basis, motivating our quarterly aggregation of dependent variables.

[14] Given our definition of share-based measures, the share of copycatting innovation is the converse of novelty-seeking innovation; an increase in one necessarily implies a decrease in the other.

$$\text{Sustaining Innovation}_{i,t+1\to t+\tau} = \frac{\text{No. of follow-up patents filed}_{i,t+1\to t+\tau}}{\text{No. of total patents filed}_{i,t+1\to t+\tau}}.$$

The key explanatory variable, $r_{i,d\to d+2,t}$, represents firm i's three-day returns around patent issuance events in quarter t, rescaled to a quarterly basis for interpretability.[15] Since a firm's tendency to innovate in a particular direction depends on various factors, ranging from its labor and capital constraints to the existing innovation capacity, we include a set of firm-level controls $Z_{i,t}$ in the regression following Kogan et al. (2017). Specifically, $Z_{i,t}$ includes the log of capital stock, the log number of employees, and the log of output to account for the influence of firm size, as larger firms with greater resources may be more likely to maintain their innovation trajectories. Additionally, we control for the log of profits, as firms with higher profit margins might invest more in R&D and generate more novelty-seeking innovations. Moreover, we incorporate the ratio of non-novel patents issued to firm i on day d and the knowledge stock (log of total patents granted in the past five years) as proxies for the firm's innovation capability and productivity. Lastly, we include the book-to-market ratio as an additional control, given its potential correlation with a firm's future growth opportunities. Firms with high book-to-market ratios may have limited growth prospects, potentially influencing their future innovation directions. In this model, we primarily exploit the within-firm variations over time by including firm fixed effects.

In Table A.1, we document that even after controlling for various firm-level factors influencing innovation indirections, firms experiencing lower equity returns around patent issuance tend to reduce sustaining innovation in the following twenty quarters. Futhermore, these firms shift toward fewer novelty-seeking patents relative to "copycatting" patents over the subsequent 12 to 20 quarters (three to five years).

To summarize, in this section, we first introduce measures of firms' innovation directions based on patent filings and citation networks, and then examine whether firms' equity returns predict changes in their future innovation directions. The OLS estimates suggest firms with lower three-day returns around patent issuance subsequently reduce their pursuit of sustaining and novelty-seeking innovations relative to imitative ones. However, these OLS results can be biased due to unobserved factors correlated with both equity returns and future innovation decisions - such as organizational changes in the R&D department that simultaneously influence investors' expectations and firms' innovation outcomes. In the next section, we address this endogeneity issue to identify the causal relationship between

[15] We convert three-day returns to quarterly returns using the formula: $r_{i,d\to d+2,t} = \frac{\text{3-day returns}\times 252}{3\times 4}$.

investors' misreaction to patent issuance and firms' future innovation directions.

5.2 Does Investors' Behavior Impact Firms' Innovation Directions?

We revisit the firm-issuance-day regression model relating future innovation outcomes to equity returns specified in Section 5.1:

$$\text{Future Innovation}_{i,t+1\to t+\tau} = \beta r_{i,d\to d+2,t} + \gamma' Z_{i,t} + \alpha_i + \varepsilon_{i,d\to d+2,t}.$$

To address the endogeneity concern, we estimate an instrumental variable (IV) regression. Specifically, we exploit investor distractions caused by plausibly exogenous sensational news events occurring simultaneously with patent issuance announcements, as these events add noise to information signals and divert investor attention away from patent-related news. Following Peress and Schmidt (2020) and Eisensee and Strömberg (2007), we define sensational news using "news pressure," measured as the median number of minutes devoted daily to the first three segments of US news broadcasts. We instrument firm returns $r_{i,d\to d+2,t}$ using the count of high news-pressure days (top decile of news pressure in a given year) within the three-day patent issuance window (Tuesday to Thursday, as patents are issued each Tuesday). To ensure that the distracting news is plausibly exogenous to firms' future innovation decisions, we manually exclude days featuring economic or technological news, leaving a set of 924 days with distracting sensational news between 1975 and 2021.

Using this instrument, we exploit the within-firm time-series variations by comparing the periods with differing levels of investor distraction due to sensational news. Specifically, we estimate the following first-stage regression:

$$r_{i,d\to d+2,t} = \beta \text{Distraction}_{d\to d+2,t} + \gamma' Z_{i,t} + \alpha_i + \varepsilon_{i,d\to d+2,t}.$$

We then regress a firm's future innovation measures on the predicted returns $\widehat{r_{i,d\to d+2,t}}$ in the second stage:

$$\text{Future Innovation}_{i,t+1\to t+\tau} = \beta \widehat{r_{i,d\to d+2,t}} + \gamma' Z_{i,t} + \alpha_i + \varepsilon_{i,d\to d+2,t}.$$

Our IV specification relies on two key identification assumptions to ensure we capture the causal effect of investor reactions to patent news on firms' future innovation directions. First, we require a strong correlation between the frequency of distracting events

$Distraction_{d\to d+2,t}$ (i.e., days with sensational news) and the firm's equity return $r_{i,d\to d+2,t}$ during the same three-day window. Specifically, we expect that a higher frequency of sensational news events increases investor distraction, weakening their return responses to patent issuance announcements.[16] The second key assumption, the exclusion restriction, is not directly testable. However, because our sensational news measure explicitly excludes economic and technology-related events by construction, it is plausibly exogenous and unlikely to directly influence firms' future innovation strategies.

In this model, the null hypothesis, consistent with the Modigliani-Miller theorem, states that fluctuations in short-term equity returns should not affect firms' future investment or production decisions, including innovation strategies. We empirically test this hypothesis by examining changes in the two innovation directions defined earlier. Starting with firms' changes in novelty-seeking innovations, Table 5 presents IV estimates and the corresponding first-stage results. Columns (2), (4), and (6) confirm the strength of our instrument: higher investor distraction from sensational news ($Distraction_{d\to d+2,t}$) consistently lowers firms' three-day equity returns around patent issuance events. Columns (1), (3), and (5) further show how firms' shares of novelty-seeking patents filed (relative to "copycatting" patents) evolve in the subsequent four, twelve, and twenty quarters following short-term equity returns. The IV estimates demonstrate that such exogenous equity return declines lead firms to shift future innovation away from novel patents. Specifically, on average, a 10 percent decline in equity returns (on a quarterly basis) reduces the share of novel patents by approximately 1.1 percent over five years. One concern is that the firms' total returns can be driven by systematic risk premia that are not related to firm-specific performance. We conduct robustness checks using three-day abnormal returns[17] around patent issuance as the key independent variable. Results in Table I.B.1 remain consistent, further supporting the causal relationship between disappointing stock returns and shifts in firms' innovation direction.

A particularly interesting question is whether the same firm's pursuit of novel technology is more sensitive to market reactions during periods when a greater share of its patents are novel. We hypothesize that investors' undervaluation of novel patents could dispropor-

[16] This "strong instrument" assumption can be empirically tested using the effective F-statistics from the first-stage regression, which we report in the results tables presented later.

[17] We calculate three-day abnormal returns by subtracting market returns and retain only non-negative abnormal return observations. Negative abnormal returns around patent issuance could reflect unrelated negative news events, where investor distraction would weaken market reactions, reversing the intended effect and undermining instrument validity.

tionately discourage firms from future investment in novel technologies during the period in which they have a higher proportion of novel patents granted.[18] To test this hypothesis, we split our sample into high- and low-novelty periods, defined by whether the percentage of novel patents issued exceeds 50% in a given quarter, and repeat our IV analyses separately on each subsample. The results in Table 6 strongly support our hypothesis. We find that disappointing equity returns have more significant negative impact on firms' future novelty-seeking innovation during high-novelty periods. Specifically, in these periods, a 10 percent decline in quarterly equivalent equity returns reduces the share of novel patent filings by approximately 0.7 percent over the next twelve quarters, cumulating to around a 1 percent decrease over five years. In contrast, the impact is considerably weaker during low-novelty periods.

Having established that market reactions affect firms' novelty-seeking innovation, we now investigate the impact on sustaining innovation. Repeating the IV analysis using Sustaining Innovation$_{i,t+1\to t+\tau}$ as the outcome, we find that exogenous declines in equity returns around patent issuance - triggered by investor distractions from sensational news - significantly reduce firms' future filings of follow-up patents. Intuitively, lower market returns may signal to the firm that the market undervalues its recently developed technologies, discouraging further investment. Statistically, as shown in Table 7, on average, a 10 percent equity return decrease (on a quarterly basis) reduces the share of sustaining patents by 1.0 percent over the subsequent four quarters and cumulatively by 0.7 percent over five years. Robustness checks using three-day abnormal returns yield very similar results (as shown in Table I.B.3).

We also investigate whether market reactions differently affect firms' sustaining innovation during high- and low-novelty periods. Unlike novelty-seeking innovations, which are primarily influenced during high-novelty periods, we hypothesize that disappointing returns discourage firms from pursuing follow-up innovations regardless of current novelty levels. To test this, we apply our IV specification separately to high- and low-novelty period subsamples. Results in Table 8 confirm our hypothesis, showing that equity return declines significantly reduce firms' future sustaining innovation shares in both high- and low-novelty contexts.

[18] One possible mechanism is that disappointing market reactions lead firms to believe that investors systematically undervalue novel technologies. Due to managerial short-termism or agency conflicts, managers consequently reduce investments in novel innovation.

5.3 Mechanism and Discussion

We provide causal evidence that disappointing stock returns around patent issuance lead novel firms—those with a higher proportion of newly granted novel patents—to shift innovation strategies away from investing further in their existing novel technologies or pursuing other novel ideas, toward imitating market trends. However, the underlying mechanism remains unclear. One plausible channel involves financial constraints: firms relying heavily on external financing are especially sensitive to stock prices, which directly influence their cost of capital. Consistent with the equity dependence channel in Baker et al. (2003), financially constrained firms might distort investment due to short-term stock performance. For example, Kodak, the company that invented the first-ever digital camera in 1977, was granted a patent for this revolutionary invention[19]. However, this novel technology did not gain significant market recognition or stock returns at the time. Facing financial constraints, Kodak executives abandoned further investment in digital technologies. Instead, they decided to follow the market trend and join the innovation race in "medical equipment".

Beyond financial constraints, other mechanisms, such as agency conflicts between managers and shareholders, may also drive the causal effects we document. Managers have tenure pressure and career concerns, which can induce managerial myopia and short-termism. In addition, stock-based managerial compensation further incentivizes managers to pursue short-term stock market gains. We plan to explore and empirically test these alternative channels in future research.

6 Conclusion

In this paper, we document that investors systematically differ in their reactions to patent issuance news based on patent novelty, underreacting to novel technologies but overreacting to non-novel ones. We argue against a rational risk-based explanation - that novel patents predict higher risk - and provide direct evidence of investor mispricing between novel and non-novel patents. A bounded-rationality model, where investors face cognitive limitations and uncertainty regarding patent novelty at issuance, effectively explains these empirical patterns of mispricing.

We further examine the real economic consequences of investor mispricing, providing

[19]The US patent 4131919, titled "Electronic still camera."

causal evidence that stock market reactions significantly influence novel firms' future innovation trajectories. Specifically, disappointing equity returns around patent issuance push innovative firms away from further developing their original technologies and pursuing other novel innovations, causing a shift toward producing more copycat innovations. These findings suggest that managers pay close attention to short-term stock price movements when making innovation decisions, potentially driven by managerial short-termism (due to stock-based incentives or career concerns) or by financial constraints that force equity-dependent firms to rely on costly external financing.

Our findings have significant policy implications. Financial market misperceptions about patent novelty discourage firms from pursuing future innovations in novel technologies, despite evidence (Figure B.1 and Table B.1) that novel patents produce higher private and social value. Instead, firms disproportionately invest in established technologies already favored by markets but possessing lower residual economic potential. Over time, this bias might lead to fewer breakthrough innovations and economic inefficiencies. Policies designed to enhance investors' understanding of patent novelty, such as improved patent novelty disclosure, investor education on the patent system, and clearer patent classifications, could help improve welfare. One promising future research question is to quantify the economic welfare losses arising from innovation misallocation driven by market misreactions. Another interesting direction is to examine how public-market misperceptions influence private-market innovation, ultimately shaping society's broader innovation trajectory.

References

Acemoglu, Daron, "Distorted Innovation: Does the Market Get the Direction of Technology Right?," Technical Report, National Bureau of Economic Research 2023.

_ , Ufuk Akcigit, and Murat Alp Celik, "Radical and incremental innovation: The roles of firms, managers, and innovators," *American Economic Journal: Macroeconomics*, 2022, *14* (3), 199–249.

Akcigit, Ufuk and William R Kerr, "Growth through heterogeneous innovations," *Journal of Political Economy*, 2018, *126* (4), 1374–1443.

Babina, Tania, Asaf Bernstein, and Filippo Mezzanotti, "Financial disruptions and the organization of innovation: Evidence from the great depression," *The Review of Financial Studies*, 2023, *36* (11), 4271–4317.

Baker, Malcolm, Jeremy C Stein, and Jeffrey Wurgler, "When does the market matter? Stock prices and the investment of equity-dependent firms," *The quarterly journal of economics*, 2003, *118* (3), 969–1005.

Bernstein, Shai, "Does going public affect innovation?," *The Journal of finance*, 2015, *70* (4), 1365–1403.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer, "Diagnostic expectations and stock returns," *The Journal of Finance*, 2019, *74* (6), 2839–2874.

_ , _ , Yueran Ma, and Andrei Shleifer, "Overreaction in macroeconomic expectations," *American Economic Review*, 2020, *110* (9), 2748–82.

Bouchaud, Jean-Philippe, Philipp Krüger, Augustin Landier, and David Thesmar, "Sticky expectations and the profitability anomaly," *The Journal of Finance*, 2019, *74* (2), 639–674.

Chemmanur, Thomas J, Dongmei Li, Kevin Tseng, and Yu Yvonne Wang, "Measuring the economic value of an innovation when some investors are inattentive: Theory and evidence," 2022. Available at SSRN 3504261.

Chen, Qi, Itay Goldstein, and Wei Jiang, "Price informativeness and investment sensitivity to stock price," *The Review of Financial Studies*, 2007, *20* (3), 619–650.

Cheng, Stephanie F, Gus De Franco, Haibo Jiang, and Pengkai Lin, "Riding the blockchain mania: Public firms' speculative 8-K disclosures," *Management Science*, 2019, *65* (12), 5901–5913.

Cohen, Lauren, Karl Diether, and Christopher Malloy, "Misvaluing innovation," *The Review of Financial Studies*, 2013, *26* (3), 635–666.

Dong, Ming, David Hirshleifer, and Siew Hong Teoh, "Misvaluation and corporate inventiveness," *Journal of Financial and Quantitative Analysis*, 2021, *56* (8), 2605–2633.

Edmans, Alex, Itay Goldstein, and Wei Jiang, "The real effects of financial markets: The impact of prices on takeovers," *The Journal of Finance*, 2012, *67* (3), 933–971.

Eisensee, Thomas and David Strömberg, "News droughts, news floods, and US disaster relief," *The Quarterly Journal of Economics*, 2007, *122* (2), 693–728.

Eisfeldt, Andrea L, Edward Kim, and Dimitris Papanikolaou, "Intangible value," Technical Report, National Bureau of Economic Research 2020.

Fama, Eugene F and James D MacBeth, "Risk, return, and equilibrium: Empirical tests," *Journal of political economy*, 1973, *81* (3), 607–636.

_ **and Kenneth R French**, "The cross-section of expected stock returns," *the Journal of Finance*, 1992, *47* (2), 427–465.

_ **and** _ , "A five-factor asset pricing model," *Journal of financial economics*, 2015, *116* (1), 1–22.

Ferreira, Miguel A and Pedro Matos, "The colors of investors' money: The role of institutional investors around the world," *Journal of financial economics*, 2008, *88* (3), 499–533.

Fitzgerald, Tristan, Benjamin Balsmeier, Lee Fleming, and Gustavo Manso, "Innovation search strategy and predictable returns," *Management science*, 2021, *67* (2), 1109–1137.

Hirshleifer, David, Po-Hsuan Hsu, and Dongmei Li, "Innovative efficiency and stock returns," *Journal of financial economics*, 2013, *107* (3), 632–654.

_ , _ , and _ , "Innovative originality, profitability, and stock returns," *The Review of Financial Studies*, 2018, *31* (7), 2553–2605.

Hou, Kewei, Chen Xue, and Lu Zhang, "Digesting anomalies: An investment approach," *The Review of Financial Studies*, 2015, *28* (3), 650–705.

Kang, Min Jung and Y Han Kim, "Stock market liquidity and short-termism driven CEO turnover," *Available at SSRN 1876331*, 2017.

Kelly, Bryan, Dimitris Papanikolaou, Amit Seru, and Matt Taddy, "Measuring technological innovation over the long run," *American Economic Review: Insights*, 2021, *3* (3), 303–320.

_ , L'uboš Pástor, and Pietro Veronesi, "The price of political uncertainty: Theory and evidence from the option market," *The Journal of Finance*, 2016, *71* (5), 2417–2480.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, "Technological innovation, resource allocation, and growth," *The Quarterly Journal of Economics*, 2017, *132* (2), 665–712.

Kothari, Sagar P and Jerold B Warner, "Econometrics of event studies," in "Handbook of empirical corporate finance," Elsevier, 2007, pp. 3–36.

Krieger, Joshua, Danielle Li, and Dimitris Papanikolaou, "Missing novelty in drug development," *The Review of Financial Studies*, 2022, *35* (2), 636–679.

Kwon, Spencer Yongwook and Johnny Tang, "Extreme Events and Overreaction to News," 2021. Available at SSRN: https://ssrn.com/abstract=3724420.

Lerner, Josh, Morten Sorensen, and Per Strömberg, "Private equity and long-run investment: The case of innovation," *The Journal of Finance*, 2011, *66* (2), 445–477.

Ma, Song, "Technological obsolescence," 2023. Working paper.

Mitchell, Mark L and Erik Stafford, "Managerial decisions and long-term stock price performance," *The Journal of Business*, 2000, *73* (3), 287–329.

Novy-Marx, Robert, "The other side of value: The gross profitability premium," *Journal of financial economics*, 2013, *108* (1), 1–28.

Payne, Jeff L and Wayne B Thomas, "The implications of using stock-split adjusted I/B/E/S data in empirical research," *The Accounting Review*, 2003, *78* (4), 1049–1067.

Peress, Joel and Daniel Schmidt, "Glued to the TV: Distracted noise traders and stock market liquidity," *The Journal of Finance*, 2020, *75* (2), 1083–1133.

Stein, Jeremy C, "Efficient capital markets, inefficient firms: A model of myopic corporate behavior," *The quarterly journal of economics*, 1989, *104* (4), 655–669.

Wang, Chen, "Under-and Overreaction in Yield Curve Expectations," 2021. Available at SSRN: https://ssrn.com/abstract=3487602.

Woodford, Michael, "Modeling imprecision in perception, valuation, and choice," *Annual Review of Economics*, 2020, *12*, 579–601.

Figure 1: Cumulative IRF of Firm Returns on (Non-)Novel Issuance

This figure plots the cumulative impulse response of future returns on patent issuance for different levels of novelty. In particular, we run the following regression for each $\tau \in [1, 36]$ at the firm-month level:

$$r_{i,t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel} \mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,non-novel} \mathbb{1}\{i \in \text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau},$$

where the two indicator variables represent that the firm issues at least one novel/non-novel patent. We control for industry×month fixed effects and firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. We plot the cumulative coefficients, $\sum_{\tau=1}^{t} \beta_{\tau,d}$, over $t \in [1, 36]$ for $d \in \{novel, non-novel\}$. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

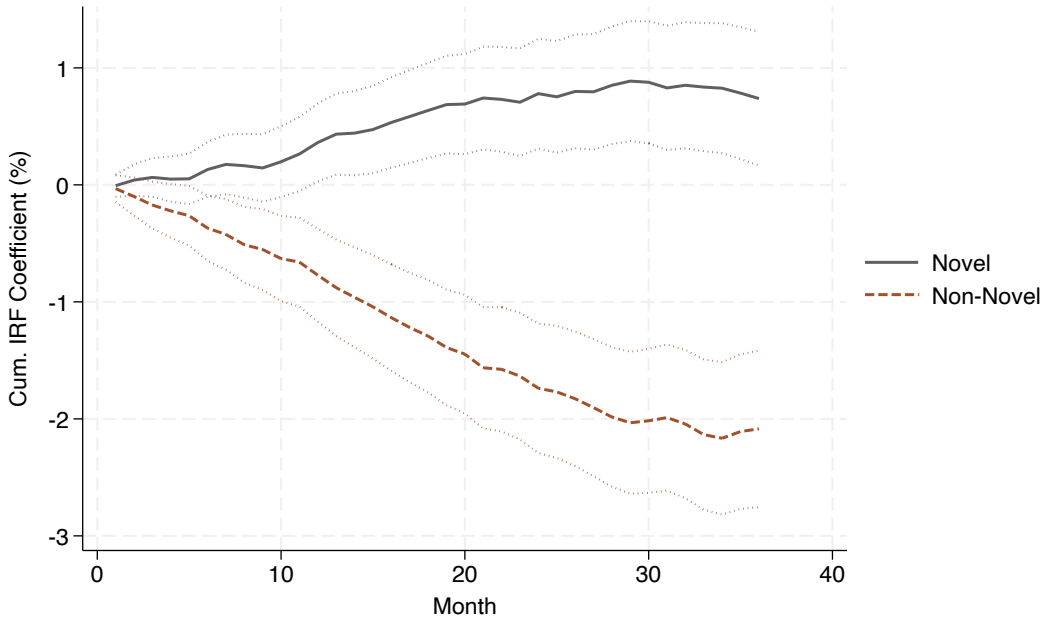


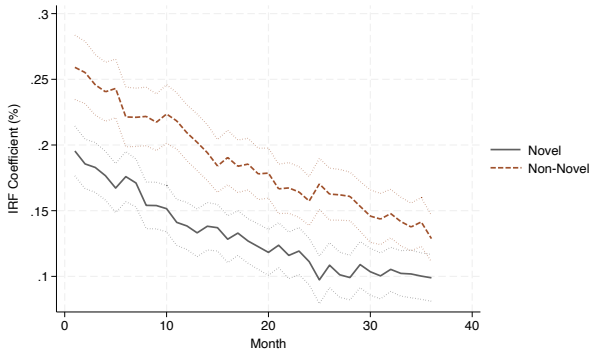
Figure 2: Impulse Response of Firm Realized Volatility after (Non-)Novel Patent Issuance

This figure plots the impulse response of future return volatility after patent issuance for different levels of patent novelty. We run the following regression for each $\tau \in [1, 36]$ at the firm-month level:

$$vol_{i,t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau},$$

where $vol_{i,t+\tau}$ represents two definitions of volatility for firm i in month $t+\tau$: in Panel (a), it is the standard deviation of daily returns and in Panel (b), it is the implied volatility for standardized ATM options maturing in 30 days. "(Non-)Novel" equals to 1 if the firm issues at least one patent with above(below)-median novelty. We control for industry×month fixed effects and firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. We plot coefficients, $\beta_{\tau,d}$, over $t \in [1, 36]$ for $d \in \{novel, non-novel\}$. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

(a) Realized Volatility



(b) Implied Volatility

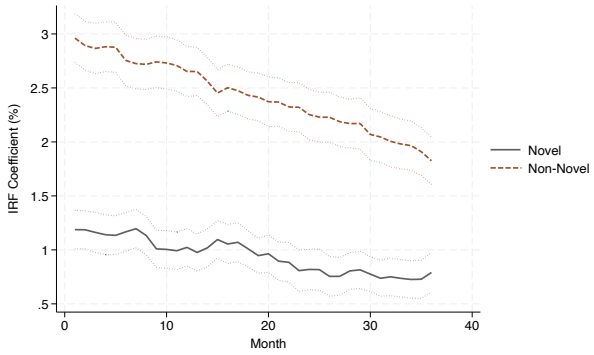


Figure 3: Theoretical Predictions of Issuance Returns to Novelty

This figure plots the model-predicted expected return of the firm on the day of patent issuance for different levels of true novelty. We pick reasonable numerical values for the exogenous model parameters and compute the model implied expected return. We assume that the firm return on patent issuance follows a normal distribution truncated at zero, whose mean is positively related to the logarithm of the perceived novelty. We specify that the prior distribution of true novelty follows a lognormal distribution with a mean of one and a standard deviation of one. We further assume that investors' unbiased signals have a standard deviation of 0.5, 0.8, or 1, ranging from precise to noisy signals. We relate perceived novelty to return response by assuming $\lambda_0 = 0$, $\lambda_1 = 0.1$, $\sigma_x = 0.1$, and $\sigma_\varepsilon = 0.12$. We are interested in the conditional return expectation, $E[R|x]$, which we estimate numerically using 1,000,000 random independent draws.

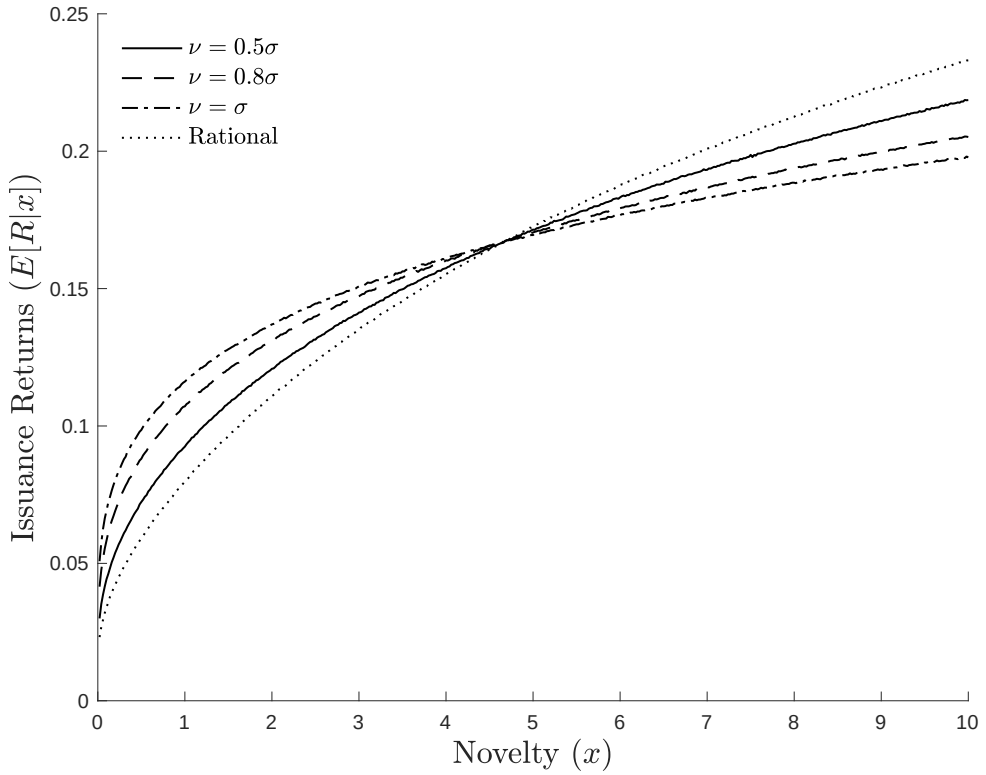


Figure 4: Theoretical Predictions of Dynamic Return Reaction by Novelty

This figure plots the model-predicted dynamic return expectation for ten values of true novelty ($x \in \{1, ..., 10\}$). We pick reasonable numerical values for exogenous model parameters and compute the model-implied expected novelty. We assume that the firm return on patent issuance follows a normal distribution truncated at zero, with a mean that is positively related to the logarithm of the perceived novelty. The prior distribution of true novelty follows a lognormal distribution with a mean of one and a standard deviation of one. Investors' unbiased signals have a standard deviation of 2. We relate perceived novelty to return response by assuming $\lambda_0 = 0$, $\lambda_1 = 0.1$, $\sigma_x = 0.1$, and $\sigma_\varepsilon = 0.12$. We are interested in the evolution of the conditional return expectations over 60 periods after the patent issuance, $E[R_t|x]$, which we estimate numerically using 1,000,000 random independent draws.

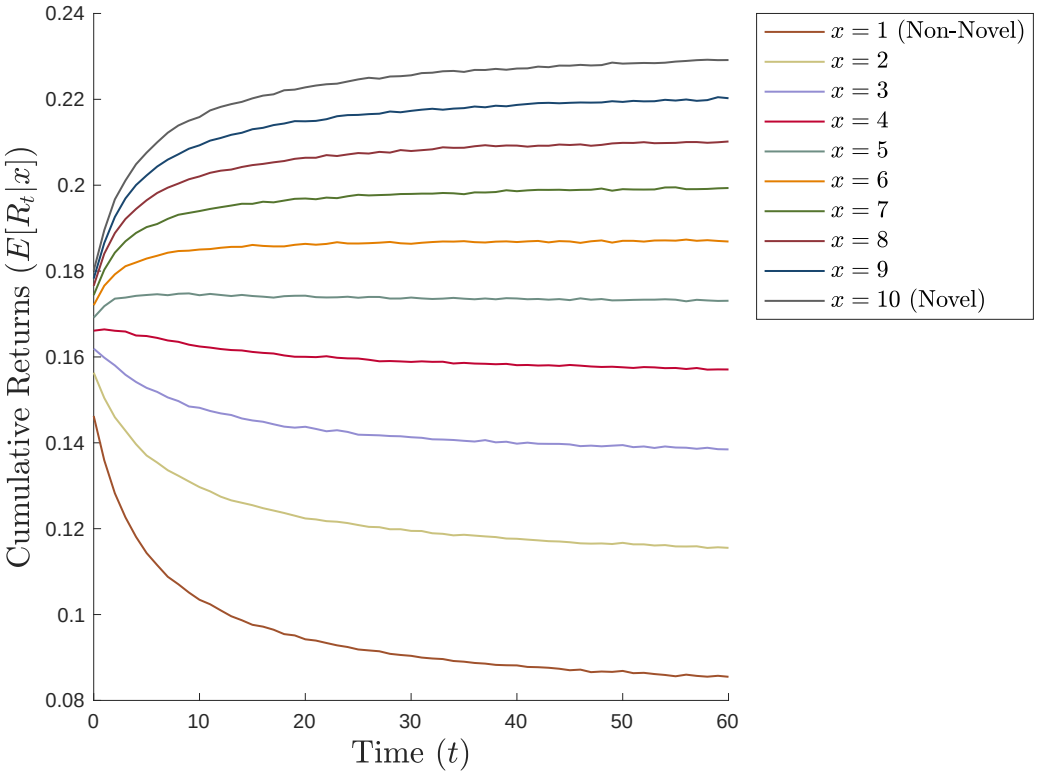


Figure 5: Theoretical Predictions of Dynamic Return Reaction by Signal Precision

This figure plots the comparative statics of model-predicted dynamic return expectations for ten values of true novelty ($x \in \{1, ..., 10\}$) over different levels of signal precision. We pick the reasonable numerical values for the exogenous model parameters and compute the model-implied expected novelty. We assume that the firm return on patent issuance follows a normal distribution truncated at zero, with a mean that is positively related to the logarithm of the perceived novelty. The prior distribution of true novelty follows a lognormal distribution with a mean of one and a standard deviation of one. We compare two scenarios where investors' unbiased signals have a standard deviation of 1 (precise) or 2 (noisy). We relate perceived novelty to return response by assuming $\lambda_0 = 0$, $\lambda_1 = 0.1$, $\sigma_x = 0.1$, and $\sigma_\varepsilon = 0.12$. We are interested in the evolution of the conditional return expectations over 60 periods after the patent issuance, $E[R_t|x]$, which we estimate numerically using 1,000,000 random independent draws.

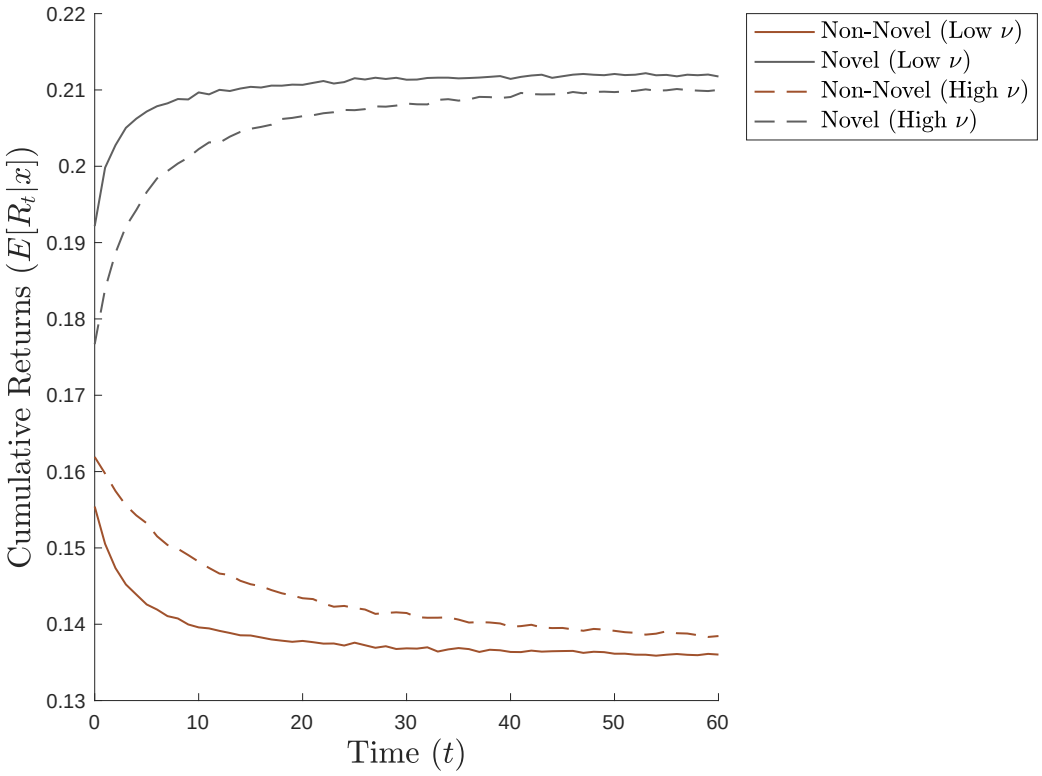


Figure 6: 3-Day Issuance Return across Patent Novelty

This figure depicts the 3-day returns after patent issuance for different levels of patent novelty. We run the following regression at the firm-day level:

$$R_{i,t\to t+2} = \alpha_{ind,t} + \sum_{k=1}^{10} \beta_k \mathbb{1}\{i \in \text{Novelty Decile}_{k,t}\} + \gamma' X_{i,t} + \varepsilon_{i,t\to t+2},$$

where the ten indicator variables represent that the firm issues at least one patent in a certain novelty decile on date t. We control for industry$\times$ issuance date fixed effects and firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. We plot the issuance coefficients, β_k, across ten deciles. The error bars are 90% confidence intervals with clustered standard errors at the issuance date level.

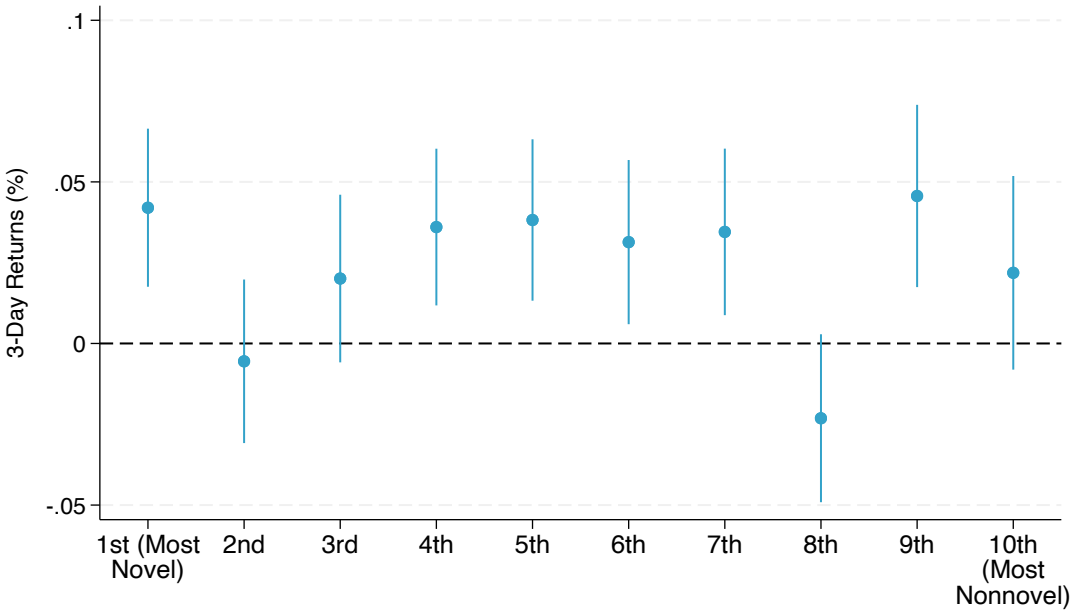


Figure 7: Cumulative IRF of Firm Returns after Patent Issuance across Patent Novelty

This figure plots the cumulative impulse response of future returns after patent issuance for different levels of patent novelty. In particular, we run the following regression for each $\tau \in [1, 36]$ at the firm-month level:

$$r_{i,t+\tau} = \alpha_{ind,t} + \sum_{d=1}^{10} \beta_{\tau,d} \mathbb{1}\{i \in \text{Novelty Decile}_{d,t}\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau},$$

where the ten indicator variables represent that the firm issues at least one patent in a certain novelty decile in month t. We control for industry×month fixed effects and firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. We plot the cumulative coefficients, $\sum_{\tau=1}^{t} \beta_{\tau,d}$, over $t \in [1, 36]$ for the ten deciles. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

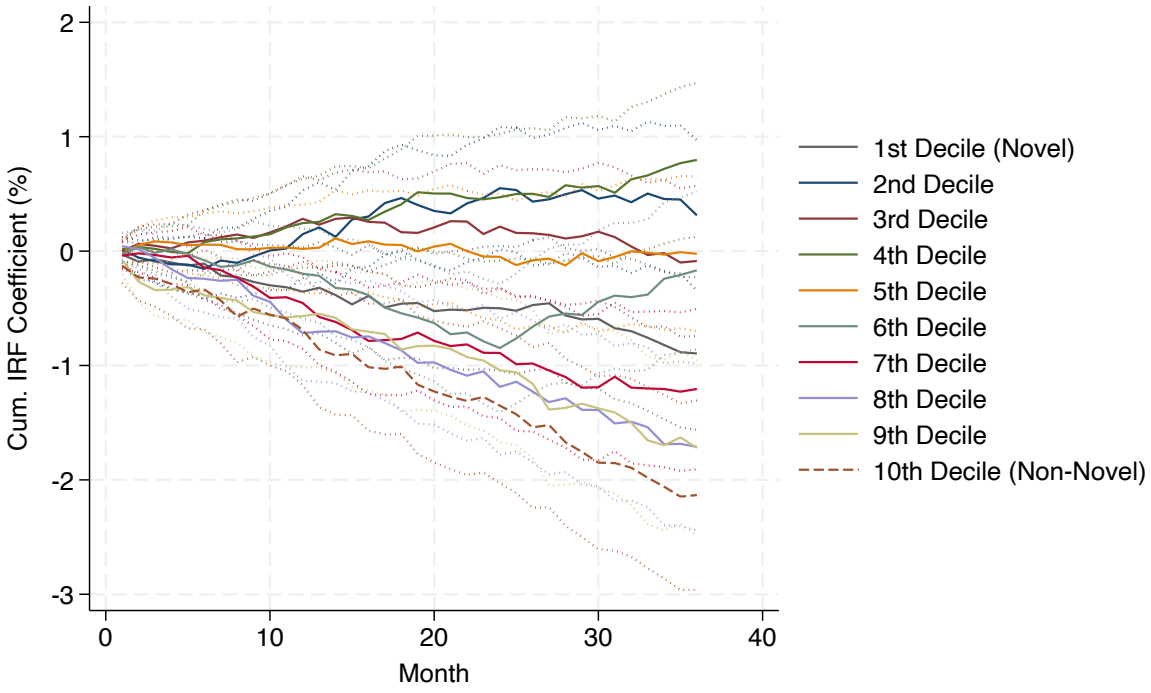


Figure 8: Cumulative IRF of Firm Returns after Patent Issuance by Institutional Holdings

This figure compares the cumulative impulse response of future returns after novel versus non-novel patent issuance for firms with high versus low institutional holdings. We run the following regression for each $\tau \in [1, 60]$ at the firm-month level:

$$r_{i,t+\tau} = \alpha_{ind,t} + \sum_{d \in \{Novel, Non-Novel\}} \beta_{\tau,d,high} \mathbb{1}\{i \in d_t\} \times \mathbb{1}\{i \in \text{High Inst Hold}_t\}$$
$$+ \sum_{d \in \{Novel, Non-Novel\}} \beta_{\tau,d,low} \mathbb{1}\{i \in d_t\} \times \mathbb{1}\{i \in \text{Low Inst Hold}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}$$

where we interact (non-)novel issuance indicators with dummies for high and low institutional holdings (IO). High IO firms have above-median institutional holdings, defined by Ferreira and Matos (2008). We control for industry×month fixed effects and firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. We plot the cumulative coefficients, $\sum_{\tau=1}^{t} \beta_{\tau,d,high}$ and $\sum_{\tau=1}^{t} \beta_{\tau,d,low}$ over $t \in [1, 60]$, for $d \in \{novel, non-novel\}$. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

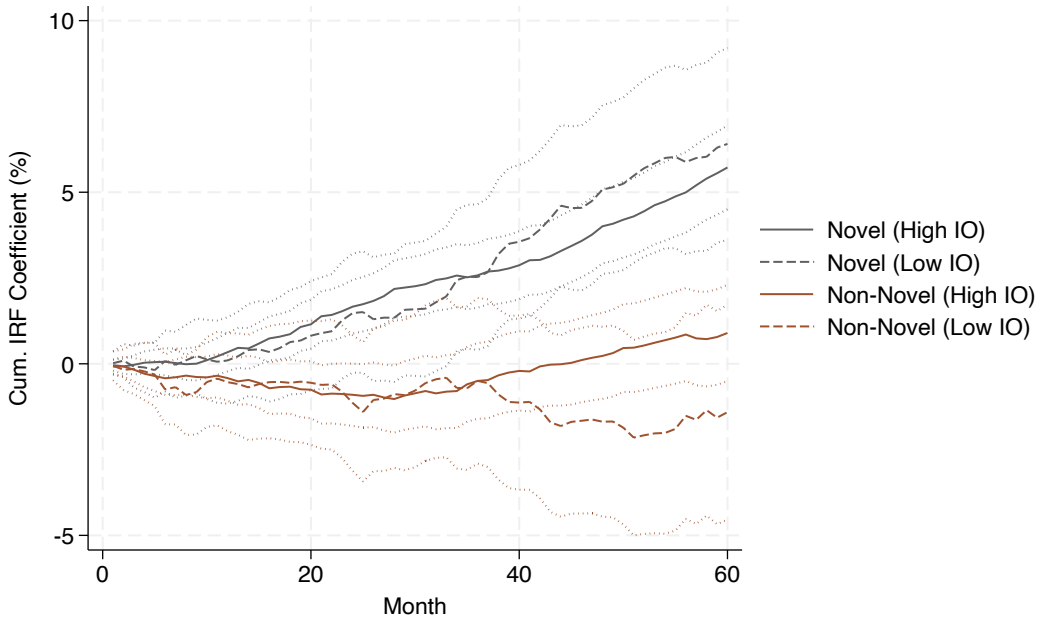


Table 1: Short-Term Returns on Patent Issuance Indicators

This table presents the OLS estimates of regressing the 3-day short-term returns on (novel/non-novel) patent issuance. In particular, we run the following regression at the firm-day level:

$$R_{t,t+2} = \alpha_{ind,t} + \beta \text{Patent Issuance Dummy}_{i,t} + \gamma' X_{it} + \varepsilon_{i,t},$$

where $R_{t,t+2}$ is the 3-day returns after patent issuance, the patent issuance dummies capture that the firm issues at least one (novel/non-novel) patent. We control for industry×issuance date fixed effects and firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. Standard errors are clustered at the issuance date level.

	(1)	(2)	(3)
		$R_{t,t+2}$ (%)	
Novel Issue$_t$	0.074***		0.009
	(5.01)		(0.45)
Non-Novel Issue$_t$		0.083***	0.022
		(5.18)	(1.32)
Patent Issue$_t$			0.061***
			(2.70)
R^2	0.153	0.153	0.153
Controls	Yes	Yes	Yes
Industry x Date FE	Yes	Yes	Yes
Observations	49687279	49687279	49687279

t statistics in parentheses

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

Table 2: Cumulative Returns on (Non-Novel) Issuance

This table examines the predictability of novel and non-novel patent issuance on future cumulative returns. In particular, we run the following firm-month panel regression:

$$r_{t\to t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau},$$

where the two indicator variables represent that the firm issues at least one novel/non-novel patent. We control for industry×month fixed effects and firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. We report the key estimates in the table. Standard errors are clustered at the year-month level.

	(1)	(2)	(3)	(4)
	6-Month Returns	1-Year Returns	2-Year Returns	3-Year Returns
Novel Issue$_t$	0.0616	0.3141*	0.9541***	1.3408***
	(0.55)	(1.92)	(4.05)	(4.54)
Non-Novel Issue$_t$	-0.2368	-0.4269**	-0.9200***	-0.7603**
	(-1.62)	(-2.03)	(-3.09)	(-2.14)
R^2	0.300	0.313	0.325	0.338
Controls	Yes	Yes	Yes	Yes
Industry x Month FE	Yes	Yes	Yes	Yes
Observations	2292514	2292514	2292514	2292514

t statistics in parentheses

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

Table 3: Earnings Forecast Errors on (Non-)Novel Issuance

This table examines the predictability of novel and non-novel patent issuance on earnings forecast error. In particular, we run the following firm-year panel regression:

$$\frac{\pi_{i,t+\tau} - F_t\pi_{i,t+\tau}}{P_{i,t-1}} = \alpha_\tau + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_{t-1}\} + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_{t-1}\} + \gamma' X_{i,t-1} + \varepsilon_{i,t+\tau},$$

where $\pi_{i,t+\tau} - F_t\pi_{i,t+\tau}/P_{i,t-1}$ are the forecast errors based on one- and two-year consensus earnings forecast, scaled by stock price at the end of fiscal year $t-1$ and the two indicator variables represent that the firm issues at least one novel/non-novel patent in year t. We control for firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. We report the key estimates in the table. Standard errors are double clustered at firm and year level.

	One-year		Two-year	
	(1)	(2)	(3)	(4)
	$(\pi_{t+1} - F_t\pi_{t+1})/P_{t-1}$		$(\pi_{t+2} - F_t\pi_{t+2})/P_{t-1}$	
Novel Patent Issuance$_{t-1}$	0.0274***	0.0205**	0.0584*	0.0452
	(2.79)	(2.51)	(1.89)	(1.68)
Non-Novel Patent Issuance$_{t-1}$	-0.0031	-0.0058	-0.0419	-0.0184
	(-0.36)	(-1.10)	(-1.29)	(-1.02)
R^2	0.000	0.002	0.000	0.006
Controls	No	Yes	No	Yes
Observations	97884	82783	80885	69007

t statistics in parentheses

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

Table 4: Average Approval Length between Novel and Non-Novel Patents

This table shows results from a patent-level regression of the time length in months between grant and filing date on whether or not the patent is a novel patent. The intercept is the average length of a non-novel patent granted and the novel coefficient is the additional months it takes for a novel patent to get granted. We also control for year-month FEs and CPC class indicators. Standard errors are clustered at the year-month level.

	(1)	(2)	(3)
Novel	2.037***	2.034***	2.347***
	(24.34)	(24.57)	(31.11)
Constant	32.958***	32.960***	32.347***
	(124.97)	(798.59)	(615.78)
R^2	0.003	0.161	0.164
Month FE	No	Yes	Yes
CPC Class	No	No	Yes
Observations	3578422	3578422	3575773

t statistics in parentheses

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

Table 5: Firm's Equity Returns and Future Novelty-seeking Innovations

This table examines whether firms' three-day return around patent issuance causes changes in their future novelty-seeking innovations. In particular, we run the following firm-quarter-week level IV regression:

$$\text{Novelty-seeking Innovation}_{i,t+1\to t+\tau} = \beta r_{i,d\to d+2,t} + \gamma' Z_{i,t} + \alpha_i + \varepsilon_{i,d\to d+2,t},$$

where we instrument a firm's short-term returns $r_{i,d\to d+2,t}$ with the number of days with sensational news within the three-day window surrounding patent issuance, capturing the exogenous distractions to investors in the first stage (the first-stage estimates are reported in columns (2), (4) and (6)). The dependent variable is a firm's future ratio of novelty-seeking innovation as defined in Section 5.1 in the subsequent four quarters (columns (1)), twelve quarters (columns (3)) and twenty quarters (column (5)) following its short-term returns in the quarter t. We include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including the log value of the capital stock, the log number of employees, the log value of the output, the log value of the profits, age, innovation capacity, and book-to-market ratio. We also control for firm fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	FS	$\tau = 12$	FS	$\tau = 20$	FS
$r_{i,d\to d+2,t}$	0.1138***		0.0932***		0.1113***	
	(2.68)		(3.12)		(2.93)	
Sensational News$_{d\to d+2,t}$		-0.0187***		-0.0238***		-0.0182***
		(-5.80)		(-7.20)		(-5.29)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	1975-2021	1975-2021	1975-2019	1975-2019	1975-2017	1975-2017
Effective F-stats		34		52		28
Observations	381169	381169	376231	376231	359897	359897

t statistics in parentheses

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

Table 6: Firm's Equity Returns and Future Novelty-seeking Innovations with Subsamples

This table examines, for the same firm, whether it is more likely to be affected by market reactions and change its future innovation directions when more novel patents are granted today. In particular, we categorize our sample into high- and low-novelty periods based on whether the firm's ratio of novel patents granted is above 50% in the quarter. Then, we run the following firm-quarter-week level IV regression:

$$\text{Novelty-seeking Innovation}_{i,t+1\to t+\tau} = \beta r_{i,d\to d+2,t} + \gamma' Z_{i,t} + \alpha_i + \varepsilon_{i,d\to d+2,t},$$

where we instrument a firm's short-term returns $r_{i,d\to d+2,t}$ with the number of days with sensational news within the three-day window surrounding patent issuance, capturing the exogenous distractions to investors in the first stage. The dependent variable is a firm's future ratio of novelty-seeking innovation as defined in Section 5.1 in the subsequent four quarters (columns (1) and (4)), twelve quarters (columns (2) and (5)) and twenty quarters (column (3) and (6)) following its short-term returns in the quarter t. We include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including the log value of the capital stock, the log number of employees, the log value of the output, the log value of the profits, age, innovation capacity, and book-to-market ratio. We also control for firm fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are clustered at the firm level.

	High-novelty			Low-novelty		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$r_{i,d\to d+2,t}$	0.0681*	0.0776***	0.1007***	0.0612	0.0295	0.0255
	(1.80)	(2.63)	(2.85)	(0.76)	(0.63)	(0.39)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	1975-2021	1975-2019	1975-2017	1975-2021	1975-2019	1975-2017
Observations	219186	216881	207778	161594	158970	151727

t statistics in parentheses

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

Table 7: Firm's Equity Returns and Future Sustaining Innovations

This table examines whether firms' three-day return around patent issuance causes changes in their future sustaining innovation. In particular, we run the following firm-quarter-week level IV regression:

$$\text{Sustaining Innovation}_{i,t+1\to t+\tau} = \beta r_{i,d\to d+2,t} + \gamma' Z_{i,t} + \alpha_i + \varepsilon_{i,d\to d+2,t},$$

where we instrument a firm's short-term returns $r_{i,d\to d+2,t}$ with the number of days with sensational news within the three-day window surrounding patent issuance, capturing the exogenous distractions to investors in the first stage (the first-stage estimates are reported in columns (2), (4) and (6)). The dependent variable is a firm's future shares of sustaining innovation as defined in Section 5.1 in the subsequent four quarters (columns (1)), twelve quarters (columns (3)) and twenty quarters (column (5)) following its short-term returns in the quarter t. We include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including the log value of the capital stock, the log number of employees, the log value of the output, the log value of the profits, age, innovation capacity, and book-to-market ratio. We also control for firm fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	FS	$\tau = 12$	FS	$\tau = 20$	FS
$r_{i,d\to d+2,t}$	0.0995***		0.0621***		0.0663***	
	(3.89)		(3.76)		(3.11)	
Sensational News$_{d\to d+2,t}$		-0.0190***		-0.0239***		-0.0183***
		(-5.89)		(-7.24)		(-5.31)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	1975-2021	1975-2021	1975-2019	1975-2019	1975-2017	1975-2017
Effective F-stats		35		52		28
Observations	382448	382448	376881	376881	360341	360341

t statistics in parentheses

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

Table 8: Firm's Equity Returns and Future Sustaining Innovations with Subsamples

This table examines, for the same firm, whether it is more likely to be affected by market reactions and change its future innovation directions when more novel patents are granted today. In particular, we categorize our sample into high- and low-novelty periods based on whether the firm's ratio of novel patents granted is above 50% in the quarter. Then, we run the following firm-quarter-week level IV regression:

$$\text{Sustaining Innovation}_{i,t+1\to t+\tau} = \beta r_{i,d\to d+2,t} + \gamma' Z_{i,t} + \alpha_i + \varepsilon_{i,d\to d+2,t},$$

where we instrument a firm's short-term returns $r_{i,d\to d+2,t}$ with the number of days with sensational news within the three-day window surrounding patent issuance, capturing the exogenous distractions to investors in the first stage. The dependent variable is a firm's future shares of sustaining innovation as defined in Section 5.1 in the subsequent four quarters (columns (1) and (4)), twelve quarters (columns (2) and (5)) and twenty quarters (column (3) and (6)) following its short-term returns in the quarter t. We include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including the log value of the capital stock, the log number of employees, the log value of the output, the log value of the profits, age, innovation capacity, and book-to-market ratio. We also control for firm fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are clustered at the firm level.

	High-novelty			Low-novelty		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$r_{i,d\to d+2,t}$	0.0848***	0.0559***	0.0614***	0.1160**	0.0599**	0.0720
	(3.36)	(3.11)	(2.84)	(1.97)	(2.05)	(1.52)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	1975-2021	1975-2019	1975-2017	1975-2021	1975-2019	1975-2017
Observations	219984	217301	208066	162065	159192	151880

t statistics in parentheses

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

A Additional Figures and Tables

A.1 Figures

Figure A.1: Cumulative IRF of Firm Market Beta after (Non-)Novel Patent Issuance

This figure plots the impulse response of future market beta after patent issuance for different levels of patent novelty. We run the following regression for each $\tau \in [1, 36]$ at the firm-month level:

$$\beta^{mkt}_{i,t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau},$$

where $\beta^{mkt}_{i,t+\tau}$ is the market beta of firm i in month $t+\tau$, computed by regressing daily returns for firm i on the market daily returns in month $t+\tau$. "(Non-)Novel" equals to 1 if the firm issues at least one patent with above(below)-median novelty. We control for industry×month fixed effects and firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. We plot coefficients, $\beta_{\tau,d}$, over $t \in [1, 36]$ for $d \in \{novel, non-novel\}$. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

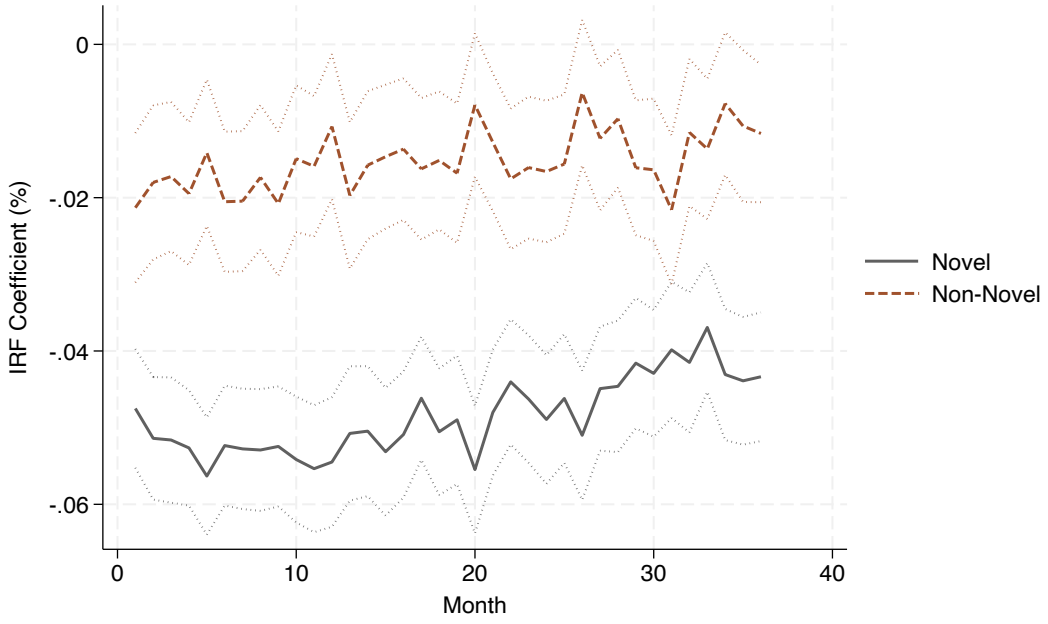


Table A.1: Firm's Future Innovation and Equity Return (OLS)

This table examines whether firms' 3-day returns surrounding patent issuance correlate with their changes in future innovation directions. In particular, we run the following firm-quarter-week level OLS regression:

$$\text{Future Innovation}_{i,t+1\to t+\tau} = \beta r_{i,d\to d+2,t} + \gamma' Z_{i,t} + \alpha_i + \varepsilon_{i,d\to d+2,t}$$

The dependent variable is a firm's future sustaining innovation or novelty-seeking innovation as defined in Section 5.1 in the subsequent four quarters (as shown in columns (1) and (4)), twelve quarters (columns (2) and (5)) and twenty quarters (columns (3) and (6)) following its' short-term three-day returns post patent issuance (i.e., from d to $d+2$) in a quarter t. We include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including the log value of the capital stock, the log number of employees, the log value of the output and profits, the innovation capability and book-to-market ratio. We also control for firm fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are clustered at the firm level.

	Sustaining			Novelty-seeking		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$r_{i,d\to d+2,t}$	0.0009**	0.0010***	0.0011***	0.0005	0.0011*	0.0013**
	(2.57)	(3.54)	(3.84)	(0.71)	(1.96)	(2.52)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	1975-2021	1975-2019	1975-2017	1975-2021	1975-2019	1975-2017
Adj. R^2	0.47	0.54	0.57	0.73	0.83	0.86
Observations	202572	199756	190771	201865	199412	190540

t statistics in parentheses

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

B Patent Private and Social Value

Figure B.1: Patent Private Value on Novelty

This figure plots the average patent's private value (as estimated in the Kogan et al. (2017)) against the patent novelty. In particular, we run the following patent-level OLS regression:

$$KPSS_i = \alpha_{yr} + \alpha_{cpc} + \sum_{d=1}^{10} \beta_d \mathbb{1}\{\text{Novelty Decile}_i = d\} + \varepsilon_i,$$

where $KPSS_i$ represents the private value of patent i in millions of nominal dollars (in red) or deflated to 1982 (million) dollars using the CPI (in blue). The term $\mathbb{1}\{\text{Novelty Decile}_i = d\}$ is a dummy variable that indicates which novelty decile d the patent i belongs to. We also include the patent's grant year and CPC-class fixed effects. We designate the tenth novelty decile - representing the most non-novel patents - as our benchmark group. We then plot the coefficient β_i for all remaining decile groups $i \in [1, 9]$. The error bars are 95% confidence intervals with clustered standard errors at the year level.

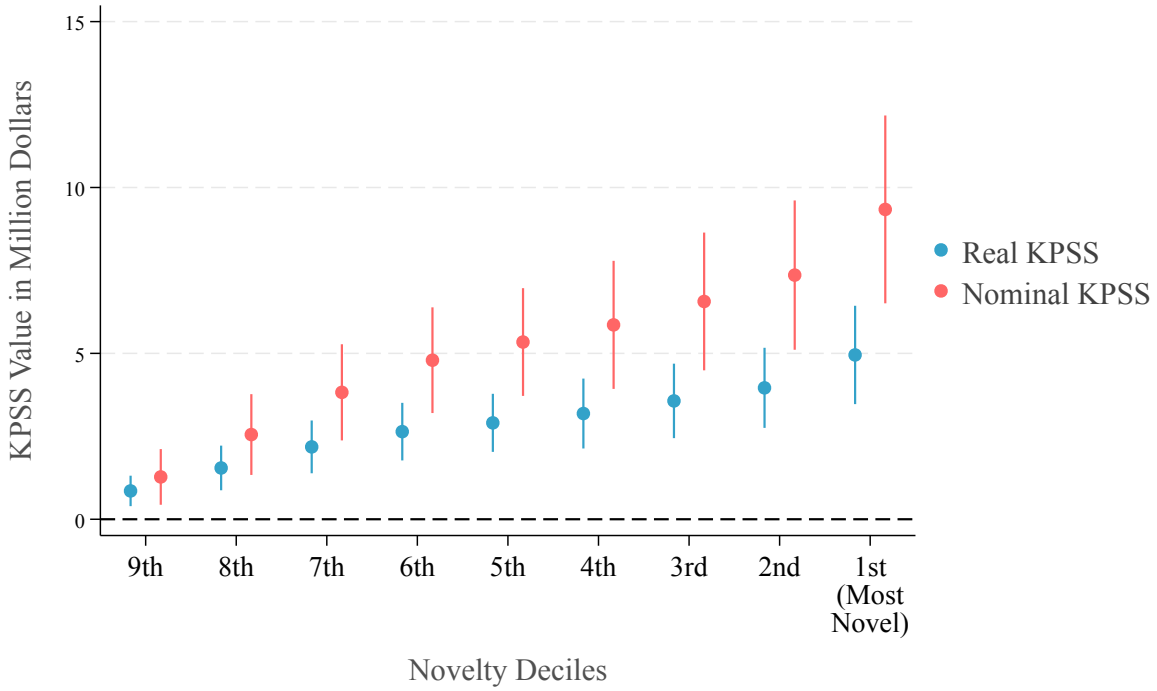


Table B.1: Patent Social Value on Novelty

This table examines the relationship between a patent's social value and novelty. We proxy a patent's social value using its total forward citations or the total private values (as estimated in the Kogan et al. (2017)) of all patents that cite it. In particular, we run the following patent-level OLS regression:

$$\text{Social Value Proxy}_i = \beta BS_i^5 \text{ Decile} + \gamma KPSS_i + \eta X_i + \varepsilon_i,$$

where Social Value Proxy$_i$ denotes our proxy for the social value of patent i as defined above. The term BS_i^5 Decile represents the novelty decile of the patent. We include $KPSS_i$ to control for a patent's private value. The vector X_i represents the additional controls, such as firm market capitalization and firm idiosyncratic volatility, that potentially influence the social value of a patent. We also control for multiple types of fixed effects in different specifications, including patent grant-year fixed effects, patent's CPC class-year fixed effects, firm-level fixed effects, and firm-year fixed effects. We report the key estimates in the table. Standard errors are clustered at the grant year level.

	(1)	(2)	(3)	(4)	(5)
	Total forward citations				
BS_i^5 Decile	-0.307***	-0.287***	-0.277***	-0.069**	-0.069**
	(-4.99)	(-4.85)	(-4.87)	(-2.49)	(-2.49)
Private Value	0.083***	0.070***	0.068***	0.003	0.003
	(9.72)	(10.14)	(9.94)	(0.63)	(0.62)
	Total private values of citing patents				
BS_i^5 Decile	-7.414***	-6.846***	-6.754***	-4.498***	-3.775***
	(-5.08)	(-4.92)	(-4.94)	(-5.19)	(-5.13)
Private Value	2.350***	1.984***	1.966***	1.148***	0.006
	(7.91)	(8.14)	(8.13)	(6.72)	(0.06)
Firm Size	No	Yes	Yes	Yes	Yes
Firm Volatility	No	No	Yes	Yes	Yes
Year-CPC FE	Yes	Yes	Yes	Yes	Yes
Firm-year FE	No	No	No	No	Yes
Firm FE	No	No	No	Yes	No

t statistics in parentheses

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

Online Appendix

I.A Robustness of Novelty Misreaction

I.A.1 Alternative Measures

Firm-level intensity measure as a proxy for novelty We provide an alternative definition of the novelty of firms' innovations. The new measure is the fraction of novel patents among all patents granted to the firm each month. In particular, we compute the "novel intensity", defined as:

$$\text{Novel intensity}_{i,t} = \frac{\text{\# of Novel Patents (Above-Median Novelty)}_{i,t}}{\text{Total \# of Patents}_{i,t}}.$$

We aim to use this measure to capture the intensive margin of investors' reactions to patent novelty. If investors under-react to novel innovations, firms with a larger fraction of novel patents should exhibit stronger positive return predictability.

We run return predictability regressions by replacing the novelty decile dummies with the (non-)novel intensity measure:

$$r_{i,t+\tau} = \alpha_t + \alpha_{ind} + \beta_\tau(\text{Non-})\text{Novel patent intensity}_{i,t} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}.$$

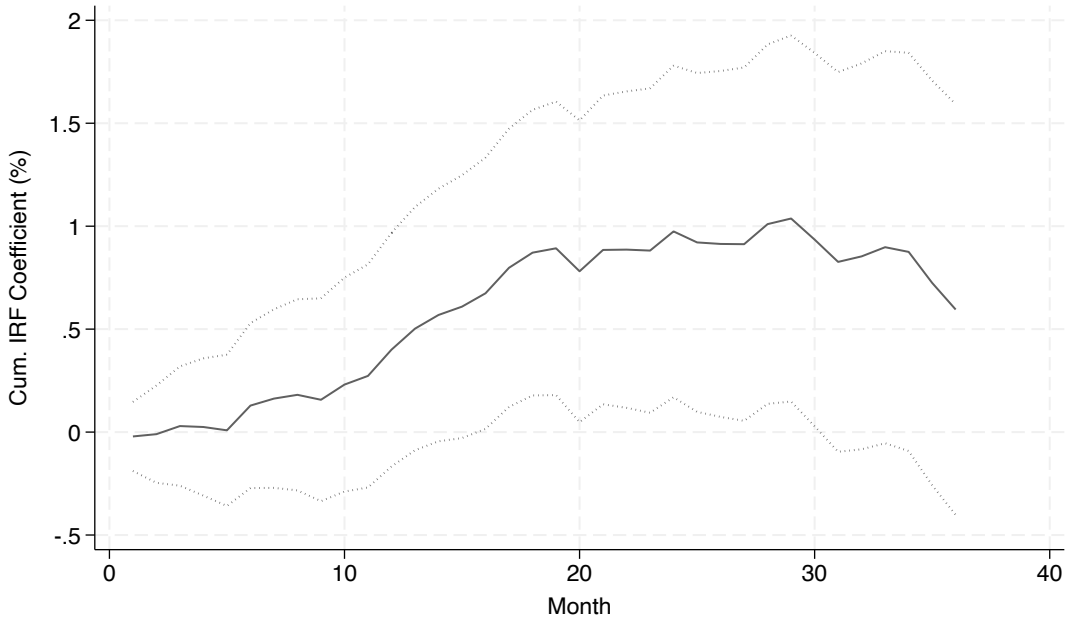
In Figure I.A.1, we see that novel intensity positively predicts future returns in the next two years, suggesting that investors underreact more strongly to firms with more novel patents. We lose some power in this specification because we are conditioning only on the firms that have at least one patent issuance. However, the advantage of this measure is that it is scaled by the number of patents issued; as such, the return predictability is not driven by one firm issuing many patents at the same time. Even with weaker power, we still find significant positive predictability for novel intensity; the predictability becomes insignificant in the long term, providing evidence that the mispricing is corrected after two years.

Figure I.A.1: Cumulative IRF of Firm Returns on Novel Patent Intensity

This figure plots the cumulative impulse response of future returns on novel patent intensity. We run the following regression for each $\tau \in [1, 36]$ at the firm-month level:

$$r_{i,t+\tau} = \alpha_{ind,t} + \beta_\tau \text{Novel intensity}_{i,t} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau},$$

where novel intensity is the fraction of novel patents over total patent issuance for each firm in each month. We define a patent as a novel patent if it has an above-median novelty. We control for industry×month fixed effects and firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. We plot the cumulative coefficients, $\sum_{\tau=1}^{t} \beta_\tau$, over $t \in [1, 36]$. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.



Firm-level multi-valued similarity score as a proxy for novelty Another alternative measure we use is the firm-level multi-valued similarity score. To implement this, we again classify patents into decile groups based on their backward similarity. This classification enables us to compute a similarity score at the firm-month level by directly averaging the firm's patents' decile values. Under this measurement scheme, a higher average similarity score indicates a firm's inclination towards non-novel innovations. If investors overreact to

non-novel innovations, we would expect to see a strong negative predictability of future returns by the firm's similarity score.

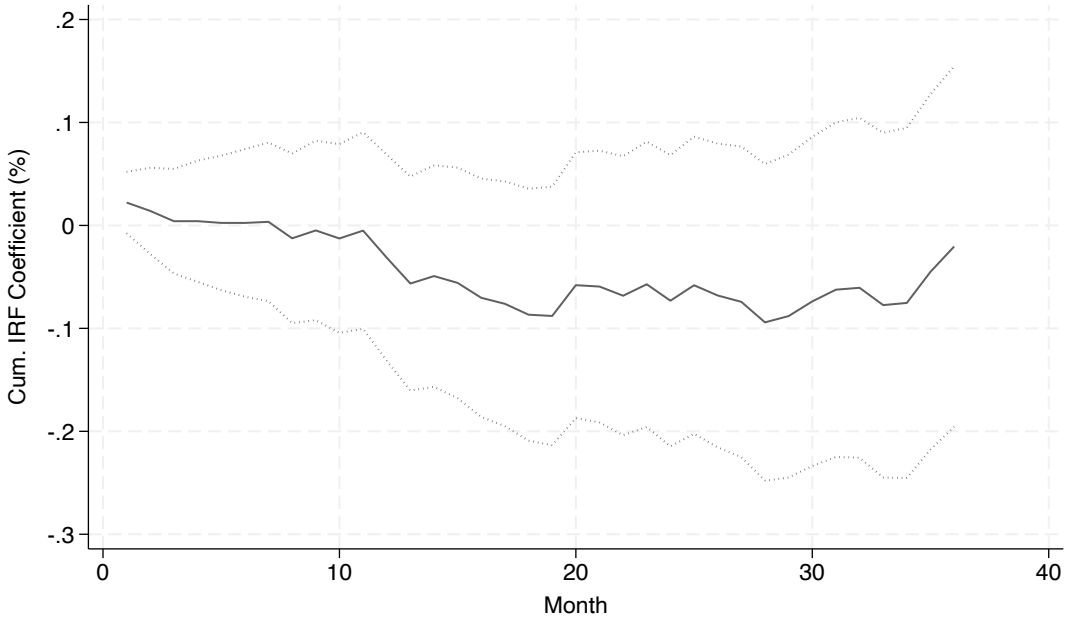
We run local projection regressions with the similarity score. As shown in Figure I.A.2, the similarity score displays negative predictability of future returns, confirming that investors overreact to incremental innovations.

Figure I.A.2: Cumulative IRF of Firm Returns on Similarity Score

This figure plots the cumulative impulse response of future returns on average similarity score. We run the following regression for each $\tau \in [1, 36]$ at the firm-month level:

$$r_{i,t+\tau} = \alpha_{ind,t} + \beta_\tau \text{Similarity score}_{i,t} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau},$$

where similarity score is the average patent similarity decile of all patents issued at the firm-month level. We control for industry×month fixed effects and firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. We plot the cumulative coefficients, $\sum_{\tau=1}^{t} \beta_\tau$, over $t \in [1, 36]$. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.



Dissecting the quality of novel patents We distinguish whether investors' misreactions to novelty is driven only by the issuance of "bad" novel patents. Do investors display underreactions because they perceive these novel patents as faltering endeavors? Or do they also undervalue impactful breakthrough innovations?

To address this, we use the 10-year *forward* similarity measure from Kelly et al. (2021), categorizing patents into "Good" and "Bad" patents based on their relative impact. A patent with higher forward similarity is more impactful because it opens up more future follow-up innovations. We define "good" as being above the median of the 10-year forward similarity in a given month. Akin to our main empirical strategy, we implement the following firm-month level regressions:

$$\begin{aligned} r_{i,t+\tau} = \alpha_{ind,t} &+ \beta_{\tau,good} \mathbb{1}\{i \in \text{Good}_t\} \times \text{Novel Intensity}_{i,t} \\ &+ \beta_{\tau,bad} \mathbb{1}\{i \in \text{Bad}_t\} \times \text{Novel Intensity}_{i,t} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}. \end{aligned}$$

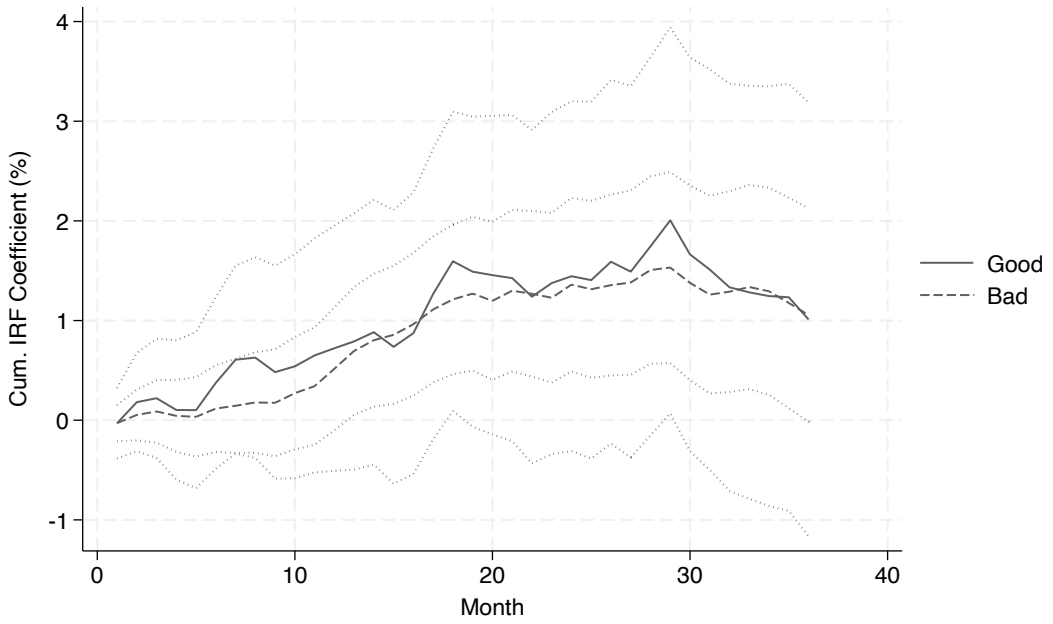
We plot the cumulative impulse response function (IRF) in Figure I.A.3. The underreactions to novelty are similar among firms with high versus low-quality firms, indicating that misreactions are not driven by investors' perception of patent quality.

Figure I.A.3: Cumulative IRF of Firm Returns on Good/Bad Novel Patent Intensity

This figure plots the cumulative impulse response of future returns on novel patent intensity for good versus bad patents. We run the following regressions for each $\tau \in [1, 36]$ at the firm-month level:

$$r_{i,t+\tau} = \alpha_{ind,t} + \beta_{\tau,good}\mathbb{1}\{i \in \text{Good}_t\} \times \text{Novel Intensity}_{i,t} + \beta_{\tau,bad}\mathbb{1}\{i \in \text{Bad}_t\} \times \text{Novel Intensity}_{i,t} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau},$$

where "Good"("Bad") equals to 1 if the firm issues more (less) than 50% impactful patents. Novel intensity is the fraction of novel patents over total patents issuance at the firm-month level. We define a patent as a novel patent if it has an above-median novelty, and as a good/bad patent if it has an above/below-median 10-year forward similarity. We control for industry×month fixed effects and firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. We plot the cumulative coefficients, $\sum_{\tau=1}^{t} \beta_\tau$, over $t \in [1, 36]$. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.



Portfolio sorts We investigate whether a trading strategy that longs firms with novel patents and shorts firms with non-novel patents generates positive alphas. We impose several

different portfolio approaches. First, following the canonical financial event study literature (Kothari and Warner, 2007), we use the Jensen-alpha (or calendar-time portfolio approach) to capture risk-adjusted long-horizon event study performance. Advocated by Mitchell and Stafford (2000), this approach automatically accounts for the cross-sectional correlations of the individual event firms, which is likely to be crucial in a patent issuance setting. In particular, each month, we form value-weighted portfolios of firms granted a (non-)novel patent within the prior three years. To maximize portfolio performance, we define (non-)novel patents as the ones in the most novel (similar) decile, and a firm is in the portfolio if there is a month in the past three years when it issues only (non-)novel patents. In Figure I.A.4, we plot the cumulative alpha of the long-short portfolio against three asset pricing models: CAPM, Fama and French (1992) 3-factor, and 3-factor after replacing the value factor with the intangible-adjusted value factor from Eisfeldt et al. (2020). We see that cumulative alpha is positive throughout the time series, and the average annualized alpha is 2.1% against CAPM, 1.5% against FF3F, and 0.6% against intangible-adjusted FF3F.

We also evaluate the performance of conventional characteristic-based long-short portfolio sorts. In particular, we construct value-weighted long-short portfolios based on the fraction of novel patents granted to a firm (novel intensity). A (non-)novel firm has a novel intensity above 70th (below 30th) percentile. We sort with two frequencies: every month and every three years to capture the long-term effects. Both portfolios are monthly rebalanced. Figure I.A.5 shows the cumulative alpha of three-year sorts, and Figure I.A.6 shows the cumulative alpha of monthly sorts. Both approaches generate positive alphas in most periods against CAPM and FF3F models, though portfolios do better in earlier time periods before the 1980s, when one would expect it's harder to figure out patent novelty with slower technology.

Figure I.A.4: Cumulative Alpha of Calendar-Time Portfolio Approach

This figure plots the cumulative alphas of a long-short calendar-time portfolio approach of novel vs. non-novel portfolio issuance. In each month, we sort each firm into the (non-)novel portfolio if it only issues patents with top (bottom)-decile novelty in any month in the past three years. Monthly rebalancing portfolio weights are determined by the ex-ante market cap. We plot the cumulative alpha against CAPM one-factor, Fama and French (1992) (FF) three-factor, and FF three-factor after replacing the value factor with the intangible-adjusted value factor (Eisfeldt et al., 2020).

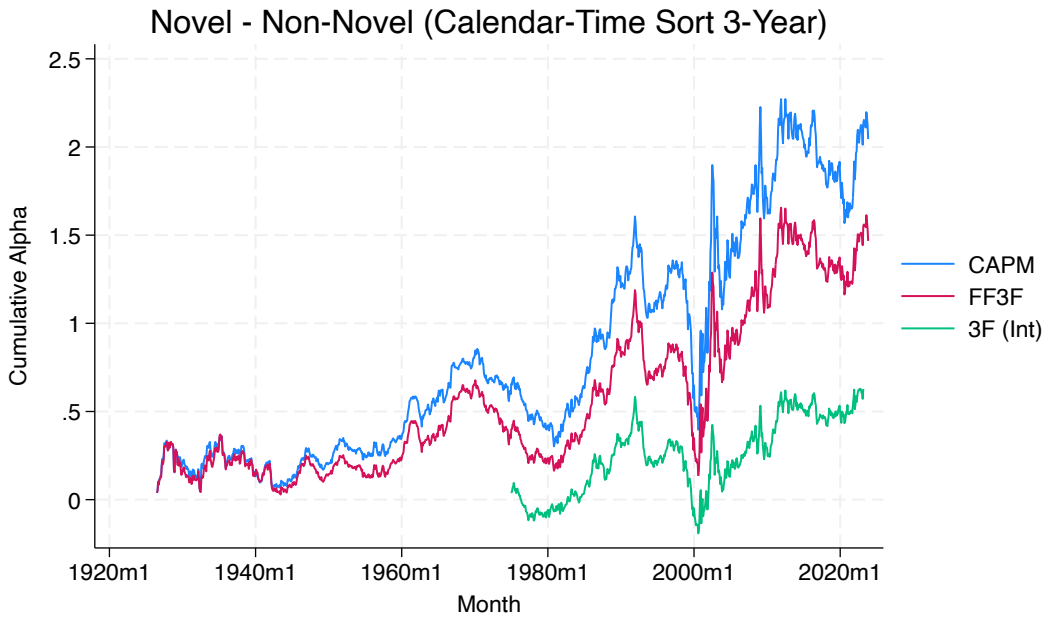


Figure I.A.5: Cumulative Alpha of 3-Year Portfolio Sorts on Novel Intensity

This figure plots the cumulative alphas of a value-weighted long-short portfolio with 3-year sorting on novel intensity and monthly rebalancing. Every three years, we sort firms into 30-70 percentiles based on their novel intensity (fraction of novel patents in the patents issued) in the last month of the previous 3 years. We long firms with novel intensity above 70th percentile and short firms with non-novel intensity below 30th percentile. Monthly rebalancing portfolio weights are determined by the ex-ante market cap. We plot the cumulative alpha against CAPM one-factor, Fama and French (1992) (FF) three-factor, and FF three-factor after replacing the value factor with the intangible-adjusted value factor (Eisfeldt et al., 2020).

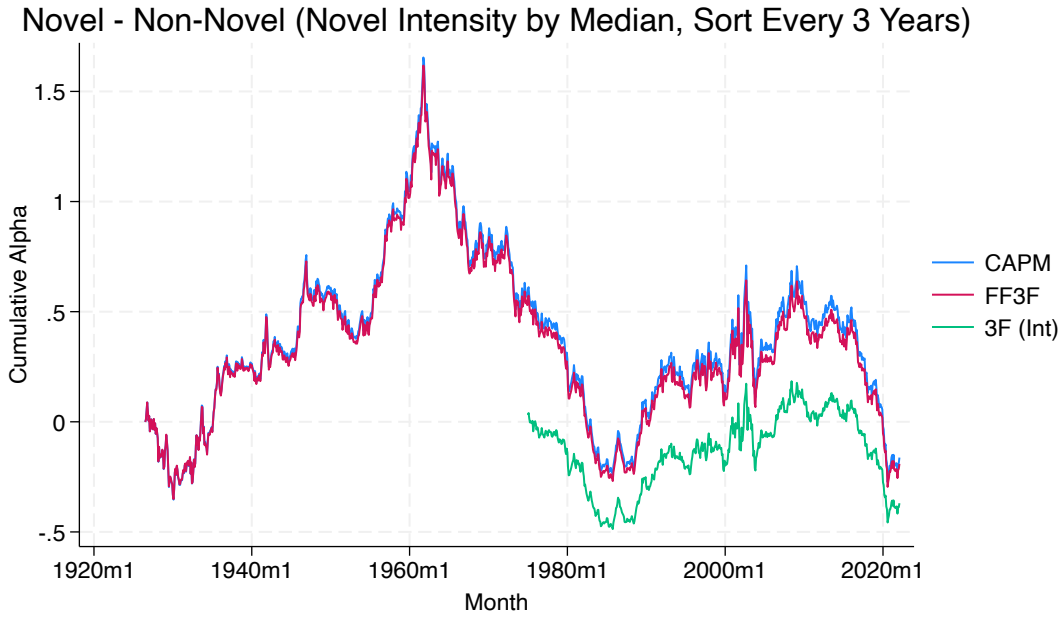
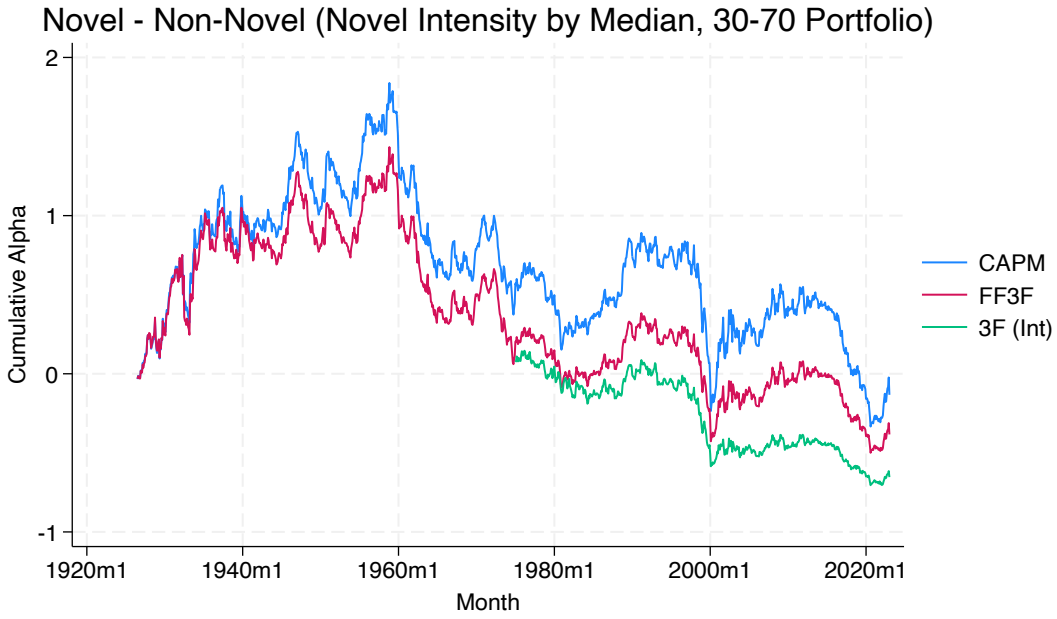


Figure I.A.6: Cumulative Alpha of Monthly Portfolio Sorts on Novel Intensity

This figure plots the cumulative alphas of a value-weighted long-short portfolio with monthly sorting on novel intensity and monthly rebalancing. In each month, we sort firms based on their novel intensity (fraction of novel patents in the patents issued) into 30-70 percentiles. We long firms with novel intensity above 70th percentile and short firms with non-novel intensity below 30th percentile. Monthly rebalancing portfolio weights are determined by the ex-ante market cap. We plot the cumulative alpha against CAPM one-factor, Fama and French (1992) (FF) three-factor, and FF three-factor after replacing the value factor with the intangible-adjusted value factor (Eisfeldt et al., 2020).



In summary, our robustness checks, with diverse methods and measures, consistently confirm our primary conclusion: public-market investors, while responsive to patent announcements, display a systematic underreaction to pioneering innovations and an overreaction to non-novel ones.

I.A.2 Additional Mechanism Tests

Identifying Treatment Effects of Novelty Issuance One may be concerned that the return predictability results are not driven by patent issuance events but by unobserved firm

characteristics. To test this, we introduce a placebo test where we keep the exact patent issuance timing and number of patents issued but randomize patents into pseudo novelty levels. If the misreactions are driven by firm unobservables, not the novelty of the patents, we should see similar predictability even with randomized patent novelty. By contrast, if the results are muted with randomized novelty, this is more consistent with investors' misreactions to patent novelty. Note that this placebo test takes into account the time-varying firm-specific unobservables that can be related to patent issuance but not those that are directly linked to patent novelty. For example, if a firm with a novel patent issuance is unique in a way that makes it more capable of obtaining novel patents and investors misreact to that, the placebo test cannot separate it out. When we consider investors' reactions to patent novelty, we are agnostic about whether it is the novel patents themselves or the firm ability to issue novel patents – both should be counted as the value of innovation to the firm.

In particular, for each firm, we keep the same number of patents issued each month, but we randomly put these patents into ten novelty deciles. We then calculate novel and non-novel indicators using the reshuffled novelty decile levels, where the novel indicator equals 1 if there is at least one patent reshuffled to decile 1-5 and vice versa. We then run the same impulse response regressions with the actual returns and firm characteristics but replace actual (non-)novel indicators with the pseudo ones:

$$\begin{aligned} r_{i,t+\tau} = \alpha_{ind,t} &+ \beta_{\tau,novel} \mathbb{1}\{i \in \text{Shuffled Novel}_t\} \\ &+ \beta_{\tau,non-novel} \mathbb{1}\{i \in \text{Shuffled Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}. \end{aligned} \tag{1}$$

Figure I.A.7 gives the results from one of such randomization exercises. With randomized patent novelty, we find null results for both "pseudo" novel and non-novel issuance with the exact timing and firm characteristics. We also see that the coefficients of "pseudo" novel and non-novel issuance are not statistically significant. The findings imply that the misreactions are driven by patent novelty, not other firm characteristics.

To avoid the results driven by one random realization, we conduct 100 randomization exercises and extract the coefficients from regressions of 2-year cumulative returns ($\tau = 24$) on reshuffled (non-)novel issuance:

$$\begin{aligned} r_{t\to t+\tau} = \alpha_{ind,t} &+ \beta_{\tau,novel} \mathbb{1}\{i \in \text{Shuffled Novel}_t\} \\ &+ \beta_{\tau,non-novel} \mathbb{1}\{i \in \text{Shuffled Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}. \end{aligned} \tag{2}$$

Figure I.A.8 plots the distribution of coefficients on reshuffled novel versus non-novel patent issuance. Throughout the 100 samples, both the novel and non-novel coefficients are close to 0, and the coefficients from actual data are statistically significant given the empirical distribution from 100 simulations. This again indicates that the under-(over-)reaction to (non-)novel is unlikely to be driven by anything other than the issuance of (non-)novel patents.

Figure I.A.7: Cumulative IRF of Firm Returns on Randomized (Non-)Novel Issuance

This figure plots the cumulative impulse response of future returns on patent issuance with randomized novelty. We run one randomization to get pseudo novelty and classify patents into pseudo novel versus non-novel groups. Then, we run the following regression for each $\tau \in [1, 36]$ at the firm-month level:

$$r_{i,t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel} \mathbb{1}\{i \in \text{Shuffled Novel}_t\} + \beta_{\tau,non-novel} \mathbb{1}\{i \in \text{Shuffled Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau},$$

where the two indicator variables represent that the firm issues at least one randomized novel/non-novel patent. We control for industry×month fixed effects and actual firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. We plot the cumulative coefficients, $\sum_{\tau=1}^{t} \beta_{\tau,d}$, over $t \in [1, 36]$ for $d \in \{novel, non-novel\}$. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

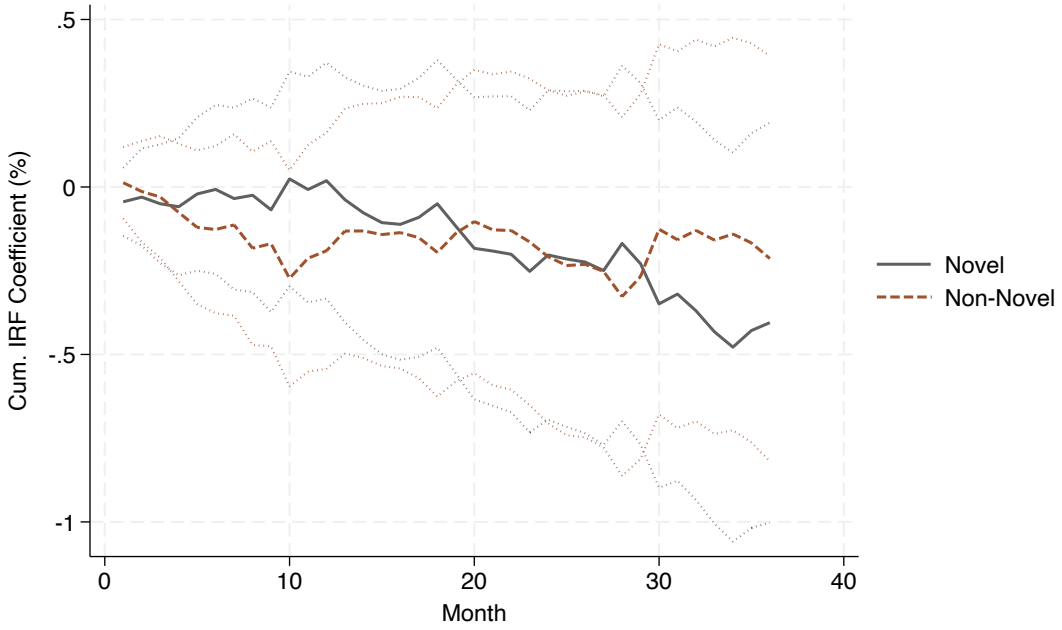


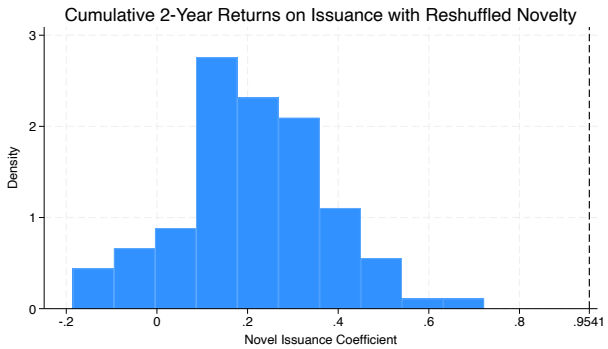
Figure I.A.8: Coefficient Distribution of Cum. Return on Randomized (Non-)Novel Issuance

This figure plots the coefficient distribution of 100 randomization samples where we regress 2-year cumulative returns on patent issuance with randomized novelty. In each sample, we randomly assign patent issued by each firm in each month to novelty levels. Then, we run the following regression for each $\tau = 24$ at the firm-month level:

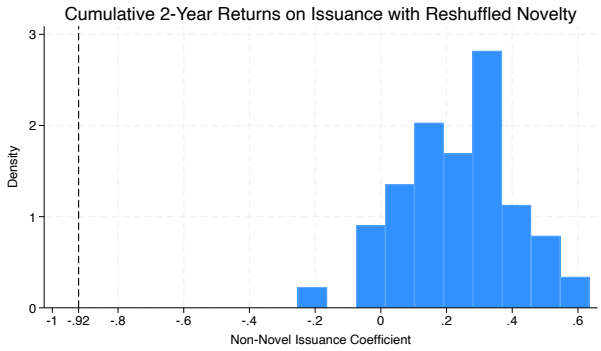
$$r_{t\to t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Shuffled Novel}_t\} + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Shuffled Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau},$$

where the two indicator variables represent that the firm issues at least one randomized novel/non-novel patent. We control for industry×month fixed effects and actual firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. In Panel (a), we plot the novel coefficient, $\beta_{24,novel}$, and in Panel (b), we plot the non-novel coefficient, $\beta_{24,non-novel}$.

(a) Reshuffled Novel Issuance



(b) Reshuffled Non-Novel Issuance



Another approach to confirm the validity of this approach to identify the effects of novel versus non-novel patent issuance can be borrowed from difference-in-differences literature, which is to conduct a test for pre-trends. If the return responses for firms with novel and non-novel patent issuance are similar before the actual issuance events, the return responses afterward are likely to be driven by patent issuance. In particular, we estimate the predictability of (non-)novel issuance on lagged returns:

$$r_{i,t-\tau} = \alpha_{ind,t} + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}.$$

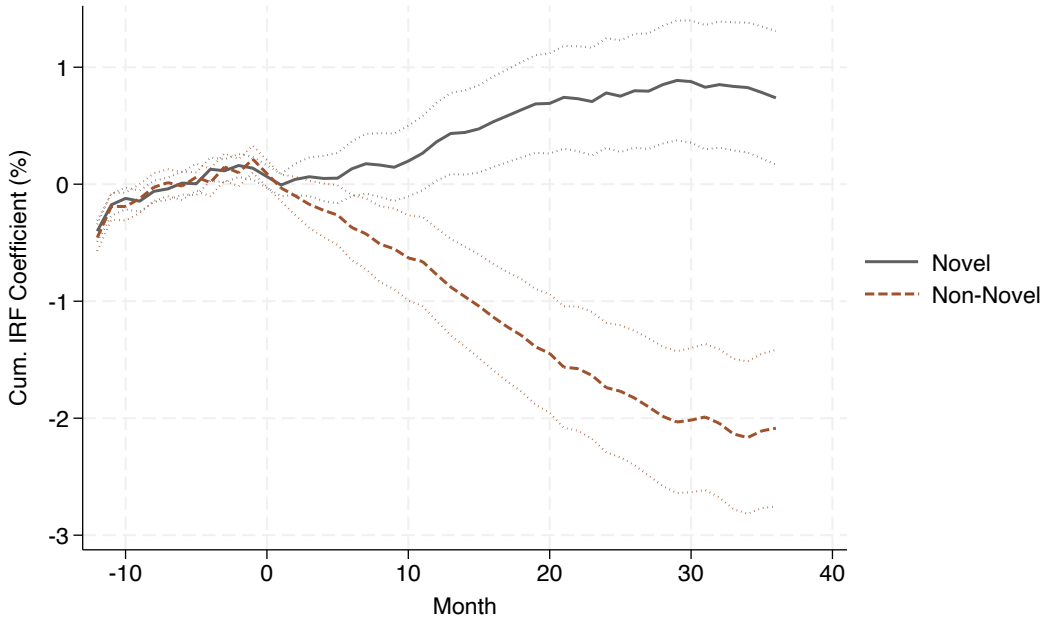
We run lagged returns in the past 12 months. In Figure I.A.9, we see that the pre-period returns are all, on average, close to 0, and more importantly, the pre-trend moves in parallel with novel and non-novel patent issuance, suggesting that the return predictability we see in the post-periods are likely driven by the issuance of novel versus non-novel patents.

Figure I.A.9: Pre-Test: Impulse Response of Firm Returns before (Non-)Novel Patent Issuance

This figure plots the impulse response of returns before patent issuance for different levels of patent novelty, as a parallel pre-trend test of (non)-novel patent issuance as treatment. We run the following regression for each $\tau \in [-12, -1]$ at the firm-month level:

$$r_{i,t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel} \mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,non-novel} \mathbb{1}\{i \in \text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau},$$

where $r_{i,t+\tau}$ is the returns of firm i in month $t+\tau$. "(Non-)Novel" equals to 1 if the firm issues at least one patent with above(below)-median novelty. We control for industry×month fixed effects and firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. We plot coefficients, $\beta_{\tau,d}$, over $t \in [-12, -1]$ for $d \in \{novel, non-novel\}$ together with the cumulative post-effects, $\sum_{\tau=1}^{t} \beta_{\tau,d}$ over $t \in [1, 36]$ as in Figure 1. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.



Forecast error on novel intensity To capture the intensive margin of effects on the earnings forecast error, we regress future one-year and two-year earnings forecast errors on novel intensity, defined as the share of patents with above-median novelty among all patents granted to each firm in each month.

Table I.A.1: Earnings Forecast Errors on Novel Patent Intensity

This table reports the results from regressing firm-level EPS forecast errors on novel intensity. In particular, we run the following firm-year panel regression:

$$\frac{\pi_{i,t+\tau} - F_t\pi_{i,t+\tau}}{P_{i,t-1}} = \alpha_\tau + \beta_\tau \text{Novel Intensity}_{t-1} + \gamma' X_{i,t-1} + \varepsilon_{i,t+\tau},$$

where $\pi_{i,t+\tau} - F_t\pi_{i,t+\tau}/P_{i,t-1}$ are the forecast errors based on one- and two-year consensus earnings forecast, scaled by stock price at the end of fiscal year $t-1$ and the two indicator variables represent that the firm issues at least one novel/non-novel patent in year t. We control for firm characteristics, including market beta, size, book-to-market, gross profit, operating profit, EPS, ROE, free cash flow, investment, short-term reversal, and medium-term momentum. We report the key estimates in the table. Standard errors are double clustered at firm and year level.

	One-year		Two-year	
	(1)	(2)	(3)	(4)
	$(\pi_{t+1} - F_t\pi_{t+1})/P_{t-1}$		$(\pi_{t+2} - F_t\pi_{t+2})/P_{t-1}$	
Novel Intensity$_{t-1}$	0.0186*	0.0110	0.0836*	0.0536*
	(1.69)	(1.40)	(1.82)	(1.82)
R^2	0.000	0.003	0.001	0.020
Controls	No	Yes	No	Yes
Observations	27642	25548	23779	22047

t statistics in parentheses

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

I.B Robustness of Innovation Directions

I.B.1 Abnormal Returns

Table I.B.1: Firm's Equity Returns and Future Novelty-seeking Innovations

This table examines whether firms' three-day return around patent issuance causes changes in their future novelty-seeking innovations. In particular, we run the following firm-quarter-week level IV regression:

$$\text{Novelty-seeking Innovation}_{i,t+1\to t+\tau} = \beta ar_{i,d\to d+2,t} + \gamma' Z_{i,t} + \alpha_i + \varepsilon_{i,d\to d+2,t},$$

where we instrument a firm's short-term abnormal returns $ar_{i,d\to d+2,t}$ (i.e, returns in excess of market returns) with the number of days with sensational news within the three-day window surrounding patent issuance, capturing the exogenous distractions to investors in the first stage (the first-stage estimates are reported in columns (2), (4) and (6)). The dependent variable is a firm's future ratio of novelty-seeking innovation as defined in Section 5.1 in the subsequent four quarters (columns (1)), twelve quarters (columns (3)) and twenty quarters (column (5)) following its' returns at time t. We include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including the log value of the capital stock, the log number of employees, the log value of the output, the log value of the profits, age, innovation capacity, and book-to-market ratio. We also control for firm fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are in parentheses and all clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	FS	$\tau = 12$	FS	$\tau = 20$	FS
$ar_{i,d\to d+2,t}$	0.0945*		0.1247**		0.1141**	
	(1.87)		(2.47)		(2.27)	
Sensational News$_{d\to d+2,t}$		-0.0192***		-0.0176***		-0.0163***
		(-5.30)		(-4.86)		(-4.25)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	1975-2021	1975-2021	1975-2019	1975-2019	1975-2017	1975-2017
Effective F-stats		28		24		18
Observations	186711	186711	184307	184307	175950	175950

t statistics in parentheses

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

Table I.B.2: Firm's Equity Returns and Future Novelty-seeking Innovations with Subsamples

This table examines, for the same firm, whether it is more likely to be affected by market reactions and change its future innovation directions when more novel patents are granted today. In particular, we categorize our sample into high- and low-novelty periods based on whether the firm's ratio of novel patents granted is above 50% in the quarter. Then, we run the following firm-quarter-week level IV regression:

$$\text{Novelty-seeking Innovation}_{i,t+1\to t+\tau} = \beta ar_{i,d\to d+2,t} + \gamma' Z_{i,t} + \alpha_i + \varepsilon_{i,d\to d+2,t},$$

where we instrument a firm's short-term abnormal returns $ar_{i,d\to d+2,t}$ (i.e, returns in excess of market returns) with the number of days with sensational news within the three-day window surrounding patent issuance, capturing the exogenous distractions to investors in the first stage. The dependent variable is a firm's future ratio of novelty-seeking innovation as defined in Section 5.1 in the subsequent four quarters (columns (1) and (4)), twelve quarters (columns (2) and (5)) and twenty quarters (column (3) and (6)) following its short-term returns in the quarter t. We include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including the log value of the capital stock, the log number of employees, the log value of the output, the log value of the profits, age, innovation capacity, and book-to-market ratio. We also control for firm fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are in parentheses and all clustered at the firm level.

	High-novelty			Low-novelty		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$ar_{i,d\to d+2,t}$	0.0323	0.0769*	0.0700*	0.0633	0.0381	0.0563
	(0.74)	(1.85)	(1.84)	(0.49)	(0.32)	(0.27)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	1975-2021	1975-2019	1975-2017	1975-2021	1975-2019	1975-2017
Observations	106932	105800	101231	79358	78031	74206

t statistics in parentheses

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

Table I.B.3: Firm's Equity Returns and Future Sustaining Innovations

This table examines whether firms' three-day return around patent issuance causes changes in their future sustaining innovations. In particular, we run the following firm-quarter-week level IV regression:

$$\text{Sustaining Innovation}_{i,t+1\to t+\tau} = \beta ar_{i,d\to d+2,t} + \gamma' Z_{i,t} + \alpha_i + \varepsilon_{i,d\to d+2,t},$$

where we instrument a firm's short-term abnormal returns $ar_{i,d\to d+2,t}$ (i.e, returns in excess of market returns) with the number of days with sensational news within the three-day window surrounding patent issuance, capturing the exogenous distractions to investors in the first stage (the first-stage estimates are reported in columns (2), (4) and (6)). The dependent variable is a firm's future shares of sustaining innovation as defined in Section 5.1 in the subsequent four quarters (columns (1)), twelve quarters (columns (3)) and twenty quarters (column (5)) following its' returns at time t. We include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including the log value of the capital stock, the log number of employees, the log value of the output, the log value of the profits, age, innovation capacity, and book-to-market ratio. We also control for firm fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are in parentheses and all clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	FS	$\tau = 12$	FS	$\tau = 20$	FS
$ar_{i,d\to d+2,t}$	0.1018***		0.0898***		0.0813***	
	(3.48)		(3.14)		(2.73)	
Sensational News$_{d\to d+2,t}$		-0.0197***		-0.0178***		-0.0165***
		(-5.46)		(-4.93)		(-4.31)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	1975-2021	1975-2021	1975-2019	1975-2019	1975-2017	1975-2017
Effective F-stats		30		24		19
Observations	187346	187346	184613	184613	176153	176153

t statistics in parentheses

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

Table I.B.4: Firm's Equity Returns and Future Sustaining Innovations with Subsamples

This table examines, for the same firm, whether it is more likely to be affected by market reactions and change its future innovation directions when more novel patents are granted today. In particular, we categorize our sample into high- and low-novelty periods based on whether the firm's ratio of novel patents granted is above 50% in the quarter. Then, we run the following firm-quarter-week level IV regression:

$$\text{Sustaining Innovation}_{i,t+1\to t+\tau} = \beta ar_{i,d\to d+2,t} + \gamma' Z_{i,t} + \alpha_i + \varepsilon_{i,d\to d+2,t},$$

where we instrument a firm's short-term abnormal returns $ar_{i,d\to d+2,t}$ (i.e, returns in excess of market returns) with the number of days with sensational news within the three-day window surrounding patent issuance, capturing the exogenous distractions to investors in the first stage. The dependent variable is a firm's future shares of sustaining innovation as defined in Section 5.1 in the subsequent four quarters (columns (1) and (4)), twelve quarters (columns (2) and (5)) and twenty quarters (column (3) and (6)) following its short-term returns in the quarter t. We include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including the log value of the capital stock, the log number of employees, the log value of the output, the log value of the profits, age, innovation capacity, and book-to-market ratio. We also control for firm fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are in parentheses and all clustered at the firm level.

	High-novelty			Low-novelty		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$ar_{i,d\to d+2,t}$	0.0919***	0.0716***	0.0651**	0.1390	0.1441	0.1935
	(3.18)	(2.64)	(2.49)	(1.50)	(1.35)	(0.76)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	1975-2021	1975-2019	1975-2017	1975-2021	1975-2019	1975-2017
Observations	107326	106000	101353	79585	78132	74277

t statistics in parentheses

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