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 news depending on its novelty, and this misreaction exerts real impact on the firms' future innovation. Using textual analyses of patent documents to measure patent novelty, we find that investors under-react to the issuance of path-breaking innovations while overreact to the trend-following ones. We rationalize the empirical patterns with a bounded-rationality model where investors cannot figure out the true novelty of a patent at issuance due to cognitive limits. We verify the key model mechanism by showing that firms which receive noisier signals (firms with more retail traders) exhibit stronger misreaction. This misreaction is economically significant because novel patents bring higher economic value to the firm and have higher social value than non-novel patents. We also find that firms, on average, follow up less on their novel technology and issue fewer future novel patents, after an issuance of novel innovation. Using price pressure from mutual fund redemptions as an instrument, we present causal evidence that novel firms change innovation directions from novelty-seeking to copycat innovations following disappointing returns. The findings highlight that investor misreaction to patent novelty has a real impact on future innovation directions by steering firms 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)). How do investors react to news about technological innovation? More importantly, this raises some fundamental questions: can investors' reactions to technological innovation affect future innovation directions?

To address these questions, in this paper, we investigate the stock price movements and firm innovation output 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 of novelty to an intermediate prior level. We further argue that this misreaction is economically meaningful because novel patents provide higher economic value to the firms that issue them and more importantly, bring higher social value to the economy. Moreover, we demonstrate that investor reactions to patent novelty change firms' decisions on the direction of future innovation. Firms that issue novel patents ("novel firms" thereafter) do not follow up on their original technology, nor do they conduct other novel innovations, which suggests that firms shift away from novel inventions and instead pursue overpriced, non-novel technologies. Using hypothetical trades from mutual fund fire sales 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. Rather than focusing on conventional channels such as financial frictions and external financing costs, we explore how investors' irrational behavior affects firms' real decisions. To our knowledge, we are the first to show that investor biases can impact firms' future decisions regarding 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 less novel technology and overprice the stock of less novel firms, which then encourages managers to over-invest in existing technologies.

The key challenge to studying the differential reaction 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 the lowest 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 most similar to prior innovations. To approximate patent quality and measure patent economic value to the firm, we use the measure from Kogan, Papanikolaou, Seru and Stoffman (2017), which, they show, predicts forward citations and future output and profitability with a positive sign. To quantify patent social value and explore the future impact of patents, 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 three 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. The impulse response gives us firms' stock return reaction following the issuance of novel patents versus non-novel patents. Suppose investors under-react to novelty. In that case, following the issuance of a novel patent, investors may react positively to this news and push up the firm's stock price, but they do not push up the price sufficiently to fully reflect the value of the innovation. Consequently, on average, the stock price will continue going up after the novelty shock, exhibiting positive predictability of novel patent issuance. Conversely, if investors overreact to non-novel technology, they will immediately overprice the firm's stock following the patent issuance. Over time, this overpricing will be corrected as investors learn about the limited value of non-novel inventions, so non-novel patents, on average, will negatively predict returns. Our findings precisely match these hypotheses: we document a persistent positive (negative) predictability of returns for around two years following the issuance of novelty (non-novelty) patents.

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, it can in principle be computed by investors. 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 lends them to under-estimate the novelty of novel patents and over-estimate the novelty of non-novel patents. With novel patents having higher expected 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 more significant misreactions than those held primarily by institutional investors, as retail investors tend to receive noisier signals.

In our second main analysis, we argue that this mispricing of patent novelty is important because novel patents bring significant value to innovators and society. To see how the value that patents create for firms varies by novelty, we compute the private economic value of patents following Kogan et al. (2017) (Henceforth, KPSS values). We find a monotonically increasing relationship between the patent's KPSS value and novelty. The most novel patents create around $10 million more value for the firm than the most non-novel patents. Besides value creation within the firm, we also analyze the positive externalities created by novel patents, quantified by the patent's "social value." Conditional on a patent's private value, a novel patent, on average, has a higher number of future citations. Moreover, patents citing novel patents also bring higher economic value for their respective innovators than those citing non-novel inventions. These results suggest that novel patents bring additional value to other firms by improving their future technological innovation and, hence, have higher social value.

Third, we characterize firms' future innovation trajectories following the issuance of novel patents. We find that for a 1% increase in the fraction of novel patents among all issued patents, the firm produces 1% fewer follow-up patents on the original novel technology.[1] Moreover, we find that novel firms, on average, decrease the fraction of novel patents (novel intensity) in future issuances: a 10% higher novel intensity predicts a 5.8% contraction in future novel intensity. Taken together, these two pieces of evidence suggest that, since the market is not enthusiastic enough about novel innovations, novel firms are discouraged and redirect their innovation endeavors toward existing technology that investors, if anything, are too excited about.

To establish a causal interpretation of the results above – that market reactions affect firms' future innovation directions – we employ a plausibly exogenous variation in stock returns around patent issuance. Specifically, we use the hypothetical trades from mutual fund fire sales as an instrument (Edmans, Goldstein and Jiang (2012)). They construct a

[1] In a robustness check, we show that this negative correlation with future follow-up patents persists when we focus only on high-impact novel patents, suggesting that the effect is not driven purely by novel innovations with low impact.

flow-induced trading measure at the firm level, driven by sudden large outflows from mutual fund investors. Since the trades are allocated to each stock using ex-ante holdings (not the actual trades), this is likely to create an exogenous variation in stock price that is unrelated to firms' future innovation directions through other channels. Using the instrument, we document that, following an exogenous 1% drop in returns, high-novelty firms issue 0.01 fewer patents that cite their own patents in the next 5 years and 0.04 fewer patents in all future years. This suggests that firms are less likely to follow up on their existing technologies if they deliver disappointing returns. We also show that a 1% drop in returns results in novel firms contributing 0.3% fewer novel patents in the next three years, suggesting a decrease in novelty-seeking activities. The two pieces of evidence combined suggest that managers of novel firms shift innovation direction to "copycat" type non-novel technologies. We find evidence of this in the data. A 1% return drop leads to a 0.14% increase in non-novel patent issuance in the next three years. We propose and discuss several channels through which firm managers take into account their firms' near-term stock price when making real 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 predict stock returns, but have important distinctions empirically and theoretically. Empirically, our measure which bases on textual similarity more directly measures how a patent is distinctive to previous patents, than citing a wide set of technologies. We also not only find positive predictability for novel patents, but also 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[2]. 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 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 traditional learning from prices channel, we propose that investors' behavioral biases, which lead to mispricing, can also 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 effect of going public on innovation quality, Lerner, Sorensen and Strömberg (2011) discuss the effects of LBO on innovation output, and Babina, Bernstein and Mezzanotti (2022) show the effect of local exposure to financial crises on local innovation players. These papers demonstrate the importance of financial frictions and the cost of external financing. We instead explore the possibility that behavioral forces in the secondary market could also contribute to the shift in innovation behavior. On this front, Dong et al. (2021) document that stock overreaction affect innovative inventiveness and output with a positive sign. They find that general overpricing affects innovation, while we focus on both under- and over-reaction around patent

[2] 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.

issuance and argue that managers care about short-term stock value created by patent when deciding future innovation strategy. Moreover, while they study the *amount* of future innovation, we are interested in the *direction* of innovation: managers pivot from novel to copycat innovations due to observed reactions.

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. 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' misreaction to patent novelty. We then develop a theoretical framework to explain the misreaction and verify its predictions in our data. Section 4 compares the patent private economic value and social value across patent novelty. In Section 5, we show results on the future innovation direction of novel firms and how misreaction slows novel technology advancements in novel firms. Section 6 concludes by discussing the implications of our results for future research.

2 Data and Measurement

One of our main objectives is to empirically examine how investors react to a particular type of news – patent issuance by public firms, but across different novelty levels of granted patents. Furthermore, we aim to explore how investors' reactions to patents' novelty impact the associated firms' future innovation directions. To establish these facts, we combine information from patent data with firms' stock price movements and financial statements.

2.1 Patent Data

Our study's first substantial data source involves the patent records filed with the United States Patent and Trademark Office (USPTO). Over a period of nearly a century (from 1926 to 2021) and covering around 3.6 million patents, 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. For example, we construct patent-pairwise citation networks and estimate each patent's private value, social value, novelty, and impact. We elaborate on the methodologies and definitions of these measures later in this section.

2.2 Firm-level Financial Data

To test the market reactions to the news of patent issuance, we match the patent data with firm-level stock returns from the Center for Research in Security Prices (CRSP) database. Our focus is on the stock market reactions after the official announcement of patent issuances. Following the methodology introduced by Kogan et al. (2017), we link the patents to publicly-traded firms by using the assignee names as the key matching criterion. We use daily returns and prices, and construct market capitalization, share and dollar volume, reversal and momentum from CRSP following standard procedure in the literature.

2.3 Other Firm-level Data

After linking patents to their issuing companies, we aggregate our patent data at the firm-year level and derive several innovation measures, including, but not limited to, the number of patents, total citations, total private values of patents, and novel intensity of patents. We aim to use these measures to capture firms' technological innovation landscape. We also combine these innovation measures with other firm-level outcomes such as output, profits, capital stock, and the number of employees, all extracted from the Compustat database. This enriched panel dataset allows us to explore the connections between firms' innovation capabilities and their actual economic performance.

2.4 Innovation Novelty, Impact, and Value

2.4.1 Measurement of Patent Novelty and Impact

The conceptual framework of our study is grounded in a nuanced understanding of patent novelty, which can be described as 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, which enables a data-driven examination of a patent's content. By analyzing the textual content of patent documents, one 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 derives its core principles from Kelly et al. (2021). Their innovative framework defined the importance of a patent by examining its contextual positioning within the broader patent ecosystem. Specifically, they proposed an indicator of patent importance, denoted as q_j^{10} for patent j, as the ratio of its forward similarity FS_j^{10}, to its backward similarity, BS_j^5:

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

Delving deeper into each component, the backward similarity (BS_j^5) represents the ***nov-***

elty aspect of the patent. It is computed by summing 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 creativity. Such a metric is essential 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 patent with the same novelty levels further into high or low-impact groups.

2.4.2 Measurement of Patent Private Value

It is plausible that a patent with high novelty introduces something distinct, potentially game-changing, to its respective field. However, this does not automatically guarantee that such a patent will have significant private value to the firm. High novelty could indicate some technological advancement, but its economic value might remain limited without the corresponding market demand or feasibility for commercial application. Therefore, evaluating how the market reacts to such novelty and how the market reaction impacts firms' future innovation requires controlling for how much economic value patents could bring to firms.

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). One of the primary strengths of the KPSS measure is its ability to robustly predict forward citations, an indicator of a patent's "scientific value".

Besides, the positive correlation between a firm's aggregate KPSS values across patents and future capital, labor, output, and profit growth suggests that the value of its patents can offer significant insights into its potential success in the innovation-driven product market. Moreover, aggregate KPSS values are associated with aggregate growth and Total Factor Productivity (TFP). They can also identify known periods of pronounced technological advancement on a macro scale. Given these reasons, we also use the KPSS value as a proxy for patent quality. This proxy for innovation quality is particularly essential when we examine how a firm decides its future innovation strategy, contingent on its existing innovations.

2.4.3 Measurement of Innovation 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 consist of 43 million patent citation pairs, specifically covering patents whose assignees are publicly-traded firms available in the CRSP database. We employ it as a tool for exploring 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 two proxies for evaluating a patent's social value. The first is the total citations a patent receives, indicating its influence and acceptance in the broader community; the second is the aggregated private values of a patent's follow-up patents (in other words, the future patents that cite the original patent). The latter captures the downstream economic value a patent introduces into the innovation ecosystem. Both metrics give us a reasonable estimate of a patent's social value.[3].

[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.

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. Investors' reactions to innovations, in particular, have become a pivotal area of exploration. In light of this, our study assesses 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 issuances. This exercise seeks to illustrate whether investors underreact or overreact to such news. We also aim to shed light on what drives the potentially different market reactions to different levels of patent novelty.

3.1 Empirical Strategy

In the empirical asset pricing literature that studies 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 the market's misreaction to information. The logic of this empirical paradigm is as follows: Suppose investors rationally respond to the information in the news. Then the firm's stock price should jump immediately to the correct level that incorporates the new information; future stock returns should therefore be unpredictable. If, instead, the revelation of news leads to positive predictability in future returns, we can infer that investors did not take account of all the information when it was initially released. This means that investors under-react to 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 mis-reactions, to patents that are categorized as novel versus non-novel. In particular, we estimate the degree to which future returns can be predicted by the issuance of novel and non-novel patents, conditional on the issuance of other types of patents.

We adopt the following empirical strategy. First, for each firm, we collate all patents granted in 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 measure of the patents issued in each month with the decile cutoffs from the previous month. As mentioned earlier, our classification uses patent backward similarity (BS_j^5) as the primary determinant of novelty. As such, patent novelty is constructed using only ex-ante information that is potentially knowable to investors.

With the indicators for patent novelty in hand, we compute local projections to examine how firm-month returns are predicted by their innovation novelty indicators. More concretely, our empirical model is:

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

In this equation, $r_{i,t+\tau}$ is the return of firm i in month $t+\tau$. The term α_t represents year-month fixed effects (FEs) that control for unobservable time-specific factors, such as macro trends, that could influence the returns. α_{ind} are industry fixed effects, capturing the unobserved factors driving the differences in industry risk premia.

The main variables of interest are the dummy variables, $\mathbb{1}\{i \in \text{Novelty Decile}_{d,t}\}$, which are equal to 1 if firm i is granted a patent in novelty decile d at time t. The coefficients, $\beta_{\tau,d}$, thus inform us whether the issuance of (non-)novel patents predicts future returns, conditional on the fact that firms can issue patents of other levels of novelty at the same time.

We also control for an extensive list of firm characteristics, $X_{i,t}$, that are widely documented in the empirical asset pricing literature as robust predictors of future stock returns. They include firm size, book-to-market ratio, profitability, investment, earnings, market beta, short-term reversal, and medium-term momentum.

To study the dynamics of return predictability by firms' novelty intensity over time, we generate a cumulative impulse response function (IRF), focusing on the horizon τ from 1 to

60 months. The IRF is a graphical representation of how a unit shock to the (non-)novel intensity translates to cumulative returns over the period. If we see a persistent increase in the cumulative IRF, this indicates that investors are gradually correcting their underreaction to the positive news. If we see a persistent decrease, this suggests that investors are gradually correcting their initial overreaction to the news. When the function goes flat, the misreaction is fully corrected.

3.2 Results

Following the empirical strategy laid out above, we investigate how the market reacts differently to issuances of novel versus non-novel patents. Our results paint a comprehensive picture of how investors respond to different levels of innovation novelty.

3.2.1 Main Result

The centerpiece of our analysis is the cumulative impulse response function (IRF), denoted mathematically as $\sum_{\tau=1}^{T} \beta_{\tau,d}$, plotted over $T \in [1, 60]$. This function illustrates how returns accumulate after novel and non-novel patent issuance across a five-year window.

As shown in Figure 1, we see two distinct patterns. The black solid line represents the cumulative IRF associated with the novel patent issuance, $\beta_{\tau,1}$, while the red dashed line tracks the trajectory for the non-novel patent issuance, $\beta_{\tau,10}$. The two lines represent the market's differential responses to innovative breakthroughs versus incremental or imitative patents.

A significant observation from the figure is the upward trajectory of the black solid line. We see that novel intensity positively predicts returns for around two years and no further. This pattern provides compelling evidence 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 lag in the adjustment of the firm's stock price. This lagged reaction is consistent with parts of the broader literature on behavioral finance, where cognitive limits often result in delayed or incomplete processing of new information. In terms of magnitude, the issuance of novel patents leads to cumulative returns of 1.5%. Given the rarity of novel patents, this effect is economically significant.

By contrast, the red dash line, shows that non-novel issuance predicts persistently negative future returns. This negative relationship implies that investors tend to overreact to patents that follow existing technologies. Such overreaction to non-novelty may reflect a market 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.

In summary, our main results show that groundbreaking innovations are initially met with under-reaction, while those that conform to existing technological paradigms elicit an exaggerated initial response, only to see a correction in subsequent periods.

3.2.2 Robustness Checks

To further support our main finding that investors under-react to novel innovations while over-reacting to non-novel innovations, we conduct several robustness checks.

Short-term return on patent issuance: While our primary analysis estimates the long-term market reactions, understanding the immediate return response post-patent issuance is 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 and date fixed effects, and the same set of firm characteristics as in our main results:

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

We find that both novel and non-novel patent issuance trigger sizable short-term returns.

As shown in Table A.1, the individual coefficients of the novel-patent and non-novel-patent issuance dummies, when analyzed separately, are both positive and statistically significant. If we include both dummies, and an additional patent issuance dummy in the regression, only the patent issuance dummy is significant. This suggest that, while patent issuance invariably sparks immediate responses, these responses may not differ by patent novelty.

The short-term return jumps combined with long-term return predictability give a comprehensive summary of misreaction 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.

Ruling out a rational risk-based explanation: Return predictability does not always signify investor misreaction. An alternative (rational) explanation of 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 patents with different levels of novelty and firms' future stock return volatility.

We do not find support for a risk-based explanation of issuance predictability, for three different definitions of volatility. In Figure A.1, we run the following local projection regressions:

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

where $\sigma_{i,t+\tau}$ is the standard deviation of realized daily returns in month $t+\tau$. Specifically, we run a regression of realized return volatility on dummy variables of patent issuance at different novelty levels, controlling for firm characteristics including firm size, book-to-market ratio, profitability, investment, earnings, market beta, short-term reversal, and medium-term momentum, and year-month and industry fixed effects.

We plot the impulse response for two deciles, the most novel and the most non-novel decile of patents, $\beta_{\tau,1}$ and $\beta_{\tau,10}$. Firms issuing novel innovations *do not* have significantly higher return volatility than firms issuing non-novel innovations. If anything, we see a slightly higher return volatility for non-novel firms in the long term, contrary to a risk-based story that novel firms have higher risk.

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

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

We estimate monthly beta using daily returns in each month. Figure A.2 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.

One may also worry 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:

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

Figure A.3 shows that non-novel patent issuance consistently predicts higher implied volatility than novel patents, which infers that investors perceive a higher volatility for 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 investor under- and over-reaction. The root of such misreaction may instead lie in investors' imprecise perception of groundbreaking innovations.

Behavioral Misreaction in Earnings Expectations: Given that we see no convincing evidence of a rational risk-based story, we proceed to investigate a behavioral explanation of this misreaction to novelty. One natural behavioral mechanism is that investors form too low expectations about a firm's future earnings when the firms issue novel versus non-novel patents. If investors trade based on earnings expectations, the misreaction in earnings expectations would directly translate into return predictability. To test this mechanism, we use subjective earnings forecasts before and after patent issuances. The earnings expectations data come from IBES. We extract the short-term (1-year) earnings expectations and the long-term earnings growth (LTG) expectations 90 days before and after each patent issuance. We measure consensus earnings forecasts by taking the median forecast from individual analyst level forecasts. We winsorize consensus expectations at 1% level to remove anomalous forecasts. We follow Kwon and Tang (2021) and run Coibion and Gorodnichenko (2015) (CG) regressions by regressing post-issuance forecast errors on forecast revisions separately for different novelty deciles:

$$EPS_{1,i,t} - E_{post}[EPS_{1,i,t}] = \alpha_1 + \beta_1(E_{post}[EPS_{1,i,t}] - E_{pre}[EPS_{1,i,t}]) + \varepsilon_{1,i,t}$$

$$\Delta_5 e_{i,t+5year}/5 - LTG_{post,i,t} = \alpha_{LTG} + \beta_{LTG}(LTG_{post,i,t} - LTG_{pre,i,t}) + \varepsilon_{LTG,i,t}$$

A positive CG coefficient would suggest underreaction since investors revise their expectations insufficiently, so the forecast errors go in the same direction as forecast revisions. On the other hand, a negative CG coefficient would suggest overreaction since the investors overshoot when updating their beliefs post-event. In Figure A.4, we report the results for short-term earnings expectations. Across all ten novelty deciles, we obtain a positive coefficient for each novelty decile. The positive coefficients are consistent with an underreaction in short-term earnings expectations that is well documented in the literature (for example Bouchaud et al. (2019)). Figure A.5 plots the CG coefficients for LTG expectations. Here, we see negative coefficients across the board. This is again consistent with the overreaction in LTG in the literature (for example Bordalo et al. (2019)). However, the key finding here is that the CG coefficients are not significantly different across different levels of novelty in both short-term earnings and LTG expectations. If misreaction to novelty is reflected in how investors form earnings expectations, we should expect a more positive CG coefficient for more novel patent issuance. However, we find no evidence of this, suggesting that the misreaction to novelty in returns is not because investors form irrational earnings forecasts about the patent issuer. Therefore, when we write out the theoretical model to explain the misreaction in Section 3.3, we directly connect misperception of novelty to return expectations.

Firm-level intensity measure as a proxy for novelty: We provide an alternative definition of the novelty of firms' innovations. The new measure describes the fraction of (non-)novel patents among all the patents issued by the firm. In particular, we compute the "novel patent intensity" for each firm in each month. This metric is defined as:

$$\text{Novel patent intensity}_{i,t} = \frac{\#\text{ of Novel Patents (Most Novel Decile)}_{i,t}}{\text{Total }\#\text{ of Patents}_{i,t}}$$

Essentially, it traces the proportion of firm i's patents that belong to the most novel decile at month t.

we also introduce its counterpart, the "non-novel patent intensity." This measure is similarly derived but focuses on patents in the least novel decile. The formal definition is:

$$\text{Non-novel patent intensity}_{i,t} = \frac{\text{\# of Non-novel Patents (Least Novel Decile)}_{i,t}}{\text{Total \# of Patents}_{i,t}}.$$

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.6, there is a similar divergence in return predictability. Novel intensity positively predict future returns for around the next two years and non-novel intensity consistently negatively predicts future returns; this is the same as in our main specification. We lose some power in this specification because we are conditioning only on the firms that have at least one patent issuance. But 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 less power, we still find significant predictability for around two years after issuance 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: Beyond the measures of (non-)novel intensity in our primary analysis, we construct an alternative measure: firm-level multi-valued similarity score. To implement this, we again classify patents within the same issuance year into decile groups based on their backward similarity. Apart from aggregating patents to calculate the (non-)novel intensity at the firm level, this classification also 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.

To validate this measure's implications, we incorporate the similarity score into a local projection model akin to our main specification. By retaining the original specification, but substituting the (non-)novel intensity with the similarity score in our local projection, we ensure that our results remain comparable. As shown in Figure A.7, the similarity score displays a negative predictability of future returns, confirming our findings: markets are over-reacting to patents that are reminiscent of past innovations and, in contrast, display a discernible under-reaction to novel innovations.

Dissecting the quality of novel patents: Lastly, we distinguish whether the market's under-reaction to novelty is driven only by the issuance of "bad" novel patents. Do investors display underreaction because they perceive these novel patents as faltering new technological endeavors?

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

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

The corresponding cumulative impulse response function (IRF) plotted in Figure A.8 suggests that the observed market under-reaction to novelty and over-reaction to non-novelty predominantly stems from the market's interpretation of "good" patents, both novel and non-novel.

In summary, our robustness checks, spanning diverse methodologies and dimensions, consistently echo our primary assertion: financial markets, while clearly responsive to patent announcements, display a systematic under-reaction to pioneering innovations and an over-reaction to more iterative, non-novel ones.

3.3 A Model of Misreaction to Novelty

In this section, we present a framework that we can use to understand the return misreaction to patent novelty and the return dynamics after patent issuance. The model intends to explain two key empirical facts in Section 3. First, immediately after a patent is issued, firm's short-term returns jump up but the jumps are not economically different across different levels of patent novelty. Second, in the long term, the impulse response of a novel patent issuance exhibits positive predictability 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 not exactly sure 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 main prediction of the model is that immediately after patent issuance, investors' perception of novelty is close to an intermediate prior; they therefore over-estimate the novelty of non-novel patents and under-estimate 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 we then directly test 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 more noisy the signals are, the larger the level of mis-reaction and the longer it takes for the price to converge to the correct level. Third, despite short-term reaction differences when patents are first issued, these differences are not economically significant. Most of the differential misreaction shows up in long-term return predictability, which is exactly what we observe in the data.

3.3.1 Short-Term Reactions

We first derive the model predictions for the return reactions to patent issuance at the moment 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:

$$\log x \sim N(\mu, \sigma^2). \tag{1}$$

We assume a lognormal prior to ensure that patent novelty is non-negative while also 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, which states that the subjective sensation of a stimulus is proportional to the logarithm of stimulus intensity. Our model, however, has a different interpretation from the Woodford (2020) model. In particular, in a model with cognitive imprecision, agents see the true value but their perceptual system encodes it imprecisely; by contrast, in our model, agents do not observe the true value.

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

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

Then, a Bayesian investor will form the posterior mean of patent novelty as

$$\hat{x}(r) \equiv E[x|r] = \exp\left[\left(\frac{\nu^2}{\sigma^2 + \nu^2}\right)\log\bar{x} + \left(\frac{\sigma^2}{\sigma^2 + \nu^2}\right)r\right] \tag{3}$$

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

$$e(x) \equiv E[\hat{x}|x] = \exp\left(\beta^2\nu^2/2\right)\bar{x}^{1-\beta}x^{\beta} \quad var[\hat{x}|x] = (\exp(\beta^2\nu^2) - 1)e(x)^2 \tag{4}$$

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

In Figure 2, we plot the mean perception of patent novelty, $E[\hat{x}|x]$, against the true novelty level. We see that for novel patents, the investor underestimates novelty, while for non-novel patents, she overestimates novelty.

Connecting Patent Novelty to Returns: For patent novelty misperception to generate a price effect, 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 positive predictability, and that non-novel patents show negative predictability, which 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 PDF of the sum of a truncated normal variable v_j and standard normal variable ε_j has no closed-form solution, we simulate 1,000,000 independent draws of the two random variables and plot the mean of the simulated joint distribution, $E[R_j|x_j]$.

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

3.3.2 Long-Term Dynamics

In the previous section, we showed that, in a static setting, we can generate under-reaction to novel patents and overreaction to non-novel patents in short-term issuance returns. However, the mispricing may not show up prominently in the short term, especially when the signal is noisy. In the long term, returns will gradually converge to the correct level of reaction, leading to more pronounced variation in returns. 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:

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

Each period, investors receive the same unbiased noisy signal:

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

The posterior distribution given the signals also has a lognormal distribution:

$$\log x | r_0, ..., r_t \sim N\left(\left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2}\right)^{-1}\left[\frac{t+1}{\nu^2}\left(\frac{1}{t+1}\sum_{i=1}^{t+1} r_i\right) + \frac{1}{\sigma^2}\mu\right], \left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2}\right)^{-1}\right). \tag{5}$$

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

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

We want to calculate the mean of investors' novelty perception given the true novelty x.

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

We calculate the two terms separately:

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

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

Figure 4 plots the dynamic conditional mean of the perception of patent novelty, $E[\hat{x}_t|x]$ for ten levels of true novelty, when the signal is relatively noisy, but not too noisy ($\nu = 2\sigma$). We can see that, at issuance, similar to the static case, we have differences in novelty perception across true novelty levels, but which are compressed toward an intermediate prior level of novelty. As time goes by, when investors receive more signals, they update their novelty perception toward the correct level of novelty. We also see that, although there are differences at issuance, a lot of the movement in perceived novelty happens several periods after the patent is issued.

Once again, we need to relate the misperception of patent novelty to the misreaction in stock returns. We consider the case where 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 can then write the distribution of patent value, v_t, as:

$$v_t \sim N^+ \left(\gamma_0 + \gamma_1 \left[\left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2} \right)^{-1} \frac{t+1}{\nu^2} \log x + \left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2} \right)^{-1} \frac{1}{\sigma^2} \left(\mu + \frac{1}{2}\sigma^2 \right) \right] \right. \tag{6}$$

$$\left. , \gamma_1^2 \left(\left(\frac{t+1}{\nu^2} + \frac{1}{\sigma^2} \right)^{-2} \left(\frac{t+1}{\nu^2} \right)^2 \frac{\nu^2}{t+1} \right) + \sigma_x^2 \right). \tag{7}$$

We again decompose the cumulative return of a given firm after patent issuance as

$$R_t = v_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_\varepsilon^2).$$

Since v_t is distributed as a truncated normal while ε_t is normally distributed, it is hard to have a closed-form distribution for patent issuance returns, R_t. Instead, we simulate 1,000,000 independent draws of the two random variables and plot the mean of the simulated joint distribution, $E[R_j|x_j]$.

In Figure 5, we plot the return reaction given 10 novelty levels for 60 periods after the patent issuance. We see several model implications. First, investors underreact to the novel patents (large x) and overreact to non-novel patents at issuance, but they converge to the correct level of returns over time. In the short term, all the returns are compressed towards a single prior, so the return difference is not significant at issuance. However, we see a large divergence in return responses across different novelty levels as these return responses converge to the correct level.

We then study the model's comparative statics for ν, which determines how noisy the signals are. A high ν indicates that investors receive a very noisy signal in each period. In reality, this approximate the case where the investors are mostly retail traders and do not have precise information on the novelty of firms' innovation. A low ν corresponds to the case where firms have a large number of institutional investors with professional knowledge. Institutional investors should have a better understanding of the technology advances and innovation strategy of the firms they invest in, and thus receive less noisy signals about patent novelty.

Figure 6 plots the return dynamics after the patent issuance. We consider two levels of signal precision. High precision is the case where $\nu = \sigma$, the standard deviation of the novelty prior; low precision is the case where $\nu = 2\sigma$. For a noisier signal, we see that the initial reaction is more similar across different novelty levels, indicating more severe misreactions. We also see that investors take longer to converge to the correct level of reaction.

3.4 Empirical test of the model

In this section, we test three of model's 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.

The model predicts that the return reaction at issuance should not be distinguishable across different novelty deciles if the signal is noisy. 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 level. Each dummy is equal to 1 if there are patents with a given novelty level granted to the firm. If there is no patent issued on the firm-day, all indicators will be 0, which means that the counterfactual returns are the returns from the firms without patent issuance that in the same industry and have similar firm observables:

$$\log(R_{i,t,t+2}) = \alpha_m + \alpha_{ind} + \sum_{k=1}^{10} \beta_k 1_{i \in \text{novelty decile } k,t} + X_{i,t} + \varepsilon_{i,t},$$

where α_m are month FEs, α_{ind} are industry FEs (SIC 2 digits), and $X_{i,t}$ are size, book-to-market, profitability, investment, market beta, short-term reversal, and medium-term momentum.

In Figure 7, on average, we see a significantly positive response for almost all deciles. However, as the model predicts, the response is not statistically significant across different novelty deciles. This is consistent with the model implication that at issuance, since investors are very unsure about patent novelty, they give an average prior valuation to all patents. Only some time after the patents are issued, as investors accumulate more information, we see a much larger response in the sense that different novelty deciles have a divergence in returns as they converge to the correct response.

We directly test this by generalizing our result in Figure 1 to all ten deciles. The model predicts that the misreaction to novelty is monotonic across ten deciles of patent novelty. We should see the strongest positive predictability for the most novel patents and the strongest negative predictability for the most non-novel patents. We examine this by plotting the cumulative impulse response of future 5-year monthly returns for the full ten deciles of patent novelty:

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

This is the exact same specification as our main result in Figure 1, but instead of plotting only the most and least novel decile, we explore the behavior of all deciles. Figure 8 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, consistent with the model predictions.

Finally, in the model, the signal precision is a key parameter that drives the return response. To test whether this model mechanism is indeed relevant in the real world, we compare the return predictability for firms with high versus low institutional holdings. Firms with high institutional holdings should have investors with less noisy signals about patent novelty, and thus should exhibit weaker misreaction and faster convergence. For this exercise, we use the institutional holdings data from FactSet and follow the construction of institutional holding percentage ini Ferreira and Matos (2008). Figure 9 shows the results from the following regressions:

$$\log(R_{i,m+\tau}) = \alpha_m + \sum_{k=1}^{10} \beta_{k,\tau,high} 1_{i \in \text{novelty decile } k,m} \times 1_{\text{high inst hold},m} + \sum_{k=1}^{10} \beta_{k,\tau,low} 1_{i \in \text{novelty decile } k,m} \times 1_{\text{low inst hold},m} + X_{i,m} + \varepsilon_{i,m+\tau},$$

where we plot only the impulse response, $\beta_{k,\tau,high}$ and $\beta_{k,\tau,low}$ from the top and bottom two deciles of patent novelty. We see exactly what we predicted: 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 misreaction is 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 market value of the patents.

4 The Value of Novelty

After documenting that investors systematically under-react to novel innovations and over-react to non-novel patents, a critical question arises: should firms' shareholders, and their stakeholders more generally, be concerned about the existence of such market misreactions? This question is not merely academic but has profound real-world implications. The market's misalignment with novelty could have substantial economic and social costs, if both of the following statements are true: (i) novel patents create more value than their non-novel counterparts; (ii) firms, in response to market mis-reactions, strategically shift their innovation focus towards existing trends (that investors overreact to) and invest less in novel patents (that investors under-react to).

In this section, we test the first statement by evaluating whether novel patents are more valuable than non-novel ones[4]. Specifically, we examine whether novel patents, despite market biases, still have both higher private and social values than their non-novel counterparts.

[4]Section 5 tests the second statement.

By bringing empirical evidence to this question, we shed light on the significance of novelty in the innovation landscape and determine if the market's misreactions generate real concerns.

4.1 Private Value of Novelty

In the complex world of patent valuations, understanding the economic value that each patent brings to the firm becomes crucial. We employ the KPSS values, as estimated in Kogan et al. (2017), to capture of private value of each patent. To assess the relationship between patent novelty and private value, we run the following patent-level regression:

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

Here, $KPSS_i$ represents the private value of patent i. The term $\mathbb{1}\{\text{Novelty Decile}_i = d\}$ is a dummy variable that indicates which novelty decile d patent i belongs to. We also include both the patent's grant year and CPC-class fixed effects to ensure that our examination of the novelty-private value relationship is free from confounding influences.

For comparison purposes, 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 $i \in [1, 9]$ in a single figure.

Figure 10 points to a compelling narrative. The coefficient β_d shows a monotonic decrease as d increases. This pattern implies that despite the market's underreaction, more novel patents, as indicated by a lower novelty decile, inherently have higher private economic value. This result emphasizes novelty's premium in patent valuations and confirms that novel patents, on average, bring high future economic growth to their inventing firms.

4.2 Social Value of Novelty

A patent's valuation consists of more than just its private economic value. A crucial aspect often overlooked is the social value a patent brings to the broader innovation ecosystem. A key question we aim to address is whether a patent's novelty creates unaccounted societal benefits, such as having a more significant influence on future innovations spanning different industry fields once we control for its private value. Suppose novel patents have higher social value than non-novels. In that case, it implies that they not only benefit their inventing companies but also create "positive externalities" that benefit other firms in society.

We empirically test this question by constructing two proxies that capture a patent's social value. The first, widely used by many academic and industry references, focuses on patents' total forward citations. The rationale is straightforward: a patent that has significantly influenced subsequent innovations will, by design, be highly cited. The second measure aggregates the private values (KPSS values) of all patents that cite the original patent. This metric captures the accumulated economic value of all downstream innovations influenced by the original patent.

Our empirical strategy employs a patent-level regression framework as follows:

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

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, while $KPSS_i$ stands for its private value. The vector X_i includes the following controls that potentially influence the social value of a patent: (1) firm market capitalization[5], given that larger enterprises might produce more influential patents; (2) firm idiosyncratic volatility, capturing that rapidly expanding entities might exhibit more volatile returns yet produce high-quality patents. We also control for multiple types of fixed effects in different specifications, including patent grant-year fixed effects, acknowledging that older patents have had more opportunity to obtain citations; patent's CPC class-year fixed effects, in recognition that citation patterns may differ across technology domains and over time; and firm-level fixed effects, controlling for intangible, firm-specific factors that could affect their patent's social value. Our most stringent specification also accounts for the potential temporal fluctuations in these unobservable

[5]We measure the firm's log market capitalization $\log M_i$ on the day prior to the patent grant.

firm fundamentals by including firm-year fixed effects. The standard errors in our analysis are all clustered at the grant year level.

Our empirical findings point to a compelling narrative. Novel patents, particularly those at the lower end of the BS_i^5 novelty spectrum, consistently display enhanced societal value, whether measured via total forward citations or the economic worth of subsequent citing patents. Our findings are robust after including different controls, ranging from patent age and firm-specific metrics to technological domain. The difference between most novel and non-novel patents, both in citation counts and citing patents' economic value, persists in all specifications.

Diving into the economic magnitudes implied by our estimates as shown in Table 1, the most novel patents (those with BS_i^5 decile equal to 1) are associated with 0.6 to 2.8 more citations compared to their most non-novel counterparts (those with BS_i^5 decile equal to 10), contingent on the controls implemented. The magnitude becomes even more pronounced when we transpose this social value to monetary terms, employing the total private economic values of subsequent citing patents. The most novel patents reflect an incremental social value of 34 to 67 million 1982-equivalent dollars (deflated using the CPI) over the least novel ones. This robust economic advantage is not just evidence of the intrinsic worth of novel patents but an indicator of the spillover effects these novel patents generate. Novel patents inspire subsequent patents, bringing higher private value to their inventing firms, thus accumulating a compounded societal and economic advantage. Compared with citation counts, this monetary metric offers a more tangible, real-world implication of the value of novel innovations.

To sum up, our results provide direct evidence of the high importance of novelty in the patent landscape. The results underscore that novel patents benefit the innovator and, more importantly, promote an ecosystem of subsequent innovations that generate social and economic advantages spanning decades.

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, despite the empirical evidence that, on average, novel patents hold more significant economic and social values.

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 a novel firm (i.e., a firm with a higher intensity in creating novel patents) changes its future innovation trajectory. After documenting that novel firms not only follow up less on their just-issued novel technology but issue fewer novel patents in the future, we then explore whether market reactions could be a factor that cause such changes. Using mutual fund redemptions as an instrument for firms' returns on the equity market, we provide causal evidence that market reactions can distort a firm's future innovation directions. Return drops on the equity market after novel patent issuance cause these firms to pivot from dedicating resources to pioneering research and to instead chase short-term gains by mimicking existing trends. Such a shift creates lower economic value for the innovating firm and decreases the positive externalities created by 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. Strategizing for innovation directions can enable corporations to provide their customers with continued value, create new market segments, and even push competitors out of their once-owned segments. Since firms' strategies in forming their future innovation trajectories vary significantly depending on their idiosyncratic preference and choice sets, documenting firms' exact decision-making procedures for future innovation directions in some systematical way could be extremely challenging. However, observing firms' future patenting behavior provides an alternative method to measure firms' innovation trajectories and outcomes.[6] Given that our study mainly focuses on patents' 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 the existing technology, in particular, built 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[7] for this revolutionary invention. Following up on that, Apple further developed a series of incremental technologies, from "pinch-to-zoom[8]," "slide between user interface[9]," to the most recent "hand-free turn on driving mode"[10] technology. Not surprisingly, these later patents by Apple all cited its original 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 a measure - "average number of follow-up patents" to represent a firm's sustaining innovation based on the patent pairwise citation network we built up. More specifically, for firm i at time t, we calculate the average number of patents granted to firm i between time $t + 1$ and $t + 6$ that self-cite firm i's patents (and particularly novel patents in some specifications) at time t. A higher number of this firm-level measure suggests that the firm creates more sustaining innovation following up on their existing 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. No matter the invention of "embedding the electronic device to wearable"[11] that helped the launch

[6]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.

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

[8]The US patent US9619132B2, titled "Device, method and graphical user interface for zooming in on a touch-screen display"

[9]The US patent US9772751B2, titled "Using gestures to slide between user interfaces"

[10]The US patent US10705794B2, titled "Automatically adapting user interfaces for hands-free interaction"

[11]The US patent US8787006B2, titled as "Wrist-worn electronic device and methods therefor"

of Apple Watch eight years ago or the most recent technology in eye and hand tracking[12] forming the revolutionary product Apple Vision Pro, they were all very novel relative to other patents when they came out. To capture firms' "novelty-seeking" innovation, we construct an outcome variable, "percentage of novel patents," which is calculated as the number of novel patents (i.e., patent with novelty decile equal to one) divided by the total number of patents granted to firm i at time t. We also exclude firms' self-citing patents when constructing the "novelty-seeking measure" because the sustaining innovations (i.e., the firm's follow-up patents that self-cite its existing patents) are less likely to be categorized as novel patents, which potentially brings bias to our measure of "novelty-seeking" innovation.

The last type of innovation we are interested in is defined as "copycat innovation." Sometimes, firms could strategically "copy" their competitors' innovation to push competitors out of their once-owned segments. Still taking Apple's innovation direction as an example, Apple is also producing inventions such as "folding device technology[13]," which is a well-known feature of its competitor- Samsung's smartphones. Besides, we hypothesize that investors' underreactions 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 construct the variable "percentage of non-novel patents" as a proxy for firms' "copycat" innovation behaviors, calculated as the number of non-novel patents (i.e., patent with novelty decile equal to ten) divided by the total number of patents granted to firm i at time t. When constructing this variable, we exclude firms' self-citing patents from our sample for the same "bias" concern as before[14].

With these measures of firms' innovation directions, we first examine the following question: do novel firms' future innovation trajectories change? To answer this question, we employ the "Novel patent intensity" metric, defined as the fraction of a firm's patents in

[12]For example, the US patent US10893801B2, titled as "Eye tracking system and method to detect the dominant eye"

[13]The US patent application US20230011092A1, titled as "Hybrid coverlay/window structure for flexible display applications"

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

the most novelty decile for a given time, to measure a firm's novelty. We start by exploring how many sustaining innovations are produced by novel firms following their established novel technology. A decrease in sustaining innovation implies that novel firms divert their innovation directions from the areas with their precedent novel technology.

We run the following firm-year level regression:

$$\text{Avg. Follow-ups on novelty}_{i,t+1\to t+\tau} = \beta \text{Novel patent intensity}_{i,t} + \gamma' Z_{i,t} + \alpha_t + \alpha_{ind} + \varepsilon_{i,t}$$

In this specification, as defined earlier, we use the average number of follow-up patents, particularly following novel patents, to measure a firm's future sustaining innovation. Considering that a firm's tendency to continue innovating in a particular direction is also influenced by multiple factors ranging from the firm's innovation quality to external competitive pressures, we include a set of controls $Z_{i,t}$ in the regression as well. Specifically, $Z_{i,t}$ includes the total KPSS values of all patents issued to firm i at time t, serving as a heuristic for the firm's innovation quality. Scaling this with the firm's book asset value offers a normalized metric that accounts for firm size, ensuring that larger firms do not overly dominate the analysis purely because of their scale. $Z_{i,t}$ also controls for a firm's competitors' innovation quality, calculated as the total KPSS values of all patents issued to all other firms in the same industry as firm i (i.e., share the same 3-digit SIC code) scaled by their total book assets. Such an index captures the competitive pressure and the innovation environment of the industry faced by firm i. If competitors are innovating rapidly and at high quality, it could incentivize the firm i to adapt its innovation directions.

Moreover, $Z_{i,t}$ 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. 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 direction. We also include fixed effects for industry and issuance year to absorb industry-specific heterogeneities and temporal dynamics. We cluster standard errors by both firm and year.

In Table 2, we document that even after controlling for the quality of the firm's innovation, novel firms tend to follow up less on their existing novel patents – both in the immediate 5-year aftermath as well as in the long run. A unit increase in a firm's novel patent intensity is correlated with a decrease of 0.39 in the number of sustaining patents following novel technology in the succeeding five years. This effect is further emphasized over the long run, with the same unit increase in the firm's novel intensity leading to roughly 1.1 fewer patents following up on existing novel patents.

One concern is that such effects merely reflect the firms' internal assessment of the quality of their novel patents and strategically stop further investment in novel but low-quality technologies, even though we control for innovation quality using the total KPSS values of a firm's patents. However, the KPSS value might be biased due to investors' differential reactions towards patent novelty, as we document in Section 3.

To address this concern, we split the novel patents into high-impact and low-impact groups based on their ten-year forward similarity measures constructed following Kelly et al. (2021). We compute an adjusted firm-level metric - high-impact novel patent intensity as the variable of interest, which captures the dynamics of high-quality novel patents more precisely.

We follow the same empirical strategy but focus on a firm's sustaining innovations following the existing high-impact novel patents as our new outcome variable. The results, as presented in Table A.2, emphasize that firms with a higher fraction of high-impact novel patents are less likely to follow up on their high-impact novel patents within five years. This trend, consistent with our earlier findings, offers an even more rigorous affirmation that novel firms change their future innovation trajectories due to some external factors instead of internal strategy adjustment.

Nevertheless, the effects fail to report statistical significance as we extend our lens into the long run. One potential explanation is that those high-impact novel patents may take time to gain recognition in the market. Once they finally breach the barriers of market myopia and become widely acknowledged, the original inventing firms may shift back their innovation directions and restart some sustaining innovations following their pioneered technologies.

A counter-argument to our findings could be that these novel firms, by their very nature, are perpetually "novelty-seeking" and looking for the next groundbreaking innovation instead of focusing extensively on sustaining innovation. To evaluate this perspective, we seek to explore whether these firms consistently produce more novel patents in subsequent years. We again employ the "Novel patent intensity" metric and run the following firm-level regression:

$$\log\left(\frac{\%\text{ of Novel Patents}_{i,t+\tau}}{\%\text{ of Novel Patents}_{i,t}}\right) = \beta_\tau \text{Novel patent intensity}_{i,t} + \gamma_\tau' Z_{i,t} + \alpha_t + \alpha_{ind} + \varepsilon_{i,t+\tau}$$

This equation quantifies the relative changes in a firm's "novelty-seeking" innovations over time. Here, $\log(\frac{\%\text{ of Novel Patents}_{i,t+\tau}}{\%\text{ of Novel Patents}_{i,t}})$ represents the firm's growth in "novelty-seeking" innovation, relative to its original level at time t. Similar to our previous empirical strategy on firm-level analysis, the vector $Z_{i,t}$ includes a suite of controls, accounting for the firm's total innovation quality, competitive landscape, size, and potential growth opportunities. We also include industry and grant year fixed effects, denoted by α_{ind} and α_t. Standard errors are clustered at the firm and year level.

Our empirical results, as presented in Table 3, suggest that controlling for innovation quality, novel firms display a decrease in the propensity for generating novel patents in subsequent periods. To be precise, a firm's present novel patent intensity can significantly and negatively predict its growth in "novelty-seeking" innovation over a five-year horizon. The magnitude of this effect is substantial: a 10 percent increase in a firm's current novel patent intensity correlates with a 5.8 percent drop in its future "novelty-seeking" innovations.

Summarizing all the findings above, we can answer our earlier question: novel firms do change their future innovation trajectories. They tend to refrain from intensively following up on their existing novel technologies nor consistently generating novel patents in subsequent periods. The reasons for such pivots could be manifold – ranging from external factors, such as market recognition, to internal management, including evolving strategic priorities. Consequentially, we explore one of the most related explanations: could market reactions, especially the underreactions to novel patents as we document in section 3, cause firms to change their future innovation directions?

5.2 Could Investors' Reactions Impact Firm Future Innovation?

To address this question, we consider a model that relates firms' future innovation directly with their equity returns:

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

where the primary outcome variables of interest Future Innovation$_{i,t+1\to t+\tau}$ are the measures for three types of innovation direction defined earlier - sustaining, novelty-seeking, and copycat innovations. The key explanatory variable is firm i's total equity returns at time t, $r_{i,t}$. Following our firm-level specification described earlier, we employ $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including firm capital stock, number of employees, total innovation quality, competitors' innovation quality, novel intensity, and idiosyncratic volatility.

Simply estimating an ordinary least squares regression (OLS) for the above model would give us biased estimates. The reason is that a firm's future innovation could correlate with unobserved determinants of the firm's equity returns. For instance, suppose a firm reorganizes its research and development department at time t by hiring new technicians, scientists, and inventors with different expertise. Such news would be priced in by investors in the equity market and affect the firm's same-period total returns. The new hiring in the firm's R&D department could also likely change the firm's future innovation directions. As a result, the biased OLS estimates could not help us identify any causal effect of a firm's equity return on its future innovation trajectories.

To address the endogeneity issue of the returns, we estimate an instrument variable regression for our model. More specifically, we exploit the "mutual fund redemption" phenomenon following Edmans et al. (2012) and instrument a firm's total equity returns $r_{i,t}$ with its idiosyncratic mutual fund price pressure $\text{MFFlow}_{i,t-1\to t}$. We first run the first-stage regression:

$$r_{i,t} = \beta \text{MFFlow}_{i,t-1\to t} + \gamma' Z_{i,t} + \alpha_t + \alpha_{ind} + \varepsilon_{i,t}$$

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:

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

Our specifications rely on two key identifying assumptions to ensure the estimates from the above IV regressions correctly capture the causal effects of firms' equity return on future innovation. First, we require mutual fund price pressure $\text{MFFlow}_{i,t-1\to t}$ to be strongly associated with the firm's total return $r_{i,t}$. Because we only consider mutual funds' extreme outflows when constructing the instrument variable, such a redemption type is likely to impact firms' stock prices. Moreover, the "strong instrument" assumption is empirically testable through the F-stats from the first-stage regression. We report the related statistics in the results table later. The second crucial assumption is "exclusion restriction." This assumption is not empirically testable. However, considering that the mutual fund "fire sales" are not induced by any information, especially innovation-related information or any firm fundamental, but rather by mutual funds' investor flows, we are confident that our instrument variable - $\text{MFFlow}_{i,t-1\to t}$, can only affect a firm's future innovation through its impact on the firm's equity returns.

The null hypothesis of this model is that under the Modigliani-Miller theorem, any equity return changes at the current period that are not led by innovation-related information or firm fundamentals should have zero predictability for the firm's future investment or production decisions, including the innovation directions. We empirically test this hypothesis for each type of the three innovation directions defined earlier. Starting from a firm's future sustaining innovation, Table 4 presents the IV estimates and the first-stage regression results. Columns (1) and (3) explore how the firm's average number of follow-up patents in the immediate 5-year aftermath and over a more extended period until the end of the sample varies following its return changes in the equity market respectively, while columns (2) and (4) show the corresponding first-stage results. Both first-stage results show that the mutual fund price pressure $\text{MFFlow}_{i,t-1\to t}$ is a strong instrument for a firm's total returns in the stock market. The more mutual fund redemption (i.e., lower value of $\text{MFFlow}_{i,t-1\to t}$) induced by investor flows between time $t-1$ and t, the lower total returns for the firm at the end of time t. Plugging the predicted return changes from the first stage into the second stage regression as a key explanatory variable, we obtain the IV estimates suggesting that the plausible exogenous return changes induced by mutual funds' "fire sales" can predict the firm's future sustaining innovation in both the short and long run. More specifically, on average, one unit decrease in a firm's total equity returns today can cause a 1.1 percent reduction in the firm's sustaining innovation in the next five years and eventually 3.8 percent fewer patents following up on the firm's existing technology in the long run.

A more interesting question is whether novel or non-novel firms are more likely to be affected by market reactions and change their future innovation directions. We hypothesize that investors' undervaluations of novel patents could drive novel firms to follow up less on their existing technology than non-novel firms. To formally examine this, we separate our sample into high- and low-novel groups by comparing each firm's average patent novelty with the industry median and then run the exact IV specification on each subsample, respectively.

Table 5 confirms our hypothesis. The effects of equity return changes on firms' future sustaining innovation are only driven by those novel firms. One remaining concern is that even those novel firms still produce patents with different levels of novelty, including non-novel patents. How do we know that firm managers attribute return drops to their novel patents and change their future sustaining innovation as a response? As a robustness check, we restrict our sample to firms with patents granted in only one novelty decile. Then, we run the exact IV specification on ten subsamples, each with a single novelty news. As results presented in Table A.3[15], the effects only show up for the most novel decile group, implying that firms with only novel patents are most likely to reduce their future patents following up on their novel technology if experiencing return drops on the equity market.

After showing the evidence that market reactions can cause changes in firms' sustaining innovation directions, we continue to explore how a firm's other two types of innovation directions, "novelty-seeking" and "copycat" innovations, are impacted by the firm's return changes on the equity market. Running the same IV regressions by only changing the outcome variables to the measure of "novelty-seek" innovation and "copycat" innovation defined earlier, we empirically test our hypothesis that investors' underreactions to novel patents and overreactions to non-novel patents could drive some firms, especially novel firms to stop the direction of "novelty-seeking," and instead start to follow the market trend and produce more non-novel patents in the future.

We plot the estimates and corresponding 90 percent confidence intervals in Figure 11 and Figure 12. Each figure shows the coefficients estimated from the entire sample and the high- and low-novel subsamples. The x-axis represents the period of firms' future innovation direction, i.e., ranging from one year to three years after they observe their equity returns. The results confirm our hypothesis: lower total returns from the equity market cause novel firms to consistently change their future innovation directions in the following three years. More specifically, a one percent drop in returns leads novel firms (i.e., points in cranberry) to produce 0.3 percent fewer "novelty-seeking" innovations but create 0.14 percent more non-novel patents (i.e., "copycat" innovation) in the next three years. However, such effects are muted for the subsample with non-novel firms (i.e., points in light green).

[15] for simplicity, we only present the results for the most-novel firm and the most-non-novel subsamples in the table.

5.3 Mechanism and Discussion

We provide causal evidence that the total equity return drops could affect novel firms' future innovation directions: they follow up less on their existing technology, contribute fewer novel patents, and produce more copycat non-novel innovations. However, it is still ambiguous through which channel those causal effects occur. One salient mechanism is that some novel firms might suffer from financial constraints. To give an example, Kodak was the company that invented the first-ever digit camera back in 1977, and the company was granted a patent[16] for this revolutionary invention. However, such a novel technology did not grab enough market attention then. 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 of "medical equipment."

We hypothesize that financially constrained novel firms are more likely to be affected by the return drops in the equity market and change their future innovation directions as a response. To empirically test this mechanism, we first generate firm-level financial constraint measures based on either firm size or the firm's size and age index following Hadlock and Pierce (2010) and identify a firm as financially constrained if its size (size and age index) below (above) the industry median. We then construct a new key variable of interest by interacting firms' financial-constrained indicators with the equity returns. We run our IV specifications with this new explanatory variable on the high-novel subsample and present the estimated results in Table A.8 and Table A.9. The results confirm our hypothesis that financially constrained novel firms change their future innovation directions more than non-constrained firms.

Besides the financial constraints channel, other channels could also result in the casual effects we document. For example, agency conflicts between firm managers and shareholders could be another channel. The firm's manager has relatively shorter tenures at the firm, resulting in their myopia and short-termism. Besides, some managers are also compensated with stock awards, which provide additional incentives for managers to chase short-term

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

gains from the stock market. Another example is the learning channel. Competitors' equity returns help the firm learn more about the market demand and drive it to change future innovation directions to maximize its profits strategically. We will consider and empirically test those channels for future studies.

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. A bounded-rationality model where investors are cognitively limited and unsure about true novelty at patent issuance can explain these mispricing patterns.

This type of mis-reaction in financial markets has economic significance. First, we show that, despite being undervalued, novel patents still provide higher private economic value to the firm. Second, we show that novel patents also have higher social value. Conducting novel research benefits the firm, but more importantly, it creates positive externalities that benefit society. These findings suggest that underreaction to novelty may exert social inefficiencies.

More consequentially, we present causal evidence showing that market reactions could lead novel firms to change their future innovation directions. We show that return drops in the equity market around patent issuance can cause novel firms to follow up less on their existing technology, contribute fewer novel patents, and produce more copycat innovations in the future. This infers that firm managers care about short-term stock return movements when deciding on future innovation directions. We argue that the effects are particularly pronounced for firms that experience financial constraints because constraint firms care more about cost of capital from external financing.

Our paper provides important policy implications. Misperception of patent value in financial markets could discourage future innovation in new technology. Firms may instead prefer to work more on already-established technologies that still garner market enthusiasm even if 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. We think one promising future research direction is quantifying the economic welfare loss from the inefficient innovation directions caused by market misreaction. Another interesting question is to explore how the misreaction 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 $\tau \in [1, 60]$ at the firm-month level:

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

where the ten indicator variables represent that the firm issues at least one patent in a certain novelty decile. We control for month and industry fixed effects and firm characteristics, including size, book-to-market, profitability, investment, market beta, short-term reversal, and medium-term momentum. We plot the cumulative coefficients, $\sum_{\tau=1}^{t} \beta_{\tau,d}$, over $t \in [1, 60]$ for the most novel ($d = 1$) and most non-novel ($d = 10$) decile. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

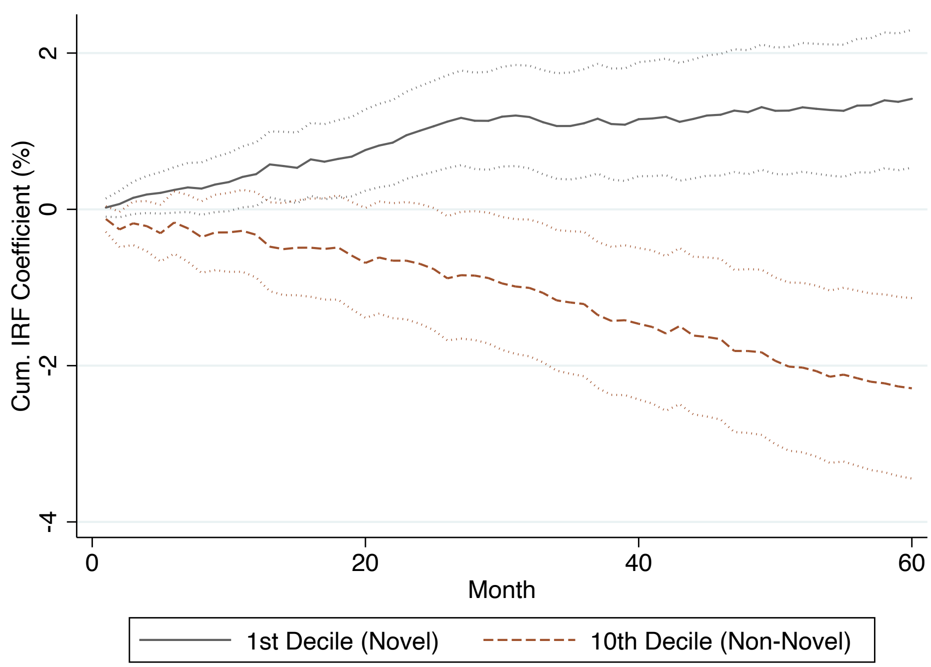


Figure 2: Theoretical Predictions of Under- & Over-Perception of Patent Novelty

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.

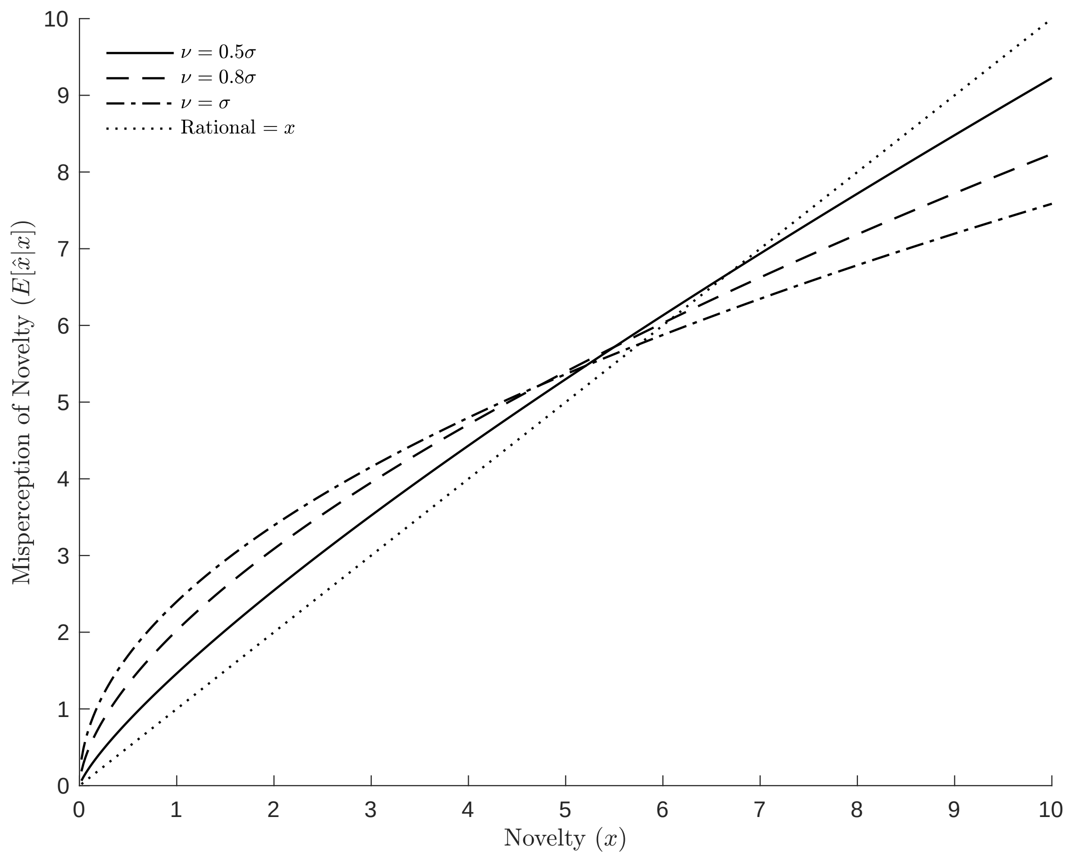


Figure 3: Theoretical Predictions of Issuance Returns to Novelty

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

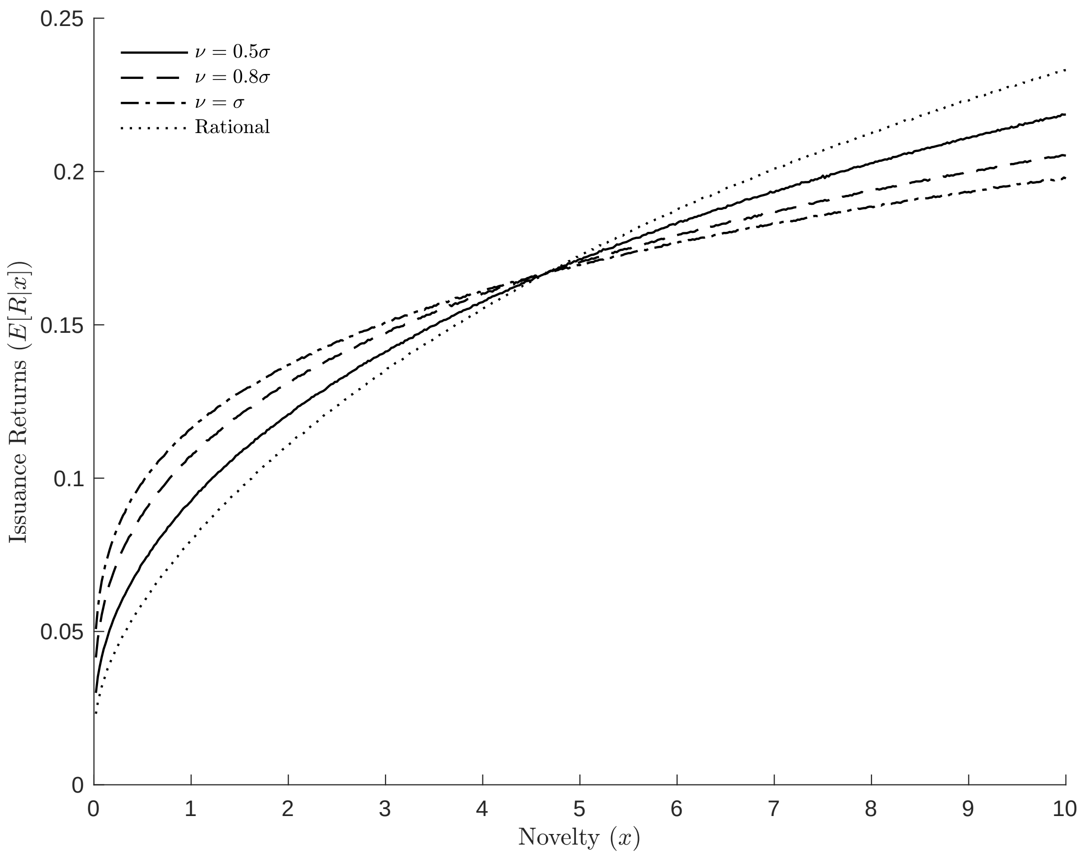


Figure 4: Theoretical Predictions of Dynamic Novelty Perception

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 $\hat{x}_t = E[x|r_1, ..., r_t]$.

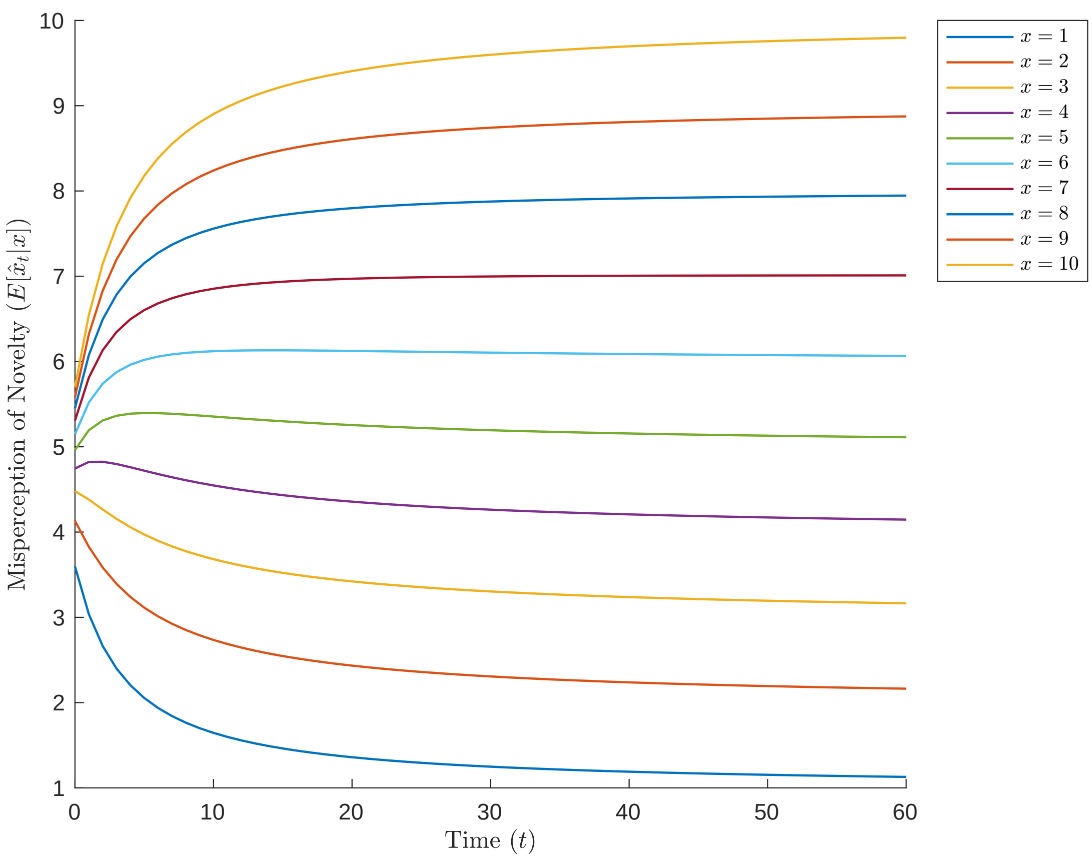


Figure 5: Theoretical Predictions of Dynamic Return Reaction by Novelty

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

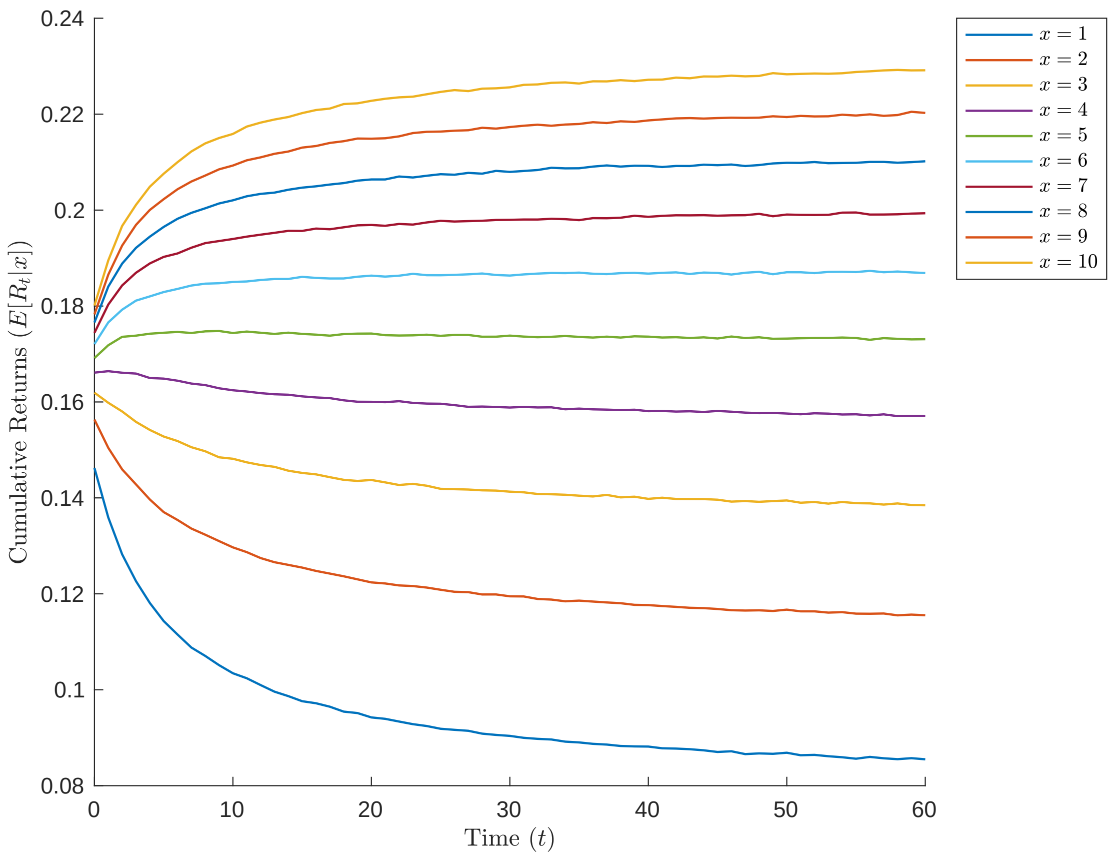


Figure 6: Theoretical Predictions of Dynamic Return Reaction by Signal Precision

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

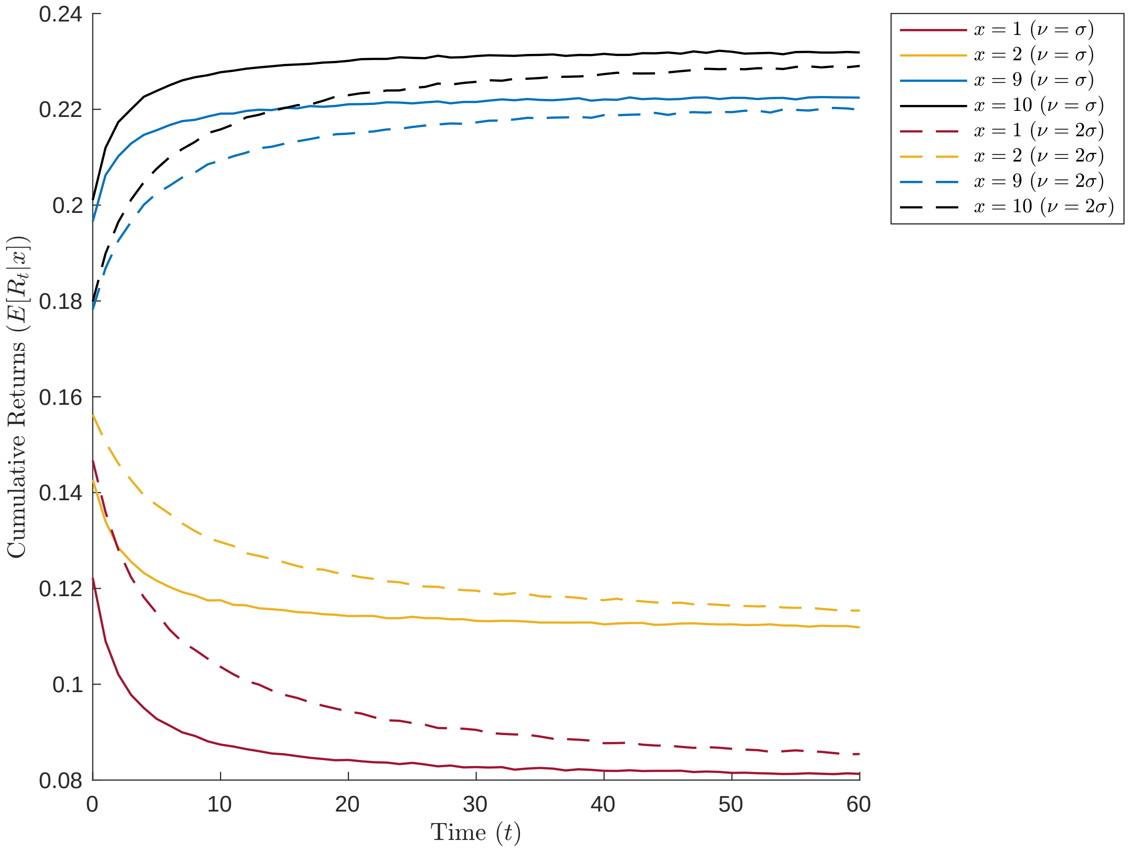


Figure 7: 3-Day Issuance Return after Patent Issuance across Patent Novelty

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

$$\log(R_{i,t,t+2}) = \alpha_m + \alpha_{ind} + \sum_{k=1}^{10} \beta_k 1_{i \in \text{novelty decile } k,t} + X_{i,t} + \varepsilon_{i,t},$$

where the ten indicator variables represent that the firm issues at least one patent in a certain novelty decile. We control for month and industry fixed effects and firm characteristics, including size, book-to-market, profitability, investment, market beta, short-term reversal, and medium-term momentum. We plot the issuance coefficients, β_k, for all ten deciles. The error bars are 90% confidence intervals with clustered standard errors at the year-month level.

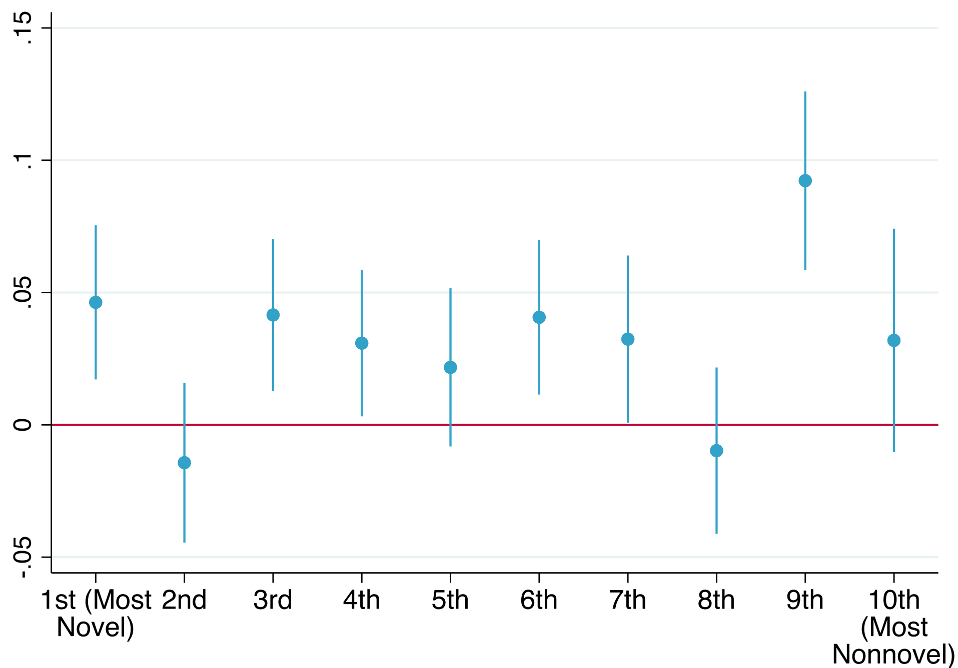


Figure 8: Cumulative IRF of Firm Returns after Patent Issuance across Patent Novelty

This figure plots the cumulative impulse response of future returns after patent issuance for different levels of patent novelty. In particular, we run the following regression for each $\tau \in [1, 60]$ at the firm-month level:

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

where the ten indicator variables represent that the firm issues at least one patent in a certain novelty decile. We control for month and industry fixed effects and firm characteristics, including size, book-to-market, profitability, investment, market beta, short-term reversal, and medium-term momentum. We plot the cumulative coefficients, $\sum_{\tau=1}^{t} \beta_{\tau,d}$, over $t \in [1, 60]$ for the ten deciles. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

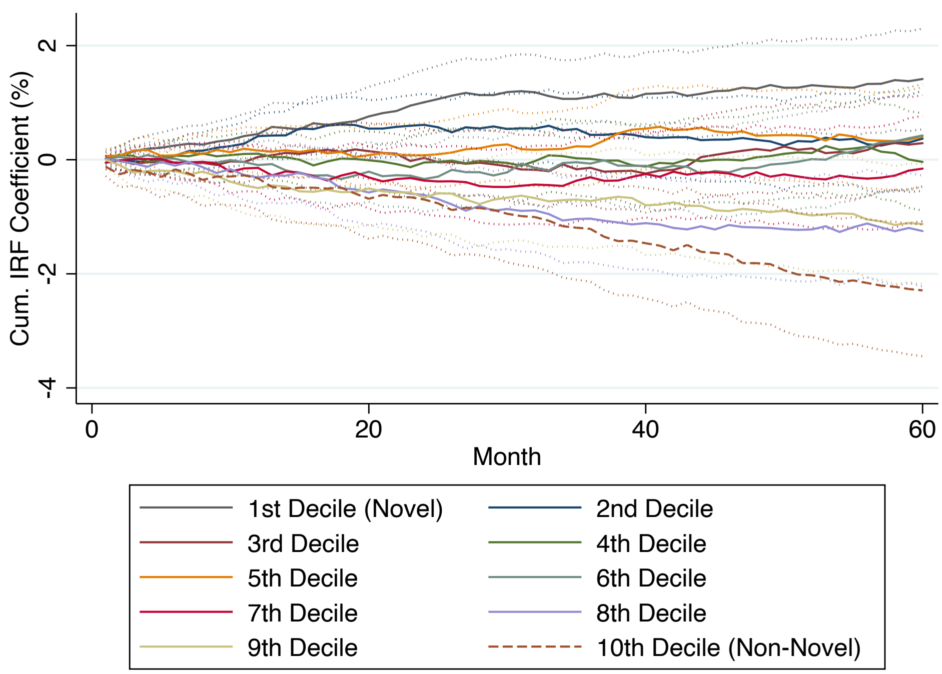


Figure 9: Cumulative IRF of Firm Returns after Patent Issuance by Institutional Holdings.

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

$$\log(R_{i,m+\tau}) = \alpha_m + \sum_{k=1}^{10} \beta_{k,\tau,high} 1_{i \in \text{novelty decile } k,m} \times 1_{\text{high inst hold},m} + \sum_{k=1}^{10} \beta_{k,\tau,low} 1_{i \in \text{novelty decile } k,m} \times 1_{\text{low inst hold},m} + X_{i,m} + \varepsilon_{i,m+\tau},$$

where we interact the ten indicator variables of firms issuing patents in each decile with dummies for high and low institutional holdings. We categorize high versus low holdings using the median institutional holdings for each month following Ferreira and Matos (2008). We control for month fixed effects and firm characteristics, including size, book-to-market, profitability, investment, market beta, short-term reversal, and medium-term momentum. We plot the cumulative coefficients, $\sum_{\tau=1}^{t} \beta_{k,\tau,high}$ and $\sum_{\tau=1}^{t} \beta_{k,\tau,low}$, over $t \in [1, 60]$ for the most novel ($d = 1$ and $d = 2$) and most non-novel ($d = 9$ and $d = 10$) deciles. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

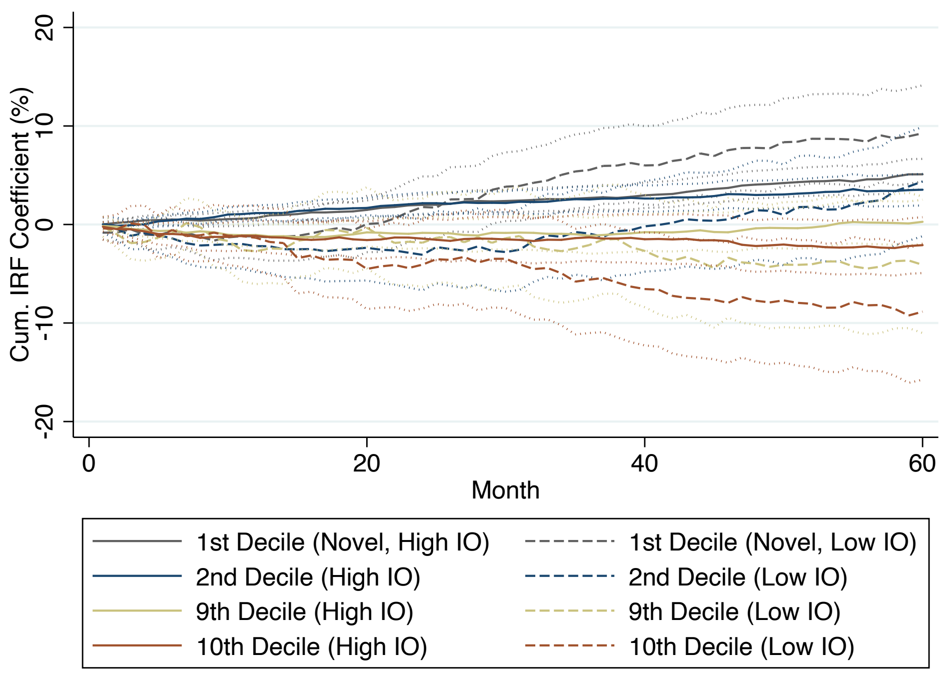


Figure 10: Patent Private Value on Novelty

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.

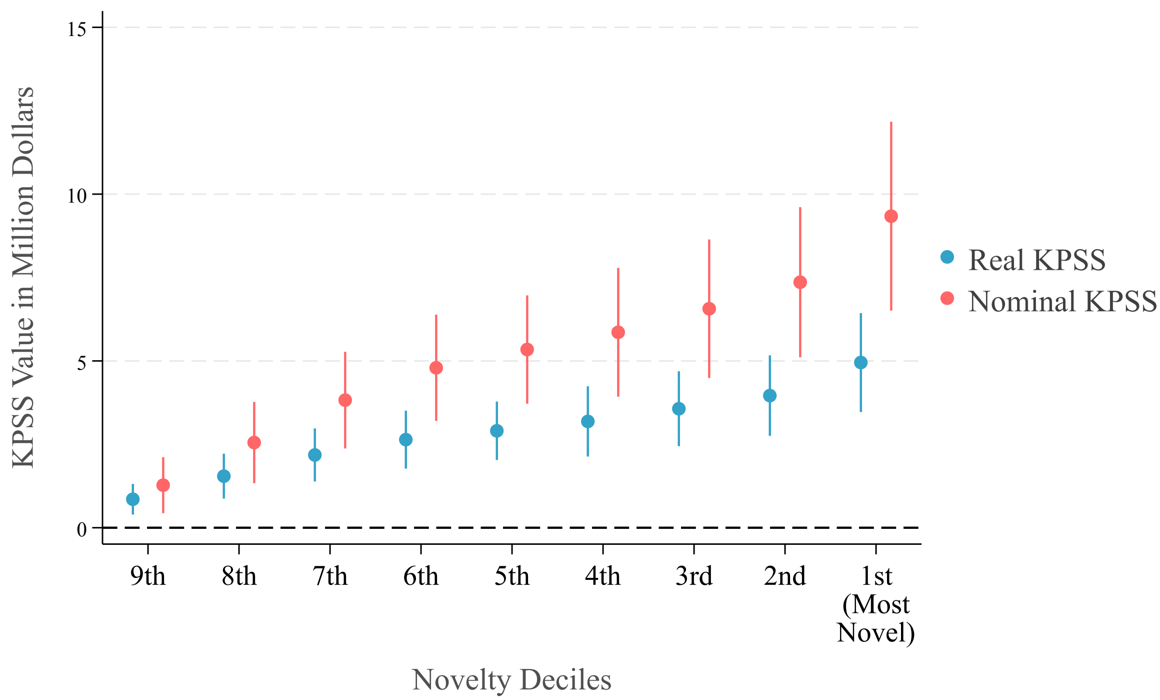


Figure 11: Firm's Equity Return and Future "Novelty-Seeking" Innovation

This figure plots the firm's future "Novelty-Seeking" innovation, as measured by the percentage of most novel patents in year $t+\tau$ against the firm's equity return at year t. In particular, we run the following firm-level IV regression for $\tau = 1, 2, 3$, respectively:

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

where we instrument a firm's total equity returns $r_{i,t}$ with its idiosyncratic mutual fund price pressure $\text{MFFlow}_{i,t-1\to t}$ in the first stage. We also include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including firm capital stock, number of employees, total innovation quality, competitors' innovation quality, novel intensity, and idiosyncratic volatility. We first run the above specification on the full sample (blue) and then separate our sample into high- (red) and low-novel (green) groups by comparing each firm's average patent novelty with the industry median. We then run the same specification on each subsample. We plot the coefficients β for $\tau = 1, 2, 3$ across all three samples. The error bars are 90% confidence intervals with clustered standard errors at the firm and year level.

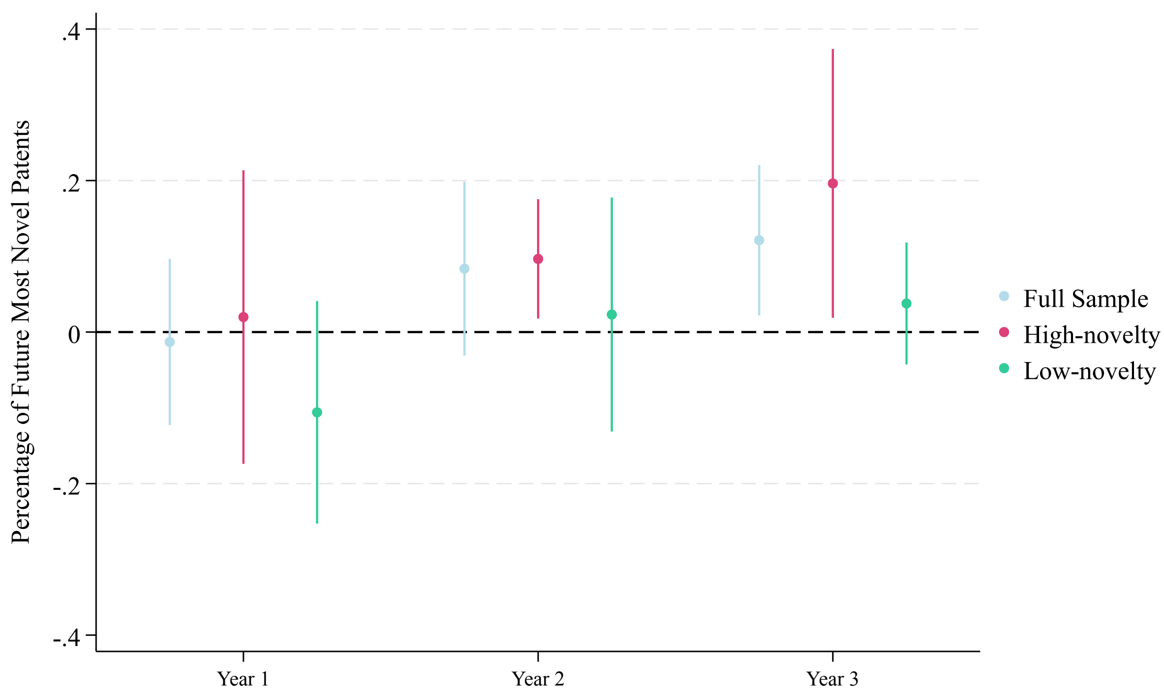


Figure 12: Firm's Equity Return and Future "Copycat" Innovation

This figure plots the firm's future "Copycat" innovation, as measured by the percentage of non-novel patents in year $t + \tau$ against the firm's equity return at year t. In particular, we run the following firm-level IV regression for $\tau = 1, 2, 3$, respectively:

$$\text{Copycat Innovation}_{i,t+\tau} = \beta r_{i,t} + \gamma' Z_{i,t} + \alpha_t + \alpha_{ind} + \varepsilon_{i,t},$$

where we instrument a firm's total equity returns $r_{i,t}$ with its idiosyncratic mutual fund price pressure $\text{MFFlow}_{i,t-1\to t}$ in the first stage. We also include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including firm capital stock, number of employees, total innovation quality, competitors' innovation quality, novel intensity, and idiosyncratic volatility. We first run the above specification on the full sample (blue) and then separate our sample into high- (red) and low-novel (green) groups by comparing each firm's average patent novelty with the industry median. We then run the same specification on each subsample. We plot the coefficients β for $\tau = 1, 2, 3$ across all three samples. The error bars are 90% confidence intervals with clustered standard errors at the firm and year level.

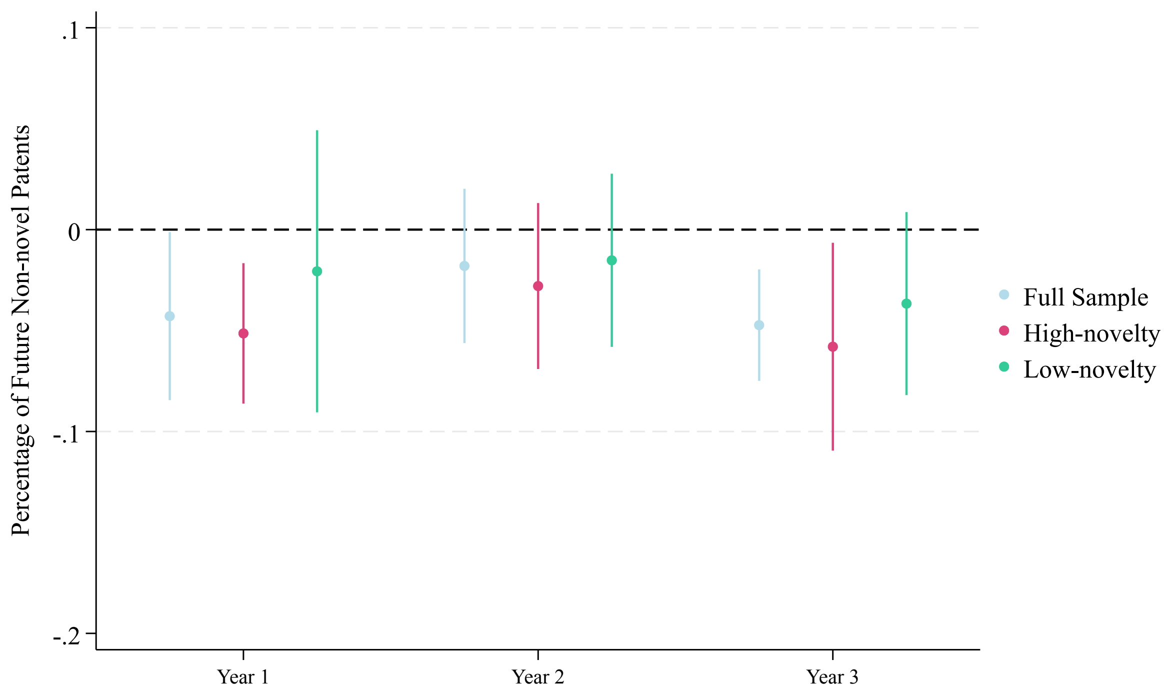


Table 1: Patent Social Value on Novelty

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

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

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

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

Table 2: Firm's Future Sustaining Innovation Following Novel Technology

This table examines how many sustaining innovations are produced by novel firms following their established novel technology. In particular, we run the following firm-year level OLS regression:

$$\text{Avg. Follow-ups on novelty}_{i,t+1\to t+\tau} = \beta\text{Novel patent intensity}_{i,t} + \gamma' Z_{i,t} + \alpha_t + \alpha_{ind} + \varepsilon_{i,t},$$

where we employ the "Novel patent intensity" metric, defined as the fraction of a firm's patents in the first decile of patent novelty for a given time, to measure a firm's level of novelty. The dependent variable is a firm's future sustaining innovation, calculated by its average number of follow-up patents following its novel patents in the short run (i.e., next five years, as shown in columns (3) and (4)) and the long run (i.e., until the end of our data period, as shown in columns (1) and (2)). We include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including firm capital stock, number of employees, total value of innovation, competitors' innovation quality, novel intensity, and idiosyncratic volatility. We also control for year and industry fixed effects. We report the key estimates in the table. Standard errors are in parentheses and all clustered at the firm and year level.

	Avg. Follow-ups$_{t+1\to 2021}$		Avg. Follow-ups$_{t+1\to t+6}$	
	(1)	(2)	(3)	(4)
Novel Patent Intensity	-1.147***	-1.050**	-0.393***	-0.365***
	(-4.65)	(-2.27)	(-6.99)	(-3.01)
Value of Innovation	24.016***	19.845***	5.040***	3.988***
	(7.67)	(5.31)	(7.45)	(5.17)
Year FE	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes

t statistics in parentheses

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

Table 3: Firm's Future Novelty-seeking Innovation

This table examines whether novel firms consistently produce more novel patents in subsequent years. In particular, we run the following firm-year level OLS regression:

$$\log\left(\frac{\text{\% of Novel Patents}_{i,t+\tau}}{\text{\% of Novel Patents}_{i,t}}\right) = \beta_\tau \text{Novel patent intensity}_{i,t} + \gamma'_\tau Z_{i,t} + \alpha_t + \alpha_{ind} + \varepsilon_{i,t+\tau},$$

where we employ the "Novel patent intensity" metric, defined as the fraction of a firm's patents in the most novelty decile for a given time, to measure a firm's novelty. The dependent variable $\log(\frac{\text{\% of Novel Patents}_{i,t+\tau}}{\text{\% of Novel Patents}_{i,t}})$ represents the firm's growth in "novelty-seeking" innovation, relative to its original level at time t. We include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including firm capital stock, number of employees, total value of innovation, competitors' innovation quality, novel intensity, and idiosyncratic volatility. We also control for year and industry fixed effects. We report the key estimates in the table. Standard errors are in parentheses and all clustered at the firm and year level.

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5
Novel Patent Intensity	-0.4353***	-0.4885***	-0.5197***	-0.5445***	-0.5824***
	(-24.68)	(-27.34)	(-24.83)	(-27.52)	(-28.13)
Value of innovation	-0.1299***	-0.1355***	-0.1469***	-0.1387***	-0.1521***
	(-3.91)	(-3.75)	(-3.68)	(-3.58)	(-3.86)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

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

Table 4: Firm's Equity Return and Future Sustaining Innovation

This table examines the relationship between firms' future sustaining innovations and their equity returns. In particular, we run the following firm-year level IV regression:

$$\text{Avg. Follow-ups on novelty}_{i,t+1\to t+\tau} = \beta r_{i,t} + \gamma' Z_{i,t} + \alpha_t + \alpha_{ind} + \varepsilon_{i,t},$$

where we instrument a firm's total equity returns $r_{i,t}$ with its idiosyncratic mutual fund price pressure $\text{MFFlow}_{i,t-1\to t}$ in the first stage (the first-stage estimates are reported in columns (2) and (4)). The dependent variable is a firm's future sustaining innovation, calculated by its average number of follow-up patents following its novel patents in the short run (i.e., the next five years, as shown in column (3)) and the long run (i.e., until the end of our data period, as shown in column (1)). We also include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including firm capital stock, number of employees, total innovation quality, competitors' innovation quality, novel intensity, and idiosyncratic volatility. We report the key estimates in the table. Standard errors are in parentheses and all clustered at the firm and year level.

	(1)	(2)	(3)	(4)
	Avg. Follow-ups$_{t+1\to t+6}$	FS	Avg. Follow-ups$_{t+1\to 2021}$	FS
$r_{i,t}$	1.0859*		3.7722**	
	(1.78)		(2.11)	
Value of Innovation	2.8891***	0.2109***	7.1434***	0.2088***
	(3.78)	(2.77)	(4.68)	(2.72)
$\text{MFFlow}_{t-1\to t}$		0.4271***		0.4138***
		(3.03)		(3.03)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
CD Wald F		119		121
Observations	29876	29876	32141	32141

t statistics in parentheses

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

Table 5: Firm's Equity Return and Future Sustaining Innovation with Subsamples

This table examines whether novel or non-novel firms are more likely to be affected by market reactions and change their sustaining innovations. In particular, we separate our sample into high- and low-novel groups by comparing each firm's average patent novelty with the industry median and then run the following firm-year level IV regression:

$$\text{Avg. Follow-ups on novelty}_{i,t+1\to t+\tau} = \beta r_{i,t} + \gamma' Z_{i,t} + \alpha_t + \alpha_{ind} + \varepsilon_{i,t},$$

where we instrument a firm's total equity returns $r_{i,t}$ with its idiosyncratic mutual fund price pressure $\text{MFFlow}_{i,t-1\to t}$ in the first stage. The dependent variable is a firm's future sustaining innovation, calculated by its average number of follow-up patents following its novel patents in the short run (i.e., the next five years, as shown in columns (1) and (3)) and the long run (i.e., until the end of our data period, as shown in columns (2) and (4)). We also include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including firm capital stock, number of employees, total innovation quality, competitors' innovation quality, novel intensity, and idiosyncratic volatility. We report the key estimates in the table. Standard errors are in parentheses and all clustered at the firm and year level.

	High-novelty		Low-novelty	
	(1)	(2)	(3)	(4)
	Follow-ups$_{t+1\to t+6}$	Follow-ups$_{t+1\to 2021}$	Follow-ups$_{t+1\to t+6}$	Follow-ups$_{t+1\to 2021}$
$r_{i,t}$	0.6796**	3.1458**	1.5016	3.9389
	(2.18)	(2.50)	(1.38)	(1.47)
Value of Innovation	2.4851***	8.2425***	3.0796***	6.7250***
	(4.93)	(5.70)	(3.09)	(3.64)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	13829	15080	16046	17060

t statistics in parentheses

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

A Additional Figures and Tables

A.1 Figures

Figure A.1: 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 $\tau \in [1, 60]$ at the firm-month level:

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

where $\sigma_{i,t+\tau}$ is the return standard deviation of firm i in month $t + \tau$, computed from daily returns. The ten indicator variables represent that the firm issues at least one patent in a certain novelty decile. We control for month and industry fixed effects and firm characteristics, including size, book-to-market, profitability, investment, market beta, short-term reversal, and medium-term momentum. We plot coefficients, $\beta_{\tau,d}$, over $t \in [1, 60]$ for the most novel ($d = 1$) and most non-novel ($d = 10$) decile. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

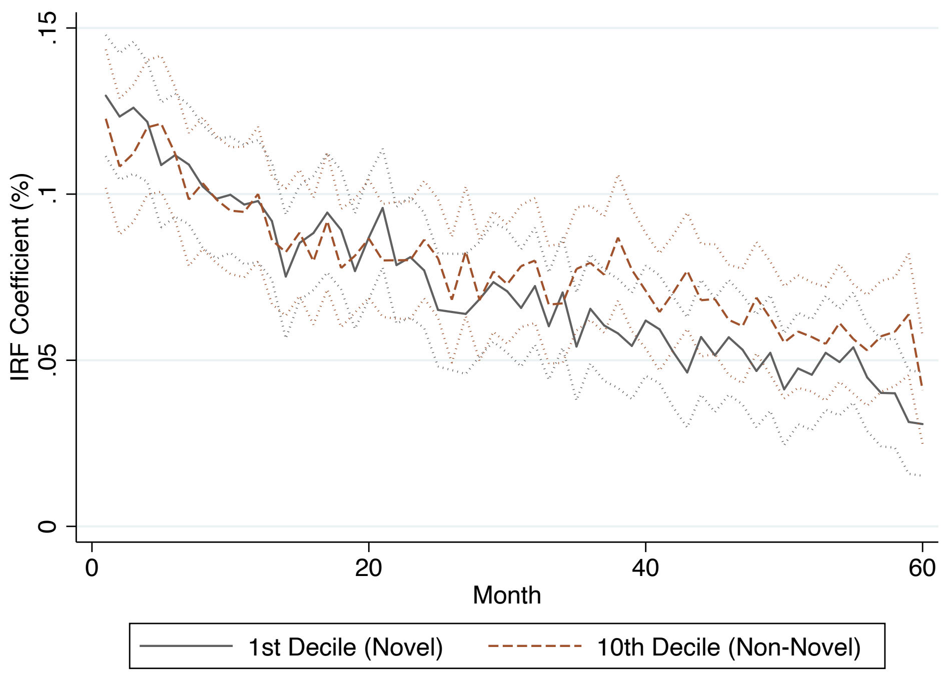


Figure A.2: Cumulative IRF of Firm Market Beta after (Non-)Novel Patent Issuance

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 $\tau \in [1, 60]$ at the firm-month level:

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

where $\beta^{mkt}_{i,t+\tau}$ 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 $t+\tau$. The ten indicator variables represent that the firm issues at least one patent in a certain novelty decile. We control for month and industry fixed effects and firm characteristics, including size, book-to-market, profitability, investment, market beta, short-term reversal, and medium-term momentum. We plot coefficients, $\beta_{\tau,d}$, over $t \in [1, 60]$ for the most novel ($d = 1$) and most non-novel ($d = 10$) decile. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

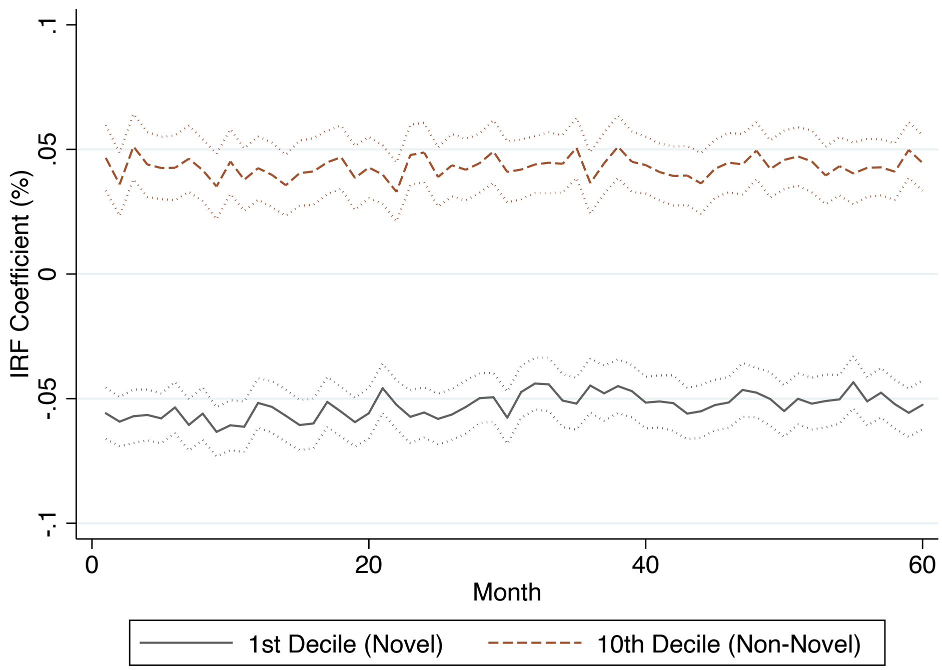


Figure A.3: Cumulative IRF of Firm Implied Volatility after (Non-)Novel Patent Issuance

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 $\tau \in [1, 60]$ at the firm-month level:

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

where 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. The ten indicator variables represent that the firm issues at least one patent in a certain novelty decile. We control for month and industry fixed effects and firm characteristics, including size, book-to-market, profitability, investment, market beta, short-term reversal, and medium-term momentum. We plot coefficients, $\beta_{\tau,d}$, over $t \in [1, 60]$ for the most novel ($d = 1$) and most non-novel ($d = 10$) decile. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

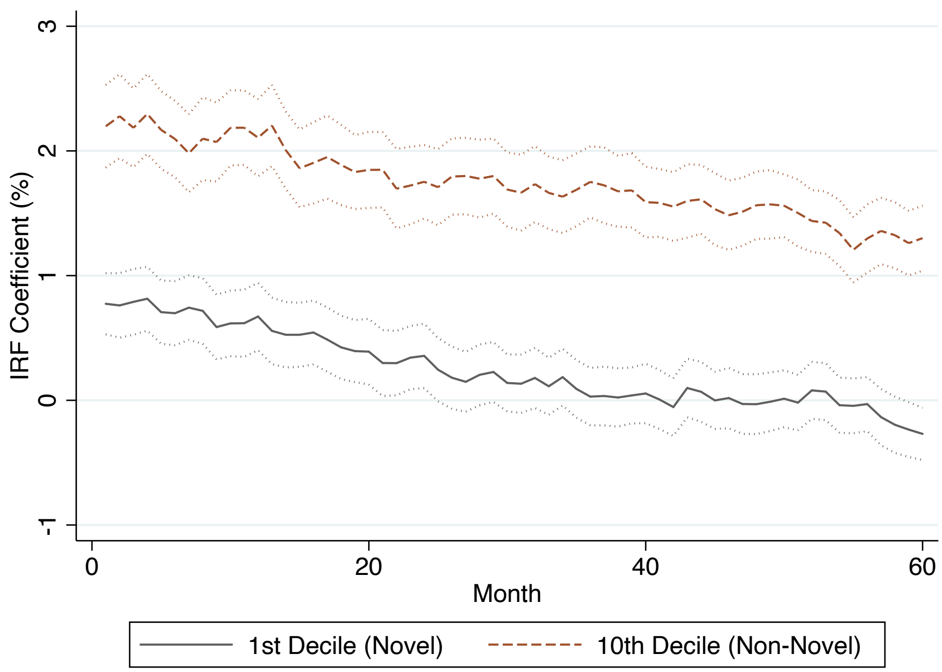


Figure A.4: Underreaction in 1-Year Earnings Expectations across Patent Novelty

This figure plots the Coibion and Gorodnichenko (2015) regression coefficients for short-term 1-year earnings expectations over ten deciles of patent novelty. In particular, we run the following regression at the firm-issuance-date level:

$$EPS_{1,i,t} - E_{post}[EPS_{1,i,t}] = \alpha_1 + \beta_1(E_{post}[EPS_{1,i,t}] - E_{pre}[EPS_{1,i,t}]) + \varepsilon_{1,i,t},$$

where we use the realized earnings and consensus earnings expectations 90 days before and after the patent issuance dates to construct forecast errors and forecast revisions. We plot coefficients, β_1, separately for the ten novelty deciles. The error bars are 95% confidence intervals with double-clustered standard errors at the firm and issuance date level.

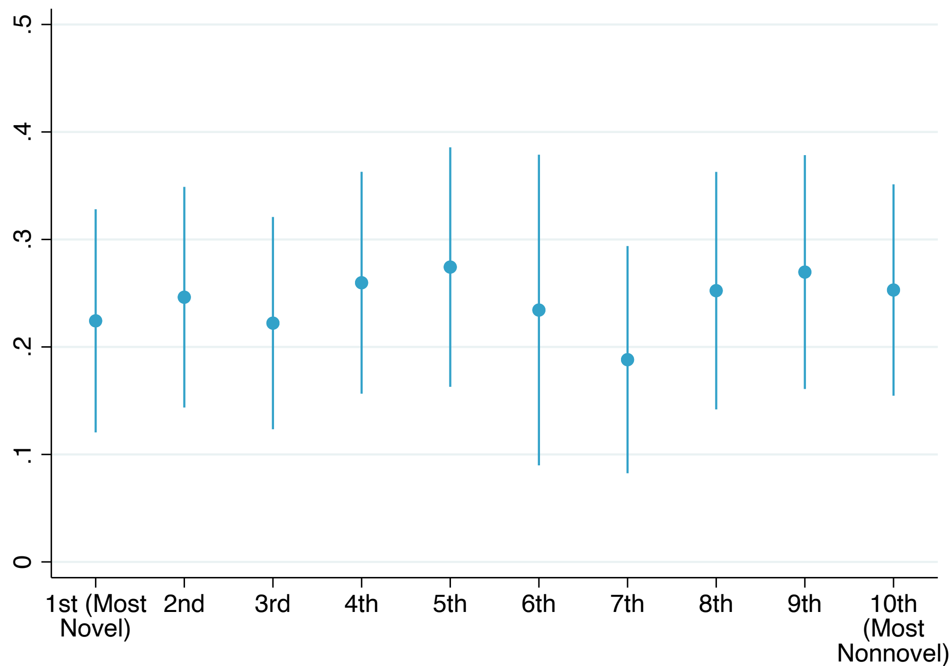


Figure A.5: Overreaction in Long-Term Growth Expectations across Patent Novelty

This figure plots the Coibion and Gorodnichenko (2015) regression coefficients for long-term earnings growth (LTG) expectations over ten deciles of patent novelty. In particular, we run the following regression at the firm-issuance-date level:

$$\Delta_5 e_{i,t+5year}/5 - LTG_{post,i,t} = \alpha_{LTG} + \beta_{LTG}(LTG_{post,i,t} - LTG_{pre,i,t}) + \varepsilon_{LTG,i,t},$$

where we use the realized 5-year annualized earnings growth and consensus earnings expectations 90 days before and after the patent issuance dates to construct forecast errors and forecast revisions. We plot coefficients, β_{LTG}, separately for the ten novelty deciles. The error bars are 95% confidence intervals with double-clustered standard errors at the firm and issuance date level.

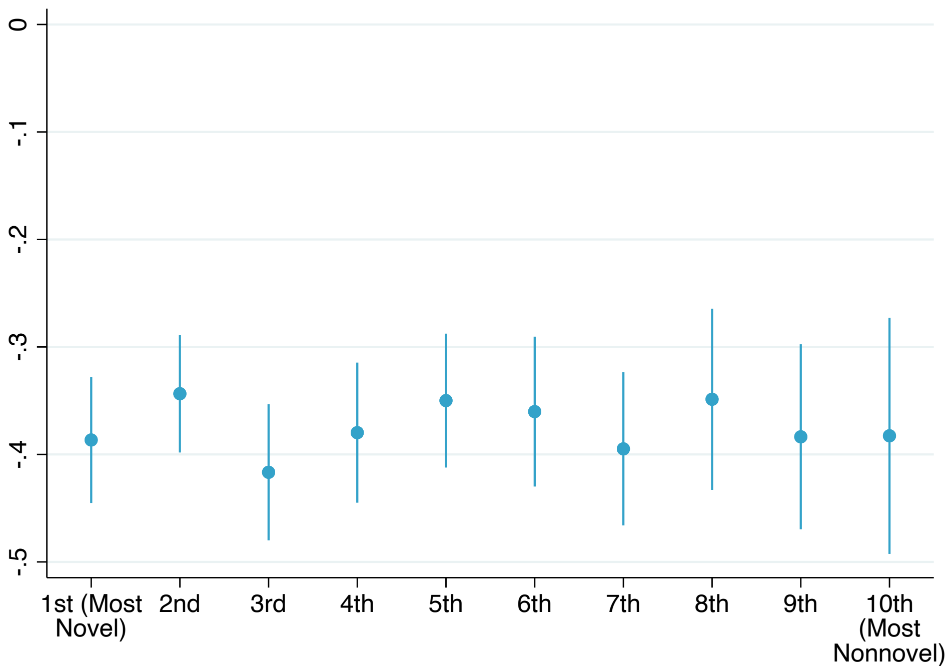


Figure A.6: Cumulative IRF of Firm Returns on (Non-)Novel Patent Intensity

This figure plots the cumulative impulse response of future returns on (non-)novel patent intensity. We run the following regression for each $\tau \in [1, 60]$ at the firm-month level:

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

where the (non-)novel patent intensity is the fraction of (non-)novel patents over total patent issuance for each firm month. We define a patent as a novel patent if it lies in the first decile of patent novelty and a non-novel patent if it belongs to the tenth decile. We control for month and industry fixed effects and firm characteristics, including size, book-to-market, profitability, investment, market beta, short-term reversal, and medium-term momentum. We plot the cumulative coefficients, $\sum_{\tau=1}^{t} \beta_\tau$, over $t \in [1, 60]$. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

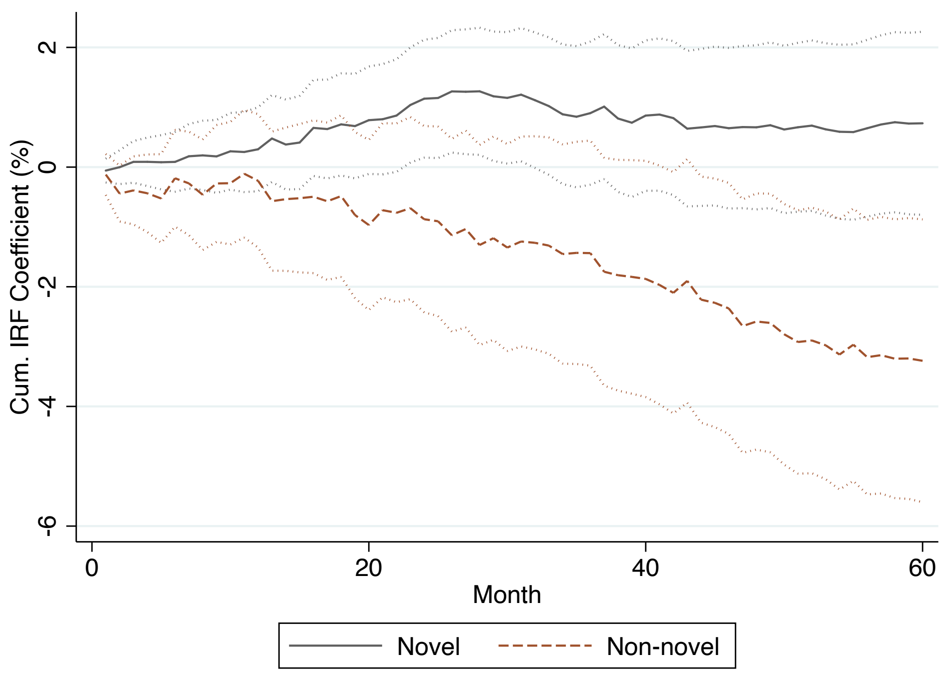


Figure A.7: Cumulative IRF of Firm Returns on Firm Similarity Scores

This figure plots the cumulative impulse response of future returns on average similarity score. We run the following regression for each $\tau \in [1, 60]$ at the firm-month level:

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

where the similarity score is the average patent novelty decile of all patents issued at the firm-month level. We control for month and industry fixed effects and firm characteristics, including size, book-to-market, profitability, investment, market beta, short-term reversal, and medium-term momentum. We plot the cumulative coefficients, $\sum_{\tau=1}^{t} \beta_\tau$, over $t \in [1, 60]$. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.

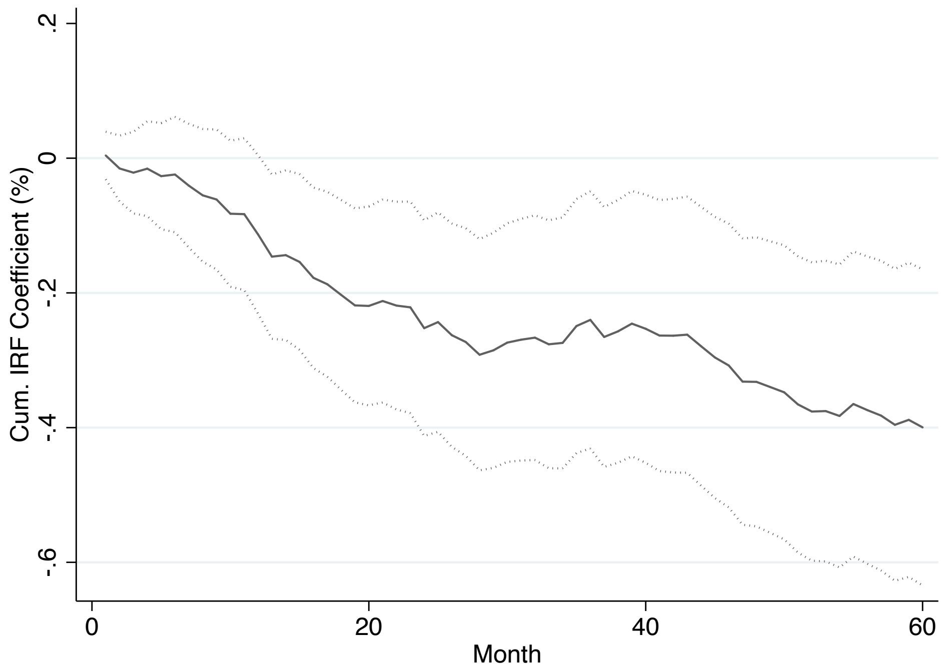
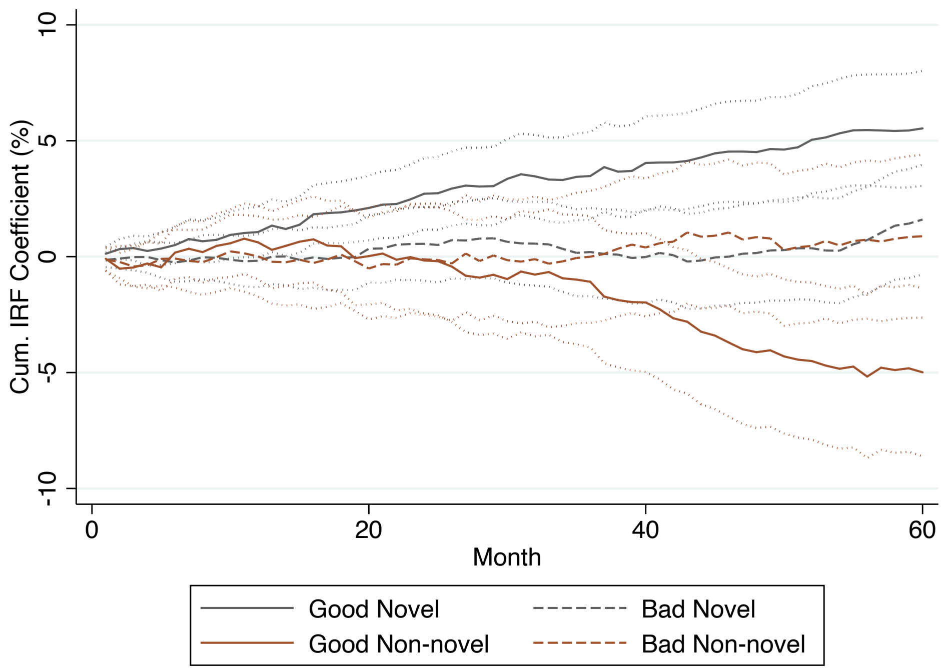


Figure A.8: Cumulative IRF of Firm Returns on Good/Bad (Non-)Novel Patent Intensity

This figure plots the cumulative impulse response of future returns on (non-)novel patent intensity for good versus bad patents. We run the following regressions for each $\tau \in [1, 60]$ at the firm-month level:

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

where the good/bad (non-)novel patent intensity is the fraction of good/bad (non-)novel patents over total patents issuance at the firm-month level. We define a patent as a novel patent if it lies in the first decile of patent novelty, a non-novel patent if it belongs to the tenth decile, and good/bad patents as above/below-median patents in terms of 10-year forward similarity (impact). We control for month and industry fixed effects and firm characteristics, including size, book-to-market, profitability, investment, market beta, short-term reversal, and medium-term momentum. We plot the cumulative coefficients, $\sum_{\tau=1}^{t} \beta_\tau$, over $t \in [1, 60]$. The error bars are 95% confidence intervals with clustered standard errors at the year-month level.



A.2 Tables

Table A.1: Short-Term Returns on Patent Issuance Dummy

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:

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

where the patent issuance dummies represent that the firm issues at least one (novel/non-novel) patent. We control for issuance date and industry fixed effects and firm characteristics, including size, book-to-market, profitability, investment, market beta, 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	0.047***		0.001
	(2.63)		(0.07)
Non-Novel Dummy		0.064**	0.022
		(2.20)	(0.93)
Patent Dummy			0.046***
			(2.80)
R^2	0.069	0.069	0.069
Industry FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	46,732,925	46,732,925	46,732,925

t statistics in parentheses

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

Table A.2: Firm's Future Sustaining Innovation Following High-impact Novel Patents

This table examines how many sustaining innovations are produced by novel firms following their established high-impact novel technology. In particular, we run the following firm-year level OLS regression:

$$\text{Avg. Follow-ups on novelty}_{i,t+1\rightarrow t+\tau} = \beta\text{High-Impact Novel Intensity}_{i,t} + \gamma' Z_{i,t} + \alpha_t + \alpha_{ind} + \varepsilon_{i,t},$$

where we employ the "High-impact Novel Intensity" metric, defined as the fraction of a firm's most novel and high-impact patents (we split the most novel patents into high-impact and low-impact groups based on their ten-year forward similarity measures constructed following Kelly et al. (2021)) for a given time. The dependent variable is a firm's future sustaining innovation, calculated by its average number of follow-up patents following its novel and high-impact patents in the short run (i.e., next five years, as shown in columns (3) and (4)) and the long run (i.e., until the end of our data period, as shown in columns (1) and (2)). We include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including firm capital stock, number of employees, total value of innovation, competitors' innovation quality, novel intensity, and idiosyncratic volatility. We also control for year and industry fixed effects. We report the key estimates in the table. Standard errors are in parentheses and all clustered at the firm and year level.

	Avg. Follow-ups$_{t+1\rightarrow 2021}$		Avg. Follow-ups$_{t+1\rightarrow t+6}$	
	(1)	(2)	(3)	(4)
High-Impact Novel Intensity	-0.574	-1.136	-0.374***	-0.376***
	(-1.49)	(-1.18)	(-6.15)	(-4.15)
Value of Innovation	39.781***	36.443***	6.737***	6.179***
Year FE	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes

t statistics in parentheses

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

Table A.3: Firm's Equity Return and Future Sustaining Innovation on Single Novelty Groups

This table examines the relationship between firms' future sustaining innovations and their equity returns. In particular, we restrict our sample to firms with patents granted in only one novelty decile and get ten subsamples (one for each novelty decile). Then, we run the following firm-year level IV regression on those ten subsamples:

$$\text{Avg. Follow-ups on novelty}_{i,t+1\to t+\tau} = \beta r_{i,t} + \gamma' Z_{i,t} + \alpha_t + \alpha_{ind} + \varepsilon_{i,t},$$

where we instrument a firm's total equity returns $r_{i,t}$ with its idiosyncratic mutual fund price pressure $\text{MFFlow}_{i,t-1\to t}$ in the first stage (the first-stage estimates are reported in columns (2) and (4)). The dependent variable is a firm's future sustaining innovation, calculated by its average number of follow-up patents following its novel patents in the long run (i.e., until the end of our data period, as shown in columns (1) and (3)). We also include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including firm capital stock, number of employees, total innovation quality, competitors' innovation quality, novel intensity, and idiosyncratic volatility. We report the key estimates in the table. Standard errors are in parentheses and all clustered at the firm and year level.

	Novel (Decile 1)		Non-novel (Decile 10)	
	(1)	(2)	(3)	(4)
	Avg. $\text{Follow-ups}_{t+1\to 2021}$	FS	Avg. $\text{Follow-ups}_{t+1\to 2021}$	FS
$r_{i,t}$	3.5196***		13.7209	
	(3.22)		(1.06)	
Value of Innovation	10.1745***	-0.5832	13.3152	-0.3959
	(4.25)	(-0.90)	(1.28)	(-0.55)
$\text{MFF}_{t-1\to t}$		0.5141***		0.2983
		(3.95)		(0.97)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
CD Wald F		14		1
Observations	2402	2402	422	422

t statistics in parentheses

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

Table A.4: Firm's Equity Return and Future Novelty-Seeking Innovation

This table examines the relationship between the firm's future "Novelty-Seeking" innovation, as measured by the percentage of most novel patents in year $t+\tau$ and the firm's equity return at year t. In particular, we run the following firm-level IV regression for $\tau = 1, 2, 3$, respectively:

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

where we instrument a firm's total equity returns $r_{i,t}$ with its idiosyncratic mutual fund price pressure $\text{MFFlow}_{i,t-1\to t}$ in the first stage (the first-stage estimates are reported in columns (2), (4) and (6)). We also include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including firm capital stock, number of employees, total innovation quality, competitors' innovation quality, novel intensity, and idiosyncratic volatility. We report the key estimates in the table. Standard errors are in parentheses and all clustered at the firm and year level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Year 1	FS	Year 2	FS	Year 3	FS
$r_{i,t}$	-0.0131		0.0837		0.1213**	
	(-0.20)		(1.23)		(2.07)	
Value of Innovation	-0.0079	0.1556*	-0.0269	0.1391*	-0.0346*	0.1374
	(-0.41)	(1.71)	(-1.57)	(1.72)	(-1.91)	(1.52)
Avg. Patent BS_t	-0.0482***	-0.0027	-0.0443***	-0.0034	-0.0394***	-0.0038
	(-7.47)	(-1.06)	(-7.96)	(-1.38)	(-7.26)	(-1.61)
$\text{MFF}_{t-1\to t}$		0.3931***		0.3718***		0.4402***
		(2.83)		(2.73)		(3.29)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
CD Wald F		96		83		103
Observations	24215	24215	22577	22577	21011	21011

t statistics in parentheses

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

Table A.5: Firm's Equity Return and Future Novelty-Seeking Innovation with Subsamples

This table examines whether novel or non-novel firms are more likely to be affected by market reactions and change their future "Novelty-Seeking" innovation, as measured by the percentage of most novel patents in year $t+\tau$. In particular, we separate our sample into high- and low-novel groups by comparing each firm's average patent novelty with the industry median and then run the following firm-level IV regression for $\tau = 1, 2, 3$, respectively:

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

where we instrument a firm's total equity returns $r_{i,t}$ with its idiosyncratic mutual fund price pressure $\text{MFFlow}_{i,t-1\to t}$ in the first stage. We also include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including firm capital stock, number of employees, total innovation quality, competitors' innovation quality, novel intensity, and idiosyncratic volatility. We report the key estimates in the table. Standard errors are in parentheses and all clustered at the firm and year level.

	High-novelty			Low-novelty		
	(1)	(2)	(3)	(4)	(5)	(6)
	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3
$r_{i,t}$	0.0199	0.0966**	0.1962*	-0.1059	0.0232	0.0378
	(0.17)	(2.07)	(1.87)	(-1.22)	(0.25)	(0.79)
Value of Innovation	0.1179***	0.0799***	0.0387	-0.0199	-0.0425**	-0.0367***
	(3.10)	(2.79)	(1.16)	(-1.25)	(-2.30)	(-2.76)
Avg. Patent BS_t	-0.0761***	-0.0688***	-0.0521***	-0.0256***	-0.0236***	-0.0202***
	(-5.46)	(-5.71)	(-5.13)	(-6.08)	(-6.72)	(-6.76)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10986	10217	9481	13228	12357	11528

t statistics in parentheses

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

Table A.6: Firm's Equity Return and Future Copycat Innovation

This table examines the relationship between the firm's future "Copycat" innovation, as measured by the percentage of non-novel patents in year $t + \tau$, and the firm's equity return at year t. In particular, we run the following firm-level IV regression for $\tau = 1, 2, 3$, respectively:

$$\text{Copycat Innovation}_{i,t+\tau} = \beta r_{i,t} + \gamma' Z_{i,t} + \alpha_t + \alpha_{ind} + \varepsilon_{i,t+\tau},$$

where we instrument a firm's total equity returns $r_{i,t}$ with its idiosyncratic mutual fund price pressure $\text{MFFlow}_{i,t-1\to t}$ in the first stage (the first-stage estimates are reported in columns (2), (4) and (6)). We also include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including firm capital stock, number of employees, total innovation quality, competitors' innovation quality, novel intensity, and idiosyncratic volatility. We report the key estimates in the table. Standard errors are in parentheses and all clustered at the firm and year level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Year 1	FS	Year 2	FS	Year 3	FS
$r_{i,t}$	-0.0429*		-0.0180		-0.0473***	
	(-1.74)		(-0.80)		(-2.90)	
Value of Innovation	-0.0053	0.1553*	-0.0150	0.1384*	-0.0093	0.1358
	(-0.60)	(1.70)	(-1.48)	(1.67)	(-1.02)	(1.51)
Avg. Patent BS_t	0.0204***	-0.0014	0.0187***	-0.0014	0.0148***	-0.0004
	(6.15)	(-0.48)	(6.29)	(-0.51)	(6.00)	(-0.16)
$\text{MFF}_{t-1\to t}$		0.3928***		0.3715**		0.4390***
		(2.67)		(2.57)		(3.07)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
CD Wald F		95		83		102
Observations	24215	24215	22577	22577	21011	21011

t statistics in parentheses

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

Table A.7: Firm's Equity Return and Future Copycat Innovation with Subsamples

This table examines whether novel or non-novel firms are more likely to be affected by market reactions and change their future "Copycat" innovation, as measured by the percentage of non-novel patents in year $t + \tau$. In particular, we separate our sample into high- and low-novel groups by comparing each firm's average patent novelty with the industry median and then run the following firm-level IV regression for $\tau = 1, 2, 3$, respectively:

$$\text{Copycat Innovation}_{i,t+\tau} = \beta r_{i,t} + \gamma' Z_{i,t} + \alpha_t + \alpha_{ind} + \varepsilon_{i,t+\tau},$$

where we instrument a firm's total equity returns $r_{i,t}$ with its idiosyncratic mutual fund price pressure $\text{MFFlow}_{i,t-1\to t}$ in the first stage. We also include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including firm capital stock, number of employees, total innovation quality, competitors' innovation quality, novel intensity, and idiosyncratic volatility. We report the key estimates in the table. Standard errors are in parentheses and all clustered at the firm and year level.

	High-novelty			Low-novelty		
	(1)	(2)	(3)	(4)	(5)	(6)
	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3
$r_{i,t}$	-0.0514**	-0.0279	-0.0580*	-0.0206	-0.0152	-0.0366
	(-2.50)	(-1.15)	(-1.90)	(-0.50)	(-0.60)	(-1.37)
Value of Innovation	-0.0226***	-0.0209***	-0.0163**	0.0033	-0.0087	-0.0095
	(-2.82)	(-2.81)	(-2.21)	(0.23)	(-0.60)	(-0.57)
Avg. Patent BS_t	0.0066***	0.0078***	0.0068***	0.0277***	0.0235***	0.0161***
	(3.69)	(5.03)	(6.99)	(6.44)	(6.53)	(6.25)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10986	10217	9481	13228	12357	11528

t statistics in parentheses

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

Table A.8: Firm's Equity Return and Future Innovation with Financial Constraints

This table examines whether financially constrained novel firms are more likely to be affected by the return drops in the equity market and change their future sustaining innovation as a response. In particular, we first generate firm-level financial constraint measures based on either firm size or the firm's size and age index following Hadlock and Pierce (2010) and identify a firm as financially constrained if its size (size and age index) below (above) the industry median. We then construct a new key variable of interest by interacting firms' financial-constrained indicators with the equity returns. We run our IV specifications with this new explanatory variable on the high-novel subsample as follows:

$$\text{Avg. Follow-ups on novelty}_{i,t+1\to t+\tau} = \beta r_{i,t} \times \text{Fin. Constrained}_{i,t} + \gamma' Z_{i,t} + \alpha_t + \alpha_{ind} + \varepsilon_{i,t},$$

where we instrument $r_{i,t} \times \text{Fin. Constrained}_{i,t}$ with $\text{MFFlow}_{i,t-1\to t} \times \text{Fin. Constrained}_{i,t}$ in the first stage. We also include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including firm capital stock, number of employees, total innovation quality, competitors' innovation quality, novel intensity, and idiosyncratic volatility. We report the key estimates in the table. Standard errors are in parentheses and all clustered at the firm and year level.

	Small Size Indicator		Size & Age Index	
	(1)	(2)	(3)	(4)
	Follow-ups$_{t+1\to t+6}$	Follow-ups$_{t+1\to 2021}$	Follow-ups$_{t+1\to t+6}$	Follow-ups$_{t+1\to 2021}$
$r_{i,t}$ × Fin. Constrained	1.3009***	3.0152***	0.6399**	0.9321
	(3.62)	(2.86)	(2.17)	(1.08)
Value of Innovation	2.2419***	8.0189***	2.3116***	8.2374***
	(3.53)	(4.43)	(3.82)	(4.77)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	13675	14916	13520	14717

t statistics in parentheses

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

Table A.9: Firm's Equity Return and Future Innovation with Financial Constraints

This table examines whether financially constrained novel firms are more likely to be affected by the return drops in the equity market and change their future "Novelty-Seeking" innovation as a response. In particular, we first generate firm-level financial constraint measures based on either firm size or the firm's size and age index following Hadlock and Pierce (2010) and identify a firm as financially constrained if its size (size and age index) below (above) the industry median. We then construct a new key variable of interest by interacting firms' financial-constrained indicators with the equity returns. We run our IV specifications with this new explanatory variable on the high-novel subsample as follows:

$$\text{Novelty-seeking Innovation}_{i,t+\tau} = \beta r_{i,t} \times \text{Fin. Constrained}_{i,t} + \gamma' Z_{i,t} + \alpha_t + \alpha_{ind} + \varepsilon_{i,t},$$

where we instrument $r_{i,t} \times \text{Fin. Constrained}_{i,t}$ with $\text{MFFlow}_{i,t-1\to t} \times \text{Fin. Constrained}_{i,t}$ in the first stage. We also include $Z_{i,t}$ to control for multiple factors that could affect a firm's future innovation directions, including firm capital stock, number of employees, total innovation quality, competitors' innovation quality, novel intensity, and idiosyncratic volatility. We report the key estimates in the table. Standard errors are in parentheses and all clustered at the firm and year level.

	Small Size Indicator			Size & Age Index		
	(1)	(2)	(3)	(4)	(5)	(6)
	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3
$r_{i,t}$ × Fin. Constrained	-0.0241	0.2463**	0.4048**	0.1159*	0.1160	0.2105*
	(-0.15)	(2.67)	(2.41)	(1.73)	(1.20)	(1.71)
Value of Innovation	0.1106***	0.0811***	0.0428	0.1085***	0.0797***	0.0455*
	(3.74)	(2.86)	(1.69)	(3.70)	(2.85)	(1.98)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
CD Wald F						
Observations	10992	10224	9485	10996	10227	9487

t statistics in parentheses

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