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

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Abstract

We show that investors misreact to technological innovations based on their novelty, and that these misreactions distort firms' subsequent innovation directions. First, using textual measures of novelty, we find that investors underreact to the issuance of novel innovations but overreact to non-novel ones. Novel patent issuance predicts lower risk and positive forecast errors, consistent with non-risk-based mispricing. A model where boundedly-rational investors are uncertain about the true novelty of a patent at issuance explains the empirical patterns well. Second, using sensational news as an exogenous shock to misreaction, we present causal evidence that, after disappointing returns to patent news, novel firms follow up less on current novel technologies, and shift future innovations from novelty-seeking to copycatting when exploring new areas. The findings highlight that investors' misreactions to patent novelty steer innovation away from higher-valued, groundbreaking research.

JEL Codes: D84, G12, G14, G31, G40, O31

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1 Introduction

Technological innovation is a central driver of economic growth. Beyond the quantity of innovation, its direction – whether firms pursue path-breaking or trend-following technologies – matters critically for aggregate productivity. A well-functioning financial market plays a crucial role in financing innovation by channeling capital toward firms developing the most promising and transformative ideas. For this mechanism to work, investors must correctly interpret and value news about firm innovation so that market prices guide capital efficiently. However, innovation news is difficult to evaluate: the novelty and economic value of a new technology are often uncertain when first granted. Because managers often monitor market reactions and incorporate them into their strategic decisions, mispricing of innovation can directly affect firms' real investment choices.[1] With this in mind, in this paper, we study the following two related questions: First, do investors misvalue innovations based on their novelty? If so, do these misreactions distort firms' future innovation directions?

To address these questions, we investigate stock price movements and firm innovations 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 provide an intuitive mechanism to explain this mispricing, inspired by Augenblick, Lazarus, and Thaler (2025). Investors are unsure about patent novelty at issuance, due to cognitive limits, and therefore shrink their perception of novelty to an intermediate prior level.[2] We further demonstrate that investor misreactions 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 and do not follow up on their current novel technology, but instead pursue overpriced, non-novel technologies. Using

[1] In a 2024 interview, the CFO of Moderna Therapeutics said that they monitor short-term price movements and learn from investors: "I take our conversations with investors as a two-way learning [...], and especially when there's a huge market move or a significant market move, they're telling you something. And the question: Did we already know that? Or we might need to think differently about one of our assumptions." (https://www.bloomberg.com/news/articles/2024-03-11/transcript)

[2] This is analogous to Augenblick et al. (2025) where agents are unsure about signal informativeness.

exogenous distracting events following patent issuance as a shock to mispricing of innovation, we provide causal evidence that firm managers are influenced by irrational returns to patents when determining future innovation directions.

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. We see on average positive stock returns three days after patent issuance, with indistinguishable differences between novel and non-novel patents. However, novel patent issuance positively predicts future returns in the next two years, suggesting that 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 followed by a gradual correction of 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 subsequent stock return volatility than non-novel patents. We provide direct evidence of incorrect beliefs: Forecast revisions around novel (non-novel) patent issuances predict positive (negative) forecast errors in earnings growth, indicating that investors are overly pessimistic (optimistic) about future cash flow growth for high- (low-) novelty firms and therefore underprice (overprice) their stocks. We also provide suggestive evidence that the effects are driven by patent issuance events and arise from a misperception of patent value, rather than from a misperception of patent grant probability.

We propose a bounded-rationality model to explain these mispricing patterns. Since our novelty variable is defined only with *ex-ante* information, investors can, in principle, compute it at the moment a patent is issued. However, due to cognitive limits, investors are likely unsure of the patent's true novelty at issuance. Instead, they receive noisy but unbiased signals of patent novelty. Such signals shrink their posterior mean toward an intermediate prior level, leading them to underestimate the novelty of novel patents and overestimate the novelty of non-novel patents. By linking perceived novelty to perceived value, the model predicts short- and long-term responses in the firm's stock price. In the short term, return responses will not differ significantly across novelty levels. However, in the long run, the model predicts significant return predictability as the firm value converges to the rational response to 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 for noisier signals. We verify this key model mechanism through two empirical tests. First, patents with higher uncertainty around their novelty exhibit stronger misreaction. Second, firms with lower institutional holdings exhibit stronger misreactions than those held primarily by institutional investors, as retail investors tend to receive noisier signals.

In our second main contribution, we demonstrate that investors' misreactions to patent novelty shift firms' innovation directions from novelty-seeking to copycatting (conducting

non-novel innovations). Because investors underreact to novel innovations, these patents generate lower short-term returns, leading managers to perceive disappointing market feedback, reduce follow-up in novel innovations, and shift new research toward copycatting rather than novelty-seeking. Using a patent citation network, we create several measures of innovation direction and examine how investors' misreactions to patents predict future innovation outcomes. Ordinary least squares (OLS) estimates show that firms experiencing lower three-day issuance returns subsequently produce fewer follow-on patents citing their current technologies over the next five years, and that novel firms reallocate innovation from novel to non-novel projects when pursuing new areas. However, these OLS results do not provide direct evidence that managers respond to mispricing – they could be responding only to the rational component of returns. Moreover, future innovation could correlate with unobserved determinants of equity returns, creating endogeneity concerns.

To deal with both issues, we introduce an exogenous shock to *misreactions* to patents. In particular, we instrument for the three-day returns using the frequency of sensational news (Peress and Schmidt, 2020) that are unrelated to the economy or technology as exogenous distractions to investors, and provide causal evidence that misreactions to patent issuance distort a firm's future innovation directions. More frequent sensational news in the three-day window after patent issuance creates greater distraction for investors, leading them to respond less strongly to patent news and generating lower short-term returns. Following these exogenous lower returns, firms continue to develop their current technologies to a lesser extent. A 10% lower 3-day return on a quarterly basis causes firms to decrease their share of follow-up innovation in all patent filings by about 1% in the next five years. When current technologies are undervalued, managers who take short-term returns at face value are less willing to build upon those innovations. Moreover, when deciding whether to pursue novel or non-novel patents in new areas, their responses depend on the novelty of current technologies. If they are predominantly novel, negative return shocks induce a shift from pursuing new novel research to imitating existing, market-favored innovations. A 10% lower

return on a quarterly basis reduces the share of novel patent filings in new technological areas (patents not citing current patents) by about 1.1% in the next five years. In contrast, when current patents are predominantly non-novel, we do not observe this shift in novel shares. These results suggest that only when novel innovations are undervalued do managers pivot toward market-favored non-novel innovations.

Together, the results reveal that investor misreactions to innovation can push firm innovation into suboptimal directions. The evidence that managers respond to mispricing induced by distraction shocks strongly suggests that they also react to mispricing arising from investors' bounded rationality. Because investors systematically undervalue novel technologies and overvalue non-novel ones, managers reduce follow-on investment in their current novel technologies but are encouraged to extend non-novel ones. When pursuing new technological areas, managers of novel firms also shift their innovation from novelty-seeking to copycatting, reinforcing the market's bias toward non-novel innovation. These misreactions to novelty in financial markets thus push corporate innovation toward safer, trend-following projects, leading to inefficient financing and a systematic underproduction of high-novelty innovation, which on average generates greater social value.

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 our paper differs in important ways, both empirically and theoretically. Empirically, our measure, which is based on textual similarity, more intuitively measures how a patent is distinctive from previous patents, while they measure originality by the breadth of knowledge used. 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 they propose a limited attention model that only predicts the under-reaction to originality. Inattention models also explain other evidence on 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 over-pricing of technology, which we then verify in the data. As such, we also add to the recent studies trying to reconcile the co-existence of under- and over-reaction. For example, 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.

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 by learning from prices. Chen, Goldstein, and Jiang (2007) 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, 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) examine 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 versus incremental innovations, focusing on 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. 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. Second, innovation is driven towards industries with a higher markup. For example, curative technologies usually have a higher markup in healthcare, thus fostering more innovation. We study innovation direction at a more granular level. Instead of focusing on industries, we study how individual 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 the 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 present results on future innovation directions and on 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 this impacts 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 our methodology and on our 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 examine the market reactions to the news of patent issuance, we match the CRSP data

with the patent data. Our focus is on the stock market reactions after the official USPTO announcement of patent issuances. Following the methodology of 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 unique US public firm.

We also construct several control variables from CRSP. We calculate the market capitalization using CRSP variables, closing price (prc) and share outstanding ($shrout$), as $|prc| \times shrout$. We use the market cap from December in the past year to calculate the book-to-market ratio (Fama and French, 1992). Short-term reversal is the return from month $t-1$ and medium-term momentum is the cumulative return from month $t-12$ to $t-2$. To study the short-term reactions, we also match CRSP daily returns to patent 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. To ensure that accounting variables are known to investors, we match the accounting data in calendar year $t-1$ with the returns in July of year t to June of year $t+1$ (Fama and French, 1992). 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 assets (`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 shares 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 Ko-

gan 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. The institutional ownership data of FactSet comes mostly from the SEC 13F filings. All institutional investment managers with more than $100 million in 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 2022Q4.

Implied volatility We obtain our 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 of the options 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 affect results (Payne and Thomas (2003)). We use a potentially different adjustment factor at the forecast date and at the earnings announcement date to make sure the adjusted earnings and forecasts are computed 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).[3] The news pressure measure is the median number of minutes that are allocated to the news in the first three segments of news broadcasts. Following Peress and Schmidt (2020), we use the median news pressure from ABC, CBS, and NBC and define sensational news events as the 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.[4] We match the sensational news events to the dates with patent issuance and use the number of days with sensational news in the 3-day window after patent issuance as our main instrument of 3-day patent issuance returns, so the instrument takes values of 0, 1, 2, or 3.

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)[5]. 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:

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

[4]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, war, technology, innovation, and patent.

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

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

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. One should note that not all novel patents necessarily represent technological breakthroughs. Therefore, to demonstrate robustness, we also 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.

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, covering patents whose assignees are publicly traded firms available in the CRSP database. We use it to explore the dynamics of firms' innovation directions. Specifically, we infer whether firms are more

willing to innovate further upon their current patents by measuring the number of patents that cite the current technology filed by themselves. We can also check whether firms follow the prevailing trends by checking their patents which cite patents from other entities.

The citation network allows us to create proxies for evaluating a patent's social value. For example, we use the total citations that a patent receives to indicate its influence and acceptance in the broader community. The metric gives us a reasonable estimate of the social value of a patent.[6]

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 returns of firms 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 empirical studies of investors' reactions to news, a common 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 will jump immediately to the correct level when news is released, so that future long-term stock returns are unpredictable. If, instead, the

[6]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.

information 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 compare investor reactions, or potential misreactions, to novel versus non-novel 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 1 to 5 and non-novel as deciles 6 to 10 so that results are not driven by extreme values.

Short-term return responses to patent issuance While our primary analysis focuses on long-term predictability, we first need to 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 reversal. To test this, we run a firm-day-level regression of 3-day returns starting on the issuance date, on the patent issuance dummy, controlling for industry×date fixed effects (we use 3-digit SIC codes 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 ($r_{t-12\to t-1}$).

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

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 non-novel issuance, when analyzed separately, are positive and statistically significant. On average, returns increase by 0.074% (0.083%) in the three days after novel (non-novel) patent issuance, which is equal to an annualized return of 6.22% (6.97%). Second, when 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 for novel and non-novel 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 one 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 patent 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 underreaction to positive news. If we see a persistent decrease, this suggests that investors are gradually correcting their initial overreaction 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 underreaction. The full value of groundbreaking 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%.

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 underreaction. 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 gradually correct downward, exhibiting negative predictability.

Magnitudes of short- and long-term response We argue that the short-term positive response together with the subsequent drift and reversal is consistent with an under- and overreaction story. In the short term, the three-day response to patent issuance is around 0.1% regardless of the novelty of the patent. In the long term, (non-)novel patents predict a drift (reversal) of 1%. In this section, we reconcile these two magnitude with a simple framework. Denote that the investors' perceived value of patent issuance news to the firm as $\xi_{j,t}$ for issuance event j and firm value as $v_{j,t}$. The perceived values can be time-varying after the patent issuance. We also denote $\pi_{j,t}$ as the investors' ex-ante perceived probability that there will be an issuance event j. In the short term around issuance events,

$$\Delta v_{j,0\to 2day} = 1 \times \xi_{j,0\to 2day} - \pi_{j,-1day}\xi_{j,-1day} \tag{3}$$

$$= (1 - \pi_{j,-1day})\xi_{j,-1day} - (\xi_{j,0\to 2day} - \xi_{j,-1day}) \tag{4}$$

In the long run after issuance, $\pi_{j,t} = 1$ and thus the change in returns comes only from the change in perceived patent value:

$$\Delta v_{j,2year} = \Delta\xi_{j,2year} = \xi_{j,2year} - \xi_{j,0\to 2day}$$

To reconcile $\Delta v_{j,0\to 2day} = -1\%$ and $\Delta v_{j,0\to 2day} = 0.1\%$ without having patent value $\xi_{j,2year} \approx \xi_{j,correct}$ being negative, $\xi_{j,0\to 2day}$ should be larger than 1%. Given that the short horizon of 3 days, we assume that $\xi_{j,0\to 2day} \approx \xi_{j,-1day}$ and this implies that

$$\Delta v_{j,0\to 2day} = (1 - \pi_{j,-1day})\xi_{j,0\to 2day} \Rightarrow \pi_{j,-1day} \geq 90\%$$

One day before the patent issuance, the investors perceive a 90% probability that there will be at least one patent grant at date t. Given that the unconditional patent grant rate is around 80% in recent decade, this does not seem like an unreasonable assumption.

3.2 Cumulative Return Regressions

We next run an alternative specification in which we regress future cumulative returns at the firm level on novel and non-novel patent issuance. We maintain the same control variable and fixed effects and control variables as in Section 3.1. The dependent variables, $r_{i,t\to t+\tau}$, are future *cumulative* returns from 1 to 36 months. Therefore, the specification resembles a buy-and-hold strategy where we hold firms with patent issuance at time t for the next τ months. We carefully eliminate the concern of survivorship bias in long-term returns. That is, for three-year cumulative returns, the sample will include only firms that remain in the market for at least three years after patent issuance, while we should also account for investors' reactions to firms that exit the market during the three years. For firms that do not exist for the full three-year period, we interpolate missing returns with their respective industry returns.

The regression specification is

$$r_{i,t\to t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau} \quad (5)$$

In Figure 2, we plot the coefficients $\beta_{\tau,novel}$ and $\beta_{\tau,non-novel}$ for each $\tau \in [1, 36]$. Similar to the impulse response function, we find that novel patent issuance positively predicts long-term cumulative returns, whereas non-novel patent issuance negatively predicts them. We observe robust results with the two different specifications.

In terms of magnitude, Table 2 presents the coefficients of half-year, 1-year, 2-year, and 3-year returns. In the two years after patent issuance, novel issuance predicts 0.95% in cumulative returns, and non-novel issuance predicts -0.92%, indicating approximately 1% of misreactions to both novel and non-novel patents in two years. The return predictability flattens after two years - novel issuance predicts a similar 1.3% in three years, and non-novel issuance predicts a smaller -0.76%, suggesting that the mispricing is fully corrected around two years after issuance. These results confirm that investors (over)under-react to

(non-)novel patent issuance.

To understand the difference in the magnitude of the results between cumulative return regressions and impulse response regressions, e.g., that non-novel issuance predicts a larger effect (-2%) in the cumulative IRF, it is helpful to distinguish average cumulative returns and cumulative average returns. In the impulse-response analysis, we compute average return predictability for each horizon separately and sum the corresponding effects. In cumulative return regressions, we first compute cumulative returns and then regress out the average effects. The former takes the perspective of an investor rebalancing at the end of each period and computes the average returns from that strategy. In contrast, the latter adopts a buy-and-hold strategy for an average firm over three years. We do not have a preferred methodology, but reassuringly, we confirm the same conclusion with both approaches.

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 misreaction, 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 we call "novel intensity". This measure also addresses the common concern that different numbers 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 take the patent-level backward similarity deciles, and average them at the firm level as another continuous measure of firm novelty. We 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 impact, we split novel and non-novel patents, respectively, into breakthrough and non-breakthrough patents. We test the return predictability of four types of patents: novel breakthrough, novel non-breakthrough, non-novel breakthrough, and non-novel non-breakthrough. We see that the strongest underreaction to novel breakthroughs, which have high true value, and the strongest overreaction to non-novel non-breakthroughs, which have low true value. This is also consistent with the theory of under and overreaction by shrinking towards the intermediate value we develop in Section 4.

Finally, we investigate whether a trading strategy that goes long novel firms and short 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) at a three-year frequency. With both approaches, we find positive average alphas under 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 evidence to rule out a rational risk-based explanation of return predictability, and then show direct evidence of mispricing in firms with novel versus non-novel patent issuance. We also provide evidence that the mispricing is driven by a misperception of patent novelty. We first argue that our results cannot be attributed to misperception of grant probability, and second, 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 3, we run the following local projection regressions:

$$\sigma_{i,t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}, \quad (6)$$

where $\sigma_{i,t+\tau}$ is the standard deviation of realized daily returns in month $t+\tau$ and "Novel" equals one 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 have significantly *lower* return volatility than firms issuing non-novel innovations, contrary to the risk-based story where novel firms have higher risk.

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 by regressing daily returns firm-by-firm with CRSP value-

weighted market 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 construct a measure 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:

$$\text{Implied Vol}_{i,t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}. \tag{7}$$

Panel (b) of Figure 3 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, in Figure 3, we see that both realized and implied volatility decrease 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 this more in our model of misreaction.

These disconnects between various definitions of risk and average returns challenge the rational story and favor a behavioral story based on investor misreaction.

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.

We examine whether investors revise their expectations after patent issuance and whether they err in these revisions. To test this, we use earnings growth forecasts formed before and after the patent issuance. We extract the sell-side analyst 2-year EPS forecasts from IBES and match them to the 90 days before and 45 days after each patent issuance date, following Kwon and Tang (2021). Denoting the actual EPS in 2 years as π_{y+1} and the forecasts issued in date t of year y as $F_t\pi_{y+1}$, we calculate the two-year earnings growth forecast as $F_t\pi_{y+1}/\pi_{y-1} - 1$. We first test the revisions before and after patent issuance by running an analyst-firm-issuance-date level regression of forecast revisions on patent issuance:

$$\frac{F_{a,i,t,post}\pi_{i,y+1} - F_{a,i,t,pre}\pi_{i,y+1}}{\pi_{i,y-1}} \equiv ForecastRevision_{a,i,t} = \alpha_a + \beta_{\tau,n}\mathbb{1}\{i \in \text{Novel}_t\} \quad (8)$$

$$+ \beta_{\tau,nn}\mathbb{1}\{i \in \text{Non-Novel}_t\} + \varepsilon_{a,i,t}. \quad (9)$$

In Panel A of Table 3, we find that investors revise up their earnings growth expectations after patent issuance, indicating that they perceive patent issuance as positive news for future firm cash flows. Additionally, we observe that the revisions are similar in response to both novel and non-novel patent issuance. Consistent with our hypothesis that at issuance, investors do not differentiate patents by novelty.

Next, we study investor biases in these forecast revisions. We use Coibion and Gorodnichenko (2015) type regressions using forecast revisions to predict forecast errors. If revisions positively predict forecast errors, it indicates that investors underreact to news; if revisions negatively predict errors, it implies overreaction. In this context, we have positive news for the firm from patent issuance, and investors revise their forecasts upwards. If investors react insufficiently, the future average realized earnings will exceed the forecast, leading to positive forecast errors. If investors respond excessively, the future average realized earnings will be

lower than the forecast, leading to negative forecast errors. We test this hypothesis using the same analyst-firm-issuance-date panel:

$$\frac{\pi_{i,y+1} - F_{a,i,t,post}\pi_{i,y+1}}{\pi_{i,y-1}} \equiv ForecastErr_{a,i,t} = \alpha_i + \alpha_t + \gamma_n ForeRev_{a,i,t} \times \mathbb{1}\{i \in \text{Novel}_t\} \tag{10}$$

$$+ \gamma_{nn} ForeRev_{a,i,t} \times \mathbb{1}\{i \in \text{Non-Novel}_t\} + \varepsilon_{a,i,t}. \tag{11}$$

In Panel B of Table 3, we find that forecast revisions positively predict forecast errors when a novel patent is granted and negatively predict errors when a non-novel patent is granted. Together with the results of the revisions in Panel A, we represent direct evidence that investors underreact to novel patents and overreact to non-novel patents. Investors perceive positive cash flow news from both novel and nonnovel patent issuance and increase their earnings growth expectations. But these revisions lead to different mistakes. For novel patents, their revisions are not large enough so that the future realized earnings growth is higher than the forecast, while for non-novel patents, their revisions overshoot so that realized value is, on average, lower than expectations.

In Appendix Table I.A.2, we also directly compare the forecast errors of firms with and without patent issuance. We show consistent results that investors form overly pessimistic expectations about a firm's future profitability when the firm is granted novel patents. These results provide a belief-based explanation for misreactions to patent novelty: investors form overly pessimistic beliefs about firms with novel patents and underprice these stocks.

Patent Grant Probability versus Value In this section, we provide evidence that issuance probability does not influence our interpretation of the magnitude of the misreaction. The magnitude of the immediate return response to patent issuance is determined by the product of the probability of a successful issuance and the perceived value of the patent.

This leads to two alternative interpretations of the misreaction to patent issuance.

First, if investors perceive a lower issuance probability of novel patents than the correct probability, this also results in an underreaction to novel patent issuance, although one that is not due to an underestimation of patent value. We address this concern by arguing that, immediately after patent issuance, investors know exactly how long it took for the patent to be granted, so the perception of the success probability will only have an effect on the immediate responses, but not on the long-term returns. This immediate correction of perceived grant probability is inconsistent with our results that the mispricing of novelty takes two years to correct.

Second, since the patent office decides which patents to grant after firms file the patents, if for example, it grants novel patents with a lower probability than non-novel ones, the magnitude of misreactions between novel and non-novel patents should adjust for the difference in grant probabilities. The same 1% misreaction to novel versus non-novel patents would predict a stronger undervaluation of novel patents compared to the extent of 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 patent-level regression of the number of days between the date when the assignee files the patent and the date when the patent office grants the patent, on novel indicators

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

where we control for grant-month fixed effects and indicators of the CPC technology class. Table 4 reports 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 a (non-)novel patent in a month being 2.9% (3.1%). The average monthly grant probability differs by just 0.2% between novel and non-novel innovations, a difference that

lacks economic significance.

4 A Model of Misreaction to Novelty

In this section, we present a framework for understanding the return misreactions to patent novelty and the return dynamics after patent issuance. The model is consistent with a mispricing mechanism, 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.

The model we present is one based on bounded rationality, 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 depends only on *ex-ante* information, it is 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. Third, 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 log-normally distributed:

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

We assume a log-normal prior to ensure that patent novelty is non-negative while maintaining tractability. Woodford (2020) also uses a log-normal 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 boundedly-rational investor does not know the true novelty of the patent; instead, he receives an unbiased but noisy signal about the patent's novelty:

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

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

$$\hat{x}(r) \equiv E[x|r] = \exp\left[\left(\frac{\nu^2}{\sigma^2 + \nu^2}\right) \log \bar{x} + \left(\frac{\sigma^2}{\sigma^2 + \nu^2}\right) r\right], \tag{12}$$

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

$$e(x) \equiv E[\hat{x}|x] = \exp\left(\beta^2\nu^2/2\right)\bar{x}^{1-\beta}x^{\beta} \quad var[\hat{x}|x] = (\exp(\beta^2\nu^2) - 1)e(x)^2, \tag{13}$$

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. 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 zero. 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 4 shows that novel patents have issuance returns lower than the rational benchmark, thus exhibiting underreaction, while non-novel patents have issuance returns higher

than the rational benchmark, thus exhibiting overreaction. Moreover, if investors receive very noisy signals, the returns differences across patent novelty will be economically insignificant. This aligns with 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 shown 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 should observe 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:

$$\log x | r_0, ..., r_t \sim N\left(\left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2} \right)^{-1} \left[\frac{t+1}{\nu^2} \left(\frac{1}{t+1} \sum_{i=1}^{t+1} r_i \right) + \frac{1}{\sigma^2}\mu \right], \left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2} \right)^{-1} \right). \tag{14}$$

Denote this conditional mean as μ_c and conditional variance as σ_c^2; the posterior mean of novelty x at time t then 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.

$$\log e_t(x) \equiv \log E[\hat{x}_t | x] = E\left[\mu_c + \frac{1}{2}\sigma_c^2 \right] + \frac{1}{2} var\left(\mu_c + \frac{1}{2}\sigma_c^2 \right), \tag{15}$$

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

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

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, we assume, as in the static case, 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:

$$v_t \sim N^+\left(\gamma_0 + \gamma_1\left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2}\right)^{-1}\left[\frac{t+1}{\nu^2}\log x + \frac{1}{\sigma^2}\left(\mu + \frac{1}{2}\sigma^2\right)\right],\right.$$
$$\left.\gamma_1^2\left(\left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2}\right)^{-2}\left(\frac{t+1}{\nu^2}\right)^2\frac{\nu^2}{t+1}\right) + \sigma_x^2\right). \tag{16}$$

From Equation 16, we obtain 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 5, we plot the return reaction to ten novelty levels for 60 periods after the patent issuance. The simulations confirm the 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 who do not have precise information about 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 6 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 the 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. The first two tests (short-term and

long-term responses) are similar to the main empirical tests in Section 3, but are conducted at a more granular level. The third test confirms the main model mechanism by verifying the comparative statics with signal noise.

Short-Term Response The model predicts that the return reaction at issuance is indistinguishable across different novelty levels. To test this, we run the same firm-day-level regressions, as in Table 1, except that we use ten deciles instead of two indicators split by median. This is to test whether the similar short-term return responses still hold with more granular novelty levels. In particular, we regress 3-day returns after patent issuance on ten decile indicators of patent novelty. Each indicator is equal to one if patents with a given novelty level are granted to the firm on this day. If no patent is issued, all indicators will be zero, 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:

$$R_{i,t,t+2} = \alpha_{ind,t} + \sum_{k=1}^{10} \beta_k \mathbb{1}\{i \in \text{Novelty Decile}_{k,t}\} + \gamma' X_{i,t} + \varepsilon_{i,t,t+2}, \tag{17}$$

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 7 shows significant positive average returns in almost all of the ten deciles. We also observe that the difference in response is not economically and statistically significant across novelty deciles. Even across 10 different levels of novelty, instead of two, we still find that average investors perceive positive patent value at issuance, and the value perception is not different across novelty, consistent with the model prediction on short-term responses.

Long-Term Response We test the monotonicity prediction in long-term returns, as demonstrated in Figure 5: The more (non-)novel the patent is, the stronger the (reversal) drift we should see, that is, a stronger (negative) positive predictability in long-term

return responses.

We test this 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:

$$r_{i,t+\tau} = \alpha_{ind,t} + \sum_{d=1}^{10} \beta_{\tau,d} \mathbb{1}\{i \in \text{Novelty Decile}_{d,t}\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}. \tag{18}$$

This is the 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 8 shows that, although in real data the average reactions are noisier, the 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.

Novelty Uncertainty and Signal Noise Finally, in the model, signal noise is a key parameter that drives the return response. If the signals are noisier, we expect stronger misreactions. We first test this mechanism by constructing a direct measure of uncertainty around the novelty level of each patent. In particular, remember our definition of novelty is the aggregate pairwise similarity with patents filed in the past five years. In addition to the first moment, we can also calculate the second moment of these pairwise similarities. We calculate a patent-level measure of novelty uncertainty:

$$\nu(Novelty)_i = \sigma_{j \in \mathcal{B}_{i,5}}(\rho_{i,j}) \tag{19}$$

This measure captures the extent of variation in pairwise similarity around the novelty level. Given the same level of novelty, if one patent exhibits greater noise in the computation of this novelty measure, it will be harder for investors to assess the patent's novelty and hence have a stronger misreaction. We then sort each patent into high- or low-novelty-uncertainty groups based on the median novelty uncertainty within the same novelty decile. Figure 9

shows the results from the following regression:

$$r_{i,t\to t+\tau} = \alpha_{ind,t} + \sum_{d\in\{Novel,Non-Novel\}} \beta_{\tau,d,high} N_{i\in d_t \& i\in \text{high uncertainty}_t} \tag{20}$$

$$+ \sum_{d\in\{Novel,Non-Novel\}} \beta_{\tau,d,high} N_{i\in d_t \& i\in \text{low uncertainty}_t} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}. \tag{21}$$

We classify patents into four categories: novel or non-novel and high or low uncertainty. The regression includes the number of patents issued to the firm in each of the four categories as independent variables; thus, the coefficients capture the perceived value change attributable to one patent in each category, making them directly comparable. We plot the cumulative return coefficients, $\beta_{\tau,d,high}$ and $\beta_{\tau,d,low}$ for $d =$ novel or non-novel issuance. The cumulative returns exhibit a pattern consistent with model predictions. Patents with higher novelty exhibit stronger misreaction both when they are novel and when they are non-novel.

Institutional Holdings and Signal Precision We also test the signal noise mechanism by comparing the return predictability of firms with high versus low institutional holdings. Institutional investors have greater knowledge of the technology and therefore receive less noisy signals about patent novelty; they hence exhibit weaker misreactions and faster convergence. We construct institutional ownership (IO) as in Ferreira and Matos (2008) using holdings data from FactSet, and split firms into high- and low-IO groups at the quarterly median. Figure 10 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 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 Sections 3 and 4, we documented that investors underreact to novel patents and overreact to non-novel ones. In this section, we argue that this type of misreaction has a real impact on firms' subsequent innovation directions. The challenge is to isolate the component of misreaction driven by the bounded-rationality mechanism in Section 4. Rather than attempting to approximate this component directly, we identify an irrational component of return reactions driven by investor distraction and show that it influences firms' innovation directions. The evidence that managers respond to distraction-induced mispricing strongly suggests that they will also respond to the mispricing stemming from bounded rationality. Combining these results, we draw aggregate implications for how financial-market misreactions shape the direction of technological progress.

We start, in Section 5.1, by classifying firms' future innovations into three categories and defining the relevant innovation directions. In Section 5.2, we relate these outcome variables to firms' short-term stock returns around patent issuance and discuss a conceptual framework in which managers respond to the *irrational* component of the issuance returns, leading to predictable changes in innovation directions. In this framework, firms' disappointing three-day patent-issuance returns subsequently lead to less follow-on innovation and a lower share of novel, as opposed to copycat, projects – particularly among firms with high novelty. In Section 5.3, we first document that ordinary least squares (OLS) estimates confirm these predictions. However, these correlations alone cannot establish that managers respond to the irrational components of returns, as they are also consistent with rational managers

responding to the rational components of returns. To address this concern, we introduce an instrumental variable that isolates an *exogenous* distraction-induced mispricing shock and show that it continues to influence firms' innovation directions. This strongly suggests that managers will also respond to the bounded-rationality type of misreaction documented in previous sections. We remain agnostic about the precise channels through which such responses occur, but in Section 5.4, we discuss several possible mechanisms. Section 5.5 concludes by connecting these findings with the novelty-mispricing results in Section 3 to derive implications for aggregate innovation efficiency.

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 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.

We tackle this challenge by inferring a firm's innovation direction from its future patenting behavior, using a sample of patents that are eventually granted.[7] Given our focus on patent novelty, we classify patents filed by the firm in the future into three categories, each closely tied to the novelty of its patenting activity. The first category is "sustaining innovation," which consists of innovations that build on the firm's current technologies. For example, Apple's pioneering multi-touch technology[8] laid the groundwork for incremental innovations such as pinch-to-zoom[9] and slide-between-user-interface[10], shaping the modern smartphone

[7] 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.

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

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

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

industry. To capture this, we construct the measure "number of follow-up patents" to quantify a firm's sustaining innovation using a patent 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 in the current quarter t. A higher value of this measure indicates that the firm follows up more on its recently issued technology.

Beyond sustaining innovations that build on the firm's own current patents, firms can pursue new ideas outside of their current technology. Among these new (non-self-citing) ideas, the firm can pursue novel technologies not discovered in the market, which we call "novelty-seeking." Apple, for instance, has consistently created novel technologies, from the embedding of electronic devices in wearables – facilitating the Apple Watch launch – to the recent eye and hand tracking technologies behind Apple Vision Pro.[11] On the other hand, among the non-self-citing innovations, the firm can also pursue technologies that follow the market trend, which we call "copycatting innovation". An example is Apple's adoption of folding device technology[12], previously introduced by Samsung. To quantify the novel and non-novel composition in a firm's new ideas, 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, that *do not* cite the firm's patents issued in quarter t.

Given the three categories of future innovation – sustaining innovation, novelty-seeking, and copycatting – we construct two share-based measures as our main dependent variables to more precisely capture the extent of follow-ups and the shift from novelty-seeking to copycatting:

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

[11] "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".

[12] "folding device technology": the US patent application US20230011092A1, titled as "Hybrid cover-lay/window structure for flexible display applications"

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

The "sustaining innovation" variable is the fraction of patents that cite current patents among all patents filed, which captures how much firms choose to follow up on current technologies. The "novelty-seeking innovation" variable focuses on the set of patents that do not cite current patents (the complement of sustaining innovation). We calculate the fraction of novel patents among this set of non-self-citing patents, where a novel patent is defined as having lower-than-median backward similarity among all patents currently issued to any firm. This variable captures how much managers seek novelty when considering new research projects.[13] In Table 5, we provide the summary statistics of the two measures in the future one, three, and five years. The average share of self-citing innovations ranges from 5.3% to 5.6%. Among the set of non-self-citing patents, 62.7% to 63.7% of them are novel, indicating that an average firm conducts slightly more than half of novelty-seeking when it explores new research areas.

5.2 Patent Issuance Returns and Innovation Directions

Using these innovation measures, we study whether firms' short-term returns after patent issuance 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 within a given quarter:[14]

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

[13] Given our definition of the share-based measures, the share of copycatting innovation is the converse of novelty-seeking innovation (the two categories sum up to all patents without self-citing); an increase in one is equivalent to a decrease in the other.

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

The dependent variable, Future Innovation$_{i,t+1\to t+\tau}$, is one of the two share-based measures defined in Section 5.1, sustaining and novelty-seeking innovation. 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 labor and capital constraints to 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. We also control for the log of profits, as firms with higher profit margins may invest more in R&D and generate more novel innovations. In addition, we control for 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 of innovation capability and productivity. Lastly, we control for book-to-market, given its potential correlation with future growth opportunities. Firms with limited growth prospects may opt for different innovation strategies than growth firms. We exploit within-firm variation over time by including firm fixed effects.

Conceptual framework Now that we have laid out the empirical model, we discuss the scenarios where we expect investors' reaction to patent news to change future innovation, that is, where we expect a nonzero β coefficient. We first outline two scenarios in which managers will respond to returns to innovation, but which differ in the assumption about the manager. Then, we distinguish the two scenarios by arguing that only in the second scenario will investor *mis*-reaction impact managerial decisions.

We assume that, when the stock market reacts to patent issuance news, there is a rational

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

component to the reaction, as well as an irrational component:

$$r_{i,d\to d+2,t} \equiv r^{Rational}_{i,d\to d+2,t} + r^{Irrational}_{i,d\to d+2,t}.$$

The rational component corresponds to the true value the patent brings to the firm, and the irrational component captures any type of mispricing of patents at issuance. This decomposition is realistic in light of Section 3, where we present strong evidence of mispricing around patent issuance. For the rest of this section, we assume that it is possible to empirically isolate an irrational component to the return reaction. In a later section, we explain how we do this.

In the following two scenarios, the investor reaction to patent issuance news matters, but managers respond to different components of the return response.

Scenario 1 (Rational Benchmark)**.** *The firm manager is rational — she knows the correct value of a patent when it is issued — and there are no frictions or agency costs. In this case, the manager reacts only to the* ***rational*** *component of the investor reaction, not to the irrational component.*

In this case, when choosing an innovation strategy, the manager will not react to the irrational component of the investor reaction because she knows that it is irrational. Moreover, there are no frictions or agency conflicts that would force her to react to this irrational component. The manager knows that the irrationality in the immediate investor response will later be corrected, and since her objective is to maximize long-term shareholder value, she will not respond to any mispricing. She will respond to the rational component because it represents the true value of the patent. For example, if the true value of the patent is lower, she understands this and thus becomes less likely to continue with this type of innovation.

Scenario 2 (Frictions or Irrational Manager)**.** *The manager is irrational, or has limited information and so needs to learn from the market, or faces frictions or agency costs. In*

these cases, the manager will respond to both the rational and ***irrational*** *components of patent-issuance returns.*

If the manager is irrational in the same way as the market, she will agree with the market that some patents have lower value, even though this perception of value is incorrect. This will lead her to change future innovation. Alternatively, if she learns from the market, she will learn from the full return, as she cannot distinguish the rational and irrational components. As a final alternative, if there are financial frictions (e.g., equity dependence) or agency costs (short-termism), the manager will react to the full short-term return even though she understands it is incorrect. In Section 5.4, we will discuss these channels in more detail. We do not attempt to determine which of them drives our findings, but it is crucial to note that *only* in these cases will a manager react to the irrational component of issuance returns.

How do reactions to patents impact innovation? Now that we have outlined the scenarios where managers respond to the rational and/or irrational components of issuance returns, we discuss the expected directions of these effects. In other words, suppose there is a coefficient β_R on the rational component and β_{IR} on the irrational component:

$$\beta r_{i,d\to d+2,t} \equiv \beta_R r^{Rational}_{i,d\to d+2,t} + \beta_{IR} r^{Irrational}_{i,d\to d+2,t}. \tag{22}$$

We now discuss whether we expect the β coefficients to be positive or negative for novelty-seeking and sustaining innovation for different types of firms. We categorize *novel firms* as those in which more than half of currently granted patents are novel.

Prediction 1.a (Sustaining Innovation, Rational Manager)**.** *In the scenario of a rational manager and no frictions, the manager will follow up less on current innovation if the rational component of issuance returns is lower, i.e.,* $\beta_R > 0$*. She will not respond to the irrational component, i.e.,* $\beta_{IR} = 0$*. This relationship holds for both novel and non-novel firms.*

When the firm manager is rational and there are no frictions, as in Scenario 1, she

increasingly follows up on current technology if the rational component is higher and less so if it is lower. If the rational component is low for a novel patent, it indicates that the company has issued a patent that is novel but has low true value. If the manager is rational and there are no frictions, she will agree and not follow up on this innovation. Hence, the coefficient β_R will be positive. The rational manager will not react to the irrational component because she recognizes it as irrational, so β_{IR} is zero.

Prediction 1.b (Sustaining Innovation, Frictions or Behavioral Manager)**.** *For both novel and non-novel firms, the stronger the undervaluation of current innovations, the lower the fraction of follow-up innovations, i.e.,* $\beta_{IR} > 0$*. The manager still reacts positively to the rational component of issuance returns, i.e.,* $\beta_R > 0$*.*

When there are frictions or the manager is irrational, she will react positively to the rational component for the same reason as in Prediction 1.a, but she will also react positively to the irrational component. Suppose that investors underreact to a patent announcement, the manager, taking the return at face value, will be less motivated to continue investing in that line of innovation. As a result, the firm will generate fewer future patents that cite the current innovation. We expect this pattern to hold for both novel and non-novel firms: if current innovations are not appreciated by the market, managers, regardless of the novelty of those innovations, will be less inclined to pursue follow-up research and more likely to explore new directions.

Prediction 2.a (Novelty-seeking Innovation, Rational Manager)**.** *In the scenario of a rational manager and no frictions, when deciding the direction of new research ideas, the rational component of issuance returns to current technology has a null effect, i.e.,* $\beta_R = 0$*. The manager will also not respond to the irrational component, i.e.,* $\beta_{IR} = 0$*. This relationship holds for both novel and non-novel firms.*

When the firm manager is rational and there are no frictions, as in Scenario 1, the manager responds only to the rational component of issuance returns. The rational returns to current

innovation, however, have no effect on whether to do novelty-seeking or copycatting in *new* research areas. A rational, frictionless manager chooses new areas of research by comparing the NPV of novel and non-novel new innovations. Since these innovations differ from current ones, the rational value of current technology is not directly correlated with the rational value of innovation in new areas.

Prediction 2.b (Novelty-seeking Innovation, Frictions or Behavioral Manager)**.** *For novel firms, if current novel patents issued are undervalued by the stock market, the manager will be discouraged from attempting novel ideas in new research ideas and shift to copycatting. The lower the irrational component of issuance returns, the lower the fraction of novel patents among non-self-citing ones, i.e.,* $\beta_{IR,novel} > 0$.
For non-novel firms, if current non-novel patents are undervalued, the manager switches to other overvalued, market-favored non-novel technology, hence a null effect. It is unlikely that a non-novel manager would switch to novelty-seeking, even when their current non-novel innovations are underappreciated. This means $\beta_{IR,non-novel} = 0$.

When deciding between novelty-seeking or copycatting in new ideas, firm managers respond differently to the irrational component of issuance returns, depending on the novelty of the current patents. If current patents are novel, managers will follow the market trend and switch to more copycatting innovation, as the market undervalues their novelty-seeking endeavors. One possible reason is that managers believe investors' lack of enthusiasm reflects a dislike for the firm's novelty, leading them to conclude that further novel innovation will not be rewarded. However, for non-novel firms, if current non-novel patents are undervalued, managers may either switch to more novel-seeking ($\beta_{IR,non-novel} < 0$) or to other more market-salient non-novel innovations ($\beta_{IR,non-novel} = 0$). We hypothesize and test empirically that managers are unlikely to switch to more novelty-seeking.[16] The average effect

[16]There are many potential reasons why non-novel managers will not switch to novelty-seeking. First, managers who conduct copycatting may be more likely to be short-term focused, that is, to care about meeting current market demand. Novel patents only give long-term benefits, and even negative short-term profits. Second, novel patents are riskier, and non-novel managers may be more risk-averse. Third, novel

across all firms can be positive if there is enough power in the novel-firm subsample.

In the table below, we summarize our predictions for the two innovation outcomes, sustaining innovation and novelty-seeking in new areas of research, under the two scenarios, rational frictionless managers, and frictional or behavioral managers.

Conceptual Framework: Managerial Response to Innovation Returns

	Sustaining Innovation	Novelty-Seeking Innovation
Rational Managers	$\beta_R > 0$, $\beta_{IR} = 0$	$\beta_R = 0$, $\beta_{IR} = 0$
Frictions or Behavioral Managers	$\beta_R > 0$, $\beta_{IR} > 0$	$\beta_R = 0$, $\beta_{IR,novel} > 0$, $\beta_{IR,non-novel} = 0$

In this conceptual framework, we first introduce measures of firms' innovation directions based on their patent filings and citation networks, and then lay out predictions for how firms' stock returns around patent issuance will affect their future innovation directions. We argue that these effects can be driven both by rational and irrational components of stock returns. We outline that when managers are irrational, have limited information, or face frictions, managers will react to the misreaction to patent issuance. In response to a lower irrational component of issuance return, managers reduce sustaining innovations, and shift from novelty-seeking innovations to imitative ones, especially in the case of novel firms.

5.3 Empirical Analysis of Returns on Innovation

In this section, we first use an ordinary least squares (OLS) regression to estimate the model in Section 5.2. However, the OLS results do not distinguish whether managers react only to the rational component of investor reactions or also to the irrational component. To confirm the effect of misreaction, we create an exogenous irrational component to issuance returns and show that managers do respond to the misreaction to issuance news in the ways

patents are more costly and capital-intensive, and managers with costly external financing may prefer non-novel R&D. Fourth, non-novel managers lack novel innovation ideas. In this paper, we do not explore the reasons why non-novel managers do not adopt novelty-seeking, a question that warrants further investigation in future studies.

predicted in Section 5.2. This will then strongly suggest that managers will also respond to the irrational component of the issuance return driven by bounded rationality that we documented in Section 3.

5.3.1 Empirical results from OLS

We run ordinary least squares to estimate the regression model of innovation directions on patent issuance 3-day returns as defined in Section 5.2:[17]

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

In Table 6, we report the results with both the fraction of sustaining innovations as well as the share of novel patents in new directions as dependent variables, using OLS regressions on the full firm sample. We find that, controlling for various firm-level characteristics, firms experiencing lower stock returns around patent issuance on average reduce sustaining innovations in the following one to five years. Furthermore, they shift their new innovation directions to fewer novelty-seeking patents relative to copycatting over the subsequent three to five years. In addition, if we separate the sample into periods with high and low novelty and separately estimate the effects in subsamples, we see in Table A.1 that the positive effect on sustaining innovation does not vary with current novelty levels. More importantly, for novelty-seeking, as in Table 7, *only* high-novelty firms reduce their share of novel innovation when attempting new directions after lower returns to their novel patents. Low-novelty firms do not switch to higher novelty, exhibiting a null effect. Our OLS results are consistent with the predictions of Scenario 2 in the previous section, in which managers react to the irrational

[17]Since the 3-day return has a low signal-to-noise ratio, running OLS with the 3-day return as the independent variable can lead to severe attenuation bias. To partially reduce noise, we use only observations with positive 3-day returns. The reason is that patent issuance is positive news for the firm (Kogan et al., 2017) and so a negative return on patent issuance is more likely to be driven by noise. Later, when we introduce the instrumental variable, we can use the full sample, since the 3-day return shocked by the instrument is less likely to be driven by noise. We also have IV results with only positive returns as a robustness check.

component of the issuance return.

However, these results are not sufficient to *prove* that managers are affected by the irrational return reactions. After all, they can also be a consequence of managers reacting *only* to the rational component of returns — this is especially true for the results on sustaining innovation. In addition, OLS estimates can be biased due to unobservables that correlate with both returns and future innovation decisions, such as organizational changes in the R&D department that simultaneously influence investor reactions and firms' innovation outcomes. To deal with both issues, in the next section, we introduce an exogenous shock to the irrational component of issuance returns and estimate the causal relationship between investors' misreaction to patent issuance and future innovation directions.

5.3.2 Exogenous Shock to Misreaction as an Instrumental Variable

In this section, we construct an exogenous shock to the *misreaction* to issuance news, and revisit the firm-issuance-day regression model relating future innovation outcomes to three-day stock returns after patent issuance, specified in Section 5.2:

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

To identify the causal effect of *misreaction* on innovation directions, 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 manually exclude days featuring economic or technological news, resulting in a set of

924 days with distracting sensational news between 1975 and 2021.[18] We instrument three-day returns $r_{i,d\to d+2,t}$ using $\text{Distraction}_{d\to d+2,t}$, which is the count of high news-pressure days within the three-day patent issuance window (Tuesday to Thursday, since patents are always issued on Tuesdays). So the instrument takes values of 0, 1, 2, or 3.

Using this instrument, we exploit within-firm time-series variation by comparing periods with different levels of investor distraction from 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 misreaction to patent news on firms' future innovation directions. First, we require a strong correlation between the frequency of distracting events $Distraction_{d\to d+2,t}$ (that is, 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 increases investor distraction and creates a misreaction to patent issuance, *lowering* the returns on patent issuance announcement days.[19] The second key assumption, the exclusion restriction, is not directly testable. However, because our sensational news measure explicitly excludes economic and technology-related news, it is unlikely to directly influence firms' future innovation directions.

[18] See Section 2.3 for details of construction of the sensational news measure.

[19] This "strong instrument" assumption is empirically testable using the effective F-statistics from the first-stage regression, which we report in the results.

We run this IV regression on all days with patent issuance with non-missing innovation direction measures and past firm characteristics, to empirically test the hypotheses in Section 5.2 on how misreaction in issuance returns impacts future innovation directions.[20]

First, we investigate the impact on sustaining innovation. We run IV regressions using Sustaining Innovation$_{i,t+1\to t+\tau}$ as the outcome variable, which is the fraction of self-citing patents among all patents filed from quarter $t+1$ to quarter $t+\tau$. We find that exogenous declines in issuance returns – triggered by investor distraction from sensational news – significantly reduce firms' future filings of follow-up patents. This is consistent with Prediction 1.b in Section 5.2: Lower market returns driven by an exogenous mispricing signal to managers that the market undervalues its recently developed technologies, discouraging further investment in the same area. In Table 8, we see that, on average, a 10 percent equity return decrease (on a quarterly basis) reduces the share of sustaining patents by 1.0 percent in the next year, and cumulatively by 0.7 percent over five years. We also see that the first-stage coefficients are significantly negative with high F-statistics, confirming a strong instrument: greater investor distraction from sensational news ($Distraction_{d\to d+2,t}$) lowers firms' three-day returns after patent issuance. One concern is that the firms' total returns may be driven by systematic risk premia unrelated to firm-specific performance. We conduct robustness checks in the Online Appendix using three-day abnormal returns around patent issuance as the independent variable.[21] The results, in Table I.B.1, remain consistent, further supporting the causal relationship between issuance returns and shifts in firms' innovation direction.

We also investigate whether the market reaction differently affects firms' sustaining innovation when firms have high and low novelty, defined by whether the percentage of novel patents issued exceeds 50% in a given quarter. Consistent with our hypothesis that dis-

[20] To check consistency with the OLS specification, we also test robustness of the IV results with only positive returns. Robust results are available on request.

[21] 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.

appointing returns discourage follow-up innovation regardless of current novelty levels, our IV regression results using high- and low-novelty subsamples in Table A.2 show that lower three-day issuance returns significantly reduce firms' future sustaining innovation shares in both high- and low-novelty samples.

Second, we test Prediction 2.b in Section 5.2 on the share of novel innovations among the set of non-self-citing patents (new directions) in the following five years. Table 9 presents the IV estimates using the *full sample*, along with first-stage results. The first-stage results again confirm a strong instrument. The IV estimates show that an exogenous equity return drop leads an average firm to shift future new innovations away from novel patents to more copycatting. On average, a 10 percent decline in equity returns (on a quarterly basis) reduces the share of novel patents by around 1.2 percent over five years. Robustness checks using three-day abnormal returns yield very similar results (as shown in Table I.B.2).

As a more direct test of Prediction 2.b, we explore the difference in effects when firms have high versus low novelty. Prediction 2.b hypothesizes that, after lower issuance returns driven by misreaction, managers are discouraged from future investment in novel technologies only in firms with high novelty, while in firms with low novelty, we should not find this strong positive coefficient. To test this hypothesis, we split our sample into high- and low-novelty subsamples, and run a separate IV regression on each subsample. The results in Table 10 strongly support our hypotheses. A disappointing equity return driven by our exogenous shock to mispricing significantly reduces future novelty-seeking only when firms have high novelty. Specifically, a 10 percent lower issuance return on a quarterly basis reduces the share of novel patent filings by 0.7 percent over the next year and around 1 percent over the next five years. In contrast, we find insignificant results for firms with low novelty.

5.4 Mechanism and Discussion

We provide causal evidence that a lower return driven by exogenous mispricing causes firms to follow up less on current patents, and causes novel firms to shift from pursuing other novel ideas toward imitating market trends. However, the underlying mechanism for why firm managers care about short-term *mis*reactions to patents when making long-term innovation decisions remains unclear. In this section, we lay out three cases where mispricing matters for real decisions. We are agnostic about which specific channel dominates. We plan to explore and empirically test these different channels in future research.

First, the manager may be irrational in the same way as investors. In particular, she shares investors' biased beliefs and underprices novel innovations and overprices non-novel ones. Therefore, if she sees lower returns to a patent announcement, even if these lower returns are driven by mispricing, she agrees with the market and does fewer follow-ups. If a manager of a novel firm sees lower returns to novel patents, she agrees with investors' underpricing of novel innovations and shifts new research areas away from novelty.

Second, the manager may be uncertain about the patent's true value and seek to learn it from the market. If the manager cannot differentiate whether the price is moving for rational or irrational reasons, she will react to the full return, both to its rational and irrational components (Goldstein, 2023). When deciding on sustaining innovation, she may learn from the market the value of current innovations. When she takes the lower returns at face value, she follows up less on current technology. When deciding on novelty-seeking in new areas, she may mistakenly learn from the market that novelty has little economic value and switch to non-novel technologies.

Third, the manager may face frictions or agency costs. In this case, she will react to the investors' mispricing even though she knows the true value of innovation. One possible friction is that 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), firms may distort investment decisions in response to the full issuance return. For example, Kodak, the company that invented the first digital camera in 1977, was granted a patent for it in 1978.[22] However, this novel technology did not gain significant stock returns at the time. Investors viewed Kodak as a high-margin company with stable returns from its film business, and the company faced significant investor pressure to maintain those returns. Therefore, Kodak executives abandoned further investment in digital technologies. Instead, they decided to follow the market trend and join the innovation race in medical equipment. Agency conflicts between managers and shareholders may also drive managers to take short-term returns at face value and respond to them, the irrational component included. For example, managers face tenure pressure and career concerns, leading to managerial myopia and short-termism. In addition, stock-based managerial compensation incentivizes managers to pursue short-term stock market gains.

5.5 Implications of Novelty Misreaction on Innovation

In this section, we start by bringing together our findings earlier in this section that short-term misreaction to patent issuance influences future innovation directions and our findings in Section 3 on misreaction to novelty. We then discuss the implications of novelty mispricing for the measurement of innovation value.

In terms of sustaining innovations, we show that when current patents are underappreciated by the stock market, managers tend to follow up less on current technologies. From Section 3, we know that novel patents, on average, are undervalued; therefore, combining the two facts implies that novel technologies are less likely to be followed up on. In contrast, non-novel patents are, on average, overvalued, which encourages managers to follow the prevailing market trend.

In terms of novelty-seeking versus copycatting in new directions, we provide evidence

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

that when investors undervalue current patents in high-novelty firms, managers of those firms tend to shift from novelty-seeking to copycatting when pursuing new ideas. On the other hand, if current patents are undervalued for non-novel firms, managers do not switch to more novelty-seeking. Since novel patents are undervalued and non-novel patents are overvalued on average, managers shift from novelty-seeking to overvalued, market-favored copycat innovations when researching in new areas.

These implications are important because they indicate that financial market misreaction can push corporate innovation in suboptimal directions. Because investors undervalue novel and overvalue non-novel technology, firms choose to continue developing novel innovations to a lesser extent and attempt fewer new novel directions. Instead, they tend to exploit the existing technology and copycat innovation trends too much because investors are overexcited about these non-novel technologies.

Finally, we discuss the implications of novelty mispricing for the measurement of innovation value. Kogan et al. (2017) (KPSS) measure innovation value as the market value the patent issuance news brings to the firm in a three-day window, effectively assuming that the three-day return captures a rational response to the news. However, we present evidence that the three-day response is too low for novel innovations and too high for non-novel innovations. In Online Appendix I.C, we argue that the KPSS value is still a valuable benchmark of the private value of innovation, as it remains a robust predictor of future firm growth. However, it can be improved upon: after adjusting it for mispricing, we find that the resulting modified KPSS value better predicts future firm growth.

6 Conclusion

In this paper, we document that investors systematically misreact to patent issuance news, underreacting to novel technologies and 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. A model where boundedly rational investors face cognitive limitations and uncertainty regarding patent novelty at issuance can explain these empirical patterns of mispricing.

We further examine the real economic consequences of investor mispricing, providing causal evidence that stock market misreactions significantly influence firms' future innovation directions. Specifically, disappointing equity returns around patent issuance, driven by exogenous misreaction to patent issuance news, push innovative firms away from further developing their current technologies, and steer novel firms away from pursuing other novel innovations, causing a shift toward more copycat innovations. These findings suggest that managers respond to investors' short-term mispricing of patent issuance when making innovation decisions.

Our findings have significant policy implications. Financial market misperceptions about patent novelty discourage firms from making future investments in novel technologies, despite evidence (Figure B.1 and Table B.1) that novel patents generate 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 improve investors' understanding of patent novelty, such as more efficient disclosure of patent novelty, investor education about 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.

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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.

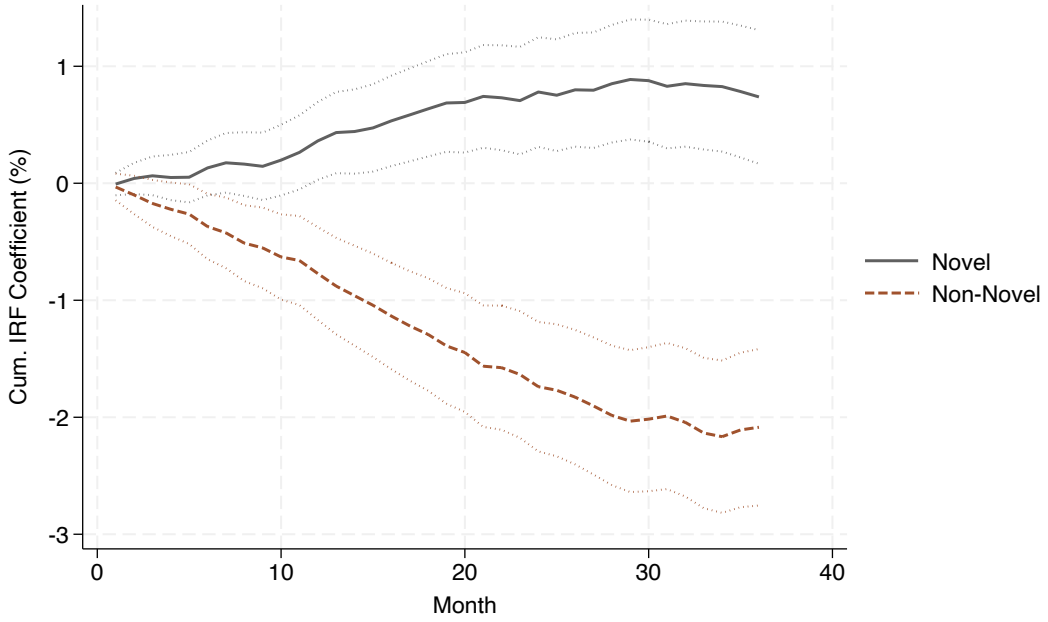


Figure 2: Cumulative Returns on (Non-)Novel Issuance

This figure plots the cumulative returns on novel and non-novel patent issuance. In particular, we run the following firm-month panel regression for each $\tau \in [1, 36]$:

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

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 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.

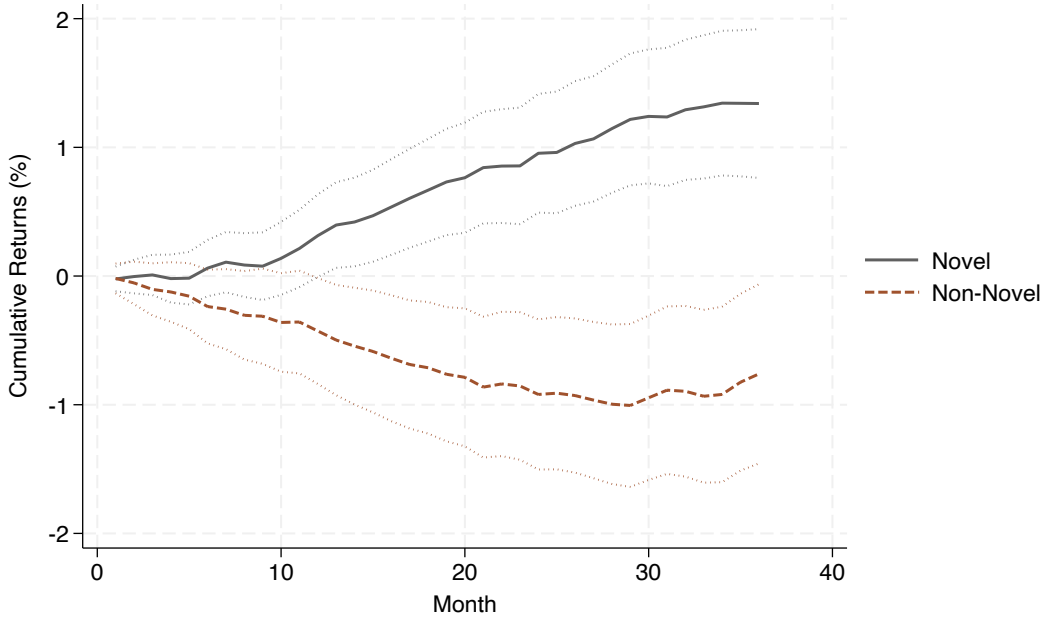


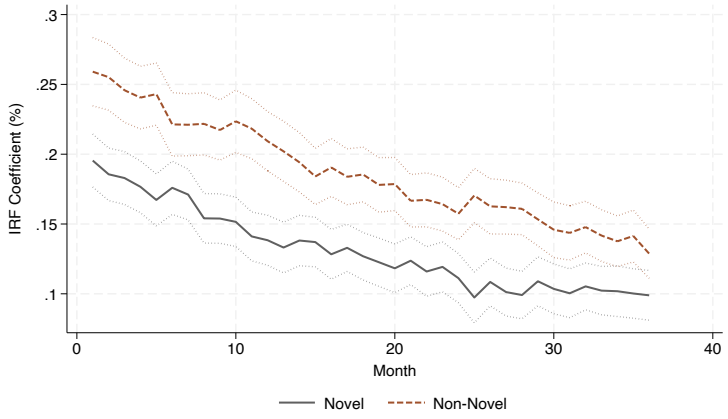
Figure 3: Impulse Response of Return Volatility after (Non-)Novel Patent Issuance

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

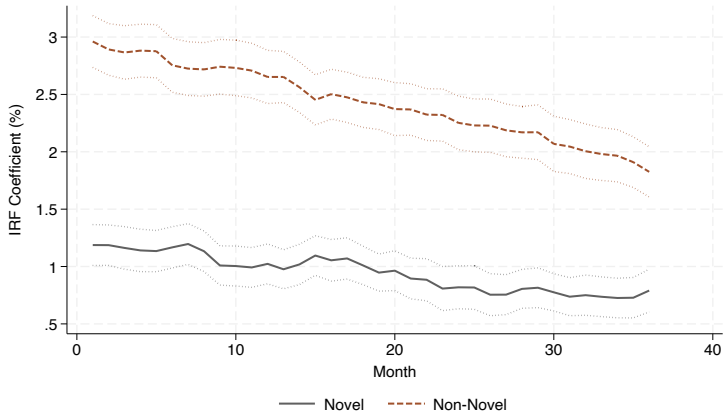


Figure 4: Theoretical Predictions of Issuance Returns to Novelty

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.

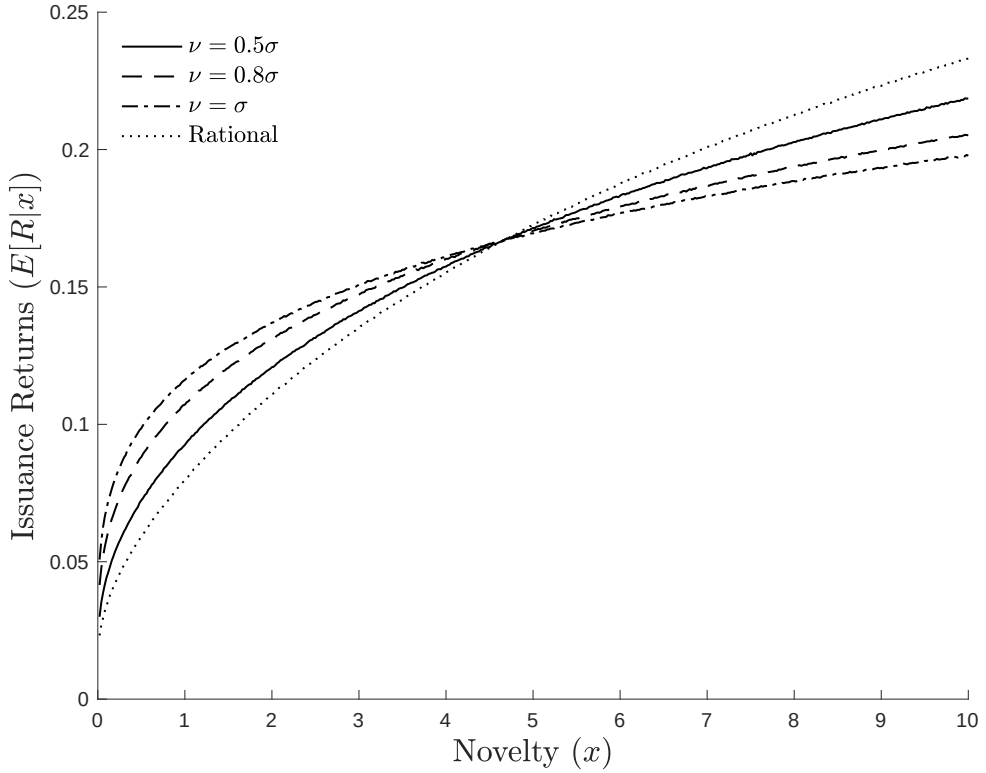


Figure 5: Theoretical Predictions of Dynamic Return Reaction by Novelty

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.

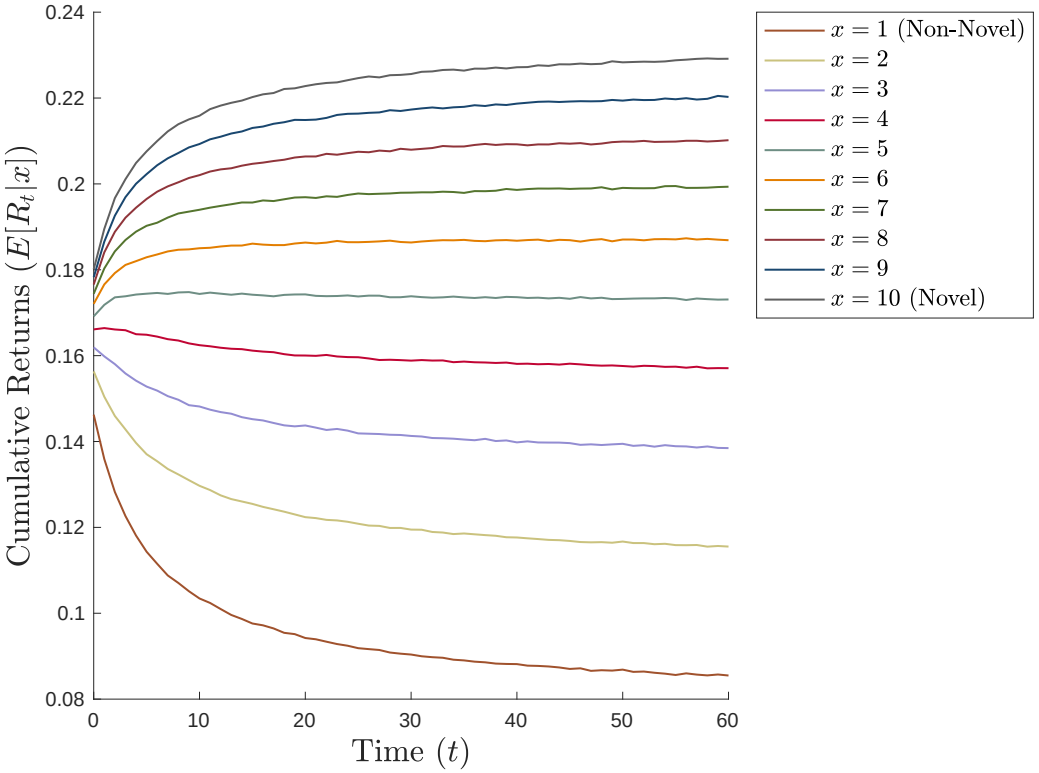


Figure 6: Theoretical Predictions of Dynamic Return Reaction by Signal Precision

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.

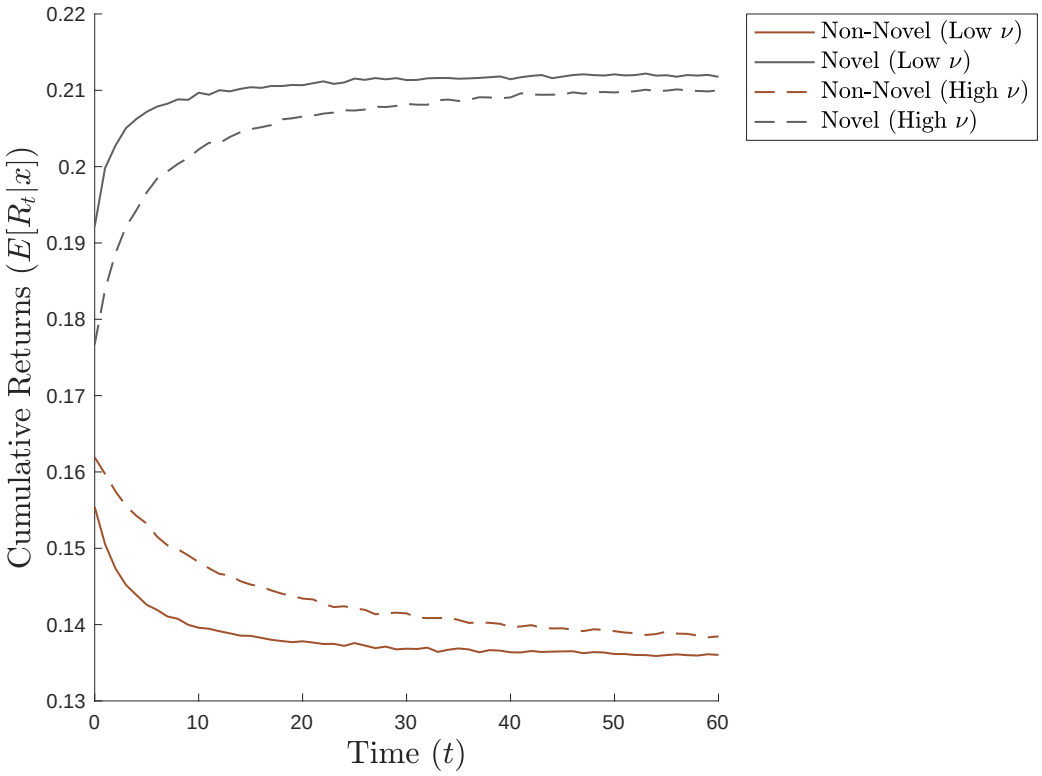


Figure 7: Three-Day Issuance Returns across Patent Novelty

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.

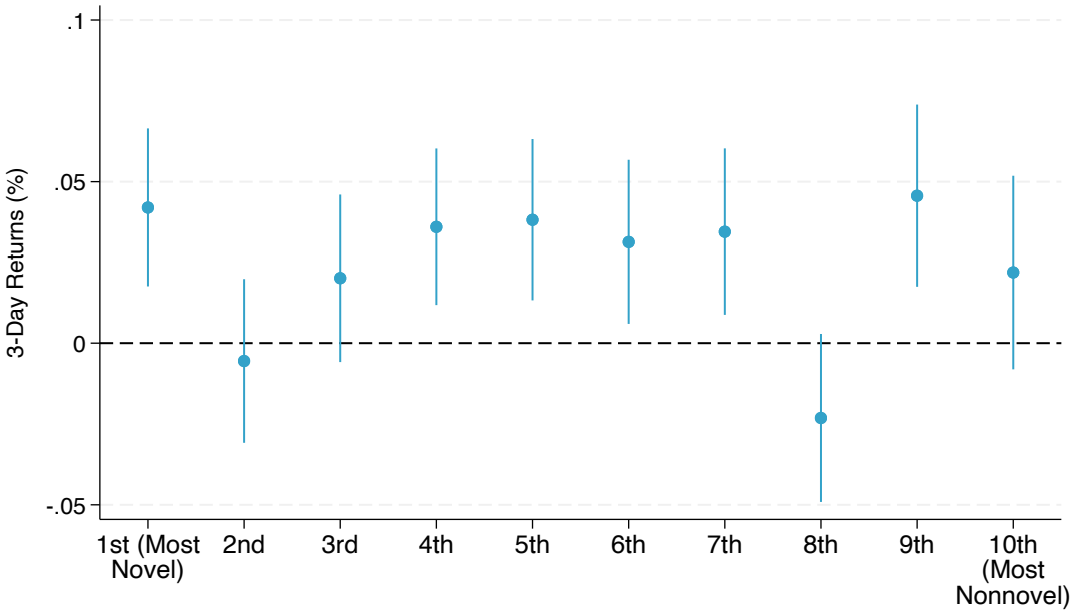


Figure 8: Cumulative IRF of Firm Returns after Patent Issuance across Patent Novelty

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.

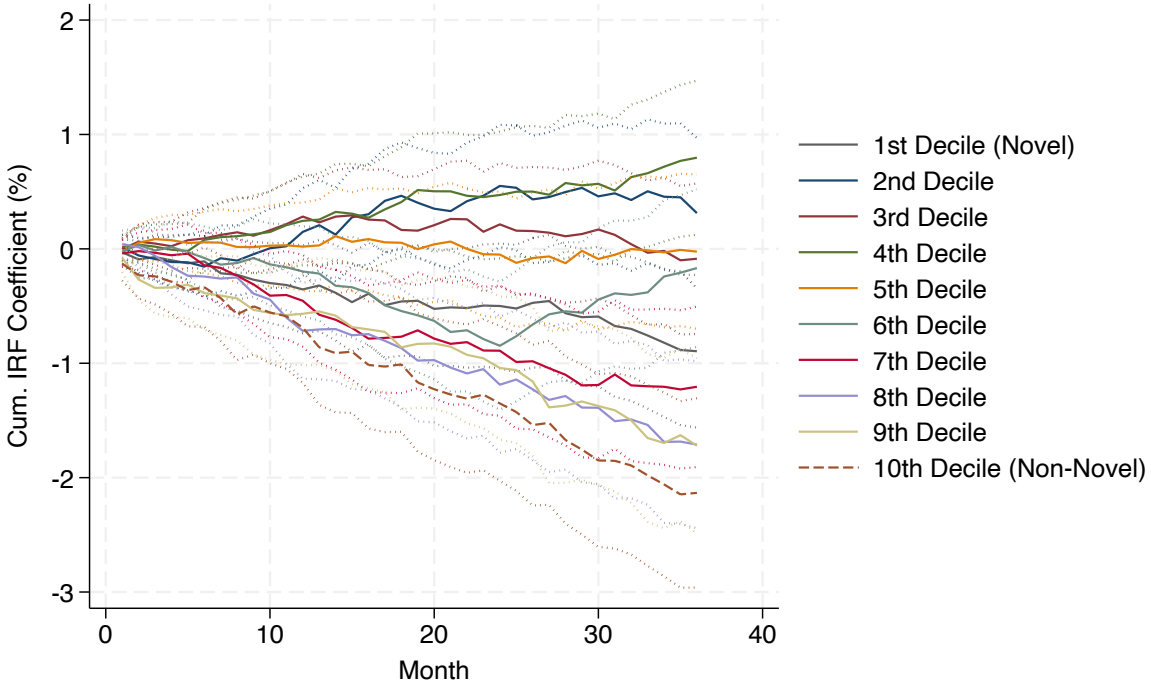


Figure 9: Cumulative Returns after Patent Issuance by Patent-Level Novelty Uncertainty

This figure compares the cumulative returns generated by each novel and non-novel patent across high- and low-novelty-uncertainty groups. We run the following regression for each $\tau \in [1, 36]$ at the firm-month level:

$$r_{i,t\to t+\tau} = \alpha_{ind,t} + \sum_{d\in\{Novel,Non-Novel\}} \beta_{\tau,d,high} N_{i\in d_t \& i\in \text{high uncertainty}_t} + \sum_{d\in\{Novel,Non-Novel\}} \beta_{\tau,d,high} N_{i\in d_t \& i\in \text{low uncertainty}_t} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}.$$

We count the number of patents in four categories: novel or non-novel, and high or low uncertainty about the novelty level. We define high (low) novelty-uncertainty patents as those with above- (below-) median standard deviation within the same novelty decile. 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 coefficients, $\beta_{\tau,d,high}$ and $\beta_{\tau,d,low}$ over $t \in [1, 36]$, for $d \in \{novel, non-novel\}$, which capture the cumulative perceived value change of one patent in each category, by the investors. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

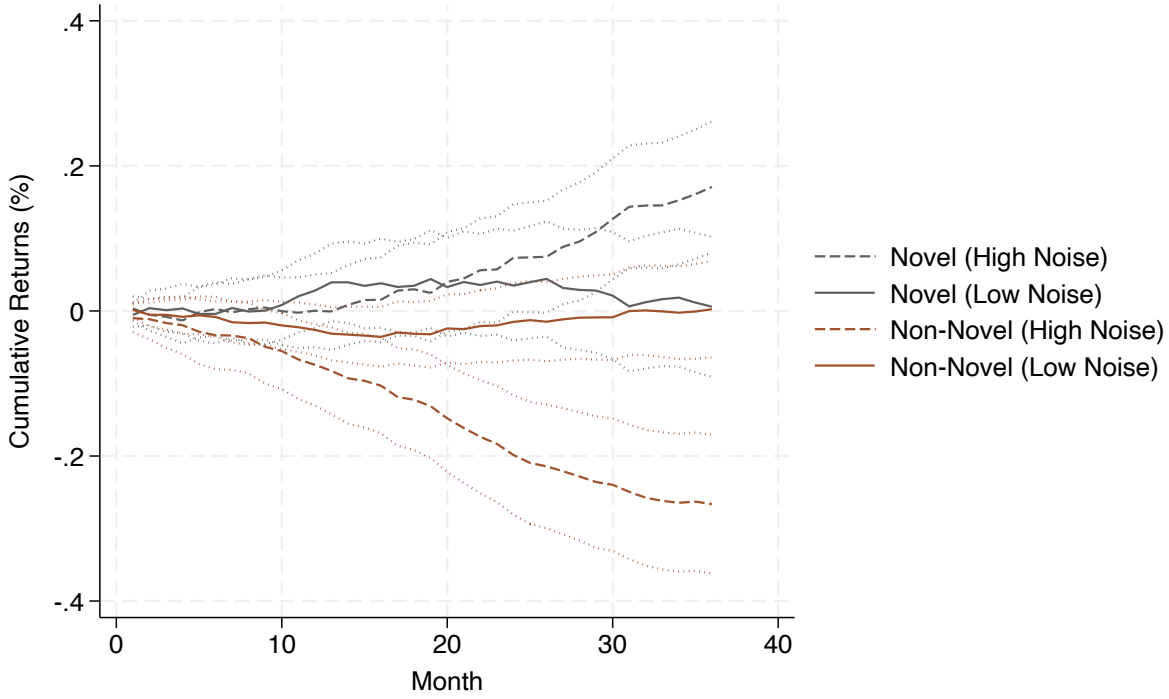


Figure 10: Cumulative IRF of Firm Returns after Patent Issuance by Institutional Holdings

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.

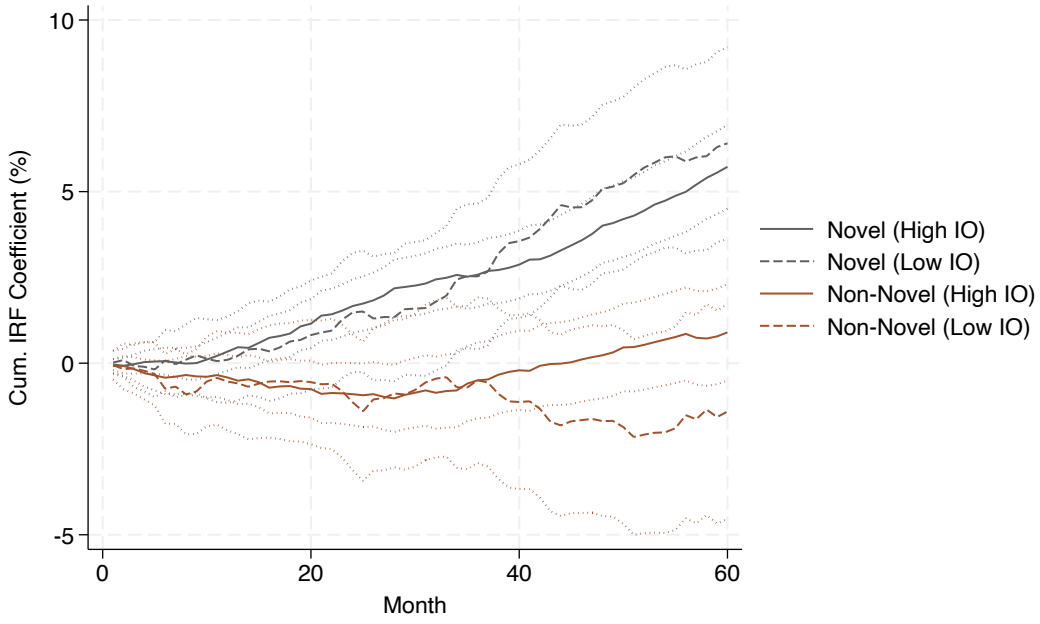


Table 1: Short-Term Returns on Patent Issuance Indicators

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	2,292,514	2,292,514	2,292,514	2,292,514

t statistics in parentheses

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

Table 3: Earnings Growth Expectations before and after Issuance

This table examines how analysts' earnings growth expectations shift before and after the issuance of novel versus non-novel patents. The analysis contains two parts. First, in Panel A, we examine the forecast revisions after the issuance events. We use forecasts made 90 days before and 45 days after patent issuance dates and measure the earnings growth forecast as the 2-year-ahead earnings forecast divided by the most recent earnings from the past year. The forecast revisions are thus the change in earnings growth forecasts from the pre- to the post-issuance period. We run the following regression at the analyst-firm-issuance-date level:

$$ForecastRevision_{a,i,t} = \alpha_a + \beta_{\tau,n}\mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,nn}\mathbb{1}\{i \in \text{Non-Novel}_t\} + \varepsilon_{a,i,t},$$

We then examine how forecast revisions predict forecast errors and show that analysts make systematic mistakes in Panel B. We define forecast errors as the realized 2-year earnings growth over the forecasted growth *after* patent issuance. We then run the following regression:

$$\begin{aligned} ForecastErr_{a,i,t} = \alpha_i + \alpha_t + \gamma_n ForeRev_{a,i,t} \times \mathbb{1}\{i \in \text{Novel}_t\} \\ + \gamma_{nn} ForeRev_{a,i,t} \times \mathbb{1}\{i \in \text{Non-Novel}_t\} + \varepsilon_{a,i,t} \end{aligned}$$

A positive coefficient suggests underreaction to issuance news, and a negative coefficient suggests overreaction. We control for analyst and issuance date fixed effects. Standard errors are clustered at the date level.

Panel A: Forecast Revisions after Issuance

	(1)	(2)
	Forecast Revisions	Forecast Revisions
Novel Issuance	0.0037***	0.0044***
	(4.37)	(5.81)
Non-Novel Issuance	0.0043***	0.0051***
	(4.69)	(6.46)
R^2	0.025	0.087
Analyst FE	Yes	Yes
Date FE	No	Yes
Observations	12,825,586	12,825,579

t statistics in parentheses

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

Panel B: Forecast Errors on Revisions

	(1)	(2)
	Forecast Errors	Forecast Errors
ForeRev×Novel Issue	0.0591***	0.0468***
	(3.45)	(3.08)
ForeRev×Non-Novel Issue	-0.0114	-0.0383**
	(-0.59)	(-2.09)
R^2	0.098	0.151
Analyst FE	Yes	Yes
Date FE	No	Yes
Observations	11,256,910	11,256,903

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: Summary Statistics of Innovation Directions

This table reports summary statistics for the innovation directions. We report future 1-, 3-, and 5-year sustaining and novelty-seeking innovations derived from patent filings at the firm-quarter level. Sustaining innovation is defined as the fraction of patent filings that cite the current technology granted to the firm at quarter t. Novelty-seeking innovation is defined as the fraction of novel patent filings among the set of patent filings that do not cite the current technology (in new research areas).

	mean	count	sd	p5	p25	p50	p75	p95
Sustaining innovation$_{t+1\to t+4}$	0.053	105,249	0.139	0.000	0.000	0.000	0.043	0.286
Sustaining innovation$_{t+1\to t+12}$	0.056	110,235	0.127	0.000	0.000	0.000	0.052	0.281
Sustaining innovation$_{t+1\to t+20}$	0.053	107,474	0.118	0.000	0.000	0.007	0.050	0.263
Novelty-seeking innovation$_{t+1\to t+4}$	0.627	104,123	0.311	0.000	0.406	0.667	0.923	1.000
Novelty-seeking innovation$_{t+1\to t+12}$	0.634	109,513	0.284	0.100	0.438	0.667	0.875	1.000
Novelty-seeking innovation$_{t+1\to t+20}$	0.637	106,988	0.274	0.136	0.447	0.667	0.870	1.000

Table 6: 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 only the estimates for the independent variable of primary interest. All variables are winsorized at 1% on both sides in each quarter. Standard errors are clustered at the firm-quarter level.

	Sustaining			Novelty-seeking		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$r_{i,d\to d+2,t}$	0.0016***	0.0018***	0.0019***	0.0011*	0.0018***	0.0022***
	(4.40)	(5.92)	(6.22)	(1.79)	(3.80)	(5.10)
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	0.31	0.40	0.43	0.67	0.78	0.82
Observations	203383	200576	191606	202670	200231	191368

t statistics in parentheses

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

Table 7: Firm's Future Novelty-Seeking and Equity Return (OLS)

This table examines whether firms' three-day issuance returns correlate more strongly with the change in novelty-seeking innovation when more novel patents are granted. 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 OLS regression:

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

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 only the estimates for the independent variable of primary interest. All variables are winsorized at 1% on both sides in each quarter. Standard errors are clustered at the firm-quarter level.

	High-novelty			Low-novelty		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$r_{i,d\to d+2,t}$	0.0013	0.0026***	0.0027***	0.0000	0.0008	0.0016***
	(1.58)	(4.05)	(4.58)	(0.04)	(1.27)	(2.65)
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	0.56	0.70	0.76	0.58	0.73	0.78
Observations	116473	115325	110417	85761	84429	80446

t statistics in parentheses

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

Table 8: 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 only the estimates for the independent variable of primary interest. All variables are winsorized at 1% on both sides in each quarter. Standard errors are clustered at the firm-quarter level.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	FS	$\tau = 12$	FS	$\tau = 20$	FS
$r_{i,d\to d+2,t}$	0.1016***		0.0643***		0.0689***	
	(4.53)		(4.75)		(3.83)	
Sensational News$_{d\to d+2,t}$		-0.0186***		-0.0231***		-0.0176***
		(-6.30)		(-7.80)		(-5.73)
Firm FE	Yes		Yes		Yes	
Controls	Yes		Yes		Yes	
Sample Period	1975-2021		1975-2019		1975-2017	
F-stats		40		61		33
Observations	382448	382448	376881	376881	360341	360341

t statistics in parentheses

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

Table 9: 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 only the estimates for the independent variable of primary interest. All variables are winsorized at 1% on both sides in each quarter. Standard errors are clustered at the firm-quarter level.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	FS	$\tau = 12$	FS	$\tau = 20$	FS
$r_{i,d\to d+2,t}$	0.1160***		0.0962***		0.1152***	
	(3.23)		(4.30)		(3.76)	
Sensational News$_{d\to d+2,t}$		-0.0184***		-0.0231***		-0.0176***
		(-6.22)		(-7.78)		(-5.72)
Firm FE	Yes		Yes		Yes	
Controls	Yes		Yes		Yes	
Sample Period	1975-2021		1975-2019		1975-2017	
F-stats		39		61		33
Observations	381169	381169	376231	376231	359897	359897

t statistics in parentheses

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

Table 10: 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 only the estimates for the independent variable of primary interest. All variables are winsorized at 1% on both sides in each quarter. Standard errors are clustered at the firm-quarter level.

	High-novelty			Low-novelty		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$r_{i,d\to d+2,t}$	0.0715**	0.0820***	0.1069***	0.0589	0.0289	0.0242
	(2.15)	(3.56)	(3.57)	(0.89)	(0.83)	(0.49)
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

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

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.

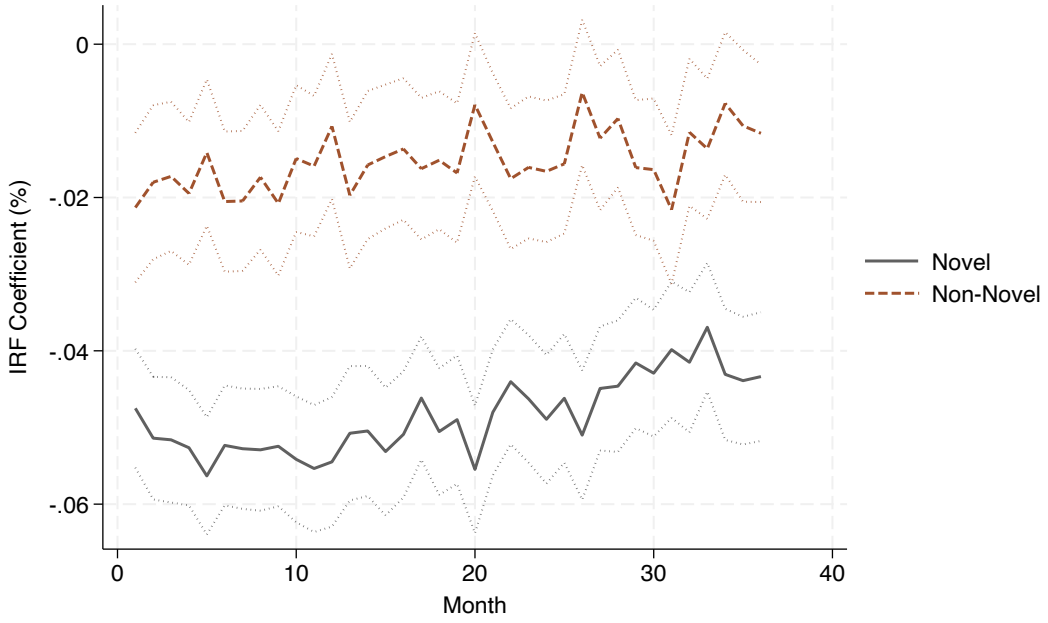


Table A.1: Firm's Future Sustaining Innovations and Equity Return (OLS)

This table examines whether firms' three-day issuance returns correlate more strongly with the change in sustaining innovations when more novel patents are granted. 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 OLS regression:

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

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 only the estimates for the independent variable of primary interest. All variables are winsorized at 1% on both sides in each quarter. Standard errors are clustered at the firm-quarter level.

	High-novelty			Low-novelty		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$r_{i,d\to d+2,t}$	0.0016***	0.0017***	0.0014***	0.0011**	0.0015***	0.0018***
	(3.06)	(3.74)	(3.31)	(2.27)	(3.85)	(4.60)
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	0.29	0.37	0.41	0.41	0.50	0.52
Observations	116915	115548	110559	86028	84544	80528

t statistics in parentheses

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

Table A.2: 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 only the estimates for the independent variable of primary interest. All variables are winsorized at 1% on both sides in each quarter. Standard errors are clustered at the firm-quarter level.

	High-novelty			Low-novelty		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$r_{i,d\to d+2,t}$	0.0890***	0.0592***	0.0653***	0.1117**	0.0588**	0.0688*
	(4.02)	(4.07)	(3.60)	(2.22)	(2.39)	(1.74)
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

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

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.

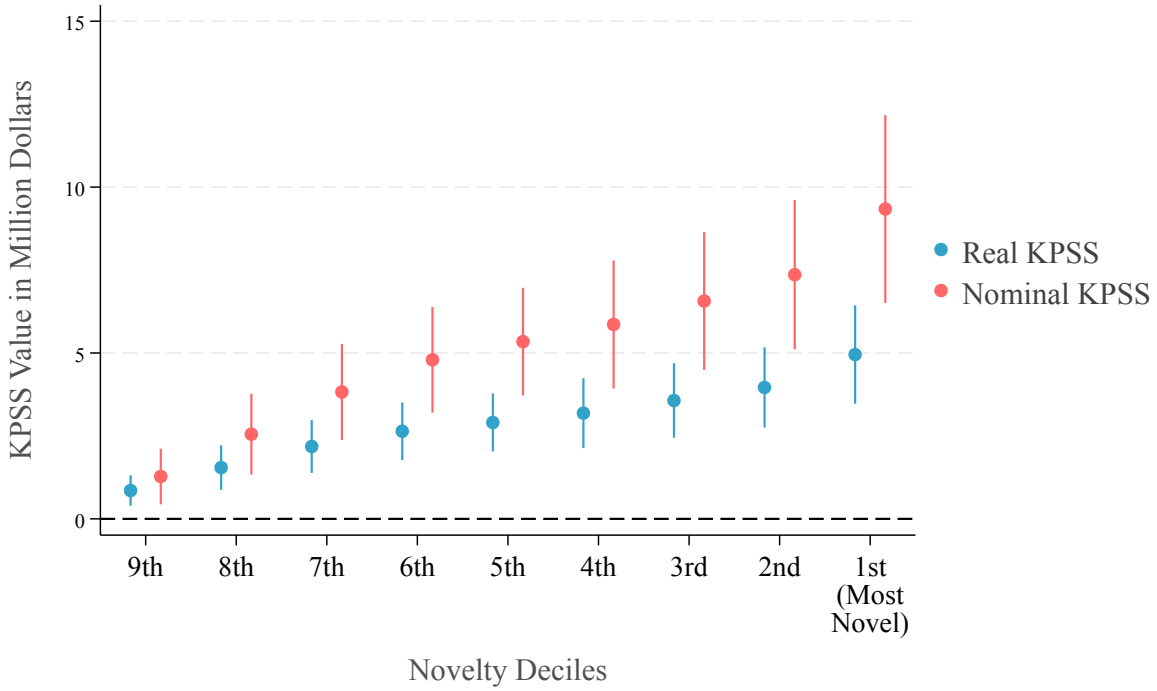


Table B.1: Patent Social Value on Novelty

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

In this section, we present several robustness checks with alternative specifications and measures of novelty. These robustness analyses all confirm that investors underreact to novel patents and overreact to non-novel patents.

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 underreact 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:

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

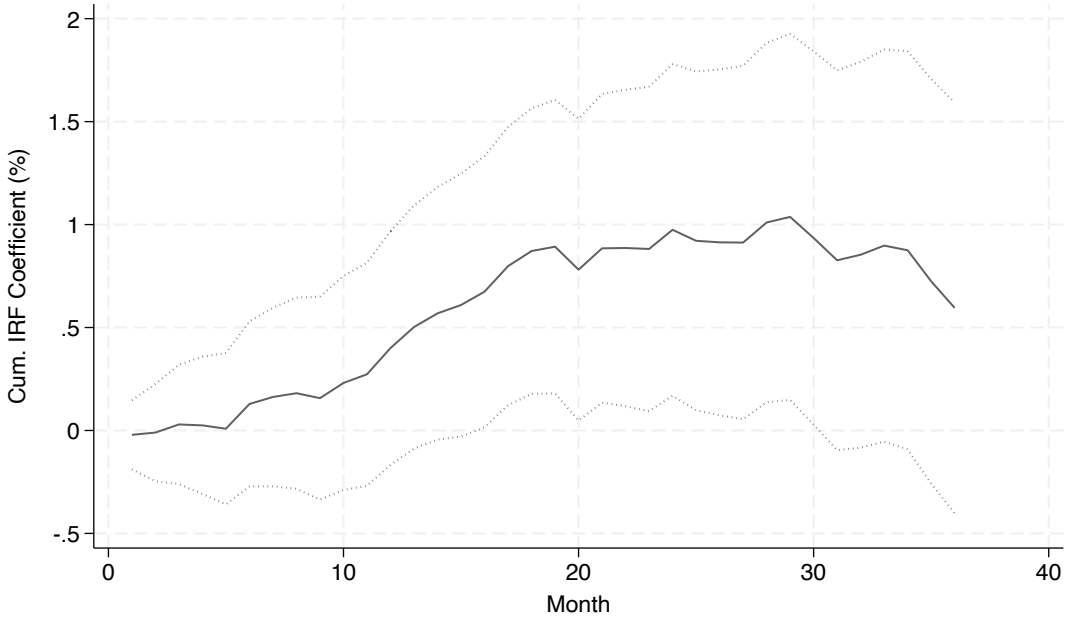
In Figure I.A.1, we see that novel intensity positively predicts future returns in the next two years, suggesting that investors underreact more strongly to firms with more novel patents. We lose some power in this specification because we are conditioning only on the firms that have at least one patent 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.

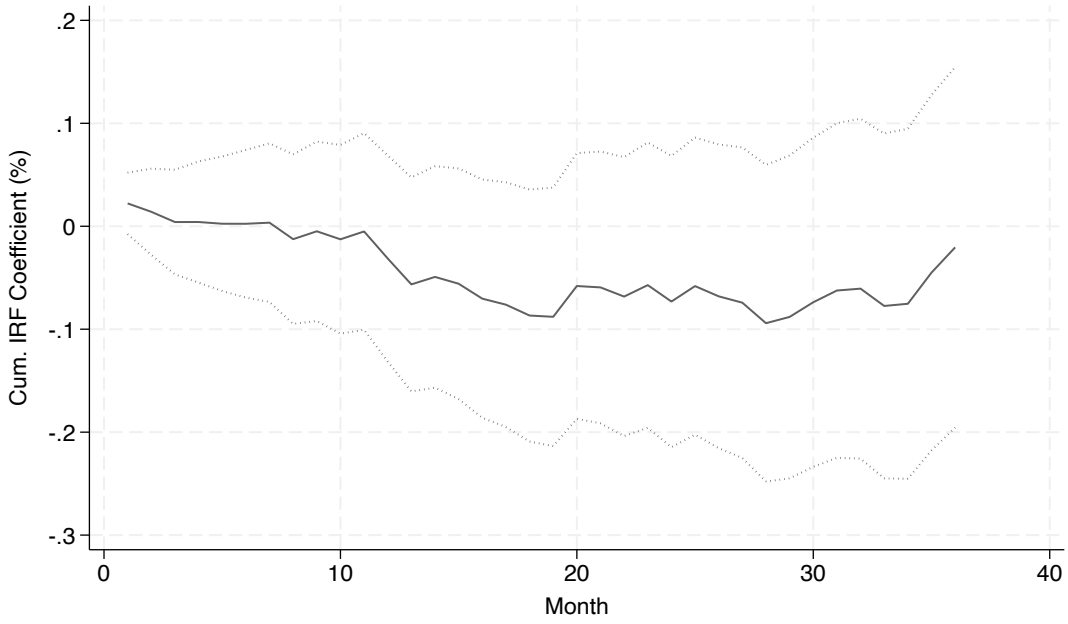
We run local projection regressions with the similarity score. As shown in Figure I.A.2, the similarity score displays negative predictability of future returns, confirming that investors overreact to incremental innovations.

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 are 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 examine whether the underreaction to novel patents and the overre-

action to non-novel patents differ depending on whether the patent is a breakthrough patent. Kelly et al. (2021) define a breakthrough patent to be one with a high ratio of 10-year forward similarity and 5-year backward similarity – one that is both novel relative to their predecessors and influential for subsequent research. We split the novel and non-novel patents, respectively, into breakthrough and non-breakthrough patents and run the cumulative return regressions jointly on four issuance events:

$$\begin{aligned} r_{i,t\to t+\tau} = \alpha_{ind,t} &+ \beta_{\tau,n,bk}\mathbb{1}\{i \in \text{Novel Breakthrough}_t\} \\ &+ \beta_{\tau,n,nbk}\mathbb{1}\{i \in \text{Novel Non-Breakthrough}_t\} \\ &+ \beta_{\tau,nn,bk}\mathbb{1}\{i \in \text{Non-Novel Breakthrough}_t\} \\ &+ \beta_{\tau,nn,nbk}\mathbb{1}\{i \in \text{Non-Novel Non-Breakthrough}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}. \end{aligned}$$

Using this specification, we obtain the cumulative response for each of the four issuance types, conditional on the occurrence of the other three. Table I.A.1 reports the regression results. We see that the underreaction to novelty is stronger for patents that are also breakthrough, and the overreaction to non-novelty is stronger for patents that are also non-breakthrough. For patents that are novel and later proven influential, we observe the strongest underreaction. For non-novel patents later proven to be non-influential, we see the strongest overreaction. These results give strong additional evidence of our mechanism of misreaction. Investors react to ex-ante novelty, and because they are unsure about patent novelty, they shrink their perceived value toward an intermediate prior. Therefore, we should expect that, for patents that ex post have high value, we observe the strongest underreaction, and for patents that ex post have low value, we observe the strongest overreaction. This is exactly aligned with our findings.

Table I.A.1: Cumulative Returns on Novelty and Breakthrough Patents

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

$$\begin{aligned} r_{i,t\to t+\tau} = \alpha_{ind,t} &+ \beta_{\tau,n,bk}\mathbb{1}\{i \in \text{Novel Breakthrough}_t\} \\ &+ \beta_{\tau,n,nbk}\mathbb{1}\{i \in \text{Novel Non-Breakthrough}_t\} \\ &+ \beta_{\tau,nn,bk}\mathbb{1}\{i \in \text{Non-Novel Breakthrough}_t\} \\ &+ \beta_{\tau,nn,nbk}\mathbb{1}\{i \in \text{Non-Novel Non-Breakthrough}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}. \end{aligned}$$

where the four indicator variables represent that the firm issues at least one novel breakthrough, novel non-breakthrough, non-novel breakthrough, or non-novel non-breakthrough 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 Breakthrough	0.5770***	1.3544***	2.4561***	3.2140***
	(2.59)	(4.70)	(5.90)	(6.29)
Novel Non-Breakthrough	-0.3413***	-0.5838***	-0.8494***	-1.3305***
	(-2.79)	(-3.22)	(-3.21)	(-3.92)
Non-Novel Breakthrough	-0.0384	0.2641	0.3888	1.1162*
	(-0.15)	(0.72)	(0.76)	(1.87)
Non-Novel Non-Breakthrough	-0.4941***	-1.1332***	-2.2368***	-2.6255***
	(-3.17)	(-5.25)	(-7.25)	(-7.16)
R^2	0.304	0.313	0.328	0.342
Controls	Yes	Yes	Yes	Yes
IndustryxMonth FE	Yes	Yes	Yes	Yes
Observations	1,970,433	1,970,433	1,970,433	1,970,433

t statistics in parentheses

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

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.3, 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.4 shows the cumulative alpha of three-year sorts, and Figure I.A.5 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.3: 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).

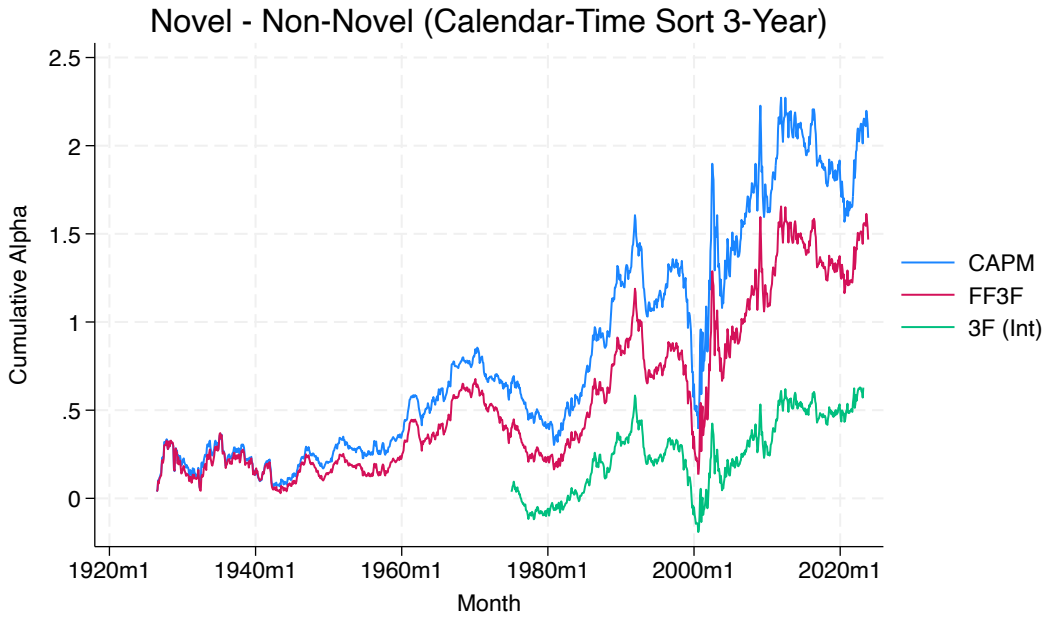


Figure I.A.4: Cumulative Alpha of 3-Year Portfolio Sorts on Novel Intensity

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).

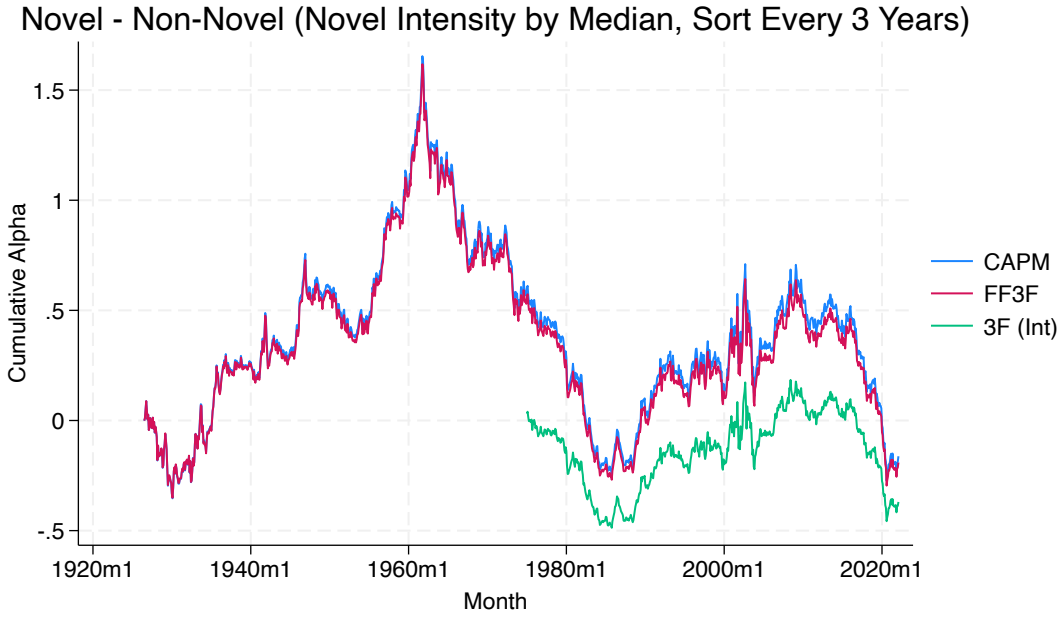
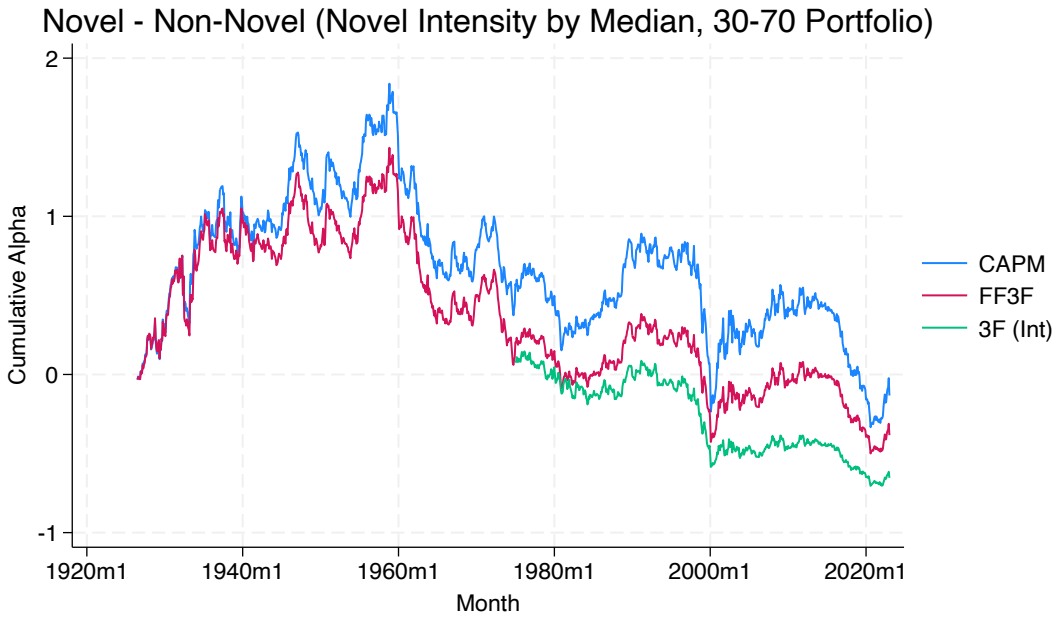


Figure I.A.5: Cumulative Alpha of Monthly Portfolio Sorts on Novel Intensity

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

In this section, we present several robustness analyses of the mispricing mechanism. We first use a reshuffling exercise to confirm that investors indeed react differently to patent novelty, not to some assignee characteristics. We also run an impulse response test on the pre-periods of patent issuance and find parallel trend, confirming that we find the treatment effects of issuance news. Finally, we run a forecast error regression with novel intensity on the intensive margin and confirm an underreaction to novel patent issuance.

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.6 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.7 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.6: 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.

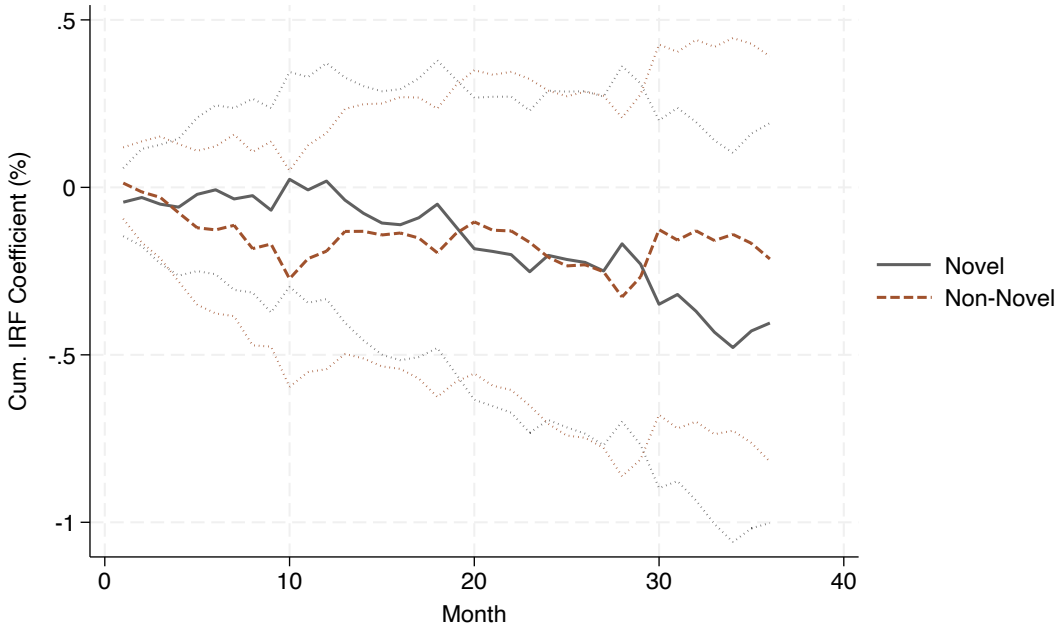


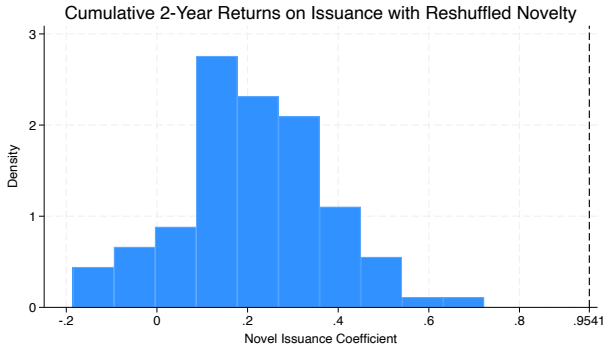
Figure I.A.7: Coefficient Distribution of Cum. Return on Randomized (Non-)Novel Issuance

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:

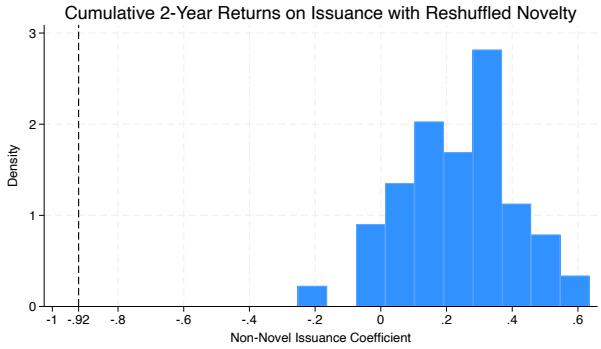
$$r_{t\to t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Shuffled Novel}_t\} + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Shuffled Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau},$$

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:

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

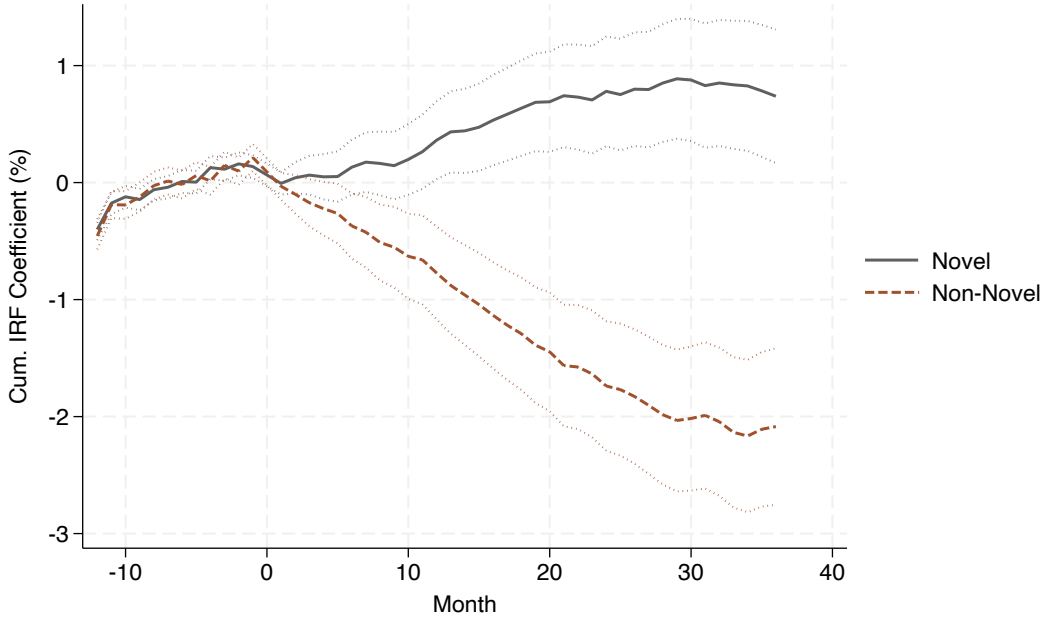
We run lagged returns in the past 12 months. In Figure I.A.8, we see that the pre-period returns are all, on average, close to 0, and more importantly, the pre-trend moves in parallel with novel and non-novel patent issuance, suggesting that the return predictability we see in the post-periods are likely driven by the issuance of novel versus non-novel patents.

Figure I.A.8: 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 and non-novel issuance As a robustness check of the mispricing of novelty, we directly compare the forecast errors of firms with and without patent issuance. We hypothesize that investors form overly pessimistic expectations about a firm's future profitability when it is granted novel patents. If investors trade based on these earnings expectations, the errors in earnings expectations will directly translate into return predictability. To test this mechanism, we examine subjective forecast errors following patent

issuance, following 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 as the median of analyst-level forecasts issued within 45 days of the prior earnings announcement. We winsorize consensus expectations at the 1% level to remove anomalous forecasts. Denoting the actual EPS in year $t+\tau$ as $\pi_{t+\tau}$ and the forecasts issued in year t as $F_t\pi_{t+\tau}$, we regress earnings forecast errors on patent issuance indicators in a firm-year panel:

$$\begin{aligned}\frac{\pi_{i,t+\tau} - F_t\pi_{i,t+\tau}}{P_{i,t-1}} &= \alpha_\tau + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_{t-1}\} \\ &\quad + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_{t-1}\} + \gamma' X_{i,t-1} + \varepsilon_{i,t+\tau}, \end{aligned} \tag{3}$$

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 idea that 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 overly pessimistic forecasts given a patent issuance. On the other hand, a negative coefficient suggests that investors are overly optimistic. In Table I.A.2, 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.3, 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.

Table I.A.2: 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	97,884	82,783	80,885	69,007

t statistics in parentheses

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

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.3: 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 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 only the estimates for the independent variable of primary interest. All variables are winsorized at 1% on both sides in each quarter. Standard errors are clustered at the firm-quarter level.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	FS	$\tau = 12$	FS	$\tau = 20$	FS
$ar_{i,d\to d+2,t}$	0.1057***		0.0976***		0.0868***	
	(3.90)		(3.58)		(3.19)	
Sensational News$_{d\to d+2,t}$		-0.0190***		-0.0164***		-0.0155***
		(-6.42)		(-5.52)		(-4.91)
Firm FE	Yes		Yes		Yes	
Controls	Yes		Yes		Yes	
Sample Period	1975-2021		1975-2019		1975-2017	
F-stats		41		30		24
Observations	187,346	187,346	184,613	184,613	176,153	176,153

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

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 only the estimates for the independent variable of primary interest. All variables are winsorized at 1% on both sides in each quarter. Standard errors are clustered at the firm-quarter level.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	FS	$\tau = 12$	FS	$\tau = 20$	FS
$ar_{i,d\to d+2,t}$	0.0976**		0.1342***		0.1206***	
	(2.19)		(3.08)		(2.76)	
Sensational News$_{d\to d+2,t}$		-0.0186***		-0.0163***		-0.0154***
		(-6.29)		(-5.50)		(-4.89)
Firm FE	Yes		Yes		Yes	
Controls	Yes		Yes		Yes	
Sample Period	1975-2021		1975-2019		1975-2017	
F-stats		40		30		24
Observations	186,711	186,711	184,307	184,307	175,950	175,950

t statistics in parentheses

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

Table I.B.3: 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 only the estimates for the independent variable of primary interest. All variables are winsorized at 1% on both sides in each quarter. Standard errors are clustered at the firm-quarter level.

	High-novelty			Low-novelty		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$ar_{i,d\to d+2,t}$	0.0325	0.0810**	0.0717**	0.0703	0.0451	0.0702
	(0.84)	(2.33)	(2.25)	(0.54)	(0.38)	(0.30)
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	106,932	105,800	101,231	79,358	78,031	74,206

t statistics in parentheses

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

I.C Modified Patent Private Value

In Section 3, we argue that investors undervalue novel innovations and non-novel innovations in their three-day response to patent issuance news. This mispricing result infers that the patent private value, measured using three-day returns after issuance (Kogan et al., 2017) (KPSS value), does not capture the entire private value of the patent for the firm. The KPSS value for novel patents will be lower than it should be and higher for non-novel patents. In this section, we adjust for the KPSS value at the patent value by the average mispricing of novel and non-novel patents, and show that the modified KPSS value, consistent with the original KPSS value, is robust in predicting future firm outcomes.

We first compute the modified KPSS value by adding an additional term to the original KPSS value at the patent level. That is, for each patent i,

$$\text{Modified KPSS}_i = \text{KPSS}_i + \text{Adjustment}_i$$

where the adjustment is the product of the estimate of mispricing in stock returns times the market capitalization M of the firm that is issued patent i on the day prior to the announcement of the patent issuance:

$$\text{Adjustment}_i = (1-\bar{\pi})^{-1}\text{Ave Misreaction}_i M_i \tag{4}$$

$$\text{Ave Misreaction}_i = \begin{cases} 0.9541\%/N_{Novel} & \text{if } i \in \text{Novel} \\ -0.92\%/N_{Non-novel} & \text{if } i \in \text{Non-novel} \end{cases} \tag{5}$$

If multiple novel or non-novel patents are issued to the same firm on the same day, we assign each patent $1/N_{Novel}$ of the adjustment if it is a novel patent or $1/N_{Non-novel}$ of the adjustment if it is a non-novel patent. This is because the estimated mispricing is the aggregate effect from all novel or non-novel patent issuance. We also adjust for the unconditional probability of a successful patent application using the same number as Kogan et al. (2017), $\bar{\pi} = 55\%$ to be on the same basis as the KPSS value. We bound the modified private value to be nonnegative as the market value of a patent needs to be a positive variable.

We aggregate the modified KPSS value to firm-year level by summing up those issued to the firm in year t and run the same predictive regression of future firm growth using the modified and original private value as in Kogan et al. (2017). In particular, we iteratively use (a) profits, (b) output, (c) capital stock, and (d) employment as dependent variables and

estimate the following regression:

$$\log X_{f,t+\tau} - \log X_{f,t} = \alpha_\tau \theta_{f,t} + cZ_{f,t} + \varepsilon_{f,t+\tau}, \tag{6}$$

where the main variable of interest, $\theta_{f,t}$ is either the original or the modified KPSS value. We include in the set of control variables, $Z_{f,t}$, the log value of output $\log Y_{f,t}$, capital stock $\log K_{f,t}$, employment $\log H_{f,t}$, and the log number of unexpired patents granted up to year t to alleviate the mechanical correlation between the growth variable and innovation caused by the size of the firm. We also control for idiosyncratic volatility as it is likely correlated with firms' future growth opportunities. Finally, we control for log firm age and industry (SIC 3-digit code) times year fixed effects. We winsorize all variables at 99% level on both sides year by year and we standardize independent variables to unit standard deviation for direct comparison of magnitude. We follow the specification from Ma (2023) who runs the same predictive regressions with a technological obsolescence measure.

The results of the regressions are reported in Table I.C.1. First, we replicate the results in Kogan et al. (2017): we see that future firm growth is strongly related to the firm's private value of innovation, using their measure. Over a five-year horizon, a one standard deviation increase in private value predicts a 5% increase in profit, 4.4% in output, 2.7% in capital investment, and 1.9% in employment. Second, more importantly, we see that our modified value has stronger predictive power on firm growth. A unit standard deviation increase in the modified innovation value predicts a 5.5% increase in profits, 5.3% in output, 3.1% in capital investment, and 2.5% in employment, which are higher than the original KPSS counterparts. This evidence suggests that the private value of innovation, as measured by Kogan et al. (2017), is still a useful benchmark because it acts as a strong predictor of a firm's future growth. However, it does not capture the entire private value of innovation – if adjusted by the underpricing of novel patents and overpricing of non-novel patents, the adjusted measure more strongly predicts future firm growth.

Table I.C.1: (Modified) Innovation Private Value and Firm Growth

This table examines the relationship between the private value of innovation with its original measurement (Kogan et al., 2017) versus our modified measurement in account for the underpricing of novelty and overpricing of non-novelty, and firm growth using the model below:

$$\log X_{f,t+\tau} - \log X_{f,t} = \alpha_\tau \theta_{f,t} + cZ_{f,t} + \varepsilon_{f,t+\tau}.$$

The outcome variables, X, include firm profits, output, capital, and employment. The table presents results estimated up to five years. We control for the log value of output $\log Y_{f,t}$, capital stock $\log K_{f,t}$, employment $\log H_{f,t}$, the log unexpired patent stock, the log firm age, and idiosyncratic volatility. All independent variables are standardized to unit standard deviation. The model includes industry (SIC3)-by-year fixed effects. Standard errors are clustered by firm and year and shown in parentheses.

	Original KPSS Value					Modified KPSS Value				
	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Panel A: Profits										
	0.015***	0.025***	0.034***	0.044***	0.050***	0.015***	0.027***	0.038***	0.050***	0.055***
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)	(0.003)	(0.004)	(0.007)	(0.008)	(0.010)
Panel B: Output										
	0.019***	0.026***	0.033***	0.043***	0.044***	0.021***	0.029***	0.038***	0.049***	0.053***
	(0.002)	(0.005)	(0.008)	(0.010)	(0.012)	(0.003)	(0.004)	(0.007)	(0.008)	(0.011)
Panel C: Capital										
	0.005***	0.007*	0.012**	0.020***	0.027***	0.005***	0.008**	0.013**	0.022***	0.031***
	(0.001)	(0.004)	(0.006)	(0.007)	(0.009)	(0.001)	(0.004)	(0.006)	(0.008)	(0.010)
Panel D: Labor										
	0.003*	0.005*	0.008	0.016**	0.019**	0.004**	0.007**	0.010*	0.021***	0.025***
	(0.002)	(0.003)	(0.005)	(0.006)	(0.007)	(0.002)	(0.003)	(0.005)	(0.006)	(0.008)
SIC3xYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48236	46245	43898	41495	39147	48236	46245	43898	41495	39147

Standard errors in parentheses

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