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

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Abstract

We propose that public investors react differently to patent issuance depending on its novelty, and these misreactions exert real impacts on the firms' future innovations. First, using textual analyses of patent documents to measure patent novelty, we find that investors underreact to the issuance of path-breaking innovations while overreact to the trend-following ones. (Non-)novel issuance predicts a return drift (reversal) of around 1% in two years. Novel patent issuance predicts lower risk but positive forecast errors, consistent with a non-risk-based novelty *mispricing* mechanism. A bounded-rationality model, where investors cannot figure out the true novelty of a patent at issuance due to cognitive limits, explains the empirical patterns well. Second, using exogenous distraction shocks, such as earthquakes, we present causal evidence that following disappointing returns, novel firms shift innovation directions from novelty-seeking to copycatting. The findings highlight that investors' misreactions to patent novelty impact firms' future innovation directions by steering them away from higher-valued, groundbreaking research.

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

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1 Introduction

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

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

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

The key challenge to studying the differential reactions to patent novelty is constructing a precise measure of patent novelty. We measure patent novelty using a comprehensive textual analysis of patent text following the methodology introduced by Kelly, Papanikolaou, Seru and Taddy (2021). They compute pairwise textual similarities between patents to quantify the commonality of each pair of patents. They identify breakthrough patents as patents that are distinct from previous innovations but that are strongly related to subsequent innovations. For our purpose, 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 overreact to non-novel patents. We run impulse response functions of firm-level subsequent returns on patent issuance of different novelty levels. Novel patent issuance positively predicts future returns in the next two years, suggesting that the initial reactions to novel patents are not sufficient, so future returns continue to drift, consistent with an underreaction to novelty. Conversely, non-novel patent issuance negatively predicts future returns, consistent with an initial overreaction as investors gradually correct for the overpricing, leading to a return reversal. (Non-)novel issuance predicts a return drift (reversal) of around 1% in the next two years. We back up this mispricing mechanism with several empirical tests. We argue against a risk-based story by showing that novel patent issuance predicts lower volatility than non-novel patents. We show direct evidence of incorrect beliefs where novel issuance predicts positive forecast errors in earnings expectations, suggesting investors are too pessimistic about future cash flows of high-novelty firms, hence under-price the stock. We also provide suggestive evidence that the effects are indeed driven by patent issuance events and come from the misvaluation of patents, instead of the misperception of patent grant probability.

We propose a bounded-rationality model of investors to explain these mispricing patterns. When a patent is issued, since the novelty is defined only with *ex-ante* information, investors can, in principle, compute it. However, due to cognitive limits, it is likely that investors will be unsure about the true novelty of the patent at its issuance. Instead, they receive noisy but unbiased signals of patent novelty. Such signals shrink their posterior mean to an intermediate prior level, which leads them to underestimate the novelty of novel patents and overestimate the novelty of non-novel patents. Connecting perceived novelty to perceived value, the model predicts the following short-term and long-term response in the firm's stock price. In the short term, return responses are insignificantly different across novelty. In the long run, however, the model predicts significant return predictability as the firm market value converges to the rational response of patent issuance. These model predictions exactly match the empirical patterns of short-term and long-term average returns in the data. The model also predicts stronger mis-reaction and slower convergence with noisier signals. We verify this key model mechanism by empirically showing that firms with lower institutional holdings have stronger misreactions than those held primarily by institutional investors, as retail investors tend to receive noisier signals.

Second, we demonstrate that investors' misreactions to novelty in turn shift firms' innovation directions from novelty-seeking to copycatting. Using the patent citation network, we create several measures to assess firms' innovation directions. We examine whether firms' stock market returns can predict future changes in their innovation directions. Reduced-form ordinary least squares (OLS) estimates suggest that firms' disappointing quarterly returns are correlated with fewer novelty-seeking innovations relative to "copycatting" (non-novel) ones in the following twenty quarters (five years). Considering that a firm's future innovation could correlate with unobserved determinants of its equity returns, to examine causal effects, we instrument for returns using "felt" earthquakes as exogenous distractions to investors and provide causal evidence that market reactions distort a firm's future innovation directions.

Specifically, we exploit the cross-time variations by comparing the same firm across periods with time-varying distractions caused by earthquakes. The period with more frequent "felt" earthquakes happening during the 3-day window around patent issuance creates more distraction to investors, so they respond less to the news of a firm's patent issuance, which leads to lower returns on the equity market relative to the period without distractions. Following the disappointing returns, firms, particularly when majority of patents granted is novel, pivot from investing in other novel research or continuing developing their newly granted patents to mimicking existing innovation trends.

Moreover, we obtain similar findings when exploiting cross-firm variations by comparing firms within the same industry during the same period. By using a firm's ex-ante retail investor shares as plausibly exogenous shares and interacting them with the frequencies of "felt" earthquakes as shocks for distractions, we calculate each firm's exposure to investors distracted by earthquakes. Leveraging this "Bartik"-type instrument, we show that firms experiencing lower returns due to higher exposure to earthquake distractions engage in fewer novelty-seeking innovations relative to those non-novel ones in the future. Such a shift could potentially create lower economic value for the innovating firm and decrease the positive externalities of novel patents. We propose and discuss several channels through which firm managers consider their firms' short-term stock returns when making future innovation decisions (Stein, 1989) for future study.

Literature Review

Our paper contributes to three strands of literature.

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

Second, the paper suggests a novel, important channel by which financial markets exert real economic impact. There is a growing literature studying the effect of the secondary

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

market on firm decisions through 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, the research on the effect of financial markets on firms' innovation strategies has focused primarily on the primary market. Bernstein (2015)) studies the impact of going public on innovation quality, Lerner, Sorensen and Strömberg (2011) discuss the effects of LBO on innovation output, and Babina, Bernstein and Mezzanotti (2023) show the effect of local exposure to financial crises on local innovation players. These papers demonstrate the importance of financial frictions. We instead explore the possibility that behavioral forces in the secondary market also contribute to the shift in innovation behavior. On this front, Dong et al. (2021) document that stock overreactions affect innovative inventiveness and output with a positive sign. They focus on general overpricing, while we look at misreactions around patent issuance and closely tie reactions to patents to managers' decisions on future innovation strategies. Moreover, while they study the *amount* of future innovation, we are interested in the *direction* of innovation from novel to copycat innovations. Krieger et al. (2022) also look at the decision of novel vs. incremental innovations, focusing on the pharmaceutical firms. They argue that risk aversion and costly external financing lead them to underinvest in novel innovation. We look at this decision in all industries and tie it directly to investors' reactions to novelty.

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

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

2 Data and Measurement

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

2.1 Patent Data

Our study's first substantial data source is the patent records from the United States Patent and Trademark Office (USPTO). Over a period of nearly a century (from 1926 to

2022) , this extensive dataset provides valuable insights into technological advancements and innovation activity across various industries. The dataset includes information on a patent's filing and issuance date, inventors and assignees, classification codes, citation patterns, and the patent's full text, enabling us to construct different measures of innovation. We elaborate on the methodologies and definitions of these measures later in this section.

2.2 Firm-level Financial Data

For the main analyses, We obtain monthly stock returns and shares outstanding from the Center for Research in Security Prices (CRSP). Our sample includes all NYSE, AMEX, and NASDAQ (CRSP exchange code 1-3) common stocks (CRSP share code 10-12). To test the market reactions to the news of patent issuance, we match it with the patent data. Our focus is on the stock market reactions after the official USPTO announcement of patent issuances. Following the methodology by Kogan et al. (2017), we link the patents to publicly-traded firms by using the assignee names as the key matching criterion. We drop patents that are matched to multiple firms to avoid double-counting. We end up with around 3.6 million patents that can be matched to a US public firm.

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

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

2.3 Other Data

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

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

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

Earthquakes We collect earthquake data from the United States Geological Services (USGS). The data includes dates, magnitudes, and coordinate locations of each earthquake happened in the United States from 2000 to 2020. We count the number of "felt" earthquakes in the US with magnitudes above 3.5 as only "felt" earthquakes can distract investors.

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)[2]. 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:

[2]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. Such a metric is important and intuitive, as it helps us approximate *ex-ante* whether an invention is groundbreaking or merely a marginal improvement upon prior art. One should note that not all novel patents necessarily represent technological breakthroughs. Under such circumstances, we take advantage of the forward similarity metric FS_j^{10}, which captures the ex-post impact of a patent, to separate the patents with the same novelty levels further into high or low-impact groups.

2.4.2 Measurement of Innovation Direction and Diffusion

We construct a pairwise patent citation network to capture the breadth and depth of technological diffusion. This methodology is built on observing each patent's subsequent citations, ensuring a comprehensive mapping of the flow of knowledge and firms' innovation directions. Our data consists of 43 million patent citation pairs, specifically covering patents whose assignees are publicly traded firms available in the CRSP database. We employ it to explore the dynamics of firms' innovation directions. Specifically, we can infer whether firms are more willing to innovate further upon their original novel patents or opt to follow prevailing trends by referencing patents from other entities. Moreover, the citation network allows us to create proxies for evaluating a patent's social value. For example, we can employ the total citations a patent receives to indicate its influence and acceptance in the broader community. The metric gives us a reasonable estimate of a patent's social value.[3]

3 Market Reactions to Novelty

In recent years, there has been a growing interest in understanding how financial markets react to various types of news, including innovation news. In this section, we study investors' differential responses to news of patent issuance by public firms, explicitly distinguishing between patents with high novelty and those that are more conventional. By integrating patent data with stock returns, we systematically estimate the predictability of firms' returns after the announcements of patent issuance. This exercise seeks to illustrate whether investors under-react or overreact to such news. We then show robustness with alternative specifications and measurements. We also investigate what drives the difference in market reactions to novelty. Using expectations data, we show direct evidence of a mispricing-based explanation. We highlight the importance of patent issuance as news using a placebo test.

3.1 Impulse Response of Patent Issuance

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

[3]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.

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

Using this framework, we aim to compare investor reactions, or potential misreactions, to patents categorized as novel versus non-novel ones. In particular, we estimate the degree to which future returns can be predicted by the issuance of 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 that is potentially knowable to investors. We categorize novel patents as similarity deciles from 1 to 5 and non-novel as 6-10 so that results are not only driven by extreme values.

We then compute local projections to examine how firm-month returns are predictable by their innovation novelty indicators:

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

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

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

To study the dynamics of return predictability by firms' novelty intensity over time, we generate a cumulative impulse response function (IRF), $\sum_{\tau=1}^{T} \beta_{\tau,d}$, from $\tau = 1$ to 36 months. The IRF is a graphical representation of how a patent issuance shock translates to cumulative returns over a three-year window. If we see a persistent increase in the cumulative IRF, this indicates that investors are gradually correcting their underreactions to the positive news. If we see a persistent decrease, this suggests that investors are gradually correcting their initial overreactions to the news. When the function goes flat, the misreactions are fully corrected.

As shown in Figure 1, we see two distinct patterns. The black solid 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 innovative breakthroughs versus incremental innovations. We see that the indicator of novel patent issuance positively predicts returns in the next two years, which suggests that investors, in their assessment of novel patents, tend to exhibit under-reaction. The full value of groundbreaking innovations is not immediately priced in, leading to a gradual adjustment in the firm's stock price. These lagged reactions are consistent with a mechanism where cognitive limits result in delayed or incomplete processing of new information. The issuance of novel patents leads to cumulative returns of 1%. Given the rarity of novel patents, this effect is economically significant.

By contrast, the red dashed line shows that non-novel issuance predicts persistently negative future returns. This negative relationship implies that investors overreact to patents that follow existing technologies. Such overreactions to non-novelty may reflect a bias towards the familiar and tried-and-true, often overvaluing incremental advancements at the expense of truly pioneering innovations. After the initial overreaction, investors gradually correct for this bias, leading to a persistent negative impact on future returns.

3.2 Cumulative Return Regressions

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

$$r_{t\to t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau} \quad (2)$$

As Table 1 shows, novel patent issuance positively predicts future long-term cumulative returns and non-novel patent issuance negatively predicts long-term returns. Novel issuance at most predicts 1.3% in the next three years, and non-novel issuance at most predicts -1% in the next two years. These results confirm that investors under(over)-react to (non-)novel patent issuance.

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

3.3 Robustness in Alternative Measures

To further support our main finding that investors underreact to novel innovations but overreact to non-novel innovations, we conduct several robustness analyses with alternative measures and specifications.

Short-term return on patent issuance While our primary analysis focuses on the long-term reactions, understanding the immediate return response post-patent issuance is also crucial to establish the empirical fact of investor mis-reaction. For example, if investors overreact to non-novel patents, we should see an immediate return jump followed by a negative predictability. To test this, we run a firm-day level regression of 3-day returns on the patent issuance dummy, controlling for industry×date fixed effects and the same set of firm characteristics as in our main results:

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

We find that both novel and non-novel patent issuance predict sizable short-term returns. As shown in Table A.1, the coefficients of novel and non-novel patent issuance indicators, when analyzed separately, are both positive and statistically significant. If we include both dummies together with an additional patent issuance dummy, only the patent issuance dummy is significant. This suggests that patent issuance predicts positive three-day returns that do not differ by patent novelty.

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

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:

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

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

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

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

In Figure 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.

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 A.2, the similarity score displays negative predictability of future returns, confirming that investors overreact to incremental innovations.

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

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

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

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

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 A.4, we plot the cumulative alpha of the long-short portfolio against three asset pricing models: CAPM, Fama and French (1992) 3-factor, and 3-factor after replacing the value factor with the intangible-adjusted value factor from Eisfeldt et al. (2020). We see that cumulative alpha is positive throughout the time series, and the average annualized alpha is 2.1% against CAPM, 1.5% against FF3F, and 0.6% against intangible-adjusted FF3F.

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

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.

3.4 Mechanism

In this section, we provide empirical evidence of the mechanism behind investor misreactions to patent novelty. We first provide suggestive evidence to rule out a rational risk-based explanation of return predictability, and then show direct evidence of mispricing in firms with novel versus non-novel innovation issuance. We also show several pieces of evidence that the mispricing pertains to patents themselves. These discussions about the mechanism serve as inspiration for a misreaction model of patent novelty 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 Figure 2, we run the following local projection regressions:

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

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

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

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

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

We estimate the monthly beta using daily returns in each month. Figure A.7 shows that non-novel patent issuance consistently predicts a higher beta than novel patents. If systematic risk is priced in returns, we should instead expect that novel patents predict higher returns. The fact that we see the converse pattern in the data suggests that the positive predictability of novel patents is unlikely to be driven by a risk-based story.

Another possible concern is that realized volatility is not the volatility that investors perceive at the time of issuance. To respond to this concern, we estimate the predictability of ex-ante implied volatility. We obtain 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:

$$\text{Implied Vol}_{i,t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel} \mathbb{1}\{i \in \text{Novel}_t\} + \beta_{\tau,non-novel} \mathbb{1}\{i \in \text{Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}. \tag{4}$$

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, implied volatility decreases as we go further away from patent issuance. This is consistent with the idea that uncertainty around patent issuance gets resolved over time. We will explore more in our model of misreaction.

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

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

$$\begin{aligned}\frac{\pi_{i,t+\tau} - F_t\pi_{i,t+\tau}}{P_{i,t-1}} &= \alpha_\tau + \beta_{\tau,novel}\mathbb{1}\{i \in \text{Novel}_{t-1}\} \\ &+ \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Non-Novel}_{t-1}\} + \gamma' X_{i,t-1} + \varepsilon_{i,t+\tau}, \end{aligned} \tag{5}$$

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 patent with above(below)-median novelty in year t. This specification captures the thought process in which an analyst in year t observes the novel vs. non-novel patents issued in year $t-1$ and needs to forecast the firm's profitability in the next two fiscal years. We use $t-1$ patent issuance to avoid lookahead bias, where patents are issued after the earnings forecasts are made.

A positive coefficient, $\beta_{\tau,d}, d \in \{novel, non{-}novel\}$, suggests an underreaction as investors form too pessimistic forecasts given a novel patent issuance. On the other hand, a negative coefficient suggests that investors are overly optimistic after the issuance event. In Table 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 A.2, 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.

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:

$$\begin{aligned} r_{i,t+\tau} = \alpha_{ind,t} &+ \beta_{\tau,novel}\mathbb{1}\{i \in \text{Shuffled Novel}_t\} \\ &+ \beta_{\tau,non-novel}\mathbb{1}\{i \in \text{Shuffled Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}. \end{aligned} \tag{6}$$

Figure 4 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:

$$\begin{aligned} r_{t \to t+\tau} = \alpha_{ind,t} + \beta_{\tau,novel} \mathbb{1}\{i \in \text{Shuffled Novel}_t\} \\ + \beta_{\tau,non-novel} \mathbb{1}\{i \in \text{Shuffled Non-Novel}_t\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}. \end{aligned} \tag{7}$$

Figure 5 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.

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 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.

Patent Grant Probability versus Value The magnitude of return reaction to patent issuance is determined by the probability of a successful issuance multiplied by the unit value of the patent. This may lead to two concerns in the interpretation of results. First, if investors perceive a lower grant probability of novel patents, this may also lead to initial underreactions in returns to novel patent issuance instead of underestimation of patent value. We address this concern by arguing that, at the patent issuance date, investors immediately know how long it takes for the patent to be granted from its filing, so they should quickly correct their perception of the success probability of novel versus non-novel patents issued at the same time. The misperception should be corrected instantly, which will be inconsistent with our results, as the mispricing takes two years to correct.

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

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

where we control the grant month fixed effects and indicators of the CPC technology class. Table A.3 demonstrates the average grant length of novel versus non-novel patents. Non-novel patents, on average, take 32.3 months to get granted, and novel patents take 2.3 months longer. Using the properties of an exponential distribution, this translates into a grant probability of (non-)novel patent in a month of 2.9% (3/1%). The approval probability in an average month of novel vs. non-novel innovation only differs by 0.2%, which is not economically significant.

4 A Model of Misreaction to Novelty

In this section, we present a framework that we can use to understand the return misreactions to patent novelty and the return dynamics after patent issuance. The model is consistent with a mispricing mechanism to patent novelty (as argued in Section 3.4) and also explains key empirical facts in Section 3. First, short-term returns jump up immediately after a patent is issued, but the jumps are not economically different across patent novelty. Second, in the long term, a novel patent issuance positively predicts returns while a non-novel patent issuance negatively predicts returns, as investors gradually learn the true value of the patent.

This is a bounded-rationality model where investors do not know the true novelty of a patent when it is first issued. Instead, they receive unbiased, noisy signals about patent novelty and are Bayesian learners of the true novelty. It is a bounded-rationality model because true patent novelty, as we define it, only depends on *ex-ante* information and is therefore knowable to investors when patents come out. However, due to cognitive limits, investors are unsure about the patent's novelty immediately after issuance, 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 immediately after 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, under- and over-reaction is monotonic across levels of novelty. The more novel the patents are, the more investors under-react to them. Second, the noisier the signals are, the stronger the misreactions are, and the longer it takes for the price to converge to the correct level. Third, when patents are first issued, return differences are not economically significant. Most of the differential misreactions show up in long-term return predictability.

4.1 Short-Term Reactions

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

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

We assume a lognormal prior to ensure that patent novelty is non-negative while maintaining tractability. Woodford (2020) also uses a lognormal prior in a model of cognitive imprecision; he argues that lognormality is consistent with Fechner's explanation for Weber's law, where the subjective sensation of a stimulus is proportional to the logarithm of stimulus intensity. Our model, however, differs from the Woodford (2020) model in a nuanced way. In a model with cognitive imprecision, agents see the true value but their perceptual system encodes it imprecisely; by contrast, in our model, agents do not observe the true value.

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

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

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

$$\hat{x}(r) \equiv E[x|r] = \exp\left[\left(\frac{\nu^2}{\sigma^2+\nu^2}\right)\log\bar{x} + \left(\frac{\sigma^2}{\sigma^2+\nu^2}\right)r\right], \tag{8}$$

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 lognormal distribution with mean and variance

$$e(x) \equiv E[\hat{x}|x] = \exp\left(\beta^2\nu^2/2\right)\bar{x}^{1-\beta}x^{\beta} \quad var[\hat{x}|x] = (\exp(\beta^2\nu^2)-1)e(x)^2, \tag{9}$$

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

In Figure A.9, we plot the mean perception of patent novelty, $E[\hat{x}|x]$, against the true novelty level. We see that the investor underestimates novelty for novel patents, while for non-novel patents, she overestimates novelty.

Connecting Patent Novelty to Returns To generate a price effect from novelty misperception, we need to relate the investor's perceived novelty of the patent to the stock price change in response to patent issuance. Our empirical findings suggest that patent value is positively correlated with patent novelty. In particular, we show that novel and non-novel patents have indistinguishable return jumps at issuance, that novel patents show return drift afterward, and that non-novel patents show return reversal. The evidence combined suggests that true patent value is positively correlated with novelty. The exact functional form of the relationship, however, is unknown. Therefore, we proceed as follows: As in Kogan et al. (2017), we decompose the return of a given firm around patent issuance as

$$R_j = v_j + \varepsilon_j.$$

We also follow Kogan et al. (2017) in imposing that patent value cannot be negative and that it has a normal distribution truncated at 0. We also 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 6 shows that novel patents have issuance returns lower than the rational benchmark, thus exhibiting under-reaction, while non-novel patents have issuance returns higher rational, thus exhibiting overreaction. Moreover, if investors receive very noisy signals, the returns differences across patent novelty will be economically insignificant. This matches our empirical findings that the firm's 3-day returns are positive for both novel and non-novel patent issuance, but they are not economically different, as presented in Table A.1.

4.2 Long-Term Dynamics

In the previous section, we showed that, in a static setting, we could generate under(over)-reaction to (non-)novel patents in short-term issuance returns that matched empirical evidence. However, the mispricing does not lead to large return difference in the short term, especially when the signal is noisy. In the long term, as returns gradually 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 again follows a lognormal distribution: $\log x \sim N(\mu, \sigma^2)$. In each period, investors receive one 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:

$$\log x | r_0, ..., r_t \sim N\left(\left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2}\right)^{-1}\left[\frac{t+1}{\nu^2}\left(\frac{1}{t+1}\sum_{i=1}^{t+1} r_i\right) + \frac{1}{\sigma^2}\mu\right], \left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2}\right)^{-1}\right). \tag{10}$$

Denote this conditional mean as μ_c and conditional variance as σ_c^2. Then we define the posterior mean of novelty x at time t as $E[x|r_1, ..., r_t] \equiv \hat{x}_t$. Using the properties of the lognormal distribution, we get

$$\log E[x|r_1, ..., r_t] \equiv \log \hat{x}_t = \mu_c + \frac{1}{2}\sigma_c^2. \tag{11}$$

We then show the average misperception of novelty of a large sample of investors for each novelty level x.

$$\log e_t(x) \equiv \log E[\hat{x}_t | x] = E\left[\mu_c + \frac{1}{2}\sigma_c^2\right] + \frac{1}{2} var\left(\mu_c + \frac{1}{2}\sigma_c^2\right), \tag{12}$$

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

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

Figure A.10 plots the dynamic conditional mean of the perception of patent novelty, $E[\hat{x}_t|x]$ for ten levels of novelty x, when the signal is relatively noisy ($\nu = 2\sigma$). We can see that, at issuance, different novelty perceptions across true novelty levels are compressed toward an intermediate prior level of novelty. As time goes by and investors receive more signals, they update their novelty perception toward the correct level of novelty.

To capture the average return response to novelty, we again relate the perception of patent novelty to returns. Same as the static case, 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, we write the distribution of patent value, v_t, in each period t:

$$v_t \sim N^+ \left(\gamma_0 + \gamma_1 \left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2} \right)^{-1} \left[\frac{t+1}{\nu^2} \log x + \frac{1}{\sigma^2} \left(\mu + \frac{1}{2}\sigma^2 \right) \right], \right.$$
$$\left. \gamma_1^2 \left(\left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2} \right)^{-2} \left(\frac{t+1}{\nu^2} \right)^2 \frac{\nu^2}{t+1} \right) + \sigma_x^2 \right). \tag{13}$$

From Equation 13, we see two key predictions about the return reactions to novelty.

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

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

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

For illustration, we again plot the average return to novelty, $E[R_t|x_t]$. The cumulative return is again denoted as $R_t = v_t + \varepsilon_t, \varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. 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, $R_t|x_t$. We thus 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 7, we plot the return reaction to ten novelty levels for 60 periods after the patent issuance. Simulations confirm key model predictions. First, investors underreact to the novel patents (large x) and overreact to non-novel ones but converge to the correct level of returns over time. In the short term, returns are compressed towards the prior, so they are not economically significantly different. However, we see a large divergence in return responses across different novelty levels as they converge to the correct level.

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

Figure 8 plots the return dynamics after the patent issuance. We consider two levels of signal precision. High precision is the case where signal precision is the same as prior standard deviation ($\nu = \sigma$); low precision is the case where $\nu = 2\sigma$. With noisier signals, the initial reaction differs less across different novelty levels, suggesting stronger misreactions. We also see that investors take longer to converge to the correct level of reaction.

4.3 Empirical test 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 the differential reactions based on the key model parameter, the signal precision.

Short-Term Response The model predicts that the return reaction at issuance should not be distinguishable across different novelty deciles with noisy signals. To test this, we run firm-day level panel regressions of 3-day returns right after patent issuance on ten-decile indicators of patent novelty. Each indicator is equal to 1 if patents with a given novelty level are granted to the firm on this day. If there is no patent issued, all indicators will be 0, which means that the counterfactual returns are the returns from the firms without patent issuance that are in the same industry and have similar firm observables:

$$R_{i,t,t+2} = \alpha_{ind,t} + \sum_{k=1}^{10} \beta_k \mathbb{1}\{i \in \text{Novelty Decile}_{k,t}\} + \gamma' X_{i,t} + \varepsilon_{i,t,t+2}, \tag{14}$$

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

Long-Term Response Despite similar short-term responses, the model predicts a much more significant difference in the long term, periods after the patents get issued, as investors receive more signals about patent novelty. We expect a divergence in returns across novelty deciles as they converge to their correct level. We expect a positive return drift for novel innovations and a return reversal for non-novel innovations. Also, the more non-novel the patent is, the stronger reversal we shall see (the strongest negative predictability).

We directly 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:

$$r_{i,t+\tau} = \alpha_{ind,t} + \sum_{d=1}^{10} \beta_{\tau,d} \mathbb{1}\{i \in \text{Novelty Decile}_{d,t}\} + \gamma' X_{i,t} + \varepsilon_{i,t+\tau}. \tag{15}$$

This is the exact same specification as our main result with Equation 1, but instead of splitting novel versus non-novel by median, we explore the behavior of ten deciles. Figure 10 shows that, although in real data, the response is noisier, we still see that positive predictability decreases as we move down the novelty deciles, and we start to see negative predictability for non-novel deciles. The impulse response differences are large and consistent with the model predictions.

Institutional Holdings and Signal Precision Finally, in the model, signal precision is a key parameter that drives the return response. If the signals investors receive are noisier, we would expect stronger misreactions and slower convergence to the correct level. To test this mechanism in real data, we compare the return predictability for firms with high versus low institutional holdings. Institutional investors should know better about the technology and receive less noisy signals about patent novelty, and thus should exhibit weaker misreactions and faster convergence. We use the institutional holdings data from FactSet and follow the construction of institutional ownership in Ferreira and Matos (2008). Figure 11 shows the results from the following regressions:

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

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 tend to have less positive predictability after novel issuance and less negative predictability after non-novel issuance, suggesting that the misreactions are weaker for firms with high institutional holdings. We also see that firms with high institutional holdings have zero return predictability earlier than firms with low institutional holdings, indicating a faster convergence to the true value of the patents.

5 Impact on Future Innovation

In previous sections, we documented a systematic difference in the equity market's response to patents with different novelty: underreaction to novel patents and overreaction to non-novel patents. The implications of this discrepancy are profound. It raises a pivotal question about the essence of innovation: could investors' reactions translate into real consequences for firms' future innovation directions? In this section, we first examine whether firms' returns can predict future changes in their innovation directions. Simple ordinary least squares (OLS) estimates suggest that firms' disappointing quarterly returns are correlated with fewer novelty-seeking innovations relative to "copycatting" (non-novel) ones in the following twenty quarters (five years). Considering that a firm's future innovation could correlate with unobserved determinants of its equity returns, to examine the existence of any causal effects, we instrument for returns using "felt" earthquakes as exogenous distractions to investors and provide causal evidence that market reactions can distort a firm's future innovation directions. Specifically, we mainly exploit the cross-time variations by comparing the same firm across periods with different distractions to investors caused by earthquakes. The period with more frequent "felt" earthquakes happening during the 3-day window around patent issuance creates more distraction to investors, so they respond less to the news of a firm's patent issuance, which leads to lower returns on the equity market relative to the period without distractions. Following the disappointing returns, firms, particularly during the periods with more novel patents granted, pivot from investing in other pioneering research or continuing developing their newly granted patents to mimicking existing innovation trends. Moreover, when exploiting cross-firm variations by comparing firms within the same industry during the same period, we obtain similar findings. By using a firm's ex-ante retail investor shares as plausibly exogenous shares and interacting them with the frequencies of "felt" earthquakes as shocks for distractions, we calculate each firm's exposure to investors distracted by earthquakes. Leveraging such a "Bartik" type instrument, we show that firms experiencing lower returns due to higher exposure to earthquake distractions engage in fewer novelty-seeking innovations relative to those non-novel ones in the future. Such a shift could potentially create lower economic value for the innovating firm and decrease the positive externalities of novel patents. Our evidence implies that financial markets could push firms in sub-optimal innovation directions by exploiting existing technology with low remaining value and not trying the high-value novel directions.

5.1 Firm Innovation Directions and Dynamics

Firms' innovation directions are essential for their long-term growth. A sound innovation strategy enables corporations to provide their customers with continued value, create new market segments, and even push competitors out of their once-owned segments. Since firms' innovation strategies vary significantly depending on their idiosyncratic preference and choice sets, documenting firms' exact decision-making procedures for future innovation directions in a systematic way is very challenging. However, observing firms' future patenting behavior provides an alternative method to measure firms' innovation trajectories and outcomes.[4]

Given that our study mainly focuses on patent novelty, we categorize firms' innovation directions into three types closely tied to the novelty of firms' patenting. The first one is sustaining innovation, an incremental improvement that follows up on existing technology, in particular, that builds on the novel technology developed by the firm. For example, Apple pioneered multi-touch technology that laid the foundation for the early-generation iPhone and was granted a patent for this revolutionary invention.[5] Following up on that, Apple further developed a series of incremental technologies, such as "pinch-to-zoom,[6]" "slide between user interface.[7]" Not surprisingly, these later patents by Apple all cited its original

[4]One limitation of our measure is that we cannot capture firms' failed research projects and patent applications or ongoing long-term planned R&D investment. Despite this, the outcome variables based on granted patents should provide a valid measurement capturing any realized changes in firms' innovation direction.

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

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

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

patent on "Multi-touch" technology, and a series of these sustaining innovations helped shape the smartphones widely used nowadays. Inspired by this anecdotal example, we construct the measure "number of follow-up patents" to represent a firm's sustaining innovation based on the patent pairwise citation network we construct. More specifically, for firm i at year-quarter t, we calculate the number of patents filed by firm i in the following four, twelve, or twenty quarters (i.e., one, three, or five years) that self-cite firm i's patents issued at time t. A higher value of this firm-level measure suggests that the firm creates more sustaining innovation following up on its just-issued technology.

The second type of innovation is "novelty-seeking." Besides sustaining innovation built on existing novel technology, firms can continuously seek other novel ideas in their innovation process. For instance, Apple has always been a "novelty-seeking" innovator. From the invention of "embedding the electronic device to wearable" that helped the launch of the Apple Watch eight years ago to the most recent technology in eye and hand tracking forming the revolutionary product Apple Vision Pro, these innovations were all very novel relative to other patents when they came out.[8] To capture firms' "novelty-seeking" innovation, we construct the outcome variable, "number of other novel patents," which is calculated as the number of novel patents filed by firm i in the next one, three or five years following i's quarterly return at time t. We exclude firms' "follow-up" patents during each period when constructing the "novelty-seeking measure" because the sustaining innovations could mechanically be less novel, which brings potential bias to our analysis.

The last type of innovation we are interested in is "copycatting innovation." Sometimes, firms strategically "copy" their competitors' innovation to push these competitors out of their once-owned segments. Taking Apple's innovation direction as an example, Apple is also producing inventions such as "folding device technology," which is a well-known feature of its competitor Samsung's smartphones.[9] Besides, we hypothesize that investors' underreaction

[8] "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".

[9] "folding device technology": the US patent application US20230011092A1, titled as "Hybrid cover-

to novel patents and overvaluation of non-novel patents could drive some firms to follow the market trend and produce more non-novel patents to chase short-term gains from the equity market. Similar to the measure of "novelty-seeking" innovation, we calculate the number of other non-novel patents during $[t+1, t+4]$, $[t+1, t+12]$ or $[t+1, t+20]$ as proxies for firms' future "copycatting" innovation behaviors following their quarterly return at time t. We also exclude firms' self-citing patents in our variable construction for the same reason as before[10].

With these measures of firms' innovation directions, we examine the following question: Can firms' returns predict their changes in future innovation directions? To answer this question, we consider a model that relates firms' future innovations directly to their quarterly equity returns[11]:

$$\text{Future Innovation}_{i,t+1\to t+\tau} = \beta r_{i,t} + \gamma' Z_{i,t} + \alpha_{indt(i)} + \varepsilon_{i,t}.$$

In this model, our main focus is on the future innovation outcomes, Future Innovation$_{i,t+1\to t+\tau}$, which are based on the previously defined innovation directions (i.e., sustaining, novelty-seeking, or copycatting innovations). To better capture the changes in future innovation directions, we have developed two relative measures instead of directly using the three innovation direction measures (based on patent filing levels) as the dependent variables. Because our primary interest lies in understanding a firm's future decisions about novelty-seeking or sustaining innovation after establishing a novel technology, we have created the following measures to capture how the changes in these two future innovation directions in comparison to the "copycatting" (non-novel) innovations:

$$\text{Novelty-seeking Innovation}_{i,t+1\to t+\tau} = \log\left(\frac{\text{No. of novel patents filed}_{i,t+1\to t+\tau}}{\text{No. of non-novel patents filed}_{i,t+1\to t+\tau}}\right),$$

lay/window structure for flexible display applications"

[10]Firms' follow-up patents are more likely to be categorized as non-novel patents, bringing upward bias to the measure of "copycatting" innovation.

[11]We propose to implement our model on a firm-year-quarter panel in order to align with real-world practices. It is observed that companies are more likely to assess their current technology and determine their future innovation trajectories at a quarterly level around earnings releases.

$$\text{Sustaining Innovation}_{i,t+1\to t+\tau} = \log\left(\frac{\text{No. of follow-up patents filed}_{i,t+1\to t+\tau}}{\text{No. of non-novel patents filed}_{i,t+1\to t+\tau}}\right).$$

Given that a firm's tendency to further innovate in a particular direction is also influenced by multiple factors ranging from the firm's capital and labor constraints to the existing innovation capacity, we include a set of firm-level controls $Z_{i,t}$ in the regression. Specifically, $Z_{i,t}$ includes the log value of the capital stock and the log number of employees, acknowledging the foundational role of firm size in its innovation direction. Larger firms, with their expansive resources, might be more likely to maintain their innovation trajectories. $Z_{i,t}$ also includes the log value of the profits, recognizing firms with higher profit margins might invest more in R&D and contribute more novelty-seeking innovations in the future. Moreover, we also include the total values of all patents issued to firm i at time t[12], serving as a heuristic for the firm's innovation quality. Furthermore, $Z_{i,t}$ also controls for a firm's age, given that younger firms might be more innovative while older companies potentially have a larger portfolio of follow-up patents filed due to accumulated innovations over time. Lastly, we also control for idiosyncratic volatility because it could be correlated with firms' future growth opportunities. A firm with high idiosyncratic volatility may have uncertain future growth opportunities. This uncertainty could influence a firm's future innovation directions.

In this model, we exploit two types of variations with different sets of fixed effects. First, we include firm fixed effect α_i to exploit the cross-time variations by comparing the same firm across periods with different quarterly equity returns.[13] Second, we exploit cross-firm variations and compare firms within the same industry during the same period by including industry interactions with year-quarter fixed effects. In both specifications, we cluster standard errors at the firm level.

[12]To measure a patent's economic value effectively, we take the off-the-shelf KPSS measure – a benchmark method based on short-term market reactions after the patent grant, as outlined by Kogan et al. (2017). Alternatively, we also use a patent's adjusted citation (i.e., total forward citations normalized by the average citations of all patents granted in the same year to address the truncation issues. One drawback of the citation measure is that it incorporates forward-looking measures, which might bring the potential endogeneity bias into our regression.

[13]When comparing the same firm across different periods, we remove the firm's age as a control to allow more cross-time variations.

In Tables A.4 and A.5, we document that, even after accounting for various firm-level factors that could impact a firm's future innovation paths, firms tend to reduce their pursuit of other novel innovations more (relative to non-novel ones) following periods of underwhelming equity returns, as opposed to periods with less disappointing returns. Additionally, within the same industry and period, firms with lower equity returns are linked to fewer filings of novelty-seeking patents compared to the "copycatting" ones in the subsequent twenty quarters. However, disappointing equity market returns do not significantly predict a difference between a firm's sustaining innovation and non-novel ones in the short run (i.e., the succeeding twelve quarters), except for a slightly increase of follow-up patents (relative to non-novel ones) in a longer timeframe (twenty quarters).

In this section, we first create several measures to assess firms' innovation directions using their patent filings and our constructed patent citation networks. We then examine whether firms' stock market performance can predict changes in their future innovation strategies. Simple OLS estimates indicate that firms with lower equity returns are more likely to experience a significant decline in their future pursuit of novelty-seeking innovations relative to imitative (non-novel) ones. We do not find strong associations between a firm's sustaining innovation changes (compared to "copycatting" innovation) and its market returns. However, the OLS estimates for a model linking a firm's future innovation direction changes to their equity returns could yield biased results. This is because, even after controlling various covariates, a firm's future innovation trajectories might still be correlated with some unobserved determinants of the firm's equity returns. For example, suppose a firm reorganizes its R&D department at time t by hiring new technicians, scientists, and inventors with different expertise. Such information would be priced in by investors and could impact the firm's market returns in the same period. Meanwhile, the new hires in the company's R&D department will likely change the firm's future innovation strategies. As a result, the biased OLS estimates would not help us identify any causal effects of a firm's equity returns on its future changes in innovation directions. In the subsequent section, we aim to address this endogeneity issue and investigate the potential causal links between investors' misreaction to firms' patent issuance news in the stock market and the firms' future innovation decisions.

5.2 Does Investors' Behavior Impact Firms' Innovation Directions?

We start by revisiting the model that relates firms' future innovation to their equity returns as we specified in 5.1:

$$\text{Future Innovation}_{i,t+1\to t+\tau} = \beta r_{i,t} + \gamma' Z_{i,t} + \alpha_{indt(i)} + \varepsilon_{i,t}.$$

The primary outcome variables of interest Future Innovation$_{i,t+1\to t+\tau}$ are still the two relative measures: Novelty-seeking Innovation$_{i,t+1\to t+\tau}$ and Sustaining Innovation$_{i,t+1\to t+\tau}$ as defined in Section 5.1. These measures reflect a firm's changes in filings of other novel patents or follow-up patents on innovations granted at time t, relative to non-novel patent filings. The main explanatory variable is firm i's equity returns at time t, $r_{i,t}$. To account for various factors that could influence a firm's future innovation trajectory, $Z_{i,t}$ controls for firm capital stock, number of employees, profits, age, and idiosyncratic volatility.

As previously discussed, using only OLS estimates for this model may lead to biased results due to the potential correlation between a firm's future innovation and unobserved determinants of the firm's equity returns. To address this endogeneity issue, we estimate an instrumental variable regression for our model. We exploit the disruptions to investors caused by certain exogenous shocks during the short-term window around the announcement of patent issuance, resulting in increased noise in the signals investors receive when processing the patent news. Specifically, we instrument a firm's quarterly equity returns $r_{i,t}$ with the number of "felt" earthquakes [14] within the three-day window surrounding patent issuance (i.e., from Tuesday to Thursday, as patent issuances are invariably announced each Tuesday) following Goetzmann et al. (2024).

[14] We define the "felt" earthquakes as those with equal or above 3.5 "Ritcher" magnitude according to https://www.earthquakescanada.nrcan.gc.ca/info-gen/scales-echelles/magnitude-en.php.

The instrument still enables us to exploit two types of variations with different sets of fixed effects in the model. First, we leverage cross-time variations by comparing the same firm across periods with different levels of distractions to investors resulting from varying frequencies of "felt" earthquakes. Specifically, we run the first-stage regression:

$$r_{i,t} = \beta \text{Earthquakes}_t + \gamma' Z_{i,t} + \alpha_{ind} + \alpha_{i,decade} + \varepsilon_{i,t}.$$

Then, we regress a firm's future innovation measure on the predicted returns $\widehat{r_{i,t}}$ obtained from the first stage in the second-stage regression:

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

Our specifications are based on two key identifying assumptions to ensure the estimates from the IV regressions correctly capture the causal effect of firms' equity return on future innovation. First, we require a strong association between the frequency of "felt" seismic events $Earthquake_t$ and the firm's quarterly equity return $r_{i,t}$. We expect that more frequent "felt" earthquakes occurring during the 3-day window surrounding patent issuance would create more distraction to investors, leading to their reduced responses to the news of a firm's patent issuance and lower returns to the firm on the equity market.[15] We also modify our model specification by including firm interaction with decade indicator fixed effects to compare the same firm across different periods but within the same decades, considering potential changes in stock market structure and investor participation over decades might dampen the "relevance" assumption. Additionally, we incorporate industry-level fixed effect

[15]It's important to note that media coverage of seismic events can potentially influence the level of distraction for investors. For quarters $t+i$ and $t+j$ with an equal number of earthquakes, if quarter $t+i$ has more news reports on these seismic events, investors may be more distracted, leading to potentially lower equity returns for firms in that quarter. To mitigate this issue, we utilize the off-the-shelf topic attention measures from Bybee et al. (2021), which involve estimating a topic model and quantifying the proportion of news attention dedicated to each theme at each point in time. Given the absence of a specific theme on "earthquakes," we decide to use the news attention allocated to "natural disaster" as a proxy and integrate it into both stages of our IV regressions.

to account for the potential shifts in a firm's primary industry due to business changes. Furthermore, the "strong instrument" assumption is empirically testable through the effective F-stats from the first-stage regression. We report the relevant statistics in the results table later. The second crucial assumption is the "exclusion restriction." This assumption is not empirically testable. However, given that aggregated "felt" earthquakes are exogenous natural disaster shocks and are unlikely to change a firm's future innovation directions directly, we are confident that our instrument variable $Earthquake_t$ does not violate the "exclusion restriction" assumption.

In this model, the null hypothesis states that, according to the Modigliani-Miller theorem, any changes in short-term equity returns should not impact the firm's future investment or production decisions, including the changes in innovation directions. We are particularly interested in empirically testing this hypothesis for changes in two innovation directions defined earlier.

Starting from a firm's future changes in novelty-seeking innovation compared to the "copycatting" ones, in Table 3, we present the IV estimates and the first-stage regression results. In columns (1), (3), and (5), we analyze how the firm's filings of novelty-seeking patents change relative to the "copycatting" ones in the subsequent four, twelve, and twenty quarters following its quarterly returns in the equity market, respectively. Columns (2), (4) and (6) show the corresponding first-stage results. All first-stage results indicate that the frequencies of "felt" seismic events $Earthquake_t$ serve as a strong instrument for a firm's quarterly returns in the stock market.[16] When comparing the same firm in two different quarters (but in the same decade), the more distractions to investor induced by "felt" earthquake (i.e., high value of $Earthquake_t$) around the patent issuance events in quarter t, the lower equity returns for the firm at that time. We obtain the IV estimates by plugging the predicted return changes from the first stage into the second-stage regression as a key explanatory variable. These results indicate that the exogenous return drops induced by earthquakes' distractions can impact

[16]To simplify interpretation, we normalize $Earthquake_t$ by dividing its standard deviation, making the standardized $Earthquake_t$ have a standard deviation of 1.

the firm's future novel patent filings relative to non-novel ones. Specifically, on average, a 10 percent decrease in a firm's quarterly equity returns can cause a 7.46 percent decrease in the firm's novel-to-non-novel patent filings ratio in the next three years (twelve quarters) and eventually 5.23 percent decrease in the subsequent five-year timeframe.

A more interesting question is, for the same firm, is it more likely to be affected by market reactions and change its future innovation directions when more novel patents are granted today? We propose that investors' undervaluation of novel patents could discourage the firm from pursuing other innovative ideas in the future, especially when they have a higher proportion of novel patents granted at present.[17] To investigate this, 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 exact IV specification on each subsample separately.

The results in Table 4 support our hypothesis. We find that the impact of equity return drop on a more rapid decrease in firms' future novelty-seeking innovation (relative to "copy-catting" innovation) is most pronounced during periods of high novelty, where firms have a greater number of novel patents granted. In particular, during these times, a 10 percent decrease in a quarter's equity returns can result in an average 8.75 percent reduction in the firm's ratio of future novel-to-non-novel patent filings over the subsequent twelve quarters, ultimately leading to a cumulative 5.75 percent decrease over the 5-year period. In contrast, we observe muted effects when analyzing the subsample from periods with lower levels of novelty.

Having shown that market reactions can cause changes in firms' future novelty-seeking innovation, we explore how a firm's other innovation direction – sustaining innovation is impacted by the firm's return changes on the equity market. Our analysis, running the same

[17]One potential underlying mechanism is that companies may develop a belief that the market does not accurately recognize the value of new technology based on disappointing market returns. As a result, when making future investment decisions regarding novel innovations, they may rely on past experiences and expect the market to be unresponsive to innovative ideas. Due to potential agency conflicts such as managerial entrenchment or short-termism, firm managers choose to reduce their investment in novel technology.

IV regressions and changing only the outcome variables to Sustaining $\text{Innovation}_{i,t+1\rightarrow t+\tau}$ defined earlier, reveals that the exogenous return drops at quarter t induced by more frequent earthquakes' distractions can impact the firm's future filings of follow-up patents (i.e., the patents cite the innovations granted at time t) relative to non-novel ones. Intuitively, lower equity returns in a given quarter may lead the firm to conclude that the market does not value the technologies it recently developed, prompting the firm's decision not to pursue them further. Statistically, as results shown in Table 5, on average, a 10 percent decrease in a firm's quarterly equity returns at time t can lead to an 18.62 percent decrease in the firm's sustaining-to-non-novel patent filings ratio over the subsequent four quarters and an accumulative 16.16 percent decrease in three years.

We further explore how firms are affected by market reactions and changes its future innovation directions during high and low-novelty periods. In contrast to the scenario that the effect of equity return drops on the changes in a firm's future novelty-seeking innovation is evident only during high-novelty periods, we propose that the decrease in market returns, resulting from investors being distracted, could dissuade the firm from pursuing follow-ups on the developed technologies, regardless of whether the technology portfolio in the period is predominantly high-novelty or dominated by low-novelty inventions.[18] To explore this further, we once again apply the exact IV specification to subsets of high- and low-novelty periods. The results in Table 6 confirm our hypothesis. We find that the impact of a decline in equity returns on a more pronounced decrease in firms' future sustaining innovation, as opposed to "copycatting" innovation, is significant in both high- and low-novelty periods.

We can leverage cross-firm variations as a second type of variation. By incorporating industry interactions with year-quarter fixed effects, we can compare firms within the same industry during the same period. Since the frequencies of "felt" earthquakes in a quarter are aggregated exogenous shocks that only vary across time, to compare firms during the same

[18] It's important to note that our analysis may reveal underlying mechanical effects. Given that, on average, novel patents result in a significantly higher number of follow-up patents compared to non-novel ones (as shown in Table A.9), the firm might naturally generate fewer follow-up patents after a period in which a higher proportion of non-novel patents are issued.

period, we can create a "Bartik" type instrument instead of directly employing $Earthquake_t$ as an instrument. Specifically, by utilizing a firm's ex-ante retail investor shares as plausibly exogenous shares and interacting them with the frequencies of "felt" seismic events $Earthquake_t$ as shocks for distractions, we can compute each firm's exposure to earthquake distractions and use it as an instrument for firm's equity return at time t:

$$r_{i,t} = \beta \text{Earthquake}_t \times \% \text{ of retail investors} + \gamma' Z_{i,t} + \alpha_{indt} + \varepsilon_{i,t}.$$

Then, we regress a firm's future innovation measure on the predicted returns $\widehat{r_{i,t}}$ obtained from the first stage as follows:

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

We make two key identifying assumptions for the above specifications. First, we expect a strong link between the firm's exposure to investors' distraction by "felt" earthquake shocks (measured as $Earthquake_t \times \%$ *of retail investors*) and its quarterly return $r_{i,t}$. We anticipate that more frequent "felt" earthquakes occurring during the 3-day window around patent issuance would lead to greater distractions among retail investors, resulting in lower equity returns for firms with higher ex-ante retail investor holdings. Second, as aggregated "felt" earthquakes are considered exogenous natural disaster shocks and the shares of retail investor holdings are known four quarters in advance, our measure of distraction exposure to "felt" earthquake shocks from retail investor holdings is plausibly exogenous.

Leveraging the "Bartik" type instrument, our analysis in Table A.6 demonstrates that firms experiencing lower returns due to heightened exposure to earthquake distractions have a more rapid decline in novelty-seeking innovations relative to those non-novel ones in the future. Furthermore, these effects are statistically significant only among those firms with a higher proportion of novel patents granted today, as shown in Table A.7. These results align with our earlier findings from earlier within-firm comparisons.

However, when comparing firms over the same period, as shown in Table A.8, disappointing stock market returns due to increased exposure to earthquake distractions do not significantly affect the ratio between a company's sustaining innovation and non-novel ones in the subsequent five years. It's important to highlight that these results do not conflict with our findings from within-firm comparisons, which underscore that a firm is likely to reduce the number of its follow-up patents following a period with lower returns compared to a period with less disappointing returns. However, in this specific scenario, we compare two different firms simultaneously with different equity returns and do not find evidence that the firm with lower stock returns shifts more from sustaining innovation to copycatting innovations.

5.3 Mechanism and Discussion

We present causal evidence that following disappointing returns in a quarter, novel firms (firms with a higher ratio of novel patents granted) shift innovation directions from novelty-seeking to copycatting. However, it is still unclear through which channel these causal effects occur. One natural mechanism is that some novel firms might be financially constrained. Constrained firms rely more strongly on external financing and thus care more about the market price of their stock, which is tightly related to the firm's cost of capital. This channel is related to equity dependence in Baker et al. (2003) where they find that firms that need equity financing to fund marginal investment have investment distortions due to short-term stock prices. To give an example, Kodak, the company that invented the first-ever digital camera back in 1977, was granted a patent for this revolutionary invention.[19] However, this novel technology did not grab much market attention and bring significant stock market returns for the company at the time. As a result, the company executives refused to continue investing in this digital technology, given Kodak's financial constraints. Instead, they decided to follow the market trend and join the innovation race in "medical equipment".

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

Besides the financial constraints channel, other channels could also result in the casual effects we document., such as agency conflicts between firm managers and shareholders. A firm's manager has a relatively shorter tenure at the firm, resulting in myopia and short-termism. Besides, some managers are also compensated with stock, which provides additional incentives for managers to chase short-term gains from the stock market. We will consider and empirically test those channels in future work.

6 Conclusion

In this paper, we document that investors react differently to patent issuance news based on patent novelty. They underreact to novel technology but overreact to non-novel technology. We argue against a rational risk-based story where firms with novel patents are riskier, and show direct evidence that investors incur mispricing to firms with novel versus non-novel patents. A bounded-rationality model where investors are cognitively limited and unsure about true novelty at patent issuance can explain these mispricing patterns.

We further investigate the real impact of such mispricing. We present causal evidence that market reactions cause novel firms to change their future innovation directions. We show that return drops in the equity market around patent issuance shift novel firms away from following up on their original technology and contributing to novel innovations, producing more copycat innovations in the future. This infers that firm managers care about short-term stock return movements when deciding on future innovation directions. This short-term focus could be attributed to managerial short-termism related to stock-based compensation or career concerns, or costly external financing where equity-dependent firms need to issue new equity to finance new projects.

Our paper provides important policy implications. Misperception of patent value in financial markets discourages future innovation in novel technology. In Figure A.11 and Table A.9, we show that novel patents bring higher private and social value to the firm. Hence, firms prefer to work more on already-established technologies with market enthusiasm, but they have lower remaining economic value. Over time, we will have fewer novel breakthroughs than is optimal, leading to welfare inefficiencies in the economy. Our results imply that policies facilitating investors' understanding of patent novelty would improve welfare. Such policies include more patent novelty disclosure, investor education on the patent system, and a better understanding of patent classification. One promising future research direction is quantifying the economic welfare loss from the inefficient innovation directions caused by market misreactions. Another interesting question is to explore how the misreactions in public markets influences private-market innovation efforts by startup companies and how it affects the interplay between public and private innovation.

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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.

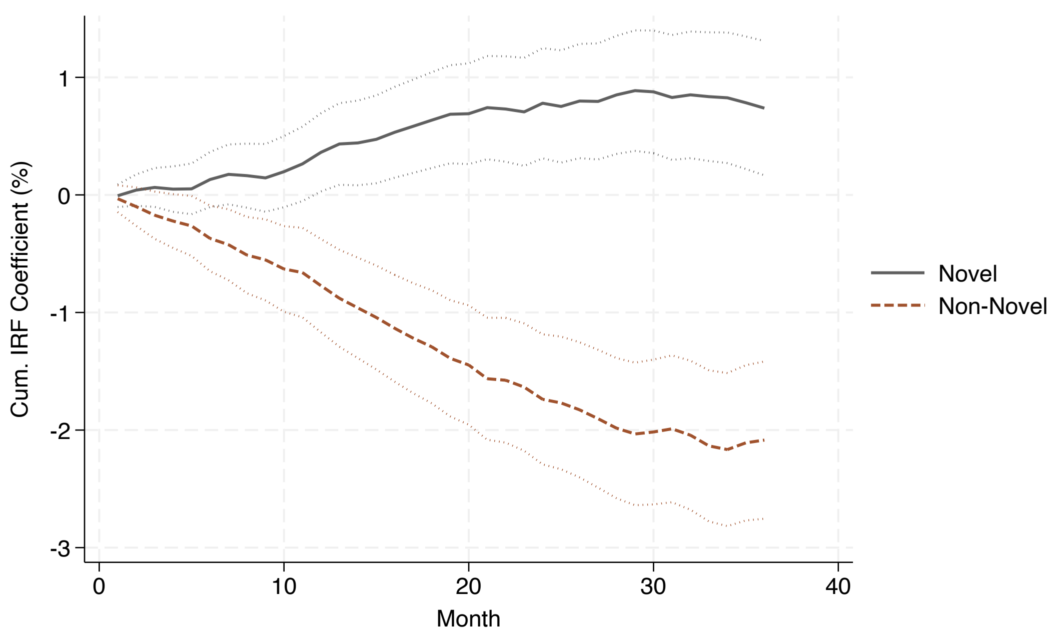


Figure 2: Impulse Response of Firm Realized Volatility after (Non-)Novel Patent Issuance

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

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

where $\sigma_{i,t+\tau}$ is the standard deviation of daily returns for 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 $t \in [1, 36]$ for $d \in \{novel, non-novel\}$. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

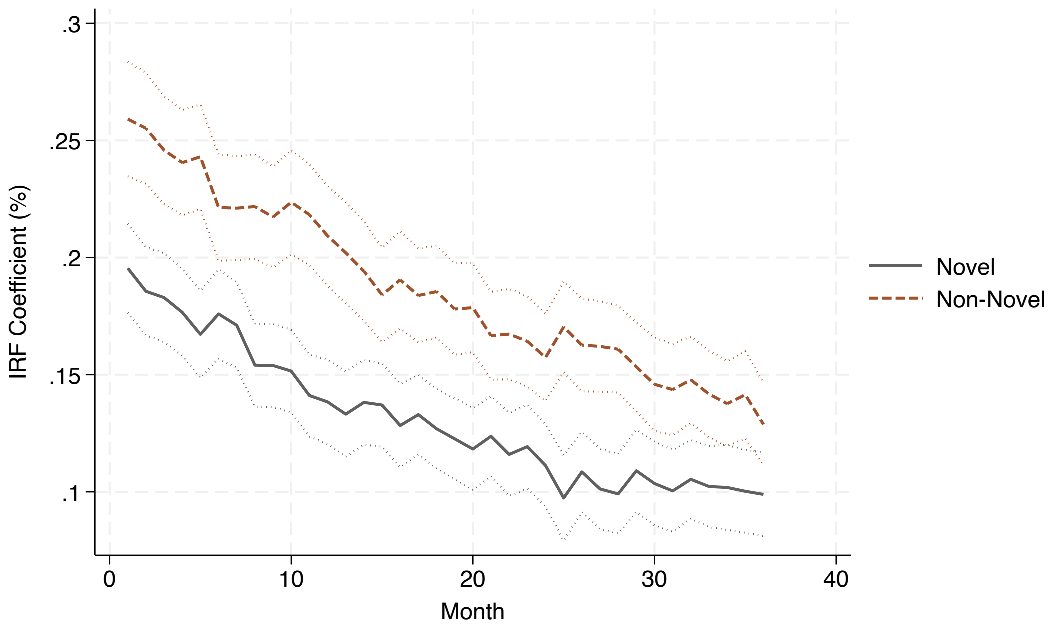


Figure 3: Cumulative IRF of Firm Implied Volatility after (Non-)Novel Patent Issuance

This figure plots the impulse response of future implied 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:

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

where Implied $\text{Vol}_{i,t+\tau}$ is the implied volatility for standardized ATM options maturing in 30 days of firm i in month $t+\tau$, provided by OptionMetrics. "(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.

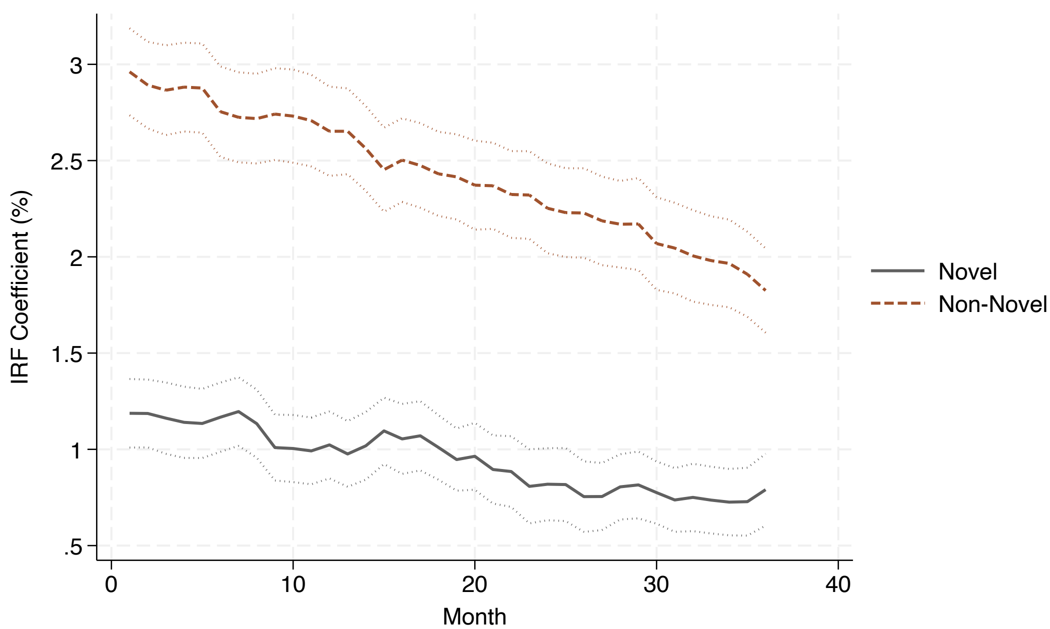


Figure 4: Cumulative IRF of Firm Returns on Randomized (Non-)Novel Issuance

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.

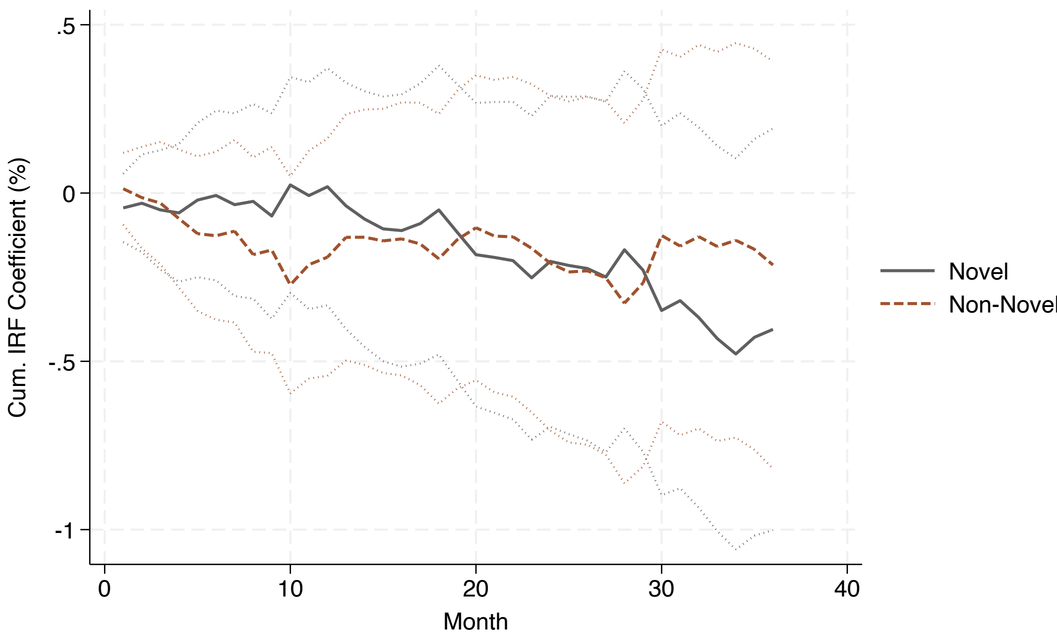


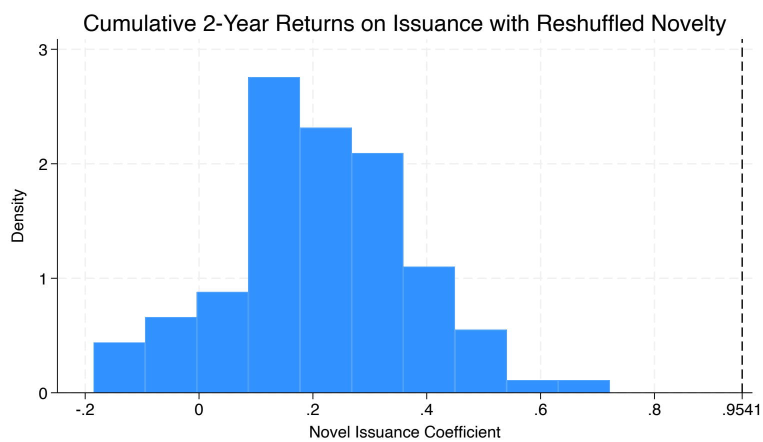
Figure 5: Coefficient Distribution of Cum. Return on Randomized (Non-)Novel Issuance

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

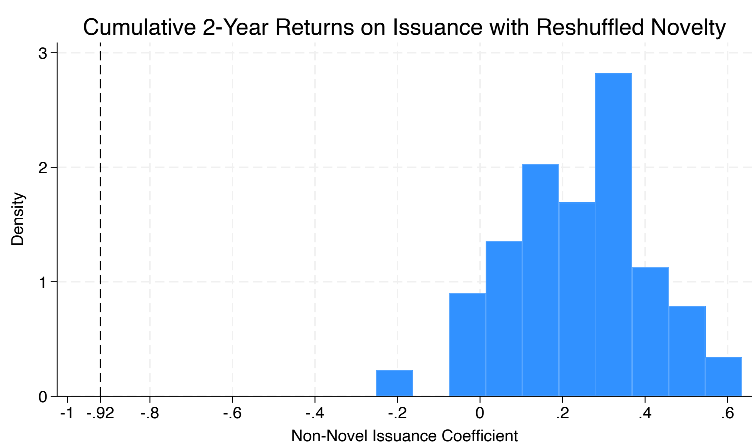


Figure 6: Theoretical Predictions of Issuance Returns to Novelty

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.

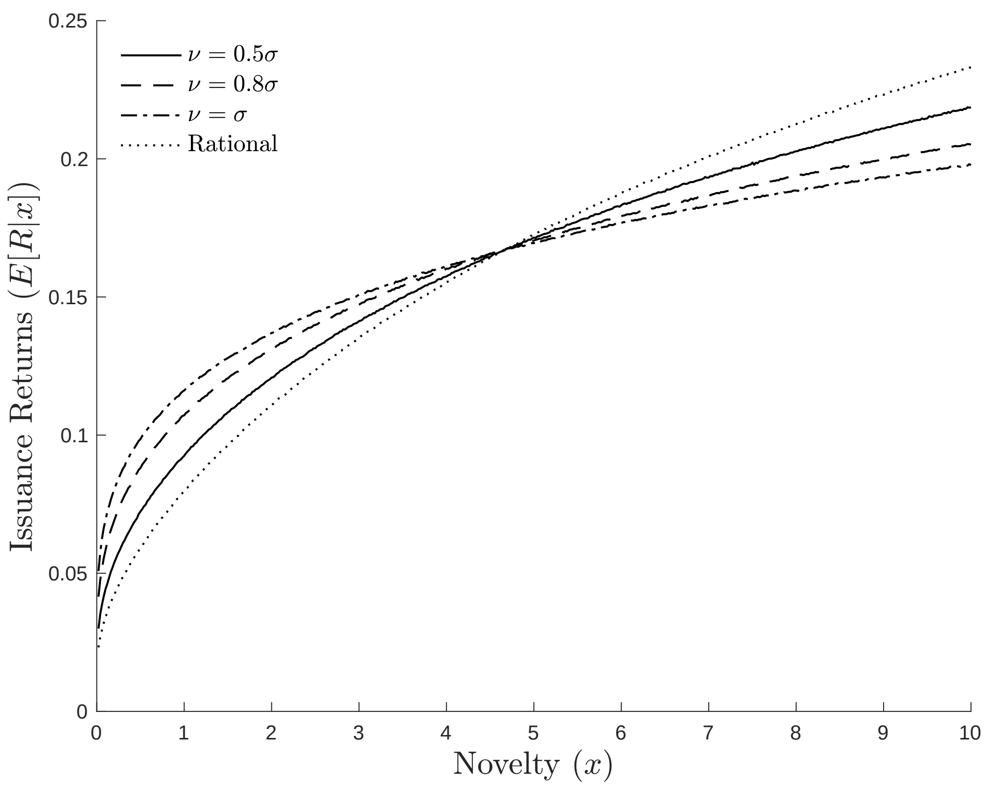


Figure 7: Theoretical Predictions of Dynamic Return Reaction by Novelty

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.

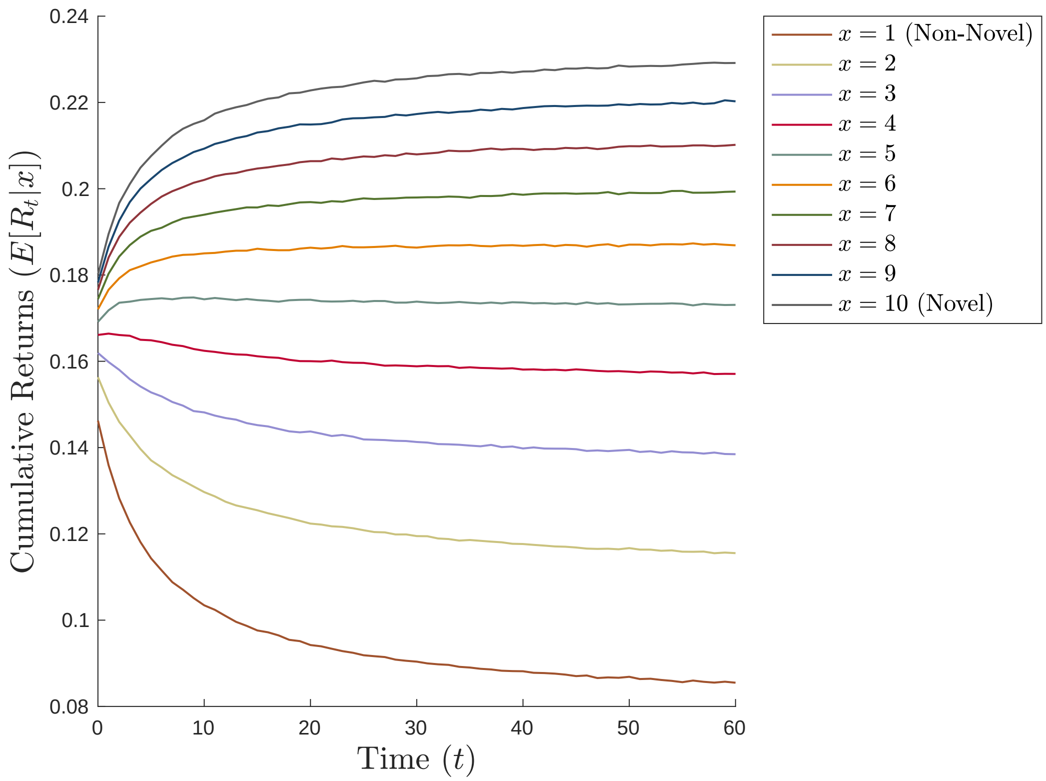


Figure 8: Theoretical Predictions of Dynamic Return Reaction by Signal Precision

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.

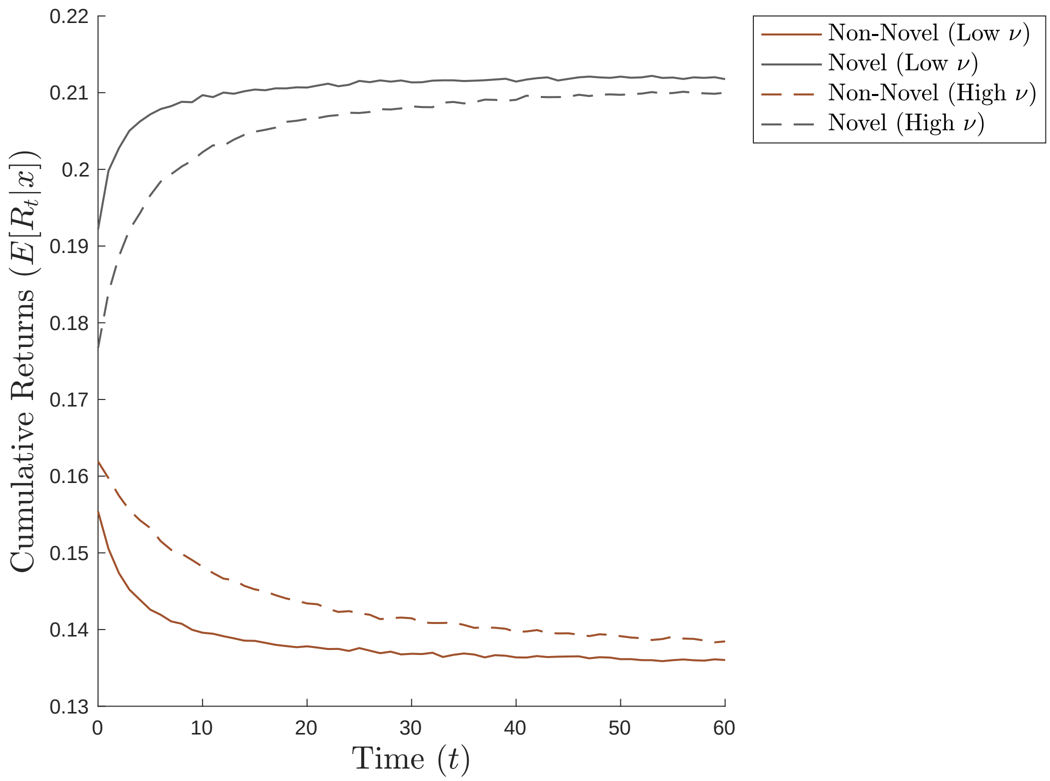


Figure 9: 3-Day Issuance Return across Patent Novelty

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

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

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

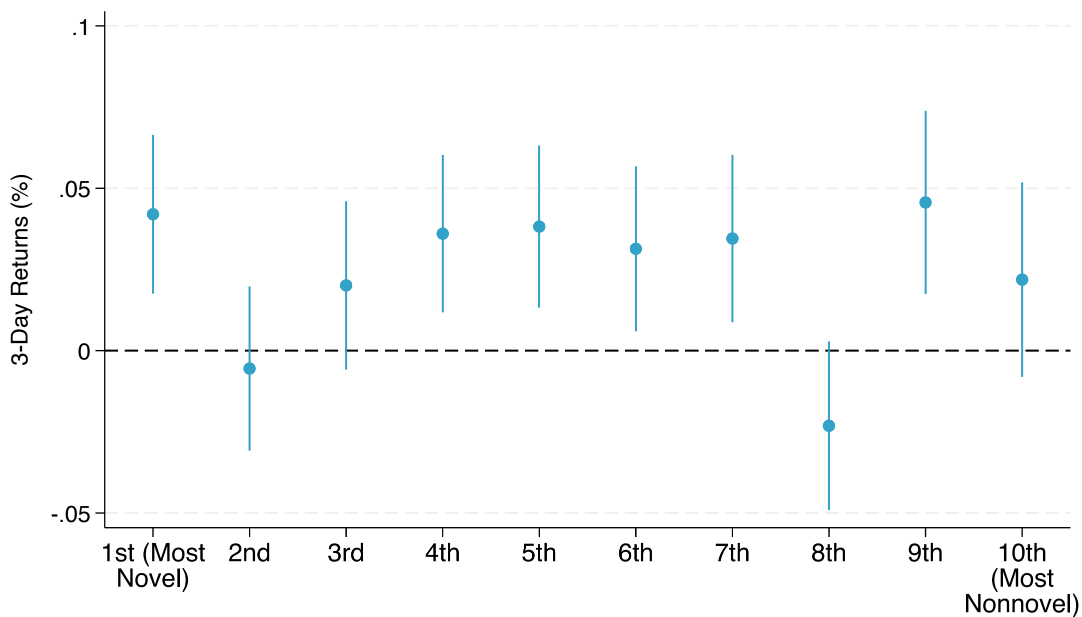


Figure 10: Cumulative IRF of Firm Returns after Patent Issuance across Patent Novelty

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.

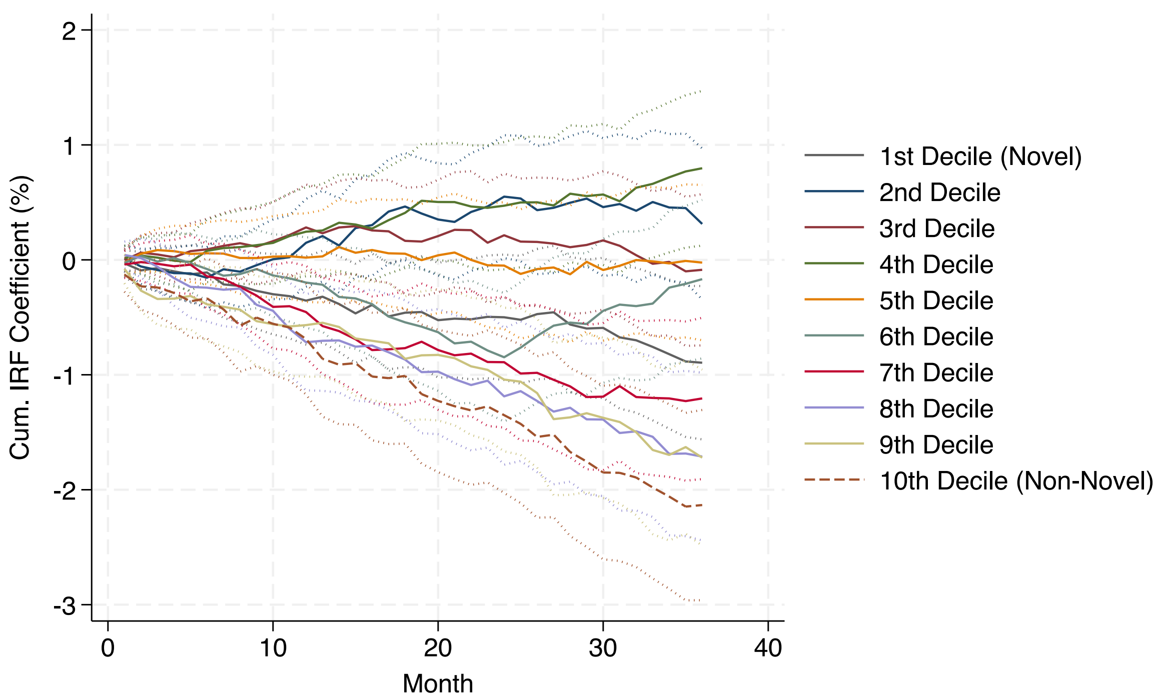


Figure 11: Cumulative IRF of Firm Returns after Patent Issuance by Institutional Holdings.

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.

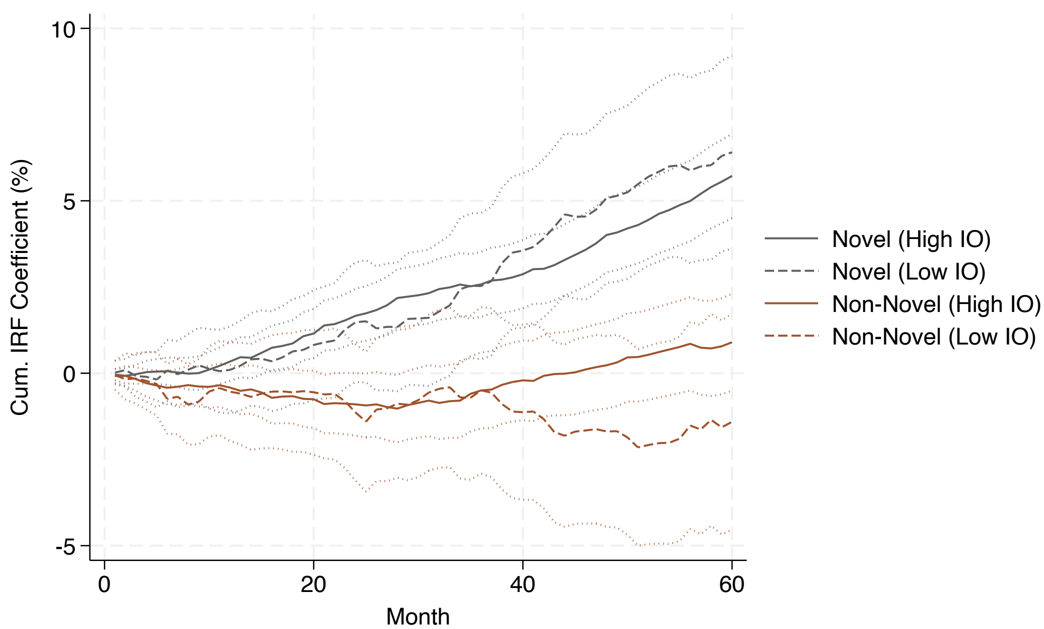


Table 1: Cumulative Returns on (Non-Novel) Issuance

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 in parentheses and all clustered at the year-month level.

	(1)	(2)	(3)	(4)
	6-Month Returns	1-Year Returns	2-Year Returns	3-Year Returns
Novel Issue	0.0616	0.3141*	0.9541***	1.3408***
	(0.55)	(1.92)	(4.05)	(4.54)
Non-Novel Issue	-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
IndustryxMonth FE	Yes	Yes	Yes	Yes
Observations	2292514	2292514	2292514	2292514

t statistics in parentheses

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

Table 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.

	(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 Dummy$_{t-1}$	0.0274***	0.0205**	0.0584*	0.0452
	(2.79)	(2.51)	(1.89)	(1.68)
Non-Novel Dummy$_{t-1}$	-0.0031	-0.0058	-0.0419	-0.0184
	(-0.36)	(-1.10)	(-1.29)	(-1.02)
R^2	0.000	0.002	0.000	0.006
Controls	No	Yes	No	Yes
Observations	97884	82783	80885	69007

t statistics in parentheses

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

Table 3: Firm's Equity Returns and Future Novelty-seeking Innovations

This table examines whether firms' quarterly returns cause changes in their future novelty-seeking innovations. In particular, we run the following firm-year-quarter level IV regression:

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

where we instrument a firm's quarterly equity returns $r_{i,t}$ with the number of "felt" earthquakes 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 novelty-seeking innovation in comparison to its "copycatting" innovations as defined in Section 5.1 in the subsequent four quarters (columns (1)), twelve quarters (columns (3)) and twenty quarters (column (5)) following its' quarterly equity 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 profits, age, and idiosyncratic volatility. In addition, we incorporate the controls for media coverage on "earthquake" proxied by the average daily news attention allocated to "natural disaster" in a quarter from Bybee et al. (2021). We also control for firm interaction with decade indicators and industry fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are in parentheses and all clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	FS	$\tau = 12$	FS	$\tau = 20$	FS
$r_{i,t}$	0.7340***		0.7463***		0.5225***	
	(2.81)		(3.35)		(2.91)	
(Standardized) Earthquake$_t$		-0.0250***		-0.0247***		-0.0249***
		(-14.25)		(-14.94)		(-15.27)
Firm x Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017
Effective F-stats		203		223		233
Observations	26804	26804	31740	31740	33050	33050

t statistics in parentheses

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

Table 4: 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-year-quarter level IV regression on each subsample separately:

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

where we instrument a firm's quarterly equity returns $r_{i,t}$ with the number of "felt" earthquakes 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 novelty-seeking innovation in comparison to its "copycatting" innovations 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' quarterly equity 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 profits, age, and idiosyncratic volatility. In addition, we incorporate the controls for media coverage on "earthquake" proxied by the average daily news attention allocated to "natural disaster" in a quarter from Bybee et al. (2021). We also control for firm interaction with decade indicators and industry fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are in parentheses and all clustered at the firm level.

	High-novelty			Low-novelty		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$r_{i,t}$	0.8978**	0.8746***	0.5745**	0.3748	0.4601	0.3471
	(2.54)	(3.11)	(2.43)	(1.02)	(1.48)	(1.48)
Firm x Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017
Observations	16754	20219	21142	9717	11180	11551

t statistics in parentheses

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

Table 5: Firm's Equity Returns and Future Sustaining Innovations

This table examines whether firms' quarterly returns cause changes in their future sustaining innovation. In particular, we run the following firm-year-quarter level IV regression:

$$\text{Sustaining Innovation}_{i,t+1\to t+\tau} = \beta r_{i,t} + \gamma' Z_{i,t} + \alpha_{ind} + \alpha_{i,decade} + \varepsilon_{i,t},$$

where we instrument a firm's quarterly equity returns $r_{i,t}$ with the number of "felt" earthquakes 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 sustaining innovation in comparison to its "copycatting" innovations as defined in Section 5.1 in the subsequent four quarters (columns (1)), twelve quarters (columns (3)) and twenty quarters (column (5)) following its' quarterly equity 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 profits, age, and idiosyncratic volatility. In addition, we incorporate the controls for media coverage on "earthquake" proxied by the average daily news attention allocated to "natural disaster" in a quarter from Bybee et al. (2021). We also control for firm interaction with decade indicators and industry fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are in parentheses and all clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	FS	$\tau = 12$	FS	$\tau = 20$	FS
$r_{i,t}$	1.8625***		1.6158***		-0.5032	
	(3.59)		(3.34)		(-1.09)	
(Standardized) Earthquake$_t$		-0.0251***		-0.0238***		-0.0237***
		(-10.74)		(-11.59)		(-12.05)
Firm x Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017
F-stats		115		134		145
Observations	13818	13818	19448	19448	21197	21197

t statistics in parentheses

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

Table 6: Firm's Equity Returns and Future Sustaining Innovations with Subsamples

This table examines how the same firm is affected by market reactions and changes its future innovation directions during high and low-novelty periods, respectively. 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-year-quarter level IV regression on each subsample separately:

$$\text{Sustaining Innovation}_{i,t+1\to t+\tau} = \beta r_{i,t} + \gamma' Z_{i,t} + \alpha_{ind} + \alpha_{i,decade} + \varepsilon_{i,t},$$

where we instrument a firm's quarterly equity returns $r_{i,t}$ with the number of "felt" earthquakes 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 novelty-seeking innovation in comparison to its "copycatting" innovations 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' quarterly equity 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 profits, age, and idiosyncratic volatility. In addition, we incorporate the controls for media coverage on "earthquake" proxied by the average daily news attention allocated to "natural disaster" in a quarter from Bybee et al. (2021). We also control for firm interaction with decade indicators and industry fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are in parentheses and all clustered at the firm level.

	High-novelty			Low-novelty		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$r_{i,t}$	1.3543*	0.9920*	-0.7572	2.8712***	2.6449***	-0.2330
	(1.96)	(1.66)	(-1.29)	(3.04)	(2.98)	(-0.35)
Firm x Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017
Observations	8430	12268	13505	5129	6853	7354

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 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 forindustry$\times$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.

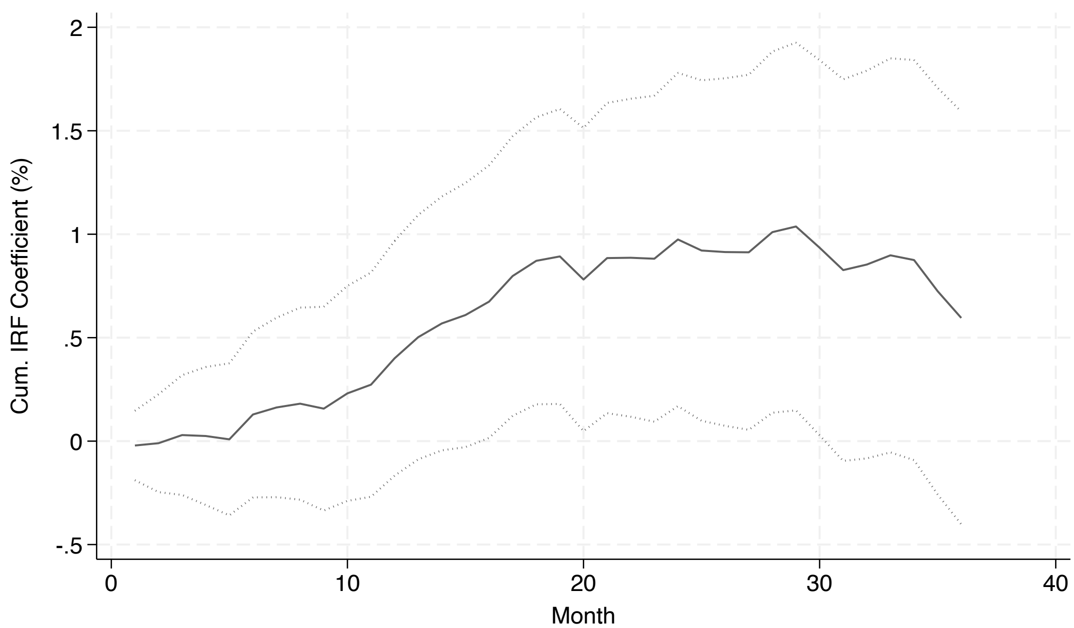


Figure A.2: Cumulative IRF of Firm Returns on Similarity Score

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.

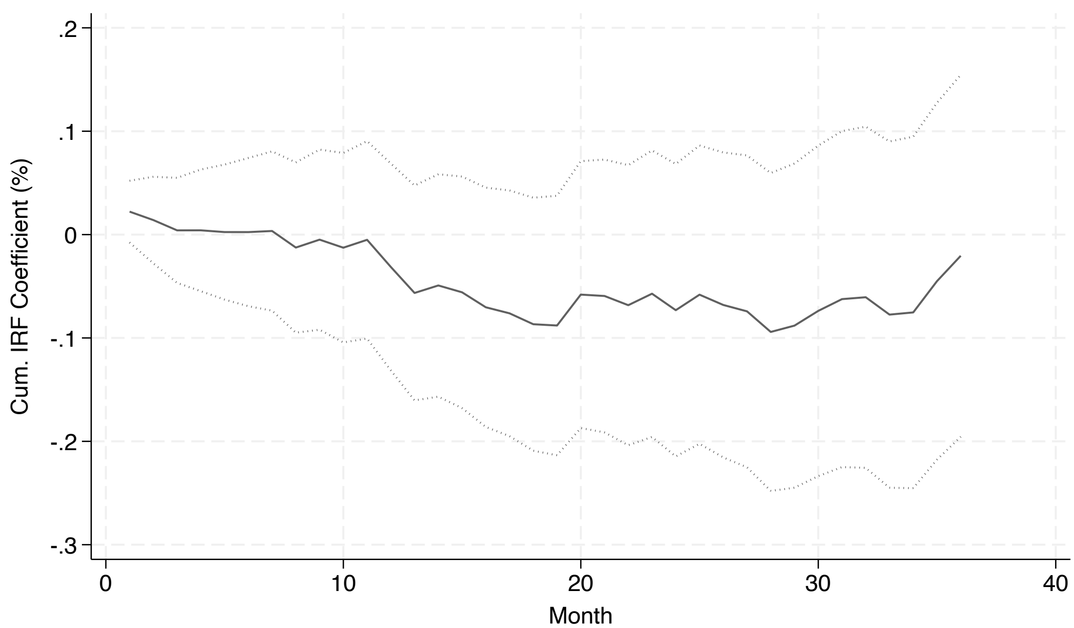


Figure A.3: Cumulative IRF of Firm Returns on Good/Bad Novel Patent Intensity

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

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

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

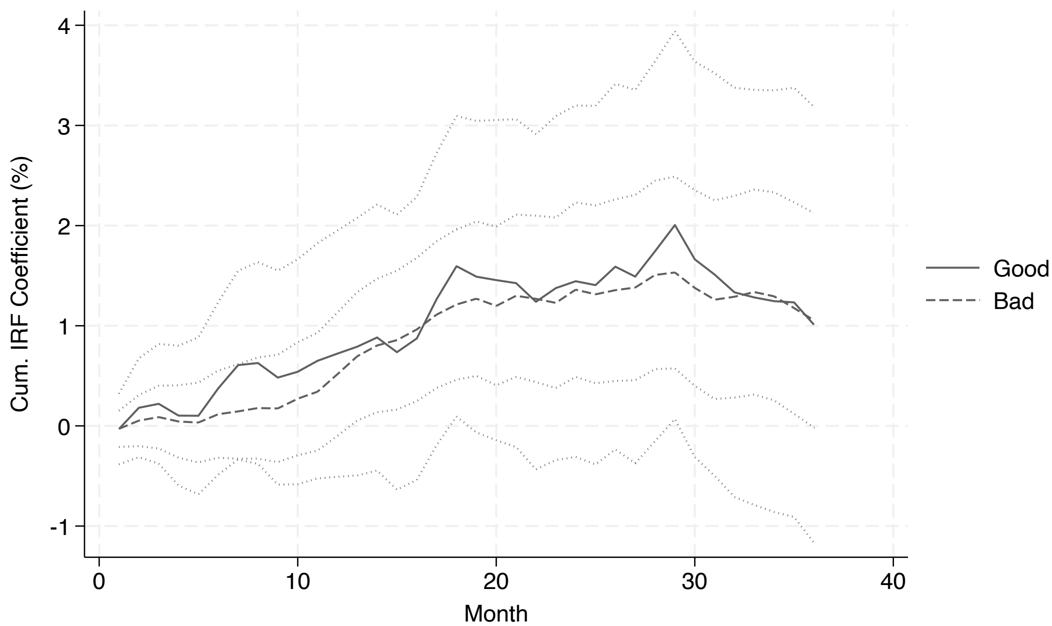


Figure A.4: Cumulative Alpha of Calendar-Time Portfolio Approach

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

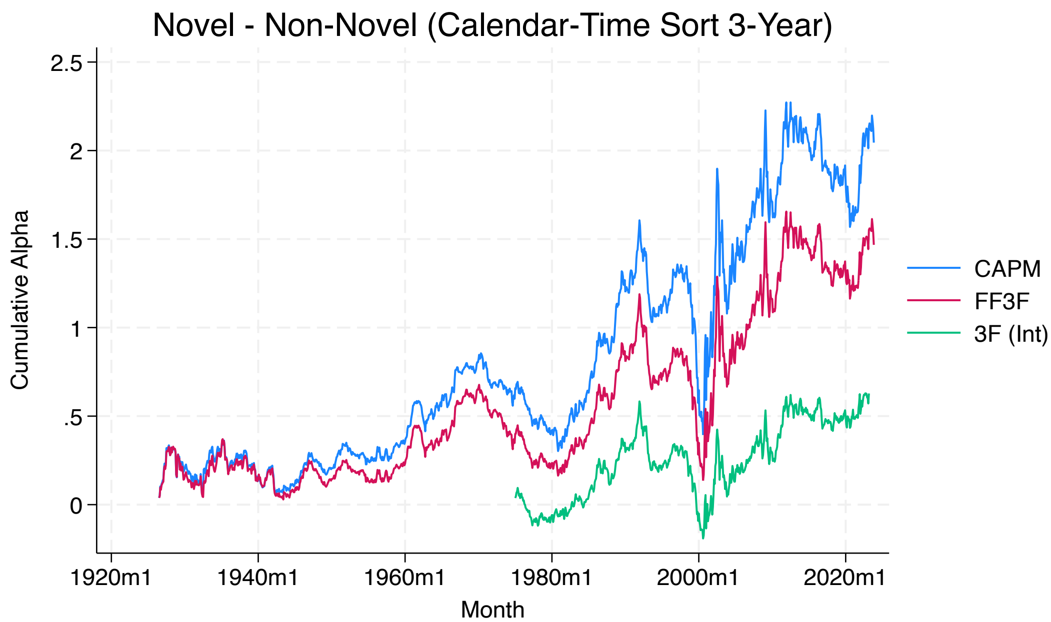


Figure A.5: Cumulative Alpha of 3-Year Portfolio Sorts on Novel Intensity

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

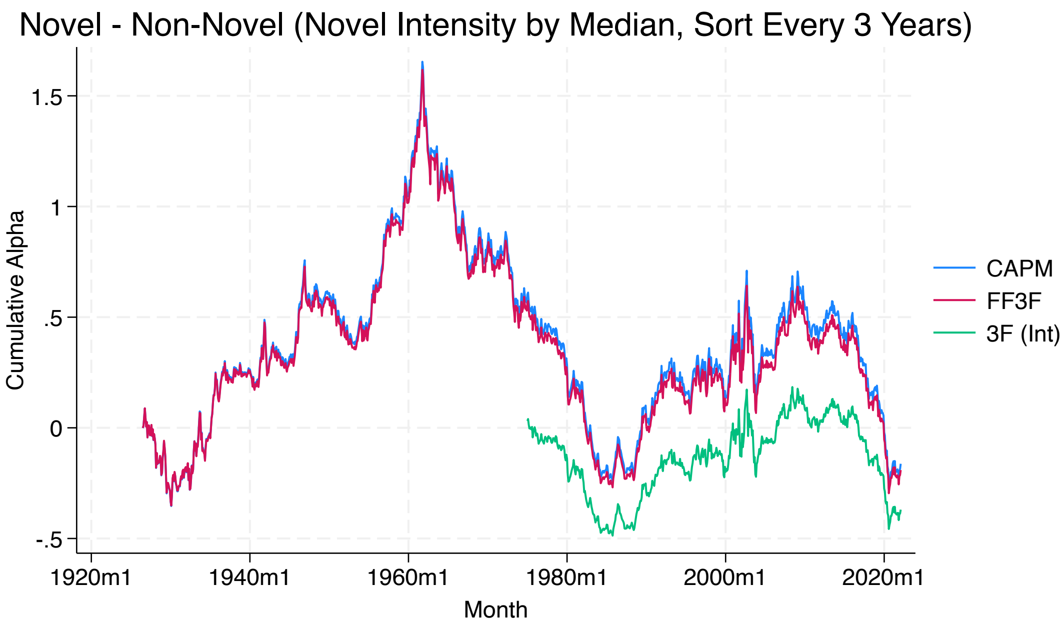


Figure A.6: Cumulative Alpha of Monthly Portfolio Sorts on Novel Intensity

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

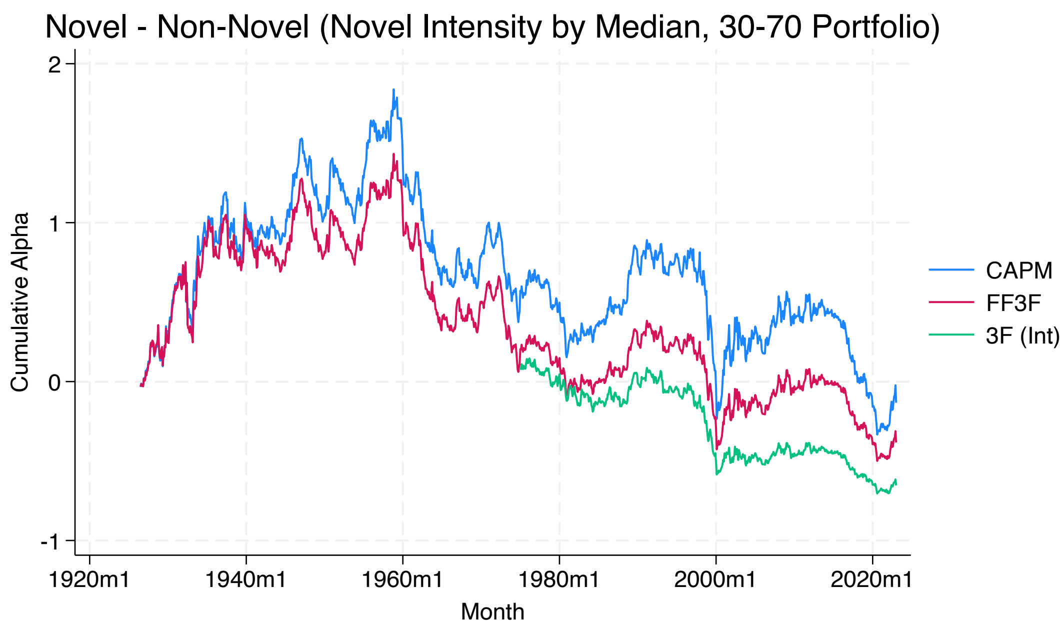


Figure A.7: Cumulative IRF of Firm Market Beta after (Non-)Novel Patent Issuance

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$\times$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.

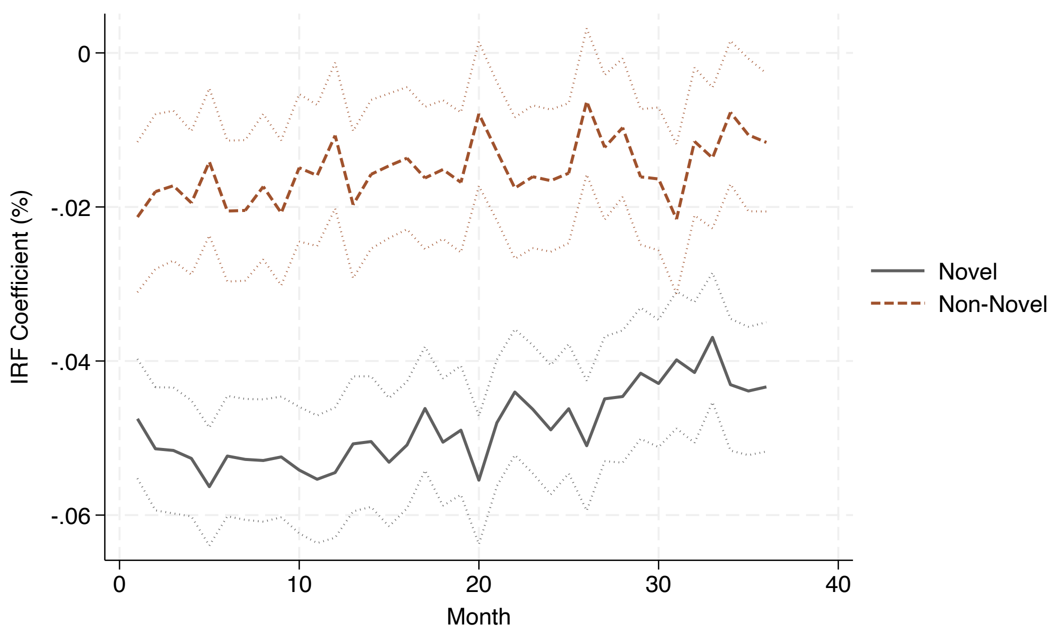


Figure A.8: Pre-Test: Impulse Response of Firm Returns before (Non-)Novel Patent Issuance

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.

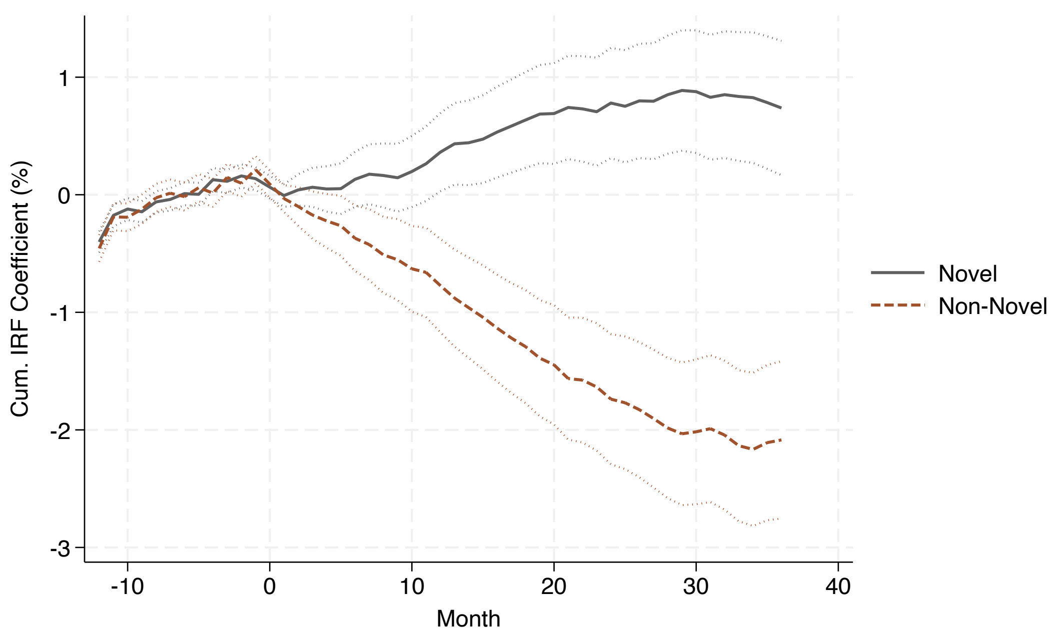


Figure A.9: Theoretical Predictions of Under- & Over-Perception of Patent Novelty

This figure plots the model-predicted perception of novelty at patent issuance for different levels of true novelty. For illustration purposes, we pick reasonable numerical values for exogenous model parameters and compute the model-implied expected 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 are interested in the conditional expectation of the posterior mean of a large cross-section of investors, $E[\hat{x}|x]$, where $\hat{x} = E[x|r]$, which is the posterior mean given the signal observed at issuance.

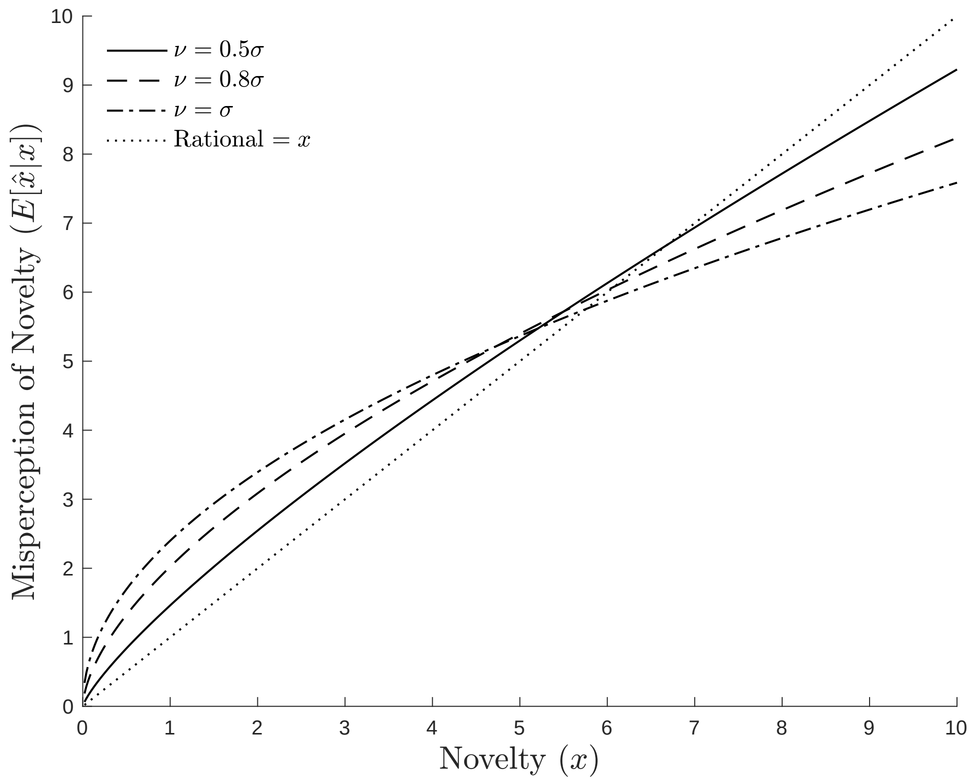


Figure A.10: Theoretical Predictions of Dynamic Novelty Perception

This figure plots the model-predicted dynamic perception of patent novelty for ten values of true novelty ($x \in \{1, ..., 10\}$). We pick reasonable numerical values for the exogenous model parameters and compute the model-implied expected 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 equal to 2. For a large cross-section of investors, we plot the evolution of the conditional expectation of the posterior mean of perceived novelty over 60 periods after patent issuance, $E[\hat{x}_t|x]$, where $\hat{x}_t = E[x|r_1, ..., r_t]$.

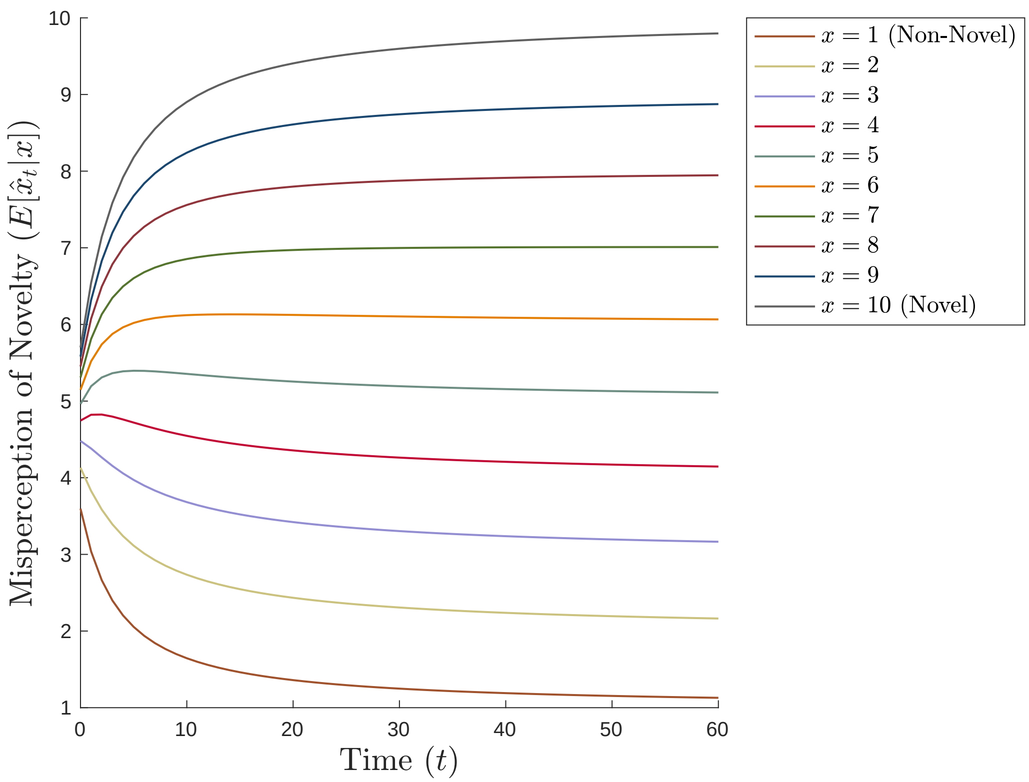
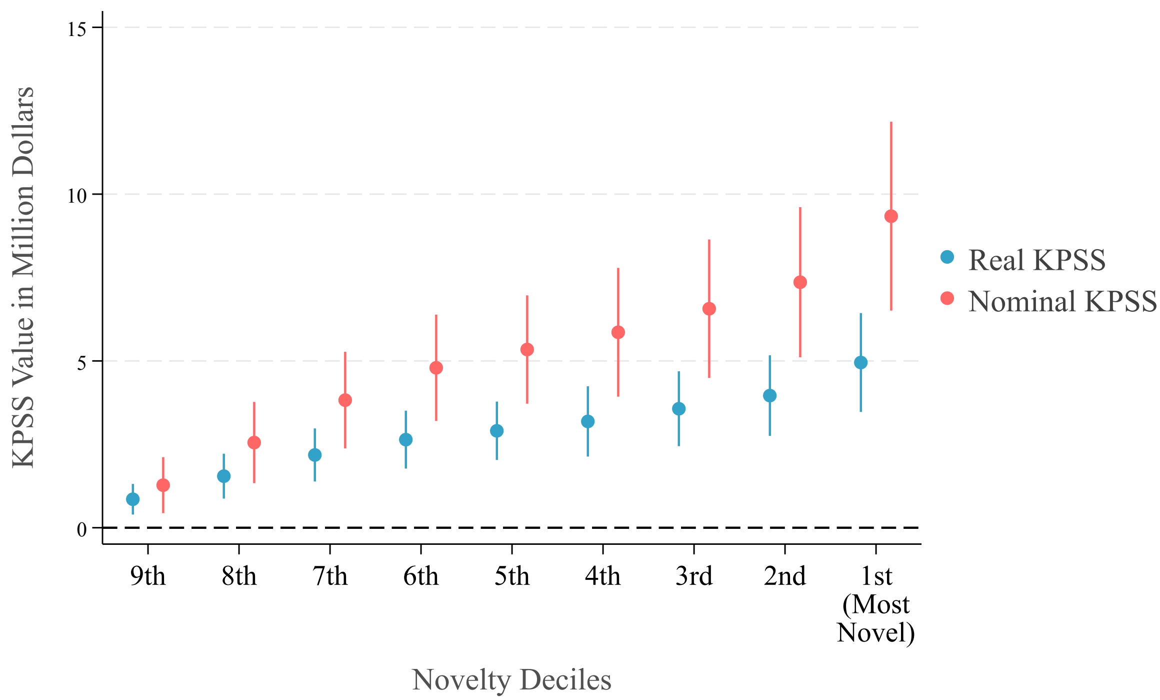


Figure A.11: Patent Private Value on Novelty

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.



A.2 Tables

Table A.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$\times$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. Standard errors are clustered at the issuance date level.

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

t statistics in parentheses

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

Table A.2: 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.

	(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

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

Table A.3: 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 A.4: Firm's Future Innovation and Equity Return (Within-firm Comparisons)

This table examines whether firms' quarterly returns are correlated with their changes in future innovation directions. In particular, we run the following firm-year-quarter level OLS regression:

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

The dependent variable is a firm's future sustaining innovation or novelty-seeking innovation relative to its "copycat" 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' quarterly equity 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 and profits, the total value of innovation and idiosyncratic volatility. We also control for firm fixed effects. Note that this specification does not include the firm's age as a control to allow more cross-time variations. We report the estimates of the independent variable with primary interest here. Standard errors are in parentheses and all clustered at the firm level.

	(Relative) Sustaining			(Relative) Novelty-seeking		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$r_{i,t}$	-0.008	-0.040	-0.067**	0.006	0.027**	0.025**
	(-0.24)	(-1.37)	(-2.31)	(0.37)	(2.19)	(2.25)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	2000-2021	2000-2019	2000-2017	2000-2021	2000-2019	2000-2017
R^2	0.62	0.65	0.68	0.76	0.84	0.88
Observations	15808	21223	21412	30505	34616	33318

t statistics in parentheses

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

Table A.5: Firm's Future Innovation and Equity Return (Cross-firm Comparisons)

This table examines whether firms' quarterly returns are correlated with their changes in future innovation directions. In particular, we run the following firm-year-quarter level OLS regression:

$$\text{Future Innovation}_{i,t+1\rightarrow t+\tau} = \beta r_{i,t} + \gamma' Z_{i,t} + \alpha_{indt} + \varepsilon_{i,t}$$

The dependent variable is a firm's future sustaining innovation or novelty-seeking innovation relative to its "copycat" innovation as defined in Section 5.1 in the following four quarters (as shown in columns (1) and (4)), twelve quarters (as shown in columns (2) and (5)) and twenty quarters (as shown in columns (3) and (6)) following its' quarterly equity 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 and profits, the total value of innovation, age, and idiosyncratic volatility. We also control for industry interactions with year-quarter fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are in parentheses and all clustered at the firm level.

	(Relative) Sustaining			(Relative) Novelty-seeking		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$r_{i,t}$	0.078	-0.031	-0.090*	0.051*	0.096***	0.090***
	(1.42)	(-0.63)	(-1.73)	(1.69)	(3.53)	(3.16)
Industry x YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	2000-2021	2000-2019	2000-2017	2000-2021	2000-2019	2000-2017
R^2	0.46	0.44	0.44	0.52	0.55	0.56
Observations	14300	20119	20620	29231	33972	33021

t statistics in parentheses

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

Table A.6: Firm's Equity Returns and Future Novelty-seeking Innovations

This table examines whether firms' quarterly returns cause changes in their future novelty-seeking innovations. In particular, we run the following firm-year-quarter level IV regression:

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

where we instrument a firm's quarterly equity returns $r_{i,t}$ with the firm's exposure to investors' distraction by "felt" earthquake shocks (measured as $Earthquake_t$ × *% of retail 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 novelty-seeking innovation in comparison to its "copycatting" innovations as defined in Section 5.1 in the subsequent four quarters (columns (1)), twelve quarters (columns (3)) and twenty quarters (column (5)) following its' quarterly equity 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 profits, age, and idiosyncratic volatility. We also control for the quarter and industry interactions with year fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are in parentheses and all clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	FS	$\tau = 12$	FS	$\tau = 20$	FS
$r_{i,t}$	0.2364		1.2105*		1.9621**	
	(0.30)		(1.75)		(2.07)	
% retail investor$_{i,t-4}$ × Earthquake$_t$		-0.0352***		-0.0493***		-0.0509***
		(-5.03)		(-8.62)		(-7.62)
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	2001-2020	2001-2020	2001-2019	2001-2019	2001-2017	2001-2017
Effective F-stats		77		163		133
Observations	22536	22536	25442	25442	24076	24076

t statistics in parentheses

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

Table A.7: Firm's Equity Returns and Future Novelty-seeking Innovations with Subsamples

This table examines whether firms with more novel patents granted are more likely to be affected by market reactions and change their future innovation directions. In particular, we categorize our sample into high- and low-novelty groups based on whether the firm's ratio of novel patents granted is above 50% in the quarter. Then, we run the following firm-year-quarter level IV regression on each subsample separately:

$$\text{Novelty-seeking Innovation}_{i,t+1\rightarrow t+\tau} = \beta r_{i,t} + \gamma' Z_{i,t} + \alpha_{indt} + \varepsilon_{i,t},$$

where we instrument a firm's quarterly equity returns $r_{i,t}$ with the firm's exposure to investors' distraction by "felt" earthquake shocks (measured as $Earthquake_t$ × *% of retail investors*) in the first stage. The dependent variable is a firm's future novelty-seeking innovation in comparison to its "copycatting" innovations 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' quarterly equity 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 profits, age, and idiosyncratic volatility. We also control for the quarter and industry interactions with year fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are in parentheses and all clustered at the firm level.

	High-novelty			Low-novelty		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	$\tau = 12$	$\tau = 20$	$\tau = 4$	$\tau = 12$	$\tau = 20$
$r_{i,t}$	1.7831	2.5512**	3.5637**	-1.3884	-0.3932	0.2739
	(1.54)	(2.45)	(2.15)	(-1.31)	(-0.53)	(0.32)
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	2001-2020	2001-2019	2001-2017	2001-2020	2001-2019	2001-2017
Observations	14079	16192	15452	8130	8900	8288

t statistics in parentheses

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

Table A.8: Firm's Equity Returns and Future Sustaining Innovations

This table examines whether firms' quarterly returns cause changes in their future sustaining innovations. In particular, we run the following firm-year-quarter level IV regression:

$$\text{Sustaining Innovation}_{i,t+1\rightarrow t+\tau} = \beta r_{i,t} + \gamma' Z_{i,t} + \alpha_{indt} + \varepsilon_{i,t},$$

where we instrument a firm's quarterly equity returns $r_{i,t}$ with the firm's exposure to investors' distraction by "felt" earthquake shocks (measured as $Earthquake_t$ × *% of retail 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 sustaining innovation in comparison to its "copycatting" innovations as defined in Section 5.1 in the subsequent four quarters (columns (1)), twelve quarters (columns (3)) and twenty quarters (column (5)) following its' quarterly equity 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 profits, age, and idiosyncratic volatility. We also control for the quarter and industry interactions with year fixed effects. We report the estimates of the independent variable with primary interest here. Standard errors are in parentheses and all clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 4$	FS	$\tau = 12$	FS	$\tau = 20$	FS
$r_{i,t}$	-1.7722		-1.3968		-2.0601	
	(-1.01)		(-1.02)		(-1.37)	
% retail investor$_{i,t-4}$ × Earthquake$_t$		-0.0453***		-0.0570***		-0.0522***
		(-4.62)		(-7.98)		(-6.74)
Industry x Year FE	Yes		Yes		Yes	
Controls	Yes		Yes		Yes	
Sample Period	2001-2020		2001-2019		2001-2017	
CD Wald F		61		121		89
Observations	11962	11962	15834	15834	15694	15694

t statistics in parentheses

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

Table A.9: 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 in parentheses and all 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

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