

How Do Firms Respond to Patent Grants to Related Firms?*

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Abstract

Patent grants can create either opportunities or threats for technologically related firms, but their net effect is difficult to predict. Economic theory offers competing predictions. Knowledge spillovers imply that a focal firm's innovation may create complementary investment opportunities for technologically related peers, whereas stronger intellectual property rights and product-market rivalry imply competitive threats that discourage follow-on innovation in the protected domain. To distinguish between these competing forces, I use abnormal stock returns around patent grant dates to classify whether markets interpret a focal firm's patent as creating opportunities or threats for technologically related peers. I then examine how peers adjust their innovation, acquisition, and financing policies following these patent grants. I find that peers increase R&D, pursue follow-on innovation in related technological domains, and engage in technology-related acquisitions following complementary patent grants, but redirect innovation toward different technologies following rivalrous patent grants. These responses are stronger when peers possess greater absorptive capacity and financial flexibility. Legal constraints dampen expansion following complementary patent grants and intensify the redirection of innovation following rivalrous patent grants.

Keywords: Patent; Technological Complementarity; Product-Market Rivalry; Innovation; Absorptive Capacity; Financial Flexibility; Knowledge Diffusion.

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1. Introduction

When a firm (hereafter, a focal firm) is granted a patent, its peers face uncertainty about the implications of the innovation. The disclosure of a new invention can expand technological opportunities by revealing new knowledge, but it can also impose constraints by strengthening exclusive rights in overlapping technological domains. Whether a focal firm's innovation represents an opportunity or a threat depends on a range of underlying technological and competitive relationships—such as complementarities, product-market rivalry, and the peer firm's own capacity to adapt.

Consider Apple's "Slide to Unlock" patent in October 2011, which was widely perceived as both a technological success and a competitive threat. Apple's stock price rose following the announcement, while the shares of its close competitors—Samsung and Motorola Mobility—declined. The market appeared to anticipate that Apple's design edge would strengthen its position in the smartphone interface market, tightening constraints on rivals. In contrast, Pfizer and BioNTech's collaboration during the development of mRNA vaccine technology showed how one firm's breakthrough can expand opportunities for others. BioNTech's scientific discovery and Pfizer's scale and distribution capacity were complementary, and both firms experienced positive stock market reactions to key patent-related milestones. These contrasting cases illustrate the central question motivating this paper: when does a focal firm's innovation diffuse as an opportunity, and when does it impose a constraint that redirects peers' innovation?

Understanding the nature of peers' responses to a focal firm's innovation is fundamental to theories of competition and technological progress. Classical models of competition and innovation offer conflicting predictions. With Arrow's (1962) replacement effect, competition enhances the incentive to innovate because the marginal benefit of cost reduction is greater for firms without monopoly power. Schumpeter (1942), by contrast, posits that concentration and market power facilitate innovation by allowing incumbents to appropriate returns. Aghion et al. (2005) reconcile these views through an inverted-U relationship between competition and innovation: moderate rivalry spurs technological races, but intense competition erodes incentives. Further, Bloom, Schankerman, and Van Reenen (2013) show that firms

connected in technology space experience two opposing forces—knowledge spillovers that foster growth and business-stealing effects that suppress it. These frameworks collectively highlight that the net impact of competition depends on both technological complementarity and market rivalry. Yet, empirical tests often treat innovation as endogenous and continuous, overlooking discrete shocks that clearly reveal opportunities or threats.

This paper exploits a specific and observable form of competitive shock: a focal firm’s patent grant that is recognized by financial markets as economically meaningful. Patent grants are well-suited to study this problem because they embody both disclosure and exclusivity. When a patent is granted, new knowledge becomes public through detailed claims and descriptions, but legal protection simultaneously limits imitation. Crucially, markets process these opposing dimensions in real time. Stock price reactions around patent grant dates capture investors’ collective interpretation of whether a particular innovation benefits or harms related firms. By conditioning on these market signals, I can distinguish between events interpreted as complementary—where diffusion and opportunity dominate—and those viewed as threatening—where exclusion and market-stealing prevail.

Thus, a natural starting point of the analysis is the stock market reaction of peer firms to focal firm’s patent grants. These reactions are informative about how economically meaningful such events are and how they are perceived by technologically related firms. Much of the prior literature studies the average effect of innovation shocks across broad samples of firms. For example, Bloom et al. (2013) document that innovation generates two opposing forces: positive knowledge spillovers and negative business-stealing effects. Because these forces operate simultaneously, average estimates may obscure substantial heterogeneity in how firms respond to innovation. Recent work by Haddad et al. (2022) further emphasizes that stock-market reactions to innovation may differ across firms, arguing that peers may overreact while focal firms underreact to innovation-related news. If market reactions merely reflect temporary mispricing, one would expect limited consequences for subsequent real outcomes. However, if these reactions contain information about future technological opportunities and competitive threats, they should predict meaningful adjustments in firms’ innovation strategies.

Examining the distribution of abnormal returns around peer patent grants reveals three key facts. First, the vast majority of patent grants generate little to no measurable market reaction, suggesting that most innovations are not economically significant. Second, among the subset of events that do trigger positively significant responses for the focal firm, peers' abnormal returns are dispersed on both sides of zero, indicating that focal firm's innovations can be interpreted as either opportunities or threats to the peers. Third, positive abnormal returns are more prevalent than negative ones for peer firms, implying that economically meaningful patent grants are, on average, more likely to be associated with value-enhancing spillovers than competitive displacement.

I exploit this heterogeneity in market reactions by using cumulative abnormal returns (CARs) around patent grant dates for both the patenting firm and its technological peers. Following Testoni (2022), CARs are computed over a five-trading-day window centered on the patent grant date, capturing investor responses as legal uncertainty is resolved and exclusion rights become enforceable. The sign of these returns serves as a contemporaneous measure of perceived complementarities versus rivalry. When both the focal firm and peer firms experience positive abnormal returns (AR+), markets infer that the new patent opens opportunities for diffusion, collaboration, or complementary investment. When the peer firms' return is negatively significant (AR-), while the focal firm's abnormal return is significantly positive, investors perceive the patent as threatening—potentially by foreclosing technological routes or intensifying product-market competition. I refer to these events as AR+ and AR- peer patent grants, respectively, and describe their formal construction in a later section. This approach shifts attention from *ex post* indicators of innovation value, such as citation counts or breakthrough classification, to contemporaneous market interpretation—an inherently forward-looking and strategic dimension of innovation dynamics.

Empirically, I construct a sample of U.S. publicly traded firms between 2001 and 2021 and identify technologically connected peers using two criteria: co-location in Cooperative Patent Classification (CPC) subclasses and direct citation links between their patents. These dual filters ensure that peers share overlapping technological domains and genuine knowledge flows. For each peer pair, I examine how a focal firm's patent grant affects the peers' subsequent innovation activity, acquisition behavior, and

financing choices. To address endogeneity in the timing of focal firm's patent grants, I exploit variation in examiner leniency as an instrumental variable. Patent examiners differ systematically in their propensity to approve applications, and firms are quasi-randomly assigned to examiners within art units (Farre-Mensa et al., 2020). This leniency-based instrument provides exogenous variation in whether a peer receives a grant, allowing me to estimate the causal impact of focal firm's patent approvals on peers' strategic responses.

The results reveal clear evidence of the opportunity and threat channels. When market reactions indicate complementarity (AR+), peers increase both R&D investment and acquisition activity in the years following the focal firm's patent grant. The effects are stronger among peers with high innovation capability, consistent with absorptive capacity arguments (Cohen and Levinthal, 1990). The magnitude is economically meaningful: R&D investment rises by roughly 7–8 percent relative to baseline, while the probability of engaging in an acquisition increases by about 5 percentage points. These patterns are consistent with diffusion-driven expansion, where knowledge flows between technologically connected firms lead to co-investment in innovation.

In contrast, when market reactions indicate rivalry (AR–), peers exhibit a different kind of adaptive behavior. Instead of withdrawing from innovation, they redirect their inventive efforts toward new technological domains. Specifically, I find that the number of patent filings does not change after AR– patent grants, but the new patents are more likely to appear in CPC subclasses where the firm had little or no prior activity. The exploration ratio—defined as the share of patents filed outside the firm's preexisting top three CPC categories—rises significantly, indicating that peers diversify into unfamiliar technological spaces. This pattern aligns with theories of defensive or exploratory innovation (Christensen, 1997; Adner and Snow, 2010; Danneels, 2004), in which firms respond to competitive threats by exploring new areas rather than contesting existing ones. Thus, AR– does not imply passivity but a reallocation of innovative effort away from direct rivalry.

The diffusion channel also extends beyond R&D and acquisitions to financing behavior. After AR+ patent grants, peers increase net equity issuance, defined as gross issuance minus repurchases and dividends, suggesting that they raise external capital to support their strategic response. Consistent with this

interpretation, R&D investment also increases following these shocks. The increase in R&D accounts for a meaningful share of the rise in equity issuance, although it does not fully explain it. This pattern is consistent with the view that firms raise external capital in part to support innovation activity, while also potentially funding other investment or adjustment margins. One possibility, suggested by models of financing-driven innovation (Brown and Petersen, 2011; Hall and Lerner, 2010), is that equity issuance supports lumpy investments such as R&D expansion or acquisition activity. The financing response thus complements the innovation response, revealing that peers not only recognize opportunities but mobilize resources to act on them.

Peers' responses also depend on their financial flexibility and the legal environment surrounding the focal firm's innovation. Financially flexible peers respond more strongly to patent grants, consistent with greater capacity to finance innovation and strategic adjustment. Legal constraints further shape how peers respond to competitive threats. Using the focal firm's post-grant patent thickening and industry-level patent litigation risk to capture these constraints, I find that peers are more likely to redirect their innovation when competing within the protected technological domain becomes more costly. Together, these results show that peers' responses depend not only on how they interpret a focal firm's innovation, but also on their ability to respond and the constraints they face in doing so.

The evidence further indicates that diffusion is not uniform across the technological frontier. Drawing on recent work by Akcigit and Ates (2023), who document a slowdown in knowledge diffusion and concentration of innovation among frontier firms, I test whether responses differ by technological distance to the frontier. Results suggest that peers closer to the frontier, measured by the number of forward citations received by their patents in recent years, exhibit stronger AR⁺ responses, consistent with greater absorptive capacity. By contrast, laggard peers show muted or delayed reactions, reflecting barriers to diffusion. Moreover, industries with higher concentration of patenting among leaders display weaker spillover effects, implying that knowledge diffusion becomes more constrained with industry concentration. These patterns reinforce the view that innovation outcomes depend not only on the nature of technological shocks but also on the institutional and structural capacity to absorb them.

Beyond firm heterogeneity, I provide a unifying lens for interpreting competing empirical findings in the innovation literature. Studies emphasizing positive peer effects (e.g., Bena and Simintzi, 2019) and those highlighting negative competitive effects (e.g., Megna and Klock, 1993; Galasso and Schankerman, 2015) can be reconciled by recognizing that the market’s interpretation mediates whether a peer’s success is viewed as a complement or a substitute. Market reactions condense dispersed information about technological fit, product substitutability, and strategic expectations into a measurable signal. By conditioning on this signal, one can trace how opportunities diffuse through technological networks and when they stop at the boundaries of rivalry.¹²

The analysis also sheds light on the informational role of financial markets in indicating the direction of innovation. Prior work has shown that stock prices reflect the expected value of firms’ own innovations (Kogan et al., 2017; Kelly et al., 2021). This study extends that logic to peer innovations, demonstrating that markets not only price peer innovation but also indicate how it will propagate through related firms. Market reactions provide a forward-looking forecast of whether new technology will diffuse collaboratively or generate competitive displacement.

Taken together, the findings make three main contributions. First, the paper introduces a framework that conceptualizes focal firm’s patent grants as dual indicators of opportunity and constraint. This framework links the diffusion of knowledge to measurable market outcomes and clarifies how technological overlap and product market rivalry jointly shape the direction of innovation. Second, it provides causal evidence on how peers adjust their innovation and financing strategies in response to focal firm’s patent grants, leveraging variation in patent examiner leniency to address endogeneity. Third, it highlights that diffusion

¹ Empirically, positive peer valuation shocks are substantially more common than negative ones. In my sample, among the selected significant events, most focal firm’s patent grants are associated with significantly positive abnormal returns for the focal firm, and conditional on such events, peers’ market valuation responds positively about two-thirds of the time.

² In this sense, this paper is closely related to Bloom, Schankerman, and Van Reenen (2013), who distinguish between two opposing forces operating across firms: positive knowledge spillovers arising from proximity in technology space and negative business-stealing effects arising from proximity in product-market space.

is conditional—facilitated by technological complementarity and absorptive capacity, but limited by rivalry and institutional frictions.

The implications extend beyond firm strategy to the broader dynamics of innovation and competition. When knowledge diffusion is constrained by rivalry or concentrated among a few frontier firms, the aggregate pace of innovation may slow, contributing to patterns of reduced business dynamism and rising technological inequality. Conversely, environments that foster complementarity and reduce barriers to diffusion can amplify the collective benefits of innovation. Whether a patent acts as a bridge for diffusion or a barrier to competition depends not on subjective interpretations but on the objective relationships and capabilities it reveals. Market reactions provide information about these underlying conditions, and firms' subsequent behavior confirms them. By linking financial-market responses to real adjustments in innovation and financing, this paper provides a new lens on how technological progress spreads—or fails to spread—across interconnected firms in competitive markets.

The remainder of this paper is structured as follows: Section 2 develops the conceptual framework and the main hypotheses. Section 3 describes the data sources and outlines the empirical methodology. Section 4 presents empirical results. Section 5 provides robustness tests for empirical analyses. Section 6 concludes and discusses implications for future research.

2. Conceptual Framework and Hypotheses

Innovation occurs in an environment characterized by interdependence among firms. Firms rarely innovate in isolation; their technological progress both influences and is influenced by the inventive activity of others. Patents formalize this interdependence. Each grant discloses new knowledge that may stimulate complementary research, but it also defines boundaries that constrain imitation and intensify competition. The dual nature of patents—as conduits for knowledge diffusion and as instruments of exclusion—underlies the framework developed in this paper. I conceptualize a focal firm's patent grant as a discrete innovation shock whose impact on peers depends on (i) the nature of their technological and product-market

relationships, and (ii) the extent of their absorptive and financial capacity to respond. Market reactions around grant events, observed through abnormal returns, provide real-time indicators of whether these relationships are characterized by complementarity or rivalry.

The framework builds on three well-established ideas. First, the diffusion of knowledge depends on proximity in technology space. Cohen and Levinthal (1990) define absorptive capacity as a firm's ability to recognize the value of external information, assimilate it, and apply it to commercial ends. Peers with similar technological expertise are better positioned to understand and exploit the knowledge revealed in a focal firm's patent. Second, diffusion is constrained by rivalry in product markets. Bloom, Schankerman, and Van Reenen (2013) decompose cross-firm externalities into positive spillovers and negative business-stealing effects using measures of technological proximity and product-market rivalry, respectively. The balance between these forces determines whether innovation spreads or stalls. Third, peers' actions are bounded by financial capacity and strategic flexibility. Even when opportunities exist, exploiting them requires resources and commitment. Peers with stronger balance sheets can respond more aggressively to positive opportunities, while those facing leverage constraints or financing frictions may not.

To integrate these forces, I formalize the peer response as a function of two latent dimensions: technological complementarity and product rivalry. The first dimension captures the extent to which two firms share or can leverage related technological capabilities; the second reflects the degree to which they compete in overlapping product markets. A focal firm's patent grant alters the peers' expected returns from innovation by affecting both dimensions. The net effect depends on which channel dominates. When technological complementarity prevails, peers perceive the grant as an opportunity for diffusion; when rivalry dominates, the grant constitutes a constraint that encourages redirection. The resulting strategic response—expansion or reallocation—can be inferred from market reactions that aggregate investors' assessments of these relationships.

Figure 1 illustrates the diffusion–constraint space. Along one axis lies technological complementarity, proxied by the degree of technological overlap and absorptive capacity; along the other lies product-market rivalry. The diffusion of innovation occurs in the upper-left region—where complementarity is high and

rivalry moderate. In this region, a focal firm's patent disclosure expands the opportunity set for peers, encouraging R&D investment and capability acquisition. As rivalry intensifies, diffusion becomes constrained: the incentives to imitate or build upon the focal firm's innovation diminish as the expected returns from such activity fall. At extreme levels of rivalry, peers may instead pivot toward differentiated technological areas, seeking to reduce exposure to direct competition.

The market reaction to a focal firm's patent grant serves as an empirical map of this space. Positive abnormal returns for both the focal firm and the peer firms (AR+) indicate that complementarity dominates rivalry, forecasting diffusion and co-investment in innovation. Negative abnormal returns for the peer firm (AR-), when the focal firm's reaction is positive, indicate that rivalry dominates, forecasting displacement and redirection. The absence of a significant reaction suggests neutral or distant relationships where neither complementarity nor rivalry is strong. By linking firm-level market reactions to subsequent innovation outcomes, the diffusion-constraint framework provides an interpretable bridge between theoretical models of competition and observable behavior.

When focal firm's patents generate positive abnormal returns for both the focal firm and the peers, they indicate that markets forecast diffusion through technological complementarities. The disclosure of new knowledge reveals potential synergies in production or research processes, and the peer expands its innovative activity accordingly. Two mechanisms drive this response.

1. Learning and absorptive capacity: peers with high technological overlap are better able to interpret and integrate the knowledge revealed by a focal firm's patent. The proximity of technological expertise allows these peers to recombine existing capabilities with newly disclosed ideas, leading to incremental or follow-on innovation. The canonical formulation of absorptive capacity (Cohen and Levinthal, 1990) predicts precisely this pattern—firms invest more in innovation when they are close enough to external knowledge sources to understand and use them effectively.

2. Complementarity in strategic assets: focal firm's patents may create new opportunities for collaboration, licensing, or acquisition. When technologies are complementary, joint or sequential development can enhance returns for peers. This mechanism aligns with theories of innovation networks

and the accumulation of innovation capital (Hall and Lerner, 2010; Bena and Li, 2014). Positive market reactions thus forecast that new knowledge will diffuse through cooperative or parallel efforts rather than through competitive displacement.

Empirically, opportunity responses should manifest as increases in R&D spending, acquisition activity, and related investments following AR+ peer grants. The magnitude of these responses should rise with the degree of technological complementarity and the peer's absorptive capacity, and weaken when rivalry is high.

Hypothesis 1-a (Opportunity Response): Peers increase innovative activity—measured by R&D expenditure and acquisitions —following focal firm's patent grants associated with positive abnormal returns (AR+).

Hypothesis 1-b (Complementarity/Product Market Rivalry Moderation): The positive effect of AR+ patent grants on innovation is stronger for peers with high technological overlap and weaker for peers facing intense product-market rivalry.

When a focal firm's patent triggers a positive reaction for the innovator but a negative reaction for the peer, markets forecast competitive displacement. The patent is viewed as strengthening the focal firm's position in a shared market or technological domain, reducing the peer's expected profitability. In this context, the peer faces a choice between contesting the domain—by investing defensively in similar technologies—or redirecting its efforts toward less contested areas. Empirically, I find that peers choose the latter path.

Rather than reducing overall patenting, peers exposed to AR– peer grants increase innovation in new technological fields. The exploration ratio—the fraction of new patents filed outside the peer's pre-existing top CPC classes—rises following AR– events, indicating deliberate diversification of research activity. This

behavior is consistent with theories of strategic reorientation under threat (Christensen, 1997; Adner and Snow, 2010). Redirection reflects an attempt to restore differentiation by moving into less contested territories rather than directly imitating the protected innovation.

Redirection is also shaped by legal constraints that limit a peer's ability to continue operating in the newly protected domain. When a focal firm's patent strengthens exclusionary rights over a technological area, peers facing greater exposure to infringement risk or narrower freedom to operate have fewer viable options for competing along their existing trajectory. In such settings, redirecting inventive effort toward alternative technologies becomes a more attractive—and sometimes necessary—strategic response. Consequently, the likelihood and scope of redirection depend on the extent to which legal constraints restrict a peer's ability to innovate within the protected domain.

Hypothesis 2-a (Redirection Response): *Peers increase innovation in new technological domains—measured by the exploration ratio—following focal firm's patent grants associated with negative abnormal returns (AR⁻).*

Hypothesis 2-b (Legal Constraint): *The redirection response to focal firm's patent grants associated with negative abnormal returns (AR⁻) is stronger when legal constraints are stronger.*

Innovation requires not only knowledge but also financing. Even when opportunities arise through diffusion, resource constraints may limit peer's ability to respond. Following AR⁺ patent grants, peers anticipate higher returns to innovation and expand innovative activity, increasing their financing needs. To the extent that these investments cannot be fully financed with internal funds, peers may turn to external capital.

Equity financing can be particularly useful for innovation investment because innovation projects rely

heavily on intangible assets, such as knowledge and human capital, that are difficult to pledge as collateral (Acharya and Xu, 2017; Brown et al., 2009, Brown and Petersen, 2011; Hall, 2002). Peers may rely on internal cash to fund investment, especially when they have sufficient liquidity. However, internal funds may not always fully accommodate an expansion in innovation, particularly when investment needs increase sharply or when peers seek to preserve financial flexibility. In such cases, peers may turn to external financing to complement internal resources. This channel is especially relevant when focal firm's patent grants are associated with positive abnormal returns (AR+), as firms can raise external equity on more favorable terms. I therefore expect the stronger expansion in innovative activity following AR+ grants to be accompanied by greater equity issuance.

Financial flexibility, however, extends beyond access to equity markets. Balance-sheet capacity—captured by internal cash holdings and unused debt capacity—shapes how effectively peers can adjust their real activities following a focal firm's innovation. When a focal firm's patent is interpreted as favorable, financially flexible peers are better positioned to expand R&D, pursue follow-on innovation within the same technological domains, and engage in technology-related acquisitions. When a focal firm's patent is interpreted as unfavorable, financial flexibility similarly enables peers to absorb risk and redirect inventive effort toward new technological domains. Thus, financial flexibility governs both peers' ability to capitalize on diffusion opportunities and their capacity to adapt to competitive threats.

Hypothesis 3-a (Financing Response): Peers increase net equity issuance following focal firm's patent grants associated with positive abnormal returns (AR+).

Hypothesis 3-b (Role of Financial Flexibility): Financial flexibility—measured by higher cash holdings or lower book leverage—intensifies peers' responses to focal firm's patent grants.

Not all peers are equally positioned to benefit from diffusion. Recent research documents a slowdown in knowledge diffusion and an increasing concentration of innovation among technological leaders (Akcigit and Ates, 2023). This asymmetry aligns with the broader theoretical insight—emphasized in Aghion et al. (2005) on frontier competition—that a firm’s proximity to the technological frontier fundamentally shapes its innovation incentives. In Aghion et al. (2005), frontier firms respond more strongly to growth opportunities because they possess the capabilities, organizational flexibility, and accumulated knowledge needed to exploit them, whereas laggard firms face weaker incentives and greater adjustment costs. Within the diffusion–constraint framework, these patterns emerge naturally: frontier peers, endowed with recent knowledge stocks and more adaptive R&D structures, can absorb and leverage focal firm’s innovations more effectively, while laggard peers face higher costs of assimilation and weaker expected returns.

Consequently, diffusion following AR+ events should be strongest among frontier peers and weakest among laggard peers. This heterogeneity also implies an asymmetry in the propagation of innovation: knowledge disclosure may reinforce existing technological hierarchies rather than leveling them. Similarly, industries with high concentration of patenting activity among a few leaders are likely to exhibit weaker spillover effects because the remaining firms are both technologically distant and competitively constrained.

Hypothesis 4-a (Frontier Advantage): *Peers closer to the technological frontier exhibit stronger opportunity responses to AR+ patent grants.*

Hypothesis 4-b (Concentration Constraint): *The diffusion effects of focal firm’s patent grants weaken as the concentration of patenting among leader firms increases.*

Focal firm’s patent grants can influence not only the scale of peers’ innovation investment but also the production of innovation output. Importantly, the effect on patenting is not confined to a single type of market interpretation. When a focal firm’s patent generates positive reactions (AR+), it can signal

technological complementarity or shared opportunity, prompting peers to accelerate the conversion of ongoing research into patentable inventions. Conversely, when a focal firm's patent is interpreted as a competitive threat (AR–), peers may respond by intensifying their patenting activity—either to secure freedom to operate, to block competitors, or to preserve their strategic position within a contested technological space. Thus, both opportunity-driven and threat-driven mechanisms can increase the likelihood that peers produce patent filings in the aftermath of peer innovation events.

Focal firm's patent grants may also affect the direction of the peers' innovation output, not just its quantity. Focal firm's innovations can reveal promising knowledge domains or identify complementary development paths, influencing where peers choose to place their inventive effort. As a result, peers may concentrate their patenting activity toward similar technological areas, especially when building on shared scientific foundations or seeking interoperability. This directional alignment, however, is most likely when the market interprets a focal firm's patent as beneficial for peers (AR+), indicating technological complementarity rather than competitive threat. When AR+ signals that the new invention is compatible with the peers' capabilities, peers have stronger incentives to align their subsequent innovation efforts with the focal firm's technological trajectory. Prior studies show that citation-based similarity captures both knowledge spillovers and convergence in search behavior in technologically related networks (Jaffe et al., 1993; Azoulay et al., 2010).

Hypothesis 5-a (Patenting Response): *Peers are more likely to file patents following focal firm's patent grants.*

Hypothesis 5-b (Directional Alignment): *For AR+ patent grants, peers' subsequent patents are more likely to cite similar prior art as the focal firm's patent.*

Taken together, these hypotheses articulate a diffusion–constraint framework of peer responses to

innovation. A focal firm’s patent grant constitutes a technological shock whose implications vary across firm relationships and capacities. I use market reactions around the grant to classify the state of the world—whether complementarity or rivalry dominates—and examine how peers adjust along both innovation and financing margins. Peers with high technological overlap and absorptive capacity expand innovation following positive shocks, while peers facing rivalry or constraints primarily redirect their efforts. Financial flexibility governs the ability to act on either margin, amplifying expansion or enabling redirection.

This framework builds on, but goes beyond, existing work. Prior studies have identified key mechanisms in isolation: spillovers versus rivalry (Bloom, Schankerman, and Van Reenen (2013)), absorptive capacity (Cohen and Levinthal (1990)), and the uneven diffusion of innovation (Akcigit and Ates (2023)). This paper integrates these mechanisms within a unified empirical design that (i) uses market-based signals to classify the nature of innovation shocks, (ii) traces peer responses along both the scale and direction of innovation, and (iii) links these responses to financing decisions. In doing so, it provides a joint account of how technological shocks propagate across firms and how those responses are funded.

In summary, the diffusion–constraint framework predicts that the propagation of innovation is conditional and asymmetric. When complementarity dominates and capacity is sufficient, peers respond with joint expansion in innovation and financing. When rivalry dominates and capacity is constrained, peers primarily redirect their efforts. These conditional dynamics generate distinct patterns across R&D, acquisitions, financing, and technological exploration, which form the basis of the empirical analysis.

3. Data and Empirical Design

This section describes the data sources, peer definitions, and key variables used in the empirical analysis, and outlines the empirical design. I first explain how to construct a sample from the data sources and describe how technological peer relationships are defined. I then present the construction of the main variables, including abnormal returns around patent grant dates, and provide descriptive statistics characterizing the sample.

For the empirical design part, I begin by outlining the baseline specification using stacked difference-in-differences (DiD), followed by an instrumental variable approach to address endogeneity concerns. I then describe the empirical framework used to study peer responses to significant patent grants and conclude with a triple-difference design used to examine heterogeneity across firms and environments.

3.1 Sample construction using the Patent dataset

I construct the patent dataset by merging information from three complementary sources: (1) the Duke Innovation & Scientific Enterprises Research Network (DISCERN) database (Arora et al., 2021), (2) the PatentsView database, and (3) the Patent Examination Research Dataset (PatEx) (Graham et al., 2015).

The DISCERN Version 2.0 dataset includes patents granted by the U.S. Patent and Trademark Office (USPTO) between 1980 and 2021. A key advantage of this dataset is that it provides firm-level linkages to Compustat, enabling accurate assignment of patents to publicly traded firms. The database accounts for both firm name changes and patent ownership transfers, which are central challenges in identifying the correct owner of a patent over time. From the PatentsView database, I obtain detailed patent citation links, which allow me to trace the technological relationship between patents and to construct measures of technological proximity to frontiers. The PatEx dataset provides detailed information on the patent application and examination process, drawing from the Public Patent Application Information Retrieval (Public PAIR) system. PatEx includes variables covering the characteristics of inventions, applicants, attorneys, and examiners, along with a full history of procedural events and status codes throughout the examination process. This dataset is crucial for constructing measures of patent examiner leniency, which will later serve as part of an instrumental variable. I merge these three datasets using patent identifiers and restrict the sample to patents granted after the year 2000. This mitigates selection concerns stemming from the pre-2000 practice where applicants could opt to keep their applications non-public. The American Inventors Protection Act (AIPA), implemented in late 2000, introduced standardized publication procedures that significantly improved data coverage and representativeness for patent applications.

I obtain firm-level financial and organizational characteristics from Compustat and merge with the patent

data using firm identifiers provided in the DISCERN database. These variables include standard controls such as firm size (log of total assets), firm age, Tobin's Q, leverage, and cash holdings. Detailed variable definitions are provided in the appendix. Incorporating Compustat data allows me to link patenting activity to firms' balance sheet characteristics and to control for heterogeneity in firms' capacity and incentives to respond to peer innovation signals throughout the analysis.

The final sample consists of all U.S.-based publicly traded firms that were granted at least one patent between 2001 and 2021.³ Consistent with prior literature, I exclude firms in highly regulated or structurally distinct industries, including utilities (Standard Industrial Classification [SIC] codes 4900–4999), financial institutions (SIC 6000–6999), and organizations classified under public services, international affairs, or non-operating establishments (SIC 9000 and above). These exclusions help ensure comparability across firms in terms of innovation incentives and competitive dynamics. All asset-based and financial variables are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers. After applying these filters and merging across datasets, the final panel includes 445,451 firm–peer–year observations, representing 3,569 unique firms.

3.2 Defining Peer relationships

To identify peer relationships between firms, I rely on the Cooperative Patent Classification (CPC) system, which categorizes patents based on technological content using a hierarchical structure. The CPC system is jointly developed by the United States Patent and Trademark Office (USPTO) and the European Patent Office (EPO), and provides a fine-grained taxonomy of technological domains.

The CPC hierarchy consists of multiple levels. At the top level are sections, which are broad technology domains. Each section is divided into classes, and each class is further divided into one or more subclasses, representing more granular areas of technological specialization. In my sample, there are 105 unique classes and 667 unique subclasses. Figure 2 illustrates the structure of the CPC hierarchy and provides a

³ We need at least one patent grant during the sample period to identify the peer firms.

representative snapshot of the classification breakdown.

Using this classification framework, I define a technological peer relationship between two firms based on two criteria, both evaluated over a five-year rolling window prior to the focal firm's patent grant. First, both firms must have been granted at least one patent in the same CPC subclass during the previous five years, indicating sustained activity within a similar technological space rather than a transitory or incidental overlap. Second, within this same five-year window, at least one patent from one firm must cite a patent granted to the other firm, indicating a realized and economically meaningful technological linkage through prior innovation activity. This dual condition helps ensure that identified peer firms are not only active in related domains but are also technologically connected through innovation activity.

This definition is well suited for identifying technologically meaningful peer relationships. First, requiring overlap in CPC subclasses ensures that peer relationships are formed within narrowly defined technological domains, rather than broad industry classifications that may group together firms with fundamentally different innovation activities. Because CPC subclasses are designed by patent examiners to capture fine-grained technological content, this criterion provides a precise mapping of firms' innovative focus and filters out spurious peer links that arise from coarse industry or product-market classifications.

Second, incorporating patent citation links strengthens the peer definition by capturing realized technological connections rather than potential similarity alone. Patent citations reflect instances in which prior inventions are directly relevant to subsequent innovation, providing evidence of knowledge flows, technological dependence, or cumulative innovation processes. By requiring at least one directional citation between firms, this approach ensures that peer relationships are grounded in actual innovation interactions, rather than passive co-location in the same technological space.

3.3 Variable Construction

This subsection describes the construction of the core variables used in the analysis. I begin by introducing abnormal stock returns around peer patent grant dates, which serve as a market-based measure of the economic significance and direction of innovation shocks. I then describe the instrumental variable—

patent examiner leniency—used to address endogeneity in peer patent grants. Finally, I outline the peers’ patent outcome variables following these shocks. In subsequent subsections, I introduce additional measures that capture heterogeneity in technological complementarity, product-market rivalry, and legal enforcement risk, as well as acquisition activity and firm characteristics, which are used to study mechanisms and cross-sectional variation in peers’ responses.

3.3.1 Patent stock price reactions

This paper measures the economic significance of patent grants using stock market reactions around the grant date. A growing literature shows that abnormal stock returns provide a forward-looking measure of the value of innovation by capturing how investors update expectations about future cash flows and competitive positioning. In particular, Kogan et al. (2017) demonstrate that firm-value changes around innovation events contain information about the economic importance of patents.

An important advantage of this approach is that it is observable in real time, precisely when the patent grant occurs. In contrast, commonly used measures of patent importance—such as citation-based metrics or textual novelty measures (e.g., Kelly et al. (2021))—are realized only ex post and are not available at the time of the grant.

I use cumulative abnormal stock returns (CAR) around the focal firm's patent grant as a market-based measure of significance. Following Testoni (2022), CAR is measured over a window starting two trading days before the patent grant and ending two trading days after. I estimate the market model over a 250-trading-day window that ends 42 trading days prior to the patent grant, using the CRSP value-weighted market return as the market return.⁴ Abnormal returns are the residuals from this predicted return, and cumulative abnormal returns are calculated by summing the daily abnormal returns over a five-trading-day

⁴ I require a minimum of 100 non-missing return observations during the estimation window and complete return data for all five days in the event window.

window surrounding the patent grant date. I classify a patent grant as significant if the absolute value of its CAR exceeds two standard deviations based on the historical time-series variation in CARs.

For each granted patent, I compute cumulative abnormal returns (CARs) for both the patenting firm and its technologically related peer firms. The focus on the patent grant date—rather than the disclosure date—is deliberate. A grant formally certifies novelty and enforceability, converting a previously uncertain application into a legally protected technological asset. As a result, grant dates are the moments at which both legal rights and competitive implications become most salient to investors, making them natural candidates for identifying economically meaningful innovation shocks.⁵⁶

The distribution of abnormal returns around patent grant dates is sharply centered around zero and exhibits substantial skewness. For the majority of patent grants, CARs for both the granting firm and its peers are economically small and statistically indistinguishable from zero. This pattern reflects the fact that most patents are incremental, narrowly scoped, or strategically marginal, and therefore do not materially alter market expectations about firm value or competitive dynamics.

However, the distribution also features fat tails. A subset of patent grants generates large positive or negative abnormal returns, both for the granting firm and for its technologically related peers. These economically significant events are infrequent but economically important. They correspond to patents that markets interpret as meaningfully shifting technological trajectories, competitive positions, or expected future cash flows. Importantly, these reactions are heterogeneous: large positive reactions for the granting firm are sometimes accompanied by positive reactions for peers, but in other cases coincide with sharply negative peer responses.

This heterogeneity is central to the paper’s approach. Treating all patent grants as homogeneous shocks

⁵ One potential concern is that peers may instead respond when patent applications are disclosed rather than when patents are granted. I examine this possibility in a later robustness analysis and find no evidence of comparable responses around disclosure dates.

⁶ Because abnormal returns may also reflect other contemporaneous corporate news, Section 5 re-estimates the analysis after excluding patent grants occurring near earnings announcements.

would average over fundamentally different events and obscure the mechanisms through which focal firm's innovation affects peers' behavior. Instead, the abnormal return distribution itself reveals which patent grants are salient and how their implications differ across firms.

Abnormal returns around focal firm's patent grants can be interpreted as the market's assessment of two competing forces inherent in innovation: knowledge diffusion and competitive displacement. Positive abnormal returns for the focal firm indicate that investors expect the patent to enhance the innovator's future profitability, either through superior technology, stronger exclusion rights, or improved product positioning. The reaction of the peer's stock price then reveals how that same innovation is expected to affect related firms.

When the peer's abnormal return is also positive, markets appear to anticipate that the focal firm's innovation creates opportunities for diffusion, complementarities, or shared growth. Such anticipation is expected when firms operate in adjacent technological spaces, rely on similar scientific foundations, or benefit from common downstream demand. In contrast, when the peer's abnormal return is negative, markets interpret the focal firm's patent as a competitive threat—one that is expected to erode the peer's rents, constrain its technological options, or intensify rivalry in overlapping product markets. These interpretations are inherently forward-looking. Unlike citation counts or realized product outcomes, abnormal returns reflect expectations about future strategic interactions, legal constraints, and the reallocation of innovative effort.

To operationalize these insights, I use the joint distribution of abnormal returns for the focal firm and its peer to classify focal firm's patent grants into economically meaningful categories. Specifically, I define two types of patent grant events based on economically significant market reactions:

1. AR⁺ patent grants

A focal firm's patent grant is classified as AR⁺ if both the focal firm and its peer experience abnormal returns that are at least two standard deviations above the mean CAR in the $[-2, +2]$ window. These events indicate that markets expect the innovation to create value for both firms, consistent with

technological complementarity, knowledge spillovers, or mutually reinforcing innovation paths.

2. AR^- patent grants

A focal firm's patent grant is classified as AR^- if the focal firm experiences a significantly positive abnormal return while its peer experiences a significantly negative abnormal return—two standard deviations below the mean—over the same event window. These events indicate that markets view the innovation as strengthening the focal firm at the expense of its peer, consistent with business-stealing effects, exclusion, or intensified product-market competition.

The classification relies on economically significant events in the distribution of abnormal returns. The use of economically significant events reflects the empirical distribution of abnormal returns: only a small fraction of events generate clear and interpretable market signals. By focusing on these economically significant events, the analysis isolates patent grants that are most likely to induce strategic responses by peer firms.

Abnormal returns play a central role in the empirical design of the paper. First, they provide a market-based measure of economic significance, allowing the analysis to distinguish between routine patent grants and those that meaningfully affect expectations of the firm's future cash flows and their risk. Second, they offer a directional classification that separates focal firm's innovations perceived as opportunities from those perceived as threats.

This approach avoids imposing assumptions about whether focal firm's innovation is beneficial or harmful *ex ante*. Instead, it conditions on how markets interpret each event in real time. Subsequent analyses examine how peers adjust R&D investment, acquisition activity, financing decisions, and the direction of innovation following AR^+ versus AR^- patent grants. By doing so, the paper links market-based assessments of innovation to real economic adjustments, providing a unified framework for understanding when and how focal firm's innovations diffuse or constrain peers' behavior.

3.3.2 Instrument: Examiner Leniency

To address endogeneity concerns in focal firm's patent grants, I instrument for focal firm's patent grant using the leniency of the patent examiners assigned to review the focal firm's patent applications. The idea is that some examiners are systematically more likely than others to approve patents, even within the same art unit and year.

Following Farre-Mensa et al. (2020), I use this quasi-random variation in examiner approval tendencies to construct an instrument for whether the focal firm receives a patent grant. Specifically, I measure examiner leniency at the examiner–art unit–year level as the fraction of applications reviewed by examiner k in art unit a and year t that are granted:

$$EL_{kat} = \frac{n_{kat}^{granted}}{n_{kat}^{reviewed}}$$

where EL_{kat} denotes the leniency of examiner k in art unit a during year t . $n_{kat}^{granted}$ is the number of patent applications granted by examiner k in art unit a in year t . $n_{kat}^{reviewed}$ is the total number of applications reviewed by the examiner in the same unit and year. I then aggregate examiner leniency by computing a weighted average of examiner-level leniency scores. The weight corresponds to the number of patents each examiner reviewed for the focal firm in a given year. This aggregation reflects the average leniency faced by the focal firm across all its patent examinations during that year.

The first stage relates focal firm's patent grant activity to this examiner leniency measure. Intuitively, focal firms assigned to more lenient examiners should be more likely to receive patent grants, holding fixed other determinants of innovation outcomes. The identifying variation therefore comes from differences in the grant propensity of the examiners reviewing the focal firm's applications, rather than from the peers' innovation choices or financing policies.

This instrument is appealing because examiner assignment generates variation in focal firm's patent grant outcomes that is plausibly exogenous to the peers' activities. The second stage then uses the predicted component of focal firm's patent grant activity from examiner leniency to estimate how peers adjust their innovation and financing behavior in response to focal firm's innovation shocks.

3.3.3 Peers' Patent Outcome Variables

I next construct two variables that capture peers' patent outcomes. These variables are designed to reflect both the intensity and the direction of innovation output. The first variable, *PatentFiling*, measures the number of patent applications filed by a peer. The second variable, *CitShareOverlap*, captures the directional alignment of innovation by measuring the citation share overlap between a focal firm's patents and the peer's patents. For each patent granted to the peer, I calculate the proportion of backward citations that overlap with those made by the focal firm's patents. I then average this citation share overlap measure over a five-year window. That is,

$$CitShareOverlap_{ij[t,t+5]} = \frac{1}{N} * \sum_{p=1}^N \left[\frac{(|Citations_{i,p} \cap Citations_j|)}{|Citations_{i,p}|} \right]$$

where $CitShareOverlap_{ij[t,t+5]}$ is the citation share overlap between firm i and peer j in years $[t,t+5]$. N is the number of patents granted to firm i within a 6-year window. $Citations_{i,p}$ refers to the set of backward citations made by firm i 's patent p . $Citations_j$ refers to the set of backward citations made by the peer firm's patents.

The citation share overlap variable reflects whether peers shift their R&D focus toward similar technological domains. A higher degree of citation share overlap indicates stronger technological convergence and suggests that peers perceive the focal firm's innovation as strategically relevant or complementary to their own innovation paths.

3.3.4 Technological Complementarity and Product-Market Rivalry Measures

To capture technological complementarity between the focal firm and its peers, I use the lagged version of the citation share overlap measure defined in the previous subsection. A higher lagged citation share overlap indicates that two firms draw on closely related technological knowledge, enhancing the peer's ability to interpret, absorb, and potentially build upon the focal firm's newly disclosed innovation.

To measure product-market rivalry, I rely on the text-based product similarity score developed by Hoberg and Phillips (2016). I use the Text-based Network Industry Classification (TNIC2) developed by Hoberg and Phillips (2010, 2016). TNIC2 identifies pairs of firms with sufficiently similar product descriptions in their 10-K filings, providing a dynamic, text-based measure of product-market relatedness. For each focal firm–peer pair, I construct an indicator equal to one if the two firms are classified as TNIC2 peers in year $t-1$, and zero otherwise. Using the lagged classification ensures that product-market rivalry is measured prior to the focal firm’s patent grant. A value of one therefore indicates that the focal firm and peer operate in sufficiently similar product markets to be classified as direct product-market peers.

3.3.5 Legal enforcement risk variables

To capture the legal constraints surrounding follow-on innovation, I construct two measures: *Thicketing* and *LitigationRisk*. The first measure, *Thicketing*, captures the extent to which a focal firm becomes more active in filing patents following a patent grant—potentially to protect or consolidate its technological position. The measure is calculated as the change in the share of patent filings within the dominant CPC subclass, comparing an 18-month window after the grant $[t, t+18]$ to an 18-month window before $[t-18, t]$:

$$Thicketing_{jt} = \frac{Firm\ j's\ Patent\ filings\ in\ CPC_{[t, t+18]}}{Total\ Patent\ filings\ in\ CPC_{[t, t+18]}} - \frac{Firm\ j's\ Patent\ filings\ in\ CPC_{[t-18, t]}}{Total\ Patent\ filings\ in\ CPC_{[t-18, t]}}$$

A higher value of this measure indicates more aggressive patent filing activity in the dominant technological space, suggesting greater IP congestion or defensive behavior by the focal firm.

The second measure, *LitigationRisk*, is constructed at the industry level using data from the Patent Litigation Docket Reports. It is defined as the number of patent litigations filed among firms in the same industry in a given year, divided by the total number of patent holding firms in the industry:

$$LitigationRisk_{it} = \frac{Total\ patent\ litigations\ in\ industry\ i\ at\ time\ t}{Total\ number\ of\ patent\ holding\ firms\ in\ industry\ i\ at\ time\ t}$$

This measure captures the general legal environment and intensity of patent enforcement in a given technological space. Higher litigation risk reflects industries where patent-related disputes are more

frequent, potentially deterring innovation due to elevated enforcement uncertainty and costs.

3.3.6 Acquisition and firm characteristics

Data on acquisition activity are obtained from the SDC Platinum Mergers and Acquisitions database. I include all acquisitions completed from 2001, focusing on transactions in which the acquirer is a publicly traded U.S. firm. To capture meaningful ownership changes, I retain only deals classified as “Acquisition of Major Interest,” “Acquisition of Remaining Interest,” and “Acquisition.” I exclude transactions where the acquiring firm is privately held, as these firms cannot be linked to the financial and innovation data necessary for my analyses. Applying these filters, I identify a total of 8,542 completed acquisitions carried out by public firms.

3.4 Empirical Methods

To examine how peers respond to focal firm’s patent grants, I can estimate peer–focal–year panel regressions that exploit the timing of economically significant focal firm’s patent grants. The main outcome variables include R&D investment, acquisition activity, innovation output, and financing decisions.

A key empirical challenge is that focal firm’s patent grants occur at different times across firm pairs and may overlap within technological networks. Thus, a standard two-way fixed effects difference-in-differences (DiD) specification may produce biased estimates due to staggered treatment timing, contaminated control groups, and overlapping innovation shocks. To address these concerns, I adopt a stacked cohort difference-in-differences design that isolates each focal firm’s patent grant event and constructs clean control groups.

3.4.1 Baseline Specification: Stacked DiD with Market-Based Classification

For each peer–focal pair (i, j) , let τ denote the year in which focal firm j receives a patent grant. I construct cohort-specific event-time panels centered around τ , and compare treated observations to not-yet-treated controls within the same cohort. The baseline specification is:

$$Y_{ijt\tau} = \sum_{\{k \neq -1\}} \beta_{k\tau} [1\{t = \tau + k\} \times 1\{Grant_{\{j,\tau\}} = 1\}] + \Gamma' X_{\{i,\tau-1\}} + \delta_{i,\tau} + \mu_{st,\tau} + \varepsilon_{ijt,\tau}, \quad (1)$$

Where $Y_{ijt,\tau}$ denotes the outcome of peer i in year t linked to focal firm j , and k indexes event time relative to the focal firm's patent grant. The omitted category is $k = -1$. $X_{\{i,\tau-1\}}$ is a vector of lagged firm-level controls, $\delta_{i,\tau}$ denotes firm fixed effects, and $\mu_{st,\tau}$ denotes industry x time fixed effects. τ represents a cohort defined by the focal firm's patent grant year. Separate event-time panels are constructed for each cohort and then stacked together to estimate the overall treatment effect.

A central feature of the empirical design is that not all focal firm's patent grants have the same economic implications. To capture this heterogeneity, I classify patent grant events using abnormal stock returns around the grant date. Specifically, I distinguish between two types of economically significant focal firm's patent grants.

First, AR^+ events correspond to cases in which both the focal firm and its peer experience strongly positive abnormal returns around the grant date. These events are interpreted as opportunity shocks, consistent with technological complementarity, knowledge diffusion, or shared growth.

Second, AR^- events correspond to cases in which the focal firm experiences a strongly positive abnormal return while its peer experiences a strongly negative abnormal return. These events are interpreted as threat shocks, consistent with competitive displacement or exclusion.

I incorporate this classification directly into the baseline specification by interacting the treatment indicator with AR^+ and AR^- indicators:

$$Y_{ijt,\tau} = \beta_{1,\tau} [Grant_{\{j,\tau\}} \times AR^+_{\{ij\tau\}}] + \beta_{2,\tau} [Grant_{\{j,\tau\}} \times AR^-_{\{ij\tau\}}] + \beta_{3,\tau} * Grant_{\{j,\tau\}} + \Gamma' X_{\{i,\tau-1\}} + \delta_{i,\tau} + \mu_{st,\tau} + \varepsilon_{ijt,\tau}, \quad (2)$$

where $AR^+_{ij\tau}$, which equals 1 if both the focal firm j and its peer i experience abnormal stock returns that

are two standard deviations above the mean in a five-day window $[-2,+2]$ around the grant date. Section 5 further verifies that the estimated effects are tied to the timing of patent grants using placebo event dates.

3.4.2 Instrumental variable estimation

To mitigate concerns that focal firm's patent grants are correlated with unobserved shocks affecting the peer's outcomes, I complement the baseline design with a two-stage least squares (2SLS) approach that instruments for focal firm's patent grants using patent examiner leniency. The idea follows Farre-Mensa et al. (2020): conditional on application characteristics and fixed effects, some examiners are systematically more likely to allow patents, generating quasi-random variation in grant outcomes.

The first-stage regression relates the focal firm's patent grant indicator variable to its examiner leniency:

$$\mathbf{1}_{jt} = \alpha + \beta \text{Leniency}_{j,t-1} + \gamma X_{j,t-1} + \delta_j + \mu_{s,t} + \varepsilon_{j,t}, \quad (3)$$

This instrument captures exogenous variation in the likelihood of focal firm's patent grants, unrelated to peer's behavior. Second stage. I then estimate:

$$Y_{i,t} = \alpha + \beta_1 \widehat{\mathbf{1}_{jt-1}} * AR + \beta_2 \widehat{\mathbf{1}_{jt-1}} * AR - \beta_2 \widehat{\mathbf{1}_{jt-1}} * AR - \beta_2 \widehat{\mathbf{1}_{jt-1}} * AR + \gamma X_{i,t-1} + \delta_i + \mu_{s,t} + \varepsilon_{i,t}, \quad (4)$$

where $\widehat{\mathbf{1}_{jt-1}}$ is the predicted focal firm's patent grant from the first-stage regression. This IV strategy isolates variation in focal firm's patent grants arising from differences in examiner allowance tendencies, as in Farre-Mensa et al. (2020), and provides a complementary estimate of how peers respond to focal firm's innovation shocks.

3.4.3 Triple difference for heterogeneity analyses

Finally, I explore heterogeneity in peers' responses to focal firm's patent grants using a triple-differences

(DDD) framework. This approach allows me to test how the impact of focal firm's innovation depends on firm-specific capabilities as well as external constraints. The general form of the regression is:

$$Y_{ijt,\tau} = \alpha + \beta \mathbf{1}_{j\tau} * AR(+or -)_{ij\tau} * Z_{ij\tau} + \gamma X_{i,\tau-1} + \delta_{i,\tau} + \mu_{st,\tau} + \varepsilon_{ijt,\tau}, \quad (5)$$

where $Z_{ij\tau}$ (or in some cases just $Z_{i\tau}$) is a variable that moderates the effect of the focal firm's patent grant.

I examine three different types of variables:

1. Firm relationship – including technological complementarity (measured using prior citation-based relatedness with the peer) and product-market rivalry (proxied by product-market similarity from Hoberg and Phillips (2016))
2. Internal capabilities – including financial flexibility (proxied by cash holdings and leverage) and innovation capabilities (measured by using the number of citations the firm's patents receive from peer firms over the past five years).
3. Legal enforcement risk – proxied by (i) industry-level litigation intensity and (ii) focal firm's patent thickening behavior, as described in Section 3.3.5.

4. Empirical Results

4.1 Data Description

To better understand the landscape of peer relationships and innovation dynamics in my sample, I begin by characterizing the structure of technological peer networks. On average, each firm has approximately 3.8 peer firms per year, but this masks significant variation: about 12% of firms have only one peer, while over 13% have five or more. This heterogeneity underscores the importance of moving beyond simple industry classifications and instead using detailed patent-based linkages—based on CPC subclass and citation networks—to identify relevant competitive relationships.

To further illustrate the strategic relevance of significant patents in my sample, consider the case of Apple's "Slide to Unlock" patent (US 8,046,721), granted on October 25, 2011. This patent grant not only elicited a notable positive abnormal return for Apple itself but also triggered clear reactions from both the

focal firm and its peers—Samsung Electronics and Motorola Mobility experienced immediate negative abnormal returns in the days following the grant.

As shown in Figure 4, the market could have interpreted this patent as a strategic gain for Apple and a potential threat to firms operating in overlapping technological domains, especially those engaged in touchscreen interface development. This example captures the essence of why I focus on a subset of significant patents—defined as those that induce abnormal stock returns for both the granting firm and its technologically connected peers. Out of the 924,125 total granted patents to public firms in my dataset, only 6,341 patents meet this dual-market reaction criterion. By zeroing in on these high-salience events, I aim to isolate innovation signals that are immediately perceived by the market as strategically consequential. These events offer a rare window into when and how patent grants reshape competitive expectations in real time and thus provide ideal moments to test for firm-level strategic responses in innovation behavior.

4.2 Summary Statistics

Table 1 provides descriptive statistics for the main variables used throughout the empirical analysis. The sample includes 3,569 unique firms between 2001 and 2021.

Starting with the dependent variables, the average R&D investment is 8.4% of total assets, with a median of 0%, reflecting the highly skewed distribution of R&D activity. Despite the sample being restricted to patenting firms, a large fraction of firms report no R&D expenditures in a given year, consistent with prior literature documenting the lumpy nature of R&D investments. The variable *PatentFiling* has a mean of 2.31 patents filed annually, but a highly right-skewed distribution with a 90th percentile of 12 filings. *CitShareOverlap*, which measures the average share of overlapping citations between the focal firm's and its peer's patents over the next five years, has a relatively low mean of 0.038 and a median of 0.021, but a long right tail—highlighting the heterogeneity in firms' technological convergence with their peers. The *ExplorationRatio*—capturing the fraction of a firm's patents assigned to new CPC classes outside its top historical areas—is very close to zero for most observations, with a heavy right tail. This pattern suggests

that most firms continue to innovate within their established technological domains, while a small subset engages in meaningful exploration. The *NetEquityIssuance* variable, defined as stock sales minus repurchases and dividends scaled by lagged total assets, is heavily centered around zero with a long right tail, indicating that large external-equity financing events are infrequent but occasionally substantial.

Two variables capture the relationship between the focal firm and its peers. The first, Technological Complementarity, is measured using the lagged *CitShareOverlap*, which reflects the degree of technological similarity and potential knowledge spillovers between the two firms based on shared patent citations. The second, Product-Market Rivalry (*PMR*), is a dummy variable equal to one if the focal firm and its peer belong to the same industry according to the TNIC2 industry classification from Hoberg and Phillips (2016). A mean of *PMR* is 0.18, indicating that 18% of firm–peer pairs in my sample operate in the same product market, as defined by the TNIC2 industry classification.

The table also reports several interacting variables used to explore heterogeneous treatment effects. The *AR+* variable (equal to one when both the peer and focal firm experience significant positive abnormal stock returns) has a mean close to 0, reflecting the rarity of significant market responses. The *AR-* variable (equal to one when the focal firm experiences a significant positive abnormal return while the peer’s abnormal return is significantly negative) has a mean that is similarly low, indicating that sharply negative co-movements are also infrequent but economically meaningful when they occur. The limited variation in both *AR+* and *AR-* highlights that economically significant market responses to focal firm’s patent grants are infrequent events, consistent with the notion that only a subset of innovations generate clear, economically significant signals.

Two variables proxy for external constraints. *Thicketing* measure has a mean near zero but a notable spread, suggesting time variation in patenting intensity for focal firms. The *LitigationRisk* variable—constructed at the industry level—has a mean of 1.41 and a right-skewed distribution, indicating that some industries are particularly litigious, potentially deterring innovation.

For internal firm capabilities, *Cash* as a share of total assets averages 12.7%, with a wide distribution that reflects variation in financial flexibility. The *InnovCap* variable (measuring recent citations received

from peer firms) averages 0.615, with the 90th percentile reaching above 2.4, highlighting stark differences in firms' technological prominence within their networks.

Lastly, the control variables show familiar patterns. The average firm in the sample has a Tobin's Q of 3.51 and a mean firm age of about 16 years. Profitability and leverage are within expected ranges, although profitability has a negative median, indicating that a substantial portion of firms may not be earning positive net income in any given year.

4.3 Baseline Estimates: Focal firm's patent Grant and Peer Innovative Efforts

Table 2 presents the estimation results for the baseline specification (Equation (2)), which examines how a focal firm's patent grant affects a peer's innovative efforts, measured by R&D investment and the probability of engaging in acquisitions.

To capture heterogeneity in responses, I interact the focal firm's patent grant indicator with indicators for AR+ and AR− events, where AR+ corresponds to cases in which both the peer and focal firm experience positive abnormal returns, and AR− corresponds to cases in which the peer experiences negative abnormal returns following a focal firm's patent grant.

The results reveal a strong asymmetric pattern. The coefficient on $FocalPatentGrant \times AR+$ is positive and statistically significant across all specifications. In Columns (1) and (2), AR+ events are associated with increases in R&D (0.007) and acquisition activity (0.059), both significant. These effects remain robust when firm-level controls are included in Columns (3) and (4), with coefficients of 0.006 for R&D and 0.057 for acquisitions. These findings indicate that when focal firm's innovation is perceived as economically beneficial, peers respond by expanding innovative efforts along both internal and external margins.

In contrast, the coefficients on $FocalPatentGrant \times AR-$ are small and statistically insignificant across all specifications. This suggests that when focal firm's innovation is perceived as unfavorable, peers do not increase innovative investment along either internal or external margins. The absence of a strong response in these cases points to alternative adjustment channels, such as changes in the direction of innovation,

which I explore in later sections.

The main effect of *FocalPatentGrant* is positive but statistically insignificant across all columns, indicating that average effects mask substantial heterogeneity in peers' responses depending on the nature of the shock. Turning to the control variables in Columns (3) and (4), the results are broadly consistent with prior literature. Cash holdings are positively associated with both R&D and acquisitions and are statistically significant at the 5% level, suggesting that financially flexible firms are more likely to make innovation investments (Brown and Petersen, 2011). Tobin's Q is positively related to R&D but negatively associated with acquisitions, consistent with firms with stronger growth opportunities relying more on internal investment. Other controls, including profitability, leverage, and firm age, do not exhibit consistent or statistically significant effects in this baseline specification.

4.4 Interpreting Positive and Negative Peer Market Reactions

The baseline results show that peers respond very differently depending on whether a focal firm's patent grant is accompanied by a positive (AR^+) or negative (AR^-) peer market reaction. Throughout the paper, I interpret these market reactions as forward-looking signals of technological opportunity and competitive threat. This interpretation is central to the empirical framework because it motivates the distinction between complementary and rivalrous innovation shocks.

An important question, however, is whether these market-based classifications indeed capture underlying technological and competitive relationships rather than reflecting unrelated information incorporated into stock prices. To address this question, I examine whether AR^+ and AR^- systematically align with observable firm characteristics measured prior to the patent grant.

Specifically, I relate AR^+ and AR^- classifications to three ex ante measures of firm relationships. The first two—citation overlap and patent-text similarity—capture technological complementarity between the focal firm and the peer. The third measure, TNIC product similarity, captures product-market rivalry. If AR^+ represents technological opportunity, it should be concentrated among firms with stronger technological

complementarity. Conversely, if AR^- reflects competitive threat, it should primarily arise among firms that compete more directly in product markets.

Table 3 reports three clear patterns. First, AR^+ events are significantly associated with both citation overlap and patent-text similarity, indicating that positive peer market reactions occur primarily among technologically complementary firms. Second, TNIC product similarity has little association with AR^+ but is strongly related to AR^- events, suggesting that negative peer market reactions arise when firms compete more directly in product markets. Finally, these measures are all constructed using information available before the patent grant, implying that the observed relationships are not driven by ex post outcomes.

Overall, the evidence supports interpreting positive peer market reactions as signals of technological opportunity and negative peer market reactions as signals of competitive threat. This interpretation provides the economic foundation for the subsequent analyses of peer firms' innovation, acquisition, and financing responses.

4.5 Instrumental Variable Estimation

Table 4 reports the first-stage regression results for the instrumental variable strategy described in Section 3.4.2. The analysis is conducted at the peer–focal–year level to examine how peers respond to focal firm's patent grants. A potential concern in this setting is that the same focal firm may be linked to multiple peers within a given year if several technologically related firms receive patent grants. This creates complications for instrumental variable estimation because the same focal firm can appear multiple times in the sample. To address this issue, the 2SLS specification adopts a best-peer approach. Specifically, each focal firm is matched to the peer with the highest level of mutual patent citation intensity, and the analysis focuses on the peer's response to that focal firm's patent grant. This approach ensures that each focal firm contributes at most one observation in a given year and maintains consistency between the first-stage and second-stage samples.

Because the second-stage specification includes three endogenous variables—*FocalPatentGrant*,

$FocalPatentGrant \times AR^+$, and $FocalPatentGrant \times AR^-$ —the first stage consists of three corresponding regressions. Specifically, $FocalPatentGrant$ is instrumented with Examiner Leniency (EL), $FocalPatentGrant \times AR^+$ is instrumented with $EL \times AR^+$, and $FocalPatentGrant \times AR^-$ is instrumented with $EL \times AR^-$.

Columns (1)–(3) report the first-stage estimates. Column (1) examines the determinants of focal firm’s patent grants and shows that examiner leniency is positively associated with the probability that a focal firm’s patent application is granted. The coefficients on EL , $EL \times AR^+$, and $EL \times AR^-$ are all positive and statistically significant, indicating that examiner assignment generates meaningful variation in focal firm’s patent grants and in the market-based classifications used throughout the analysis.

Columns (2) and (3) report the first-stage regressions for the interaction terms $FocalPatentGrant \times AR^+$ and $FocalPatentGrant \times AR^-$. Consistent with the identification strategy, $EL \times AR^+$ strongly predicts $FocalPatentGrant \times AR^+$, while $EL \times AR^-$ strongly predicts $FocalPatentGrant \times AR^-$. Because AR^+ and AR^- are mutually exclusive indicators, each interaction term is instrumented using only its corresponding examiner-leniency interaction. The estimated coefficients are positive and highly significant, with t-statistics of 3.94 and 3.31, respectively.

The first-stage F-statistics range from 25.84 to 32.37, indicating substantial explanatory power of the excluded instruments for the endogenous variables. In addition, the Kleibergen–Paap rk Wald F-statistic equals 18.93, exceeding conventional weak-instrument thresholds and suggesting that weak identification is unlikely to be a concern. Overall, the results support the relevance condition required for the instrumental variable strategy and indicate that examiner assignment provides a powerful source of exogenous variation in focal firm’s patent grant probability.

Table 5 presents the two-stage least squares (2SLS) estimates evaluating how peers respond to significant focal firm’s patent grants. Table 5 makes clear that even after instrumenting focal firm’s patent grants, the average focal firm’s innovation shock does not generate meaningful changes in peers’ R&D or acquisition activity. This reinforces an important point: most focal firm’s patents are economically small, incremental, or strategically irrelevant, so aggregating across all patent grants dilutes the variation that actually matters

for peer behavior. In other words, peers do not respond uniformly to all innovations; instead, they react selectively to the subset of patents that meaningfully alter their expectations about the technological frontier or competitive positioning.

Given this, focusing on the average focal firm's patent can be misleading about the strategic role of innovation. What is more relevant for understanding peers' behavior are the focal firm's patents that are interpreted as significant immediately by financial markets, as reflected in abnormal stock returns. These patents represent the types of shocks that plausibly convey new information about competitive threats, technological direction, or market opportunities.

The results show that peers respond strongly to these AR+ shocks. In Column (1), R&D investment rises by 0.011, statistically significant at the 5% level. Relative to the sample mean of 0.084, this represents an economically meaningful increase of approximately 13.1%. Column (2) shows that the likelihood of engaging in acquisitions increases by 8.2 percentage points following focal firm's patent grants that trigger strong positive stock market reactions. Relative to the sample mean acquisition probability of 6.8%, this corresponds to an increase of approximately 120.6%. Together, these estimates indicate that when the market interprets a focal firm's patent as value-relevant, peers increase both internal (R&D) and external (acquisition) innovative efforts.

In contrast, focal firm's patent grants associated with negative abnormal stock returns (AR-) to the peers do not lead to meaningful changes in R&D or acquisition activity. The insignificant coefficients suggest that peers do not systematically adjust the level of innovative efforts in response to these events. There are several plausible explanations. First, even if the focal firm's patent is viewed unfavorably by the market, peers still face competitive pressure and may not find it optimal to alter their existing innovation plan—particularly if their current technological portfolios are not closely aligned with the focal firm's innovation. Second, peers may instead choose to redirect effort toward alternative or less contested technological areas, rather than retreating their innovative efforts. I also show later that these responses become stronger as peers are exposed to a greater number of economically significant focal firm's patent grants.

4.6 Dynamic Peer Response to Significant Focal firm's patents

To explore the timing and persistence of peer responses more explicitly, I examine the dynamic effects of focal firm's patent grants on peers' internal and external innovation activities. While earlier analyses establish that peers react to focal firm's innovation, they do not clarify when these responses occur or how long they persist. Understanding this temporal dimension is crucial: innovation decisions often require time to plan and execute, and different channels—such as R&D investment versus acquisition—may operate on distinct timelines. A dynamic response analysis allows me to distinguish between immediate strategic adjustments and delayed but sustained shifts in peer behavior following focal firm's patent grants.

To estimate this, I use the baseline stacked DiD framework and run the following regression:

$$Y_{ijt+k,\tau} = \sum_{k=-3}^{k=3} \beta_{1,t+k,\tau} [Post_{t+k} \times Grant_{\{j,\tau\}} \times AR_{+\{ij\tau\}}] + \sum_{k=-3}^{k=3} \beta_{2,t+k,\tau} [Post_{t+k} \times Grant_{\{j,\tau\}} \times AR_{-\{ij\tau\}}] + \Gamma'X_{\{i,\tau-1\}} + \delta_{i,\tau} + \mu_{st,\tau} + \varepsilon_{ijt,\tau},$$

where $Post_{t+k}$ are dummy variables for k periods before/after the event. The coefficients β_{t+k} trace out how the outcome evolves in the years before and after a focal firm's patent is granted, relative to a baseline year (year -1).

The left plot in Figure 5 shows the dynamic response of R&D investment. The pre-trend is flat and statistically insignificant, providing confidence in the identification assumption that treated and untreated peers followed similar paths before the focal firm's patent grant. A significant increase occurs in the year after the focal firm's patent grant, peaking at around 3 percentage points in year 0, and remains elevated through year +3. This pattern suggests that peers react quickly by reallocating resources toward internal R&D projects, likely as a first-line response to perceived competitive threats or opportunities implied by the focal firm's innovation. By contrast, AR- events show no comparable increase in R&D investment. The estimates remain small and negative after the focal firm's patent grant, with confidence intervals generally including zero. This contrast suggests that the increase in R&D is concentrated among patents that the market interprets as creating opportunities for peer firms rather than those perceived as competitive threats.

The right plot in Figure 5 presents the dynamic response of acquisition activity. Unlike the relatively fast R&D response, acquisitions respond more slowly. There is little change in years 0 and +1, but by year +2, peers exhibit a substantial and statistically significant uptick in acquisition likelihood—peaking at over 7 percentage points. This delayed response aligns with the idea that acquisitions require longer lead times due to the complexity of deal-making and due diligence. It suggests that after absorbing and evaluating the strategic implications of the focal firm’s patent, peers may seek to acquire complementary technologies or shore up their competitive position externally. These distinct temporal patterns underscore that focal firm’s patent grants shape peer behavior through multiple innovation channels on different timelines. A similar contrast emerges for acquisition activity. While acquisition likelihood rises substantially following AR+ events, the estimates for AR− events remain close to zero throughout the post-grant period and are statistically insignificant. Thus, the delayed increase in external innovation activity appears specific to positively interpreted focal patent grants.

4.7 Broader Peer Responses

In addition to examining peers’ innovative efforts, I explore whether focal firm’s patent grants generate broader adjustments in peers’ financial and operating policies. Focal firm’s innovation may influence a peer’s strategic posture in ways not fully captured by R&D spending or acquisition activity. For example, peers may revise their financial structure, accumulate precautionary liquidity, or shift real investment in response to perceived changes in technological competition. This section documents how a range of peer outcomes evolve following focal firm’s patent grants.

I focus on four firm-level outcomes: cash holdings, debt issuance, net equity issuance, and capital expenditures (CAPEX). Cash holdings capture changes in precautionary liquidity, which may increase when firms perceive greater technological uncertainty or competitive pressure. Debt and equity issuance reflect adjustments in external financing, allowing firms to either fund potential innovation responses or strengthen balance sheet flexibility. CAPEX provides a measure of real investment outside the R&D

channel and can indicate whether firms reallocate resources toward physical assets or production capabilities instead of—or in addition to—innovative effort.

I intentionally do not examine outcomes such as sales growth or operating performance (e.g., ROA). While economically important, these measures typically adjust only with a delay, reflecting the time needed for new products to reach the market, competitive dynamics to unfold, and financial results to appear in accounting data. Such product-market outcomes are unlikely to respond contemporaneously. Focusing instead on financial and investment policies provides a clearer view of the peer's near-term strategic adjustments following focal firm's innovation.

Figure 6 summarizes the dynamic responses of these four firm-level outcomes—cash holdings, debt issuance, equity issuance, and CAPEX—around focal firm's patent grants, separately for focal firm's innovations that generate positive abnormal returns (AR^+) and those that generate negative abnormal returns (AR^-). The AR^+ vs. AR^- comparison captures how peers' financial and operating policies respond to focal firm's innovations that have either favorable or unfavorable competitive implications, both of which matter economically for the peers. The dynamic event-time specifications used here follow the same empirical framework applied in Section 4.6.

The top row plots the responses for AR^+ events, where the market interprets the focal firm's patent as having favorable implications for the peer firm. Across Panels A, B, and D, the estimates fluctuate irregularly around zero, and the confidence intervals consistently overlap zero. These patterns indicate that peers do not make statistically meaningful adjustments in cash holdings, leverage, or CAPEX in the immediate aftermath of positively interpreted focal firm's innovation. The only clear response appears in Panel C: equity issuance rises sharply beginning in the year after the focal firm's patent is granted, with non-overlapping confidence intervals that indicate a statistically significant increase. This suggests that peers selectively tap external equity markets when focal firm's innovations are perceived to be important enough to justify additional financing for future strategic or innovative activities.

The magnitude of the equity response is economically meaningful: the estimates imply an increase in net equity issuance of roughly 10% of total assets in the years following AR^+ focal firm's patent grants. Despite

this sizable financing inflow, cash holdings themselves exhibit little systematic movement. This contrast is not inconsistent. Equity issuance is a flow variable that responds immediately when firms seek to expand financial flexibility, whereas cash holdings reflect the net effect of multiple concurrent uses and sources of funds. Newly raised equity may be allocated toward a range of purposes—including innovation-related spending, organizational capacity building, or general corporate needs—that do not necessarily result in a visible buildup of cash. Thus, the absence of a pronounced increase in liquidity does not contradict the strong equity response; rather, it suggests that peers raise external capital in anticipation of future strategic activity indicating that they actively expand financing capacity through equity markets in response to economically important focal firm’s innovations.

The bottom row shows the corresponding responses for AR⁻ events, where focal firm’s patent grants convey adverse implications for the peers’ competitive position. Here, the movements in Panels A through D remain small, irregular, and consistently within wide confidence bands that overlap zero. Peers neither accumulate nor deplete liquidity in a systematic way (Panel A), nor do they adjust leverage, equity issuance, or CAPEX in a directionally consistent manner (Panels B through D). Overall, the AR⁻ patterns are noisy and centered near zero, suggesting the absence of any meaningful financial or real-investment responses to focal firm’s innovations that have unfavorable implications.

Taken together, the figure indicates that peers react through financial policy adjustments only when focal firm’s innovations are perceived to have positive implications. Patent grant shocks that have positive implications generate a pronounced increase in equity issuance—the primary margin through which peers adjust—while other balance-sheet and investment policies remain unchanged. In contrast, focal firm’s innovations that have negative implications do not trigger systematic changes in liquidity, financing, or physical investment. These patterns reinforce the view that peers selectively respond to focal firm’s innovation based on its perceived economic importance, with equity financing serving as the key short-run adjustment channel. These financing patterns are also consistent with the broader literature on corporate investment opportunities. In particular, Hoberg and Phillips (2025) document that firms expanding the

scope of their activities increase both R&D investment and equity issuance while relying relatively little on debt financing. The results presented here exhibit a similar pattern.

4.8 Peer Adjustments Following Adverse Focal firm's patent News

Because peers experiencing AR- focal firm's patent grants show no meaningful adjustment in the level of innovative effort, it is natural to ask whether they instead respond along a different margin—namely, by changing the direction of their innovation. A decline in market valuation following a focal firm's patent grant may imply that the peers' existing technological path has become less attractive, raising the possibility that peers respond by exploring new areas rather than intensifying activity in their current domains.

To examine this, I compute the exploration ratio—the fraction of new patents filed outside the peer's pre-existing top CPC classes. This measure captures the extent to which a peer shifts its post-grant patenting toward technological domains that were not central to its portfolio during the pre-grant five-year period. An increase in the exploration ratio would indicate movement into unfamiliar or previously underutilized technology classes.

Table 6 reports the regression estimates for both AR+ and AR- patent grants. The results show a clear asymmetry. For AR+ patents, the interaction term $FocalPatentGrant \times AR+$ is small and statistically indistinguishable from zero across specifications. This indicates that positively interpreted focal firm's innovations do not prompt peers to branch out into new technological areas. This is consistent with earlier evidence that peers expand their financing capacity and maintain their existing innovation trajectory upon experiencing AR+ patents.

In sharp contrast, the coefficient on $FocalPatentGrant \times AR-$ is large (0.012–0.016) and statistically significant. Given that the mean exploration ratio is approximately 0.012, these estimates represent an increase exceeding 100 percent relative to the baseline level. This substantial rise indicates that AR- patent experiencing peers meaningfully redirect their limited post-grant patenting activity toward new technological fields. Although AR- experiencing peers do not scale up the overall volume of innovation,

they exhibit a pronounced shift in technological focus in response to patent grant news that has negative implications.

Taken together, these findings reveal a sharp directional asymmetry in peers' responses to focal firm's patent news. AR+ experiencing peers do not expand into new technological domains and instead continue along their established innovation paths, consistent with earlier evidence that positively interpreted focal firm's innovations reinforce existing trajectories rather than prompting exploratory shifts. In contrast, AR- experiencing peers, despite showing no increase in the level of innovative effort, substantially reallocate their limited post-grant patenting toward new technology classes, indicating a meaningful redirection of innovative activity. With these directional responses established, the next section examines how external environments, internal capabilities, and firm-peer relationships further condition the responsiveness to focal firm's innovation shocks.

4.9 Heterogeneous Responses: Triple Difference Analyses

To understand why peers react so differently to focal firm's patent grants depending on whether the market views the focal firm's innovation favorably (AR⁺) or unfavorably (AR⁻), I estimate a triple-difference specification that interacts the focal firm's patent grant indicator with both the valuation shock and a set of moderating variables capturing firm-peer relationships, external constraints, and internal firm capabilities. This framework allows for a structured comparison of heterogeneous responses across economically relevant firm characteristics.

The first source of heterogeneity arises from the relationship between the focal firm and its peer, measured along two economically distinct dimensions: technological complementarity and product-market rivalry. Technological complementarity is captured by 5-year lagged *CitShareOverlap*, which measures the extent to which the focal firm's patents cite similar prior art as the peer's patents, indicating alignment in underlying technological foundations. Product-market rivalry is proxied by *PMR*, an indicator equal to one when the two firms operate in the same TNIC2 product market.

Table 7 shows that technological complementarity, rather than product-market rivalry, is the primary dimension of firm–peer relatedness that amplifies responses to AR+ focal firm’s patent grants. The interaction term $FocalPatentGrant \times CitShareOverlap \times AR+$ is positive and statistically significant for both R&D investment and acquisition activity. The estimates indicate that peers sharing stronger technological linkages with the focal firm respond more aggressively to opportunity-type innovations. Economically, a one-standard-deviation increase in *CitShareOverlap* ($SD = 0.064$) increases the R&D response by approximately fifteen percentage points (2.319×0.064) and the acquisition response by roughly 46 percentage points (7.128×0.064). By contrast, the corresponding coefficients for *Exploration Ratio* are small and statistically insignificant, suggesting that opportunity-type responses are primarily reflected in the intensity of innovation investment and acquisition activity rather than shifts toward exploratory innovation.

In contrast, the interaction terms involving AR– are uniformly small and statistically insignificant for both technological complementarity and product-market rivalry. Thus, neither technological proximity nor product-market competition amplifies responses to negatively interpreted focal firm’s patent grants. Negative valuation shocks do not trigger stronger responses even when the focal firm is technologically close or competitively proximate, reinforcing the earlier conclusion that AR- experiencing peers adjust innovation directionally but do not meaningfully change the overall R&D investment or acquisition activity.

The second dimension of heterogeneity concerns legal-enforcement frictions. Panel A of Table 8 shows that stronger enforcement environments primarily dampen the innovation responses associated with AR+ focal firm’s patent grants. Both patent thicketing and litigation risk are associated with significantly weaker R&D investment and acquisition activity following positively interpreted focal firm’s patent grants. In contrast, the corresponding effects for AR– shocks are generally insignificant in the R&D and acquisition specifications.

This pattern is consistent with the interpretation that AR+ focal firm’s patent grants represent technological opportunities that peers seek to build upon. When a focal firm’s innovation is viewed as complementary or value-enhancing, peers often respond by increasing R&D investment and pursuing

follow-on acquisitions in technologically related areas. However, these activities bring firms closer to the focal firm's intellectual-property boundary. In environments characterized by dense patent thickets or elevated litigation risk, the expected costs of operating in these technologically adjacent spaces increase substantially. As a result, peers become less willing to intensify innovation investment or acquisition activity, leading to the observed dampening of AR+ responses.

Interestingly, legal-enforcement frictions affect the direction of innovation differently for peers experiencing AR− shocks. While neither patent thickening nor litigation risk significantly alters overall R&D investment or acquisition activity in these cases, both variables are associated with significantly higher exploration ratios. This suggests that when negatively interpreted focal firm's patent grants create competitive threats, stronger enforcement environments encourage peers to redirect their innovation efforts toward more distant and less contested technological areas rather than competing directly within the focal firm's technological domain.

The third source of heterogeneity relates to internal firm capabilities. Panel B of Table 8 shows that financial flexibility and innovative capability play important roles in shaping peer responses to focal firm's patent grants. Peers with greater cash holdings exhibit significantly stronger responses following both AR+ and AR− focal firm's patent grants. The interaction terms involving $Cash \times AR+$ and $Cash \times AR-$ are positive and statistically significant in the R&D specification, indicating that liquidity enables firms to respond more aggressively regardless of whether the focal firm's innovation is perceived as an opportunity or a threat. For AR− shock experiencing peers, higher cash holdings are also associated with greater exploratory innovation, suggesting that financial resources facilitate strategic adaptation when competitive pressures arise. A one-standard-deviation increase in cash holdings ($SD = 0.065$) increases the R&D response by approximately 9 to 12 percentage points and the acquisition response by roughly 3 to 13 percentage points, consistent with theories emphasizing the enabling role of liquidity in pursuing strategic opportunities.

Leverage has the opposite effect. The interaction terms involving $Leverage \times AR+$ and $Leverage \times AR-$ are consistently negative across the R&D and acquisition specifications, indicating that financially

constrained peers are less able to adjust their innovation strategies following focal firm's patent grants. These findings suggest that access to financial resources is a key determinant of whether peers can translate external innovation signals into meaningful strategic responses.

Innovative capability similarly amplifies responsiveness to focal firm's innovations. The interaction term $FocalPatentGrant \times InnovCap \times AR+$ is positive and significant for both R&D investment and acquisition activity, indicating that firms with stronger innovative capabilities are better positioned to exploit technological opportunities revealed by positively interpreted focal firm's patent grants. Interestingly, innovative capability also matters for AR- shock experiencing peers. Although the effects on R&D and acquisitions are weaker, peers with higher *InnovCap* exhibit significantly greater exploration ratios following negatively interpreted focal firm's patent grants. This pattern suggests that technologically capable peers are more effective at redirecting their innovation efforts toward alternative technological domains when confronted with perceived competitive threats.

Taken together, these findings show a clear asymmetry in how peers adjust after focal firm's patent grants. AR+ patents coincide with substantial increases in innovative activity, but these adjustments arise primarily when peers are technologically close to the focal firm, operate in environments with lower enforcement frictions, and possess the internal capabilities—such as liquidity and absorptive capacity—needed to pursue opportunities in related technological spaces. AR- patents, in contrast, coincide with much smaller changes in innovation intensity, and these patterns exhibit limited variation across technological complementarity, product-market rivalry, enforcement conditions, or innovative capability. The one exception is financial flexibility: peers with stronger balance sheets exhibit somewhat larger adjustments even in AR- settings, consistent with liquidity easing the shift toward alternative technological directions. Overall, the heterogeneity patterns indicate that meaningful adjustments in innovation effort arise chiefly when focal firm's innovations expand technologically relevant opportunities and when peers have the capacity to act on them, while negatively valued patents rarely coincide with broad shifts in innovative activity except when peers hold ample financial resources.

To delve deeper into the mechanism underlying the observed heterogeneity in responses to focal firm's patent grants, I examine how the marginal effect varies across these two important firm characteristics: cash holding and innovative capability. Figure 7 presents these results by plotting the marginal effect of focal firm's patent grants across percentiles of the two moderators. The green line shows the marginal effect conditional on a peer's *InnovCap* percentile (left y-axis), while the orange line corresponds to the *Cash* percentile (right y-axis). Both lines exhibit upward-sloping patterns, indicating stronger responsiveness among peers higher in each distribution. However, the slope and volatility differ across the two dimensions, pointing to distinct mechanisms. The marginal effect increases sharply and unevenly as peers move from low to high percentiles of *Cash*, suggesting that financial constraints may be binding for less liquid peers. When peers have sufficient cash reserves, they appear much more willing or able to react to peer innovation, either by intensifying R&D or engaging in strategic acquisitions.

In contrast, the *InnovCap*-based response is more gradual and exhibits smaller fluctuations. Peers near the frontier consistently show greater sensitivity to focal firm's patent grants, but the progression is smoother. This suggests that innovation readiness makes peers more responsive to focal firm's innovation, but the relationship is more stable than that of financial flexibility. Even moderately capable peers appear responsive to focal firm's innovation, while liquidity seems to act more like a threshold variable—enabling a substantial reaction only once certain internal financial conditions are met.

Taken together, the triple-difference analyses reveal that the effects of focal firm's patent grants are highly heterogeneous. While competitive shocks may stimulate innovation under the right conditions, their impact is dampened in environments with high enforcement risk and enhanced when peers are equipped with the financial and technological resources to respond. This highlights the importance of a contingent view of innovation strategy in the face of competitive dynamics.

4.10 Innovation Output: Patent Filing and Directional Alignment

In this section, I investigate whether peers' responses to focal firm's patent grants extend beyond increased innovative efforts (R&D and acquisitions) and translate into measurable innovation output.

Specifically, I examine two outcomes: (1) whether peers file more patents in response to strategically significant focal firm's patent grants (*PatentFiling*), and (2) whether these patents become more technologically aligned with the focal firm's innovation, as measured by overlapping backward citations (*CitShareOverlap*).

Table 9 presents the results, where the key variables of interest are $FocalPatentGrant \times AR^+$ and $FocalPatentGrant \times AR^-$. These interactions capture peer responses to focal firm's patent grants that are interpreted by the market as positive or negative shocks. The results reveal a clear asymmetry in both the level and direction of innovation. For AR^+ patent grants, Column (1) shows that peers significantly increase patenting activity, with a coefficient of 0.208 ($t = 2.15$). Relative to the mean of *PatentFiling* (2.311), this implies a 9% increase. Column (2) further shows a positive and statistically significant increase in *CitShareOverlap* (0.003, $t = 2.43$), corresponding to an 8 % rise relative to its mean (0.038). These results indicate that peers not only innovate more but also direct their innovation toward the focal firm's technological domain, consistent with knowledge spillovers and technological complementarity. Columns (3) and (4) confirm the robustness of these findings.

In contrast, for AR^- patent grants, the response differs sharply. The effect on patenting activity remains small and statistically insignificant in both specifications (0.048 and 0.028, $t = 0.16$ and 0.89), indicating no meaningful increase in overall innovation output. However, the effect on directional alignment is negative and statistically significant. In Column (2), the coefficient on *CitShareOverlap* is -0.004 ($t = -2.41$), and in Column (4), it becomes even larger in magnitude at -0.005 ($t = -2.01$). Relative to the mean of 0.038, these estimates imply a decline of approximately 10–13%, indicating that peers shift their innovation away from the focal firm's technological space.

Taken together, these findings show that focal firm's innovation affects not only how much peers innovate, but also where they innovate. Opportunity-type shocks (AR^+) lead to both increased patenting and convergence in technological space, whereas threat-type shocks (AR^-) primarily induce directional divergence without increasing overall innovation intensity. This asymmetry highlights that peers respond

to competitive threats not by scaling up innovation broadly, but by strategically repositioning their innovation efforts away from areas dominated by the focal firm.

5. Robustness Tests

5.1 Innovation Response around the Patent Disclosure Date

Patent disclosures occur approximately 18 months after filing, making previously private R&D projects publicly observable for the first time. In principle, this early visibility into a focal firm's technological direction could inform peers about upcoming threats, reveal areas of potential competition, or signal future product positioning. For firms operating in fast-moving or IP-intensive sectors, such early information might help shape strategic expectations and motivate preemptive innovation or acquisitions (Gans et al., 2008; Hegde and Luo, 2018). From this perspective, patent filing disclosures could serve as early, forward-looking signals of competitive intent.

However, several reasons suggest that the patent grant date is more likely to drive meaningful peer responses than the disclosure date. First, disclosures are inherently noisier and more ambiguous. Many disclosed applications are never granted (Farre-Mensa et al., 2020), and the scope or enforceability of the innovation remains uncertain until examination is complete. Peers may therefore discount disclosures as weak or tentative signals. In contrast, a grant certifies that the patent has satisfied novelty and non-obviousness requirements, providing a clear legal right to exclude and a credible assertion of technological capability. This formal recognition may be what prompts peers to reassess their strategic positioning.

Second, market reactions—which peers monitor closely as valuation signals—are much more pronounced around the grant date. Kogan et al. (2017) show that stock-price reactions contain valuable information about the economic significance of innovations. Because a patent grant resolves uncertainty regarding patentability and legal protection, investors are better able to assess the economic value of the underlying innovation at the grant stage than at disclosure. Moreover, peer firms may not respond directly to the patent document itself but rather to how financial markets interpret the event (Zheng, 2025). If the

market responds strongly to a grant (e.g., through abnormal returns), it reveals that investors perceive the patent to have economic value (Kogan et al., 2017; Testoni, 2022). Peers use this external signal to update beliefs about their focal firm's innovation's future prospects and their own relative position. Disclosures, by contrast, receive little market attention and are unlikely to generate sharp updates to focal firm valuations.

Finally, a patent grant unlocks legal enforceability. From the perspective of strategic investment decisions—particularly in R&D or M&A—firms must consider not just technological competition but legal risk (Galasso and Schankerman, 2015; Shapiro, 2000). The threat of litigation or exclusion from a key technology space only becomes credible upon grant. Thus, the grant event represents a sharper strategic inflection point, both in terms of competitive threat and option value of follow-on innovation. This motivates the focus on the grant date as the primary event of interest and sets the stage for testing whether the earlier disclosure event elicits any meaningful response.

Table 10 evaluates whether peers adjust their innovative efforts in response to the disclosure of focal firm's significant patent applications. The empirical results show no significant effect of focal firm's patent filing disclosures on either R&D investment or acquisition activity of the peers. These effects are small in magnitude and statistically indistinguishable from zero, even when accounting for firm-level controls.

The contrast with prior results on patent grants is striking. Table 5 shows that focal firm's patent grants—particularly those deemed significant by the market—lead to substantial increases in both R&D and acquisition activity, indicating that peers interpret grants as meaningful signals. In contrast, the null results in Table 10 indicate that disclosure events do not prompt strategic adjustments.

This finding reinforces the view that grant dates, rather than disclosure dates, are the true information shocks that trigger firm-level reactions. The fact that no response is detected even with an exogenous instrument highlights that peer firms appear to wait for formal validation of novelty and enforceability—as confirmed through a grant—before adjusting their innovation strategies. This result supports the interpretation that patent grants serve as sharper inflection points, likely due to their legal implications and their ability to generate observable market responses.

5.2 Focal firm's patent Grant Intensity and Innovative Efforts

In this section, I explore whether peers respond more strongly when they experience multiple significant focal firm's patent events within the same year. To do so, I construct a firm-year level measure— $\#[SignificantFocalPatents]$ —which counts the number of focal firm's patent grants that trigger abnormal stock returns for both the peer and the focal firm. This allows me to examine the intensity of focal firm's innovation shocks and test whether peers ramp up their innovative efforts as exposure to strategically salient patents increases.

Using this measure, I estimate firm-year level regressions of R&D investment and acquisition activity, controlling for firm characteristics and fixed effects as in the baseline model. As shown in Table 11, I find that an increase in the number of significant focal firm's patent grants is positively associated with both innovation inputs (R&D) and external innovation efforts (acquisitions). The effect is statistically significant and economically meaningful, particularly for R&D investment. These findings suggest that peers do not respond to patenting activity in a binary manner; rather, they intensify their response as they experience more significant patent grant events that the market views as impactful.

This subsample analysis helps buttress the core mechanism of my paper—that peers interpret focal firm's patent grants as strategically relevant signals and respond with innovation. The fact that the response scales with the frequency of such events lends further credibility to the interpretation that this is not a mechanical correlation, but a deliberate strategic adjustment.

However, this analysis is not suitable as the main empirical specification for identification reasons. Because the regressions are conducted at the firm-year level using a count variable as the main independent variable, I cannot apply the instrumental variable strategy used in the baseline specification. The core IV—based on patent examiner leniency—requires firm-peer-year variation to isolate plausibly exogenous shifts in focal firm patenting. Aggregating to the firm-year level collapses the dimension, which in turn removes the variation needed for constructing the instrument. Therefore, while this analysis provides useful supporting evidence, it lacks a causal identification strategy and should be viewed as complementary rather than standalone.

5.3 Patent Text Similarity and Technological Alignment

The results in Table 9 show that AR+ focal firm's patent grants lead peers to increase both patenting activity and citation-based technological alignment, whereas AR- focal firm's patent grants induce peers to move away from the focal firm's technological domain. While citation overlap captures directional similarity in knowledge sources, it does not directly measure the similarity of the underlying technological content. To further validate the interpretation of these results, I examine whether peers' future patents become textually more similar to—or more different from—the focal firm's patent following significant patent grants.

For each significant focal firm's patent, I construct patent-level text similarity measures using the textual descriptions contained in patent documents. Specifically, I calculate cosine similarity scores between the focal firm's patent and patents subsequently filed by technologically related peers. For each focal firm's patent–peer pair, I compute the average similarity between the focal firm's patent and the peer's patents filed during the five years before the focal firm's patent grant and compare it with the average similarity during the five years after the grant. The difference between these two measures captures whether peers move closer to or farther away from the focal firm's innovation in technological space.

The results in Table 12 provide strong support for the diffusion–constraint framework. The coefficient on $FocalPatentGrant \times AR+$ is positive and statistically significant across specifications. In Column (2), the coefficient equals 0.019 ($t = 2.42$), indicating that peers' subsequent patents become more textually similar to the focal firm's patent when the market interprets the innovation as an opportunity. The magnitude is economically meaningful and suggests that peers not only increase innovative activity following AR+ focal firm's patent grants but also direct that activity toward technologies that closely resemble the focal firm's innovation.

In contrast, the coefficient on $FocalPatentGrant \times AR-$ is negative and statistically significant. In Column (2), the estimate of -0.015 ($t = -2.08$) indicates that peers' future patents become less similar to the focal firm's patent when the market interprets the innovation as a competitive threat. Rather than building upon the focal firm's innovation, peers appear to redirect their inventive effort toward alternative

technological domains. Relative to the sample mean of TextSimilarity (0.120), the estimated coefficient of 0.019 implies an increase of approximately 15.8% in technological similarity following AR+ focal firm's patent grants. Conversely, the coefficient of -0.015 implies a decline of roughly 12.5% following AR- focal firm's patent grants.

Importantly, these findings complement the citation-overlap results reported in Table 9. The observed convergence following AR+ events and divergence following AR- events are reflected not only in citation patterns but also in the underlying textual content of subsequent inventions. Thus, the results provide direct evidence that market-based classifications of opportunity and threat correspond to meaningful differences in the technological direction of future innovation.

5.4 Placebo Grant Dates

As an additional robustness test, I construct a placebo event by shifting each significant focal firm's patent grant date forward by 90 calendar days. I then re-estimate abnormal returns around these placebo dates using the same event-study procedure and reconstruct the AR+ and AR- classifications based on the placebo CARs. Finally, I re-estimate the baseline specifications using these placebo treatment indicators. The rationale is that if peers respond specifically to the informational and legal implications of a focal firm's patent grant, shifting the event date away from the true grant should eliminate the observed effects. In contrast, if the results are driven by underlying trends or persistent differences between treated and control firms, similar patterns should emerge around the placebo date.

Table 13 reports the results. Consistent with the identification strategy, neither the placebo AR+ nor the placebo AR- interactions generate statistically significant effects on peers' R&D investment, acquisition activity, innovation output, or innovation direction. The estimated coefficients are economically small and statistically indistinguishable from zero across all specifications. This stands in sharp contrast to the main results, where AR+ focal firm's patent grants lead to significant increases in R&D, acquisitions, patent filings, citation overlap, and patent text similarity, while AR- focal firm's patent grants induce greater

technological exploration and directional divergence.

The absence of any detectable response around placebo dates suggests that peers are reacting to the focal firm's patent grant itself rather than to unrelated time trends, omitted shocks, or gradual changes in innovation activity. These findings strengthen the causal interpretation of the main results and provide additional evidence that focal firm's patent grants serve as economically meaningful innovation shocks that shape peers' subsequent strategic behavior.

5.5 Alternative Peer Definitions

A potential concern with the baseline analysis is that the peer definition itself may influence the results. Throughout the paper, peers are identified using technological proximity, requiring both overlap in CPC subclasses and direct patent citation links. While this approach is well suited for capturing knowledge diffusion and technological interactions, it may also increase the likelihood of observing positive spillover effects by construction. Consequently, one may question whether the documented responses reflect economically meaningful reactions to focal firm's patent grants or simply arise from the way peers are defined.

To address this concern, I re-estimate the baseline specifications using two alternative peer definitions that do not rely on patent-based technological relationships. First, I identify peers using the TNIC product-market network developed by Hoberg and Phillips (2016), which groups firms according to similarities in product descriptions disclosed in their 10-K filings. Second, I define peers more broadly as firms operating within the same Fama-French 48 industry (Fama and French, 1997). These alternative definitions capture competitive proximity rather than direct technological relatedness and therefore provide a useful robustness test of the paper's main findings.

Table 14 reports the results. Across both alternative peer definitions, the central pattern remains unchanged. Focal firm's patent grants associated with AR+ continue to generate positive and statistically significant increases in both R&D investment and acquisition activity. Although the estimated coefficients

are smaller than those reported in the baseline technological-peer specification, the direction and statistical significance of the effects are preserved. This attenuation is economically intuitive. Firms identified through product-market similarity or industry classifications are, on average, less connected through direct knowledge flows than technologically related peers and therefore have fewer opportunities to benefit from knowledge diffusion.

In contrast, the coefficients on $FocalPatentGrant \times AR-$ remain economically small and statistically insignificant across all specifications. As in the baseline results, negatively interpreted focal firm's patent grants do not induce meaningful changes in the overall level of innovative effort. This suggests that the asymmetry between $AR+$ and $AR-$ responses is not specific to a particular peer-network construction but instead reflects a broader difference in how firms respond to perceived technological opportunities versus perceived competitive threats.

Overall, the results indicate that the main conclusions of the paper are robust to alternative definitions of peer firms. While the strongest responses occur among technologically connected firms, similar qualitative patterns emerge when peers are defined using broader product-market and industry relationships. These findings provide additional confidence that the documented opportunity and threat effects are not artifacts of the baseline technological-peer definition.

5.6 Excluding Concurrent Corporate Announcements

Another potential concern with the market-based classification of focal firm's patent grants is that abnormal stock returns around grant dates may reflect information unrelated to the patent itself. For example, earnings announcements, acquisition announcements, seasoned equity offerings, or other major corporate disclosures occurring near the patent grant date could influence stock prices and contaminate the $AR+$ and $AR-$ classifications.

To address this concern, I re-estimate the baseline specifications after excluding all focal firm's patent grants that occur within a five-trading-day window of a firm's earnings announcement. Earnings

announcements are particularly important because they are among the most information-rich corporate events and can generate substantial stock-price movements independent of patent-related news.

Table 15 reports the results. The estimates remain qualitatively unchanged. Focal firm's patent grants associated with AR+ continue to generate statistically significant increases in both R&D investment and acquisition activity, while the coefficients on AR- remain economically small and statistically insignificant. Although the sample size declines due to the exclusion of overlapping events, the magnitude and significance of the estimated effects are broadly similar to those reported in the baseline analysis.

These findings suggest that the market reactions used to construct the AR+ and AR- classifications are not driven by earnings-related information releases. Instead, the results are consistent with the interpretation that stock-price reactions around focal firm's patent grants contain information about the technological and competitive implications of the patent itself. More broadly, the persistence of the results after removing potentially confounding corporate announcements strengthens the validity of the market-based classification strategy employed throughout the paper.

5.7 Grant Delay and Patentability Uncertainty

The interpretation of patent-grant effects depends on the type of information revealed at the grant date. By the time a patent is granted, much of the technological information may already be publicly available through the disclosure process. If the grant event matters mainly because it resolves uncertainty regarding patentability and legal protection, one would expect peer responses to be concentrated among patents whose approval outcomes were more uncertain *ex ante*. In contrast, if peer responses reflect the market's assessment of the innovation's economic significance, the effects should not depend strongly on the degree of patentability uncertainty surrounding the grant decision.

To examine this issue, I proxy for patentability uncertainty using the application-to-grant delay, defined as the number of days between the patent filing date and the patent grant date. Patents with longer delays are more likely to have faced greater uncertainty during the examination process. I classify patents with

above-median application-to-grant delays as high-uncertainty patents and interact this indicator with the baseline AR+ and AR− treatment variables.

Table 16 reports the results. The interaction terms involving *HighUncertainty* are generally small and statistically insignificant across specifications. The effects of AR+ focal firm’s patent grants remain positive and economically meaningful regardless of the degree of patentability uncertainty, while the corresponding AR− effects remain limited. These findings suggest that the responses documented throughout the paper are not driven primarily by the resolution of patentability uncertainty at the grant date.

Instead, the results are more consistent with the interpretation that peers respond to the economic implications of focal firm’s innovations. Although patent grants undoubtedly resolve uncertainty regarding legal protection, the absence of systematically stronger responses among high-uncertainty patents suggests that uncertainty resolution alone cannot explain the observed patterns. Rather, market reactions appear to capture information about future technological opportunities and competitive threats that is relevant for peers’ subsequent innovation decisions.

5.8 Robustness to Overlapping Network Exposure

The empirical design for the baseline analysis is implemented at the peer-focal-year level. Consequently, a given peer-year observation may appear multiple times in the estimation sample. This can occur for two reasons. First, the same focal firm may receive multiple patent grants within a year. Second, a peer firm may be technologically connected to multiple focal firms, causing the same peer-year outcome to be linked to several distinct focal firm’s patent grants. As a result, the same peer-year outcome may contribute to multiple observations in the estimation sample. Such repetition does not invalidate the empirical design, but it may mechanically increase the influence of highly connected peer firms or peer-years that are associated with multiple focal firm’s patent grants. If the estimated effects are primarily driven by these repeated observations rather than by the underlying economic relationship, the baseline estimates could overstate the importance of particular peer-year outcomes.

To evaluate this possibility, I implement three complementary robustness exercises. First, I restrict the sample to clean event windows by excluding peer-year observations that are simultaneously exposed to another connected focal firm's patent grant during the event window. This specification minimizes contamination arising from overlapping patent events. Second, I retain only one patent grant for each peer-focal-year observation, selecting the event associated with the largest absolute peer market reaction. This approach ensures that each peer-focal pair contributes at most one innovation shock within a given year. Third, I estimate the baseline specification using inverse duplication weights, assigning each repeated peer-year observation a weight equal to the inverse of the number of times that peer-year appears in the estimation sample. This approach preserves the full sample while preventing duplicated peer-year observations from receiving disproportionate influence.

Table 17 reports the results. Across all three alternative specifications, the estimated opportunity effect remains remarkably stable in both magnitude and statistical significance. The consistency of the estimates across these exercises indicates that the baseline findings are not driven by repeated peer-year observations or by highly connected firms that appear multiple times in the estimation sample.

5.9 Alternative Asset Pricing Models

A potential concern is that the classification of focal firm's patent grants into AR⁺ and AR[−] events may depend on the choice of asset-pricing model used to estimate abnormal returns. Since the market-based classification plays a central role throughout the paper, it is important to verify that the results are not driven by a particular specification of expected returns.

At the same time, there are reasons to expect limited sensitivity to the choice of asset-pricing model in this setting. The abnormal returns are measured over a short five-trading-day event window centered on the patent grant date. Over such a narrow horizon, differences in expected returns implied by alternative asset-pricing models are generally small relative to the firm-specific valuation effects generated by major information events. Consequently, event-study estimates based on short-window abnormal returns are

typically less sensitive to the precise specification of expected returns than analyses conducted over longer horizons.

Nevertheless, I formally examine this issue by reconstructing abnormal returns using two alternative asset-pricing models. First, I employ the Fama-French five-factor model (Fama and French, 2015), which controls for market, size, value, profitability, and investment factors. Second, I use the q-factor model (Hou et al., 2015), which controls for market, size, investment, and profitability factors. I then reclassify focal firm's patent grants into AR+ and AR− events using the abnormal returns estimated from each model and re-estimate the baseline specifications.

Table 18 reports the results. Consistent with the intuition above, the distribution of AR+ and AR− patent grants remains remarkably stable across specifications. More importantly, the main findings are virtually unchanged. Focal firm's patent grants classified as AR+ continue to generate statistically significant increases in R&D investment and acquisition activity, whereas AR− focal firm's patent grants remain economically small and statistically insignificant. The magnitudes of the estimated coefficients are highly similar to those obtained under the baseline market-model specification.

These findings suggest that the paper's conclusions are not driven by a particular choice of expected-return model. Instead, the market reactions surrounding focal firm's patent grants appear sufficiently large that alternative asset-pricing models generate nearly identical classifications and inferences. This robustness provides additional confidence that the AR+ and AR− measures capture economically meaningful differences in how markets interpret focal firm's innovations rather than artifacts of a specific abnormal-return methodology.

6. Conclusion

This paper examines how peers adjust their innovation strategies and broader policies when focal firms obtain patent grants. Using a comprehensive dataset that links patent grants, firm financials, acquisitions, market valuations, and patent citation patterns for U.S. public firms from 2001 to 2021, I study whether focal firm's patent grants are followed by systematic changes in peers' innovative effort, innovation output, and firm-level financial choices. I provide novel evidence that significant focal firm's patent grants—those perceived to be strategically important—prompt meaningful changes in peers' innovation-related behavior.

The evidence shows that the average focal firm's patent grant has little effect on the peers' valuation, R&D or acquisition activity, even after instrumenting for the grant decision. This suggests that many focal firm's patent grants do not lead to detectable adjustments in peers' innovation behavior, masking substantial heterogeneity in responses. In contrast, a subset of grants—those associated with large, positive abnormal stock returns for both the peer and the focal firm (AR^+)—coincide with sizable increases in R&D investment and the likelihood of engaging in acquisitions. Dynamic event-time estimates indicate that these adjustments unfold along distinct timelines: R&D increases quickly and remains elevated for several years, whereas acquisition activity rises more gradually, with effects peaking a few years after the grant. By comparison, grants associated with negative abnormal returns for the peer firm (AR^-) show no meaningful change in the level of innovative effort. Instead, AR^- patent experiencing peers exhibit pronounced shifts in the direction of their limited subsequent patenting, moving into new technological fields rather than scaling up activity along existing trajectories.

The analysis of broader firm-level outcomes shows that these innovation adjustments are tightly linked to equity financing. Around AR^+ patent grants, net equity issuance increases markedly, while cash holdings, leverage, and capital expenditures display no consistent movements. This pattern suggests that peers expand financing capacity through equity issuance in the wake of economically important peer patents. In contrast, AR^- patent grants are not followed by systematic changes in liquidity, capital structure, or CAPEX, reinforcing the view that adverse focal firm's patent news is associated primarily with directional shifts in

patenting rather than broad-based changes in financial or real investment policies.

The triple-difference analyses reveal that these effects are highly heterogeneous across firm–peer relationships, legal environments, and internal capabilities. First, technological complementarity—measured via citation-based overlap—is the key dimension along which AR⁺ grants coincide with stronger increases in R&D and acquisition activity, while product-market rivalry plays little systematic role. Second, stronger enforcement environments, characterized by denser patent thickets and higher litigation intensity, substantially attenuate the AR⁺ innovation effects but have limited influence in AR[−] settings, where overall changes in innovation intensity are already small and adjustments tend to move away from the focal firm’s technological space. Third, internal resources matter: peers with greater cash holdings and stronger innovation capability exhibit much larger AR⁺ effects, and even in AR[−] cases, financially flexible peers show somewhat stronger adjustments. To sum, these patterns underscore that substantial post-grant adjustments arise mainly when focal firm’s innovations expand technologically relevant opportunities, enforcement risk is not prohibitively high, and peers possess the financial and technological capacity to exploit those opportunities.

This study contributes to the literature in several important ways. It sheds light on how peers monitor and interpret the patenting behavior of technologically related firms. While prior research has largely focused on knowledge spillovers or strategic imitation in aggregate terms, this paper shows that focal firm’s patenting events can act as competitive shocks that directly alter peers’ innovation strategies, both in magnitude and direction. By integrating insights from the competition–innovation debate with recent work on peer effects and technological networks, this study offers a richer and more nuanced picture of firm behavior in dynamic innovation environments.

From a policy perspective, these findings highlight the importance of understanding how intellectual property protection interacts with market competition. If certain firms are systematically discouraged from innovating due to high litigation risk or aggressive patenting by dominant players, this may reduce the overall dynamism of innovation ecosystems. Policymakers may therefore need to consider how the legal environment and patenting norms shape the incentives of firms to innovate.

Future research can build on this work in several directions. First, while I focus on R&D and acquisitions as primary innovative responses, future studies could explore how peer patenting affects other dimensions of strategic behavior—such as talent acquisition, product development, or market entry. Second, it would be valuable to examine whether the responses documented here ultimately translate into superior long-term innovation outcomes or competitive positioning.

In sum, this paper shows that patenting is not a passive background feature of innovation markets, but an active strategic force shaping the decisions and direction of peers' innovation. Understanding these dynamics is essential for both scholars of innovation strategy and policymakers seeking to foster competitive and inclusive innovation ecosystems.

References

- Acharya, V., and Xu, Z. 2017. Financial dependence and innovation: The case of public versus private firms. *Journal of Financial Economics*, 124(2), 223-243.
- Adner, R., and Snow, D. 2010. Old technology responses to new technology threats: Demand heterogeneity and technology retreats. *Industrial and Corporate Change*, 19(5), 1655-1675.
- Aghion, P., Bloom, N., Blundell, R., Griffith, R., and Howitt, P. 2005. Competition and innovation: An inverted-U relationship. *The Quarterly Journal of Economics*, 120(2), 701-728.
- Akcigit, U., and Ates, S. T. 2023. What happened to US business dynamism?. *Journal of Political Economy*, 131(8), 2059-2124.
- Arora, A., Belenzon, S., and Sheer, L. 2021. Knowledge spillovers and corporate investment in scientific research. *American Economic Review*, 111(3), 871-898.
- Arrow, K. J. 1962. Economic welfare and the allocation of resources for invention. In *Readings in industrial economics: Volume two: Private enterprise and state intervention* (pp. 219-236). London: Macmillan Education UK.
- Azoulay, P., Graff Zivin, J. S., and Wang, J. 2010. Superstar extinction. *The Quarterly Journal of Economics*, 125(2), 549-589.
- Bena, J., and Li, K. 2014. Corporate innovations and mergers and acquisitions. *The Journal of Finance*, 69(5), 1923-1960.
- Bena, J., and Simintzi, E. 2019. Machines could not compete with Chinese labor: evidence from US firms' innovation. Rochester, NY, USA: SSRN.
- Bloom, N., Schankerman, M., and Van Reenen, J. 2013. Identifying technology spillovers and product market rivalry. *Econometrica*, 81(4), 1347-1393.
- Brown, J. R., Fazzari, S. M., and Petersen, B. C. 2009. Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *The Journal of Finance*, 64(1), 151-185.
- Brown, J. R., and Petersen, B. C. 2011. Cash holdings and R&D smoothing. *Journal of Corporate Finance*, 17(3), 694-709.
- Christenson, C. 1997. *The innovator's dilemma*. Harvard Business School Press, Cambridge, Mass, 13.
- Cohen, W. M., and Levinthal, D. A. 1990. Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1), 128-152.
- Danneels, E. 2004. Disruptive technology reconsidered: A critique and research agenda. *Journal of Product Innovation Management*, 21(4), 246-258.
- Fama, E. F., and French, K. R. 1997. Industry costs of equity. *Journal of Financial Economics*, 43(2), 153-193.
- Fama, E. F., and French, K. R. 2015. A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1-22.

- Farre-Mensa, J., Hegde, D., and Ljungqvist, A. 2020. What is a patent worth? Evidence from the US patent “lottery”. *The Journal of Finance*, 75(2), 639-682.
- Galasso, A., and Schankerman, M. 2015. Patents and cumulative innovation: Causal evidence from the courts. *The Quarterly Journal of Economics*, 130(1), 317-369.
- Gans, J. S., Hsu, D. H., and Stern, S. 2008. The impact of uncertain intellectual property rights on the market for ideas: Evidence from patent grant delays. *Management Science*, 54(5), 982-997.
- Graham, S. J., Marco, A. C., and Miller, R. 2015. The USPTO patent examination research dataset: A window on the process of patent examination. Georgia Tech Scheller College of Business Research Paper No. WP, 43.
- Haddad, V., Ho, P., and Loualiche, E. 2022. Bubbles and the Value of Innovation. *Journal of Financial Economics*, 145(1), 69-84.
- Hall, B. H. 2002. The financing of research and development. *Oxford Review of Economic Policy*, 18(1), 35-51.
- Hall, B. H., and Lerner, J. 2010. The financing of R&D and innovation. In *Handbook of the Economics of Innovation* (Vol. 1, pp. 609-639). North-Holland.
- Hegde, D., and Luo, H. 2018. Patent publication and the market for ideas. *Management Science*, 64(2), 652-672.
- Hoberg, G., and Phillips, G. 2010. Product market synergies and competition in mergers and acquisitions: A text-based analysis. *The Review of Financial Studies*, 23(10), 3773-3811.
- Hoberg, G., and Phillips, G. 2016. Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5), 1423-1465.
- Hoberg, G., and Phillips, G. M. 2025. Scope, scale, and concentration: The 21st-century firm. *The Journal of Finance*, 80(1), 415-466.
- Hou, K., Xue, C., and Zhang, L. 2015. Digesting anomalies: An investment approach. *The Review of Financial Studies*, 28(3), 650-705.
- Jaffe, A. B., Trajtenberg, M., and Henderson, R. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics*, 108(3), 577-598.
- Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. 2017. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2), 665-712.
- Kelly, B., Papanikolaou, D., Seru, A., and Taddy, M. 2021. Measuring technological innovation over the long run. *American Economic Review: Insights*, 3(3), 303-320.
- Megna, P., and Klock, M. 1993. The impact of intangible capital on Tobin's q in the semiconductor industry. *The American Economic Review*, 83(2), 265-269.
- Schumpeter, J. 1942. *Capitalism, Socialism and Democracy*. Harper and Brothers.
- Shapiro, C. 2000. Navigating the patent thicket: Cross licenses, patent pools, and standard setting. *Innovation Policy and the Economy*, 1, 119-150.

Testoni, M. 2022. The market value spillovers of technological acquisitions: Evidence from patent-text analysis. *Strategic Management Journal*, 43(5), 964-985.

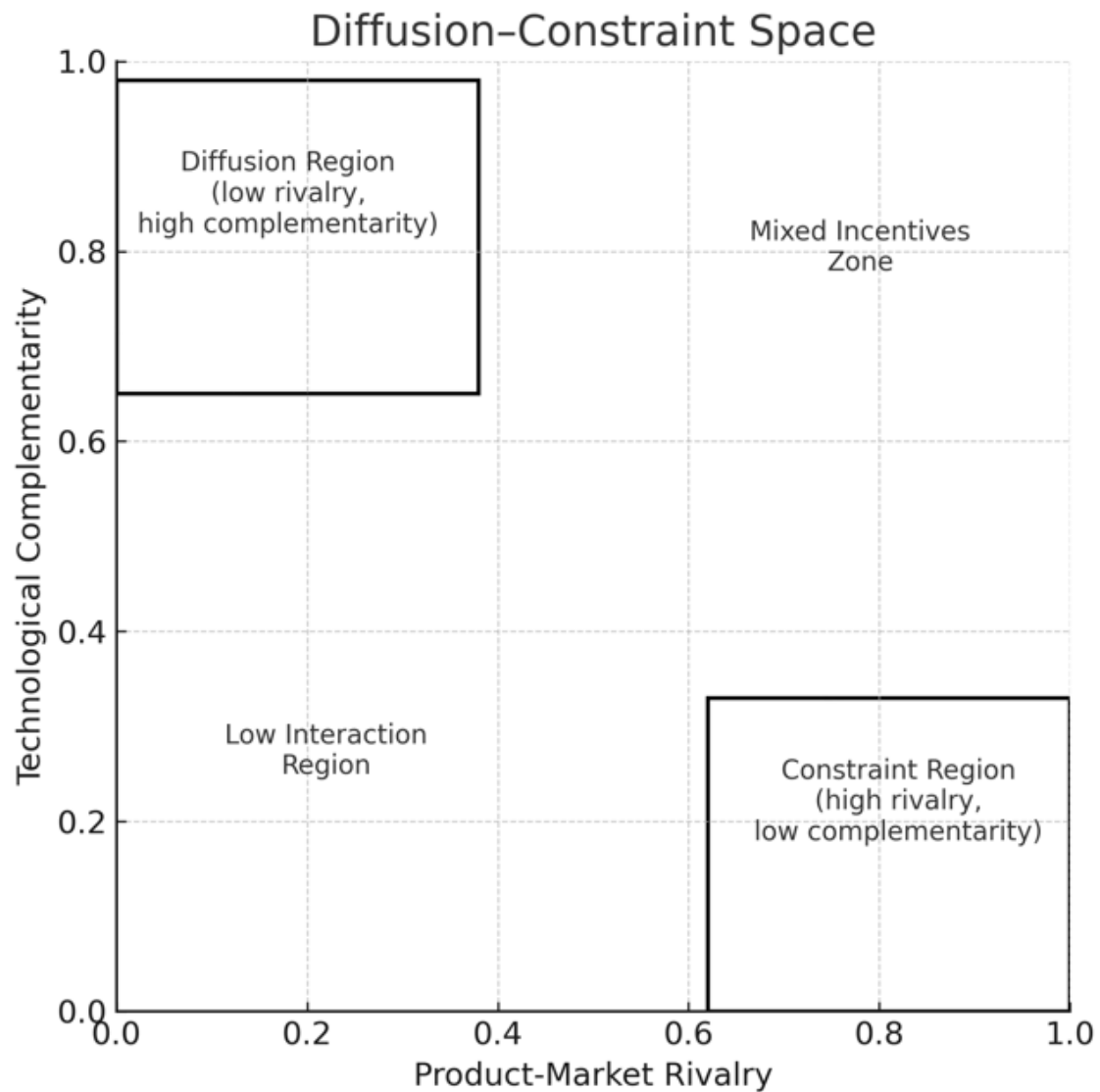
Zheng, Y. 2025. Can investors learn from patent documents? Evidence from textual analysis. *Contemporary Accounting Research*.

Appendix: Variable Definitions

Variable	Definition
<u>Dependent variables</u>	
<i>R&D</i>	R&D expenditures scaled by total assets; set to 0 when missing; (XRD/AT)
<i>Acquisition</i>	Dummy variable equal to one for deals classified as “Acquisition of Major Interest,” “Acquisition of Remaining Interest,” and “Acquisition.” from SDC Platinum M&A database. Exclude transactions where the acquiring firm is privately held.
<i>PatentFiling</i>	Number of patent applications filed by a peer in a given year.
<i>CitShareOverlap</i>	Average proportion of backward citations overlap with those made by the peer’s patents. (in a 6-year window). It is calculated using the following formula. $CitShareOverlap_{ij[t,t+5]} = \frac{1}{N} * \sum_{p=1}^N \left[\frac{(Citations_{i,p} \cap Citations_j)}{ Citations_{i,p} } \right]$
<u>Independent variables</u>	
<i>FocalPatentGrant</i>	Dummy variable equal to one if focal firm has been granted a patent in year t.
<i>FocalPatentDisc</i>	Dummy variable equal to one if focal firm has disclosed its patent in year t.
<u>Control variables</u>	
<i>Log(Asset)</i>	The logarithm of total assets; log(AT)
<i>Tobin’s Q</i>	Market value of assets over total asset; (AT-(CEQ+TXDITC)+CSHO*PRCC_F)/AT
<i>Cash</i>	The ratio of cash to total assets; CHE/AT
<i>Leverage</i>	The ratio of total book debt to total assets; (DLC+DLTT)/AT
<i>Profitability</i>	The ratio of operating income before depreciation to total assets; OIBDP/AT
<i>Age</i>	The number of years since first appearing on the CRSP tapes.
<u>Interaction variables</u>	
<i>AR+ (dummy)</i>	Dummy variable equal to one when both the peer and focal firm experience significant positive abnormal stock returns (two standard deviations above the mean).
<i>AR- (dummy)</i>	Dummy variable equal to one when the focal firm experiences a significant positive abnormal return while the peer firm’s abnormal return is significantly negative (two standard deviations above and below the mean, respectively).
<i>Thicketing</i>	Change in the share of patent filings within the dominant CPC subclass. It is calculated using the following formula. $Thicketing_{jt} = \frac{Firm\ j's\ Patent\ filings\ in\ CPC_{[t,t+18]}}{Total\ Patent\ filings\ in\ CPC_{[t,t+18]}} - \frac{Firm\ j's\ Patent\ filings\ in\ CPC_{[t-18,t]}}{Total\ Patent\ filings\ in\ CPC_{[t-18,t]}}$
<i>InnovCap</i>	The number of forward citations a firm receives from its technological peers over the past five years.
<i>PMR</i>	Dummy variable equal to one if the focal firm and its peer belong to the same industry according to the TNIC2 industry classification from Hoberg and Phillips (2016).

Figure 1: Diffusion-Constraint Space (Conceptual)

This figure shows the conceptual Diffusion-Constraint space.



This figure shows the snapshot of the CPC classification hierarchical arrays.



Figure 3: Distribution of Firms by Number of Technological Peers

This figure shows the distribution of firms by number of technological peers

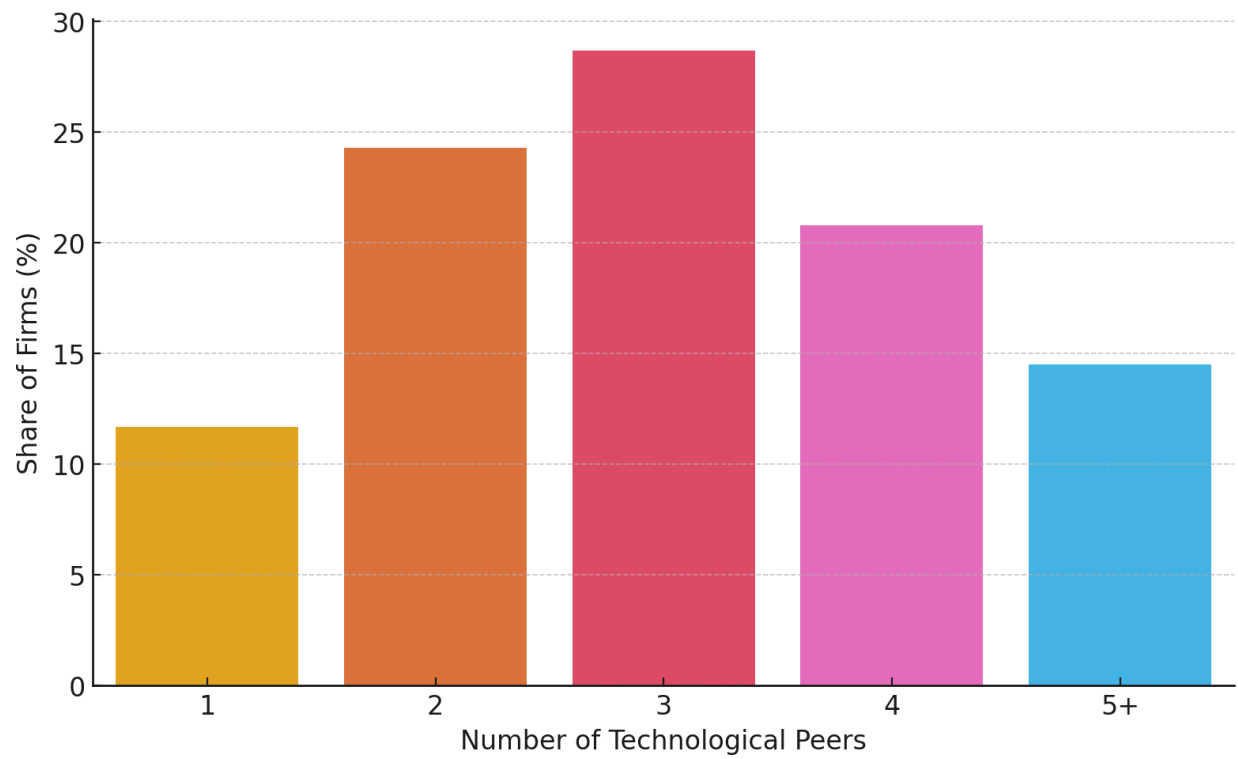


Figure 4: Abnormal Stock Returns around the Patent Grant

The figure illustrates how Apple's "Slide to Unlock" patent grant (US 8,046,721; Grant date: Oct 25, 2011) triggered a positive stock response for Apple and negative abnormal returns for its competitors.

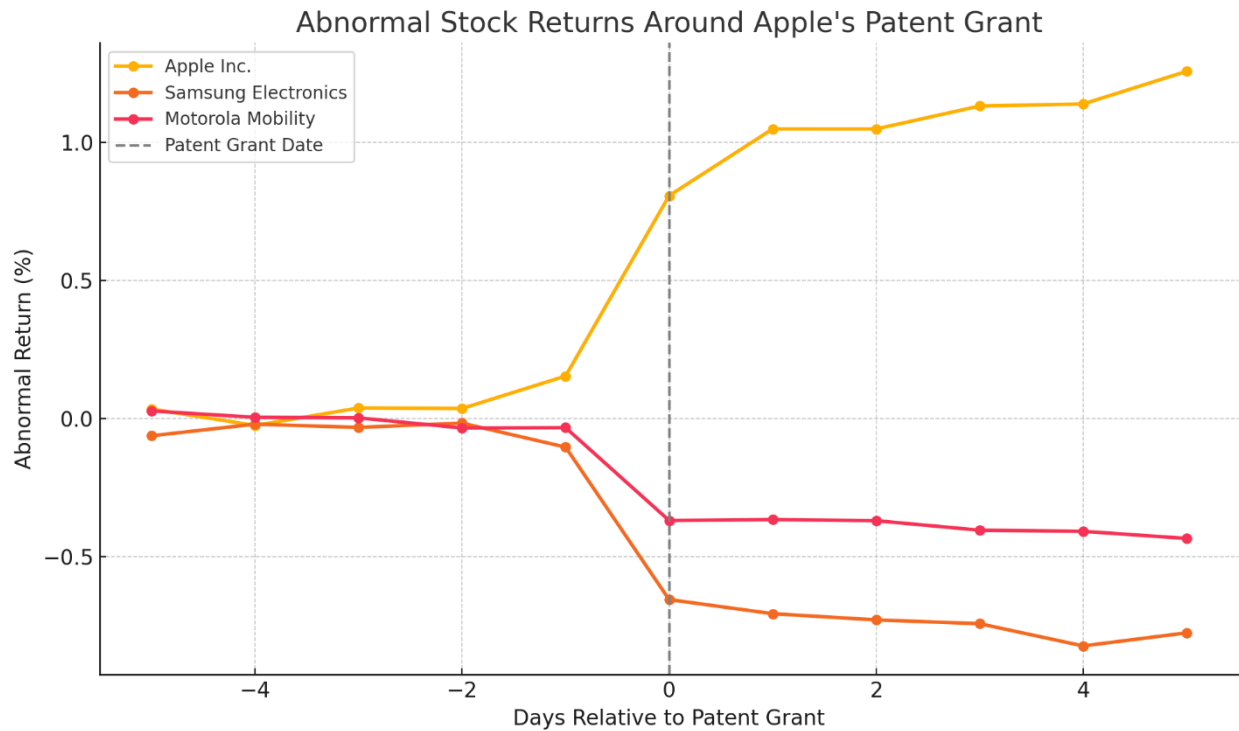


Figure 5: Dynamic Response of Peers' Innovative Efforts after Focal Firm's Patent Grant

This figure presents the dynamic response of peers' R&D investment and acquisition activity in event time relative to the focal firm's patent grant year, separately for AR+ and AR- events. The shaded areas represent 95% confidence intervals. The vertical dashed line indicates the focal patent grant year, and the horizontal dashed line indicates zero effect.

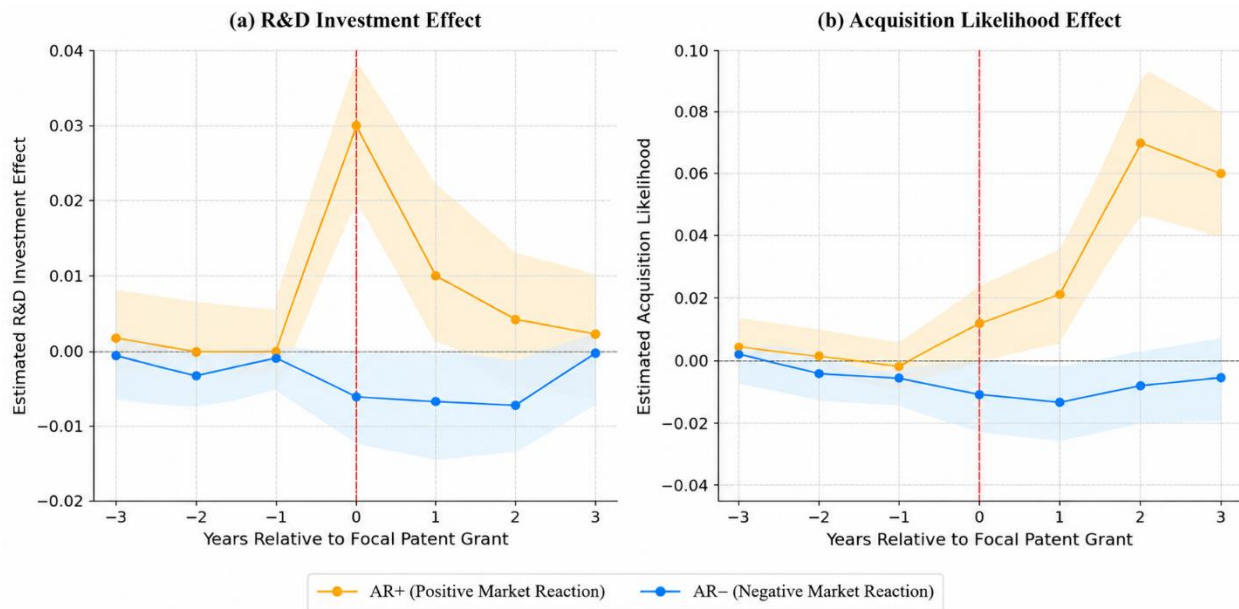


Figure 6: Dynamic Response of Peers' Financial and Investment Policies After Focal Firm's Patent Grant

The figure presents the dynamic response of four firm-level outcomes—cash holdings, debt issuance, equity issuance, and CAPEX—in event time relative to the focal firm's patent grant year. Results are shown separately for focal firm's innovations that generate positive abnormal returns (AR^+) and negative abnormal returns (AR^-). All estimates are from the event-time specification introduced in Section 4.6, and confidence intervals represent 95% uncertainty bands.

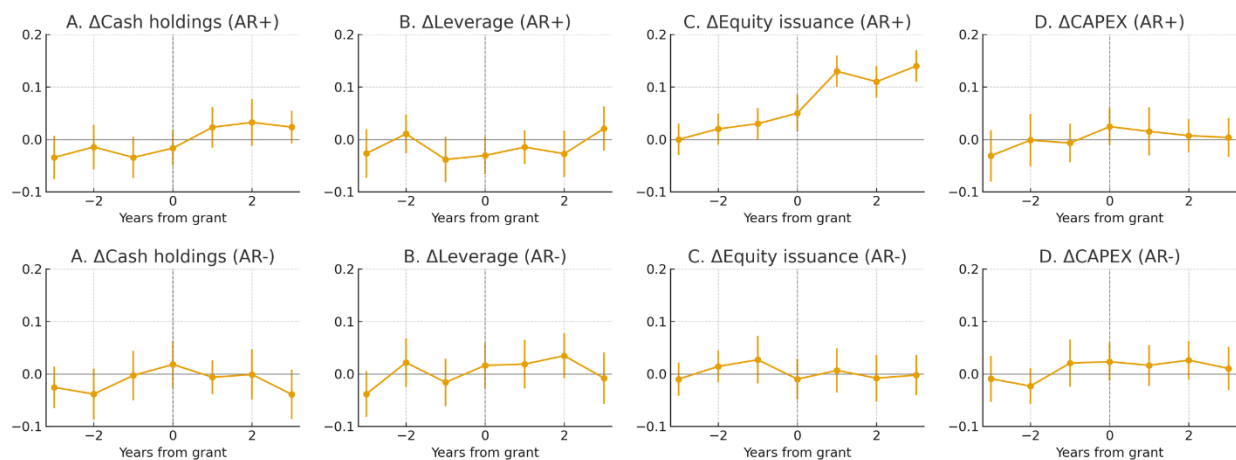


Figure 7: Marginal Effect of Focal Firm's Patent Grant by Moderator Variables Percentile

The figure shows the marginal effect of focal firm's patent grant on peer's R&D investment by two moderator variables' percentile: *Cash* and *InnovCap*.

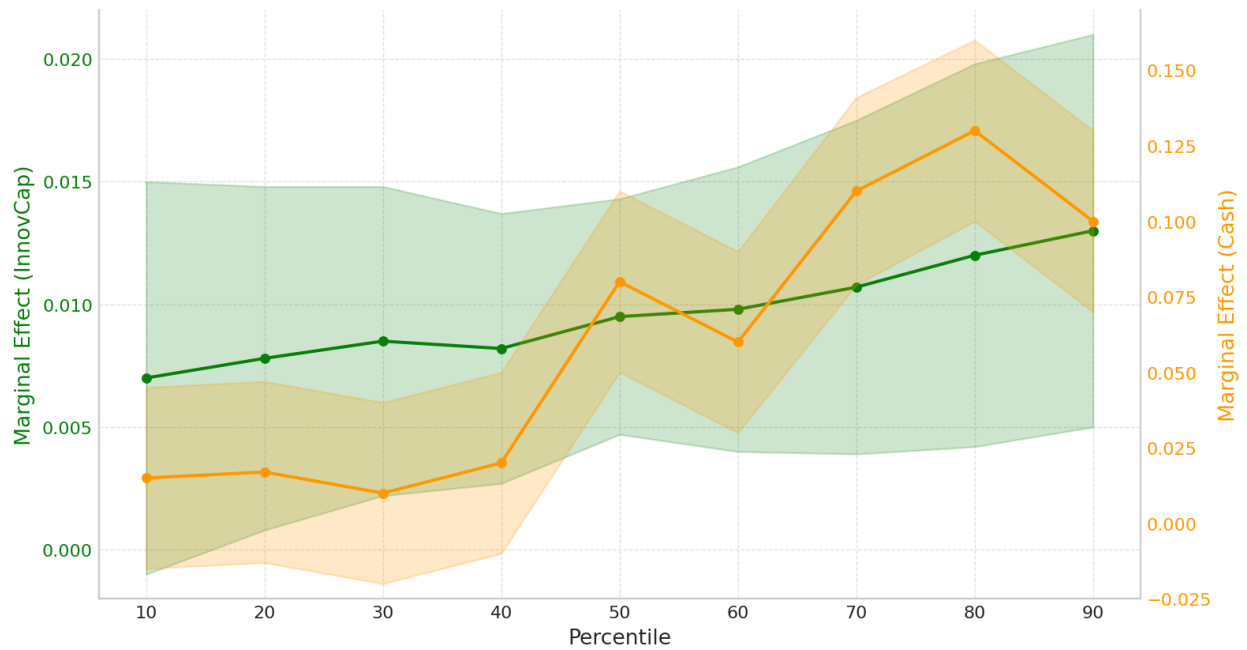


Table 1: Summary Statistics

This table presents the summary statistics for the variables used in this study.

Variable	N	Mean	SD	P10	Median	P90
<u>Dependent variable</u>						
<i>R&D</i>	445,451	0.084	0.232	0.000	0.000	0.217
<i>Acquisition</i>	445,451	0.068	0.252	0.000	0.000	0.000
<i>PatentFiling</i>	421,636	2.311	5.637	0.000	1.000	12.00
<i>CitShareOverlap</i>	413,491	0.038	0.064	0.004	0.021	0.142
<i>ExplorationRatio</i>	445,451	0.012	0.078	0.000	0.008	0.036
<i>NetEquityIssuance</i>	445,451	0.008	0.023	-0.021	0.000	0.062
<u>Independent variables</u>						
<i>FocalPatentGrant</i>	445,451	0.023	0.152	0.000	0.000	0.000
<u>Interacting variables</u>						
<i>AR+ (dummy)</i>	445,451	0.001	0.034	0.000	0.000	0.000
<i>AR- (dummy)</i>	445,451	0.001	0.032	0.000	0.000	0.000
<i>Thicketing</i>	423,219	0.013	0.051	-0.045	0.021	0.095
<i>InnovCap</i>	406,387	0.615	0.582	0.047	0.632	2.413
<i>PMR</i>	445,451	0.180	0.384	0.000	0.000	1.000
<i>PatentConc_Ind</i>	445,451	0.178	0.083	0.078	0.153	0.367
<u>Control variables</u>						
<i>Log(Asset)</i>	445,451	5.136	2.166	2.317	4.359	8.352
<i>Tobin's Q</i>	445,451	3.514	2.352	0.632	2.314	5.783
<i>Cash</i>	445,451	0.127	0.075	0.031	0.062	0.259
<i>Leverage</i>	445,451	0.244	0.139	0.000	0.196	0.352
<i>Profitability</i>	445,451	0.042	0.134	-0.251	-0.122	0.349
<i>Age</i>	445,451	16.164	8.425	0.000	14.000	37.000

Table 2: Baseline Estimates: Focal Firm's Patent Grant and Peer Innovative Efforts

This table reports the estimation results for Equation (2). The dependent variables are *R&D* and *Acquisition* (innovative effort variables). The firm-level controls (i.e., *Log(Asset)*, *Tobin's Q*, *Cash*, *Leverage*, *Profitability*, and *Age*) are included in Columns (3)-(4). Firm-cohort fixed effects as well as industry-year-cohort fixed effects are controlled for in the regression. All standard errors are double clustered at peer firm and year level. The reported coefficients are cohort-size-weighted averages of the cohort-specific treatment effects. The t-statistics in parentheses are calculated based on the clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	<i>R&D</i>	<i>Acquisition</i>	<i>R&D</i>	<i>Acquisition</i>
	(1)	(2)	(3)	(4)
<i>FocalPatentGrant</i>	0.003 (0.48)	0.008 (0.45)	0.002 (1.21)	0.006 (0.28)
<i>FocalPatentGrant</i> * <i>AR</i> +	0.007** (2.32)	0.059** (2.43)	0.006** (2.21)	0.057*** (3.08)
<i>FocalPatentGrant</i> * <i>AR</i> −	0.002 (0.15)	0.015 (0.74)	0.001 (0.93)	0.019 (0.65)
<i>Log(Asset)</i>			0.013 (1.56)	0.002 (0.98)
<i>Tobin's Q</i>			0.041* (1.75)	-0.013 (-0.67)
<i>Cash</i>			0.029* (1.92)	0.041** (2.02)
<i>Leverage</i>			-0.021 (-0.29)	0.001 (0.51)
<i>Profitability</i>			0.013 (0.85)	0.008 (0.28)
<i>Age</i>			0.041 (0.01)	0.029 (1.45)
Controls	No	No	Yes	Yes
Firm x Cohort FE	Yes	Yes	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.505	0.487	0.517	0.442
Observations	240,138	240,138	238,416	238,416

Table 3: Interpretation of Positive and Negative Peer Market Reactions

This table examines whether positive and negative peer market reactions around focal firm's patent grants are systematically associated with ex ante technological and competitive relationships between the focal firm and its peers. The sample consists of firm-year observations in which a focal firm's patent grant occurs. The dependent variables are indicator variables equal to one if the focal firm's patent grant is classified as an AR^+ event (Column (1)) or an AR^- event (Column (2)), and zero otherwise. Citation overlap and patent-text similarity measure ex ante technological complementarity between the focal firm and the peer, whereas TNIC product similarity measures ex ante product-market rivalry. All explanatory variables are measured prior to the patent grant. Firm-level controls are included in all specifications. Robust t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	AR^+	AR^-
	(1)	(2)
<i>CitShareOverlap</i>	0.006*** (3.21)	-0.001 (-0.74)
<i>TextSimilarity</i>	0.004** (2.49)	-0.002 (-1.18)
<i>ProductSimilarity</i>	0.001 (0.63)	0.005*** (2.89)
Controls	Yes	Yes
Firm x Cohort FE	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes
Adj. R-squared	0.403	0.326
Observations	62,325	62,325

Table 4: First-Stage Results for the Instrument

This table reports the first-stage regression results for the instrumental variable strategy described in Section 3.4.2. The analysis is conducted using the best-peer sample, where each focal firm is matched to the peer with the highest level of mutual patent citation intensity. Because the second-stage specification includes three endogenous variables—*FocalPatentGrant*, *FocalPatentGrant* $\times$ *AR*+, and *FocalPatentGrant* $\times$ *AR*—the first stage consists of three separate regressions. The corresponding excluded instruments are Examiner Leniency (*EL*), *EL* $\times$ *AR*+, and *EL* $\times$ *AR*-, respectively. All specifications include firm fixed effects, industry-by-year fixed effects, and the full set of control variables used in the baseline regressions. All standard errors are double clustered at the focal firm and a year level. The t-statistics in parentheses are calculated based on the clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	<i>FocalPatentGrant</i>	<i>FocalPatentGrant</i> $\times$ <i>AR</i> +	<i>FocalPatentGrant</i> $\times$ <i>AR</i> -
	(1)	(2)	(3)
<i>EL</i>	1.56*** (3.17)		
<i>EL</i> $\times$ <i>AR</i> +	1.92*** (2.97)	1.87*** (3.94)	
<i>EL</i> $\times$ <i>AR</i> -	1.46*** (2.68)		1.52*** (3.31)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Ind x Year FE	Yes	Yes	Yes
Observations	36,184	36,184	36,184
F-statistic	32.37	25.84	25.92
KP rk Wald F		18.93	

Table 5: Two-Stage Regressions for Peer Response to Significant Focal Firm's Patents

This table reports the estimation results for Equation (4). The dependent variables are *R&D* and *Acquisition*. The main explanatory variables are $\widehat{FocalPatentGrant} * AR +$ (and $-$) and $\widehat{FocalPatentGrant}$. All the firm-level controls (i.e., *Log(Asset)*, *Tobin's Q*, *Cash*, *Leverage*, *Profitability*, and *Age*) are included in all columns. Firm fixed effects as well as industry-year fixed effects are controlled for in the regression. All standard errors are double clustered at peer firm and year level. The t-statistics in parentheses are calculated based on the clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	<i>R&D</i> (1)	<i>Acquisition</i> (2)
$\widehat{FocalPatentGrant}$	0.003 (0.64)	0.010 (0.58)
$\widehat{FocalPatentGrant} * AR +$	0.011** (2.29)	0.082** (2.04)
$\widehat{FocalPatentGrant} * AR -$	-0.001 (-0.51)	0.018 (0.73)
Controls	Yes	Yes
Firm Fixed Effects	Yes	Yes
Ind x Year Fixed Effects	Yes	Yes
Adj. R-squared	0.518	0.426
Observations	36,184	36,184

Table 6: Effect of Adverse Focal Firm's Patent News on Peers' Innovation Direction

This table reports the estimation results for changes in peers' innovation direction to patents that drive adverse valuation shocks. The dependent variable is *ExplorationRatio* – defined as the fraction of new patents filed outside the peer's pre-existing top CPC classes over the next five years. The main explanatory variables are *FocalPatentGrant * AR +* (and *–*). All the firm-level controls (i.e., *Log(Asset)*, *Tobin's Q*, *Cash*, *Leverage*, *Profitability*, and *Age*) are included in column (2). Firm-cohort fixed effects as well as industry-year-cohort fixed effects are controlled for in the regression. All standard errors are double clustered at peer firm and year level. The reported coefficients are cohort-size-weighted averages of the cohort-specific treatment effects. The t-statistics in parentheses are calculated based on the clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	<i>ExplorationRatio</i>	<i>ExplorationRatio</i>
	(1)	(2)
<i>FocalPatentGrant * AR +</i>	-0.001 (-0.35)	0.004 (0.18)
<i>FocalPatentGrant * AR –</i>	0.016** (2.29)	0.012** (2.04)
Controls	No	Yes
Firm x Cohort FE	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes
Adj. R-squared	0.718	0.647
Observations	240,138	238,416

Table 7: Triple-Difference Heterogeneity Analyses (Firm Relationship)

This table reports the estimation results for Equation (5). The dependent variables are *R&D*, *Acquisition*, and *ExplorationRatio*. The main explanatory variables are *FocalPatentGrant* * *CitShareOverlap*_[t-5,t] * *AR* + (and -) and *FocalPatentGrant* * *PMR* * *AR* + (and -). All the firm-level controls (i.e., *Log(Asset)*, *Tobin's Q*, *Cash*, *Leverage*, *Profitability*, and *Age*) are included in all columns. Firm-cohort fixed effects as well as industry-year-cohort fixed effects are controlled for in the regression. All standard errors are double clustered at peer firm and year level. The reported coefficients are cohort-size-weighted averages of the cohort-specific treatment effects. The t-statistics in parentheses are calculated based on the clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	<i>R&D</i> (1)	<i>Acquisition</i> (2)	<i>ExplorationRatio</i> (3)
<i>FocalPatentGrant</i> * <i>CitShareOverlap</i> * <i>AR</i> +	2.319** (2.34)	7.128** (2.06)	0.003 (0.31)
<i>FocalPatentGrant</i> * <i>CitShareOverlap</i> * <i>AR</i> -	0.108 (0.46)	2.134 (0.12)	0.002 (0.29)
<i>FocalPatentGrant</i> * <i>PMR</i> * <i>AR</i> +	-0.014 (-0.83)	-0.008 (-0.65)	-0.001 (-0.17)
<i>FocalPatentGrant</i> * <i>PMR</i> * <i>AR</i> -	0.052 (0.39)	0.018 (0.41)	-0.003 (-0.21)
Controls	Yes	Yes	Yes
Firm x Cohort FE	Yes	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes	Yes
Adj. R-squared	0.465	0.583	0.508
Observations	238,416	238,416	238,416

Table 8: Triple-Difference Heterogeneity Analyses (Constraints and Enablers)

This table reports the estimation results for Equation (5). The dependent variables are *R&D*, *Acquisition*, and *ExplorationRatio*. The explanatory variables are *FocalPatentGrant * Thicketing * AR + (and -)*, *FocalPatentGrant * LitigationRisk * AR + (and -)*, *FocalPatentGrant * Cash * AR + (and -)*, *FocalPatentGrant * Leverage * AR + (and -)*, and *FocalPatentGrant * InnovCap * AR + (and -)*. All the firm-level controls are included in all columns. Firm-cohort fixed effects as well as industry-year-cohort fixed effects are controlled for in the regression. All standard errors are double clustered at peer firm and year level. The reported coefficients are cohort-size-weighted averages of the cohort-specific treatment effects. The t-statistics in parentheses are calculated based on the clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A (External Constraints)

Variable	<i>R&D</i> (1)	<i>Acquisition</i> (2)	<i>ExplorationRatio</i> (3)
<i>FocalPatentGrant * Thicketing * AR +</i>	-0.502** (-2.16)	-2.937** (-1.98)	0.017 (0.42)
<i>FocalPatentGrant * Thicketing * AR -</i>	-2.401 (-0.65)	-1.837 (-1.03)	0.124 ** (2.04)
<i>FocalPatentGrant * LitigationRisk * AR +</i>	-2.203* (-1.85)	-1.138* (-1.93)	-0.001 (-0.32)
<i>FocalPatentGrant * LitigationRisk * AR -</i>	-0.519 (-0.17)	-2.361 (-0.13)	0.021** (2.54)
Controls	Yes	Yes	Yes
Firm x Cohort FE	Yes	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes	Yes
Adj. R-squared	0.442	0.417	0.423

Panel B (Internal Enablers)

Variable	<i>R&D</i> (1)	<i>Acquisition</i> (2)	<i>ExplorationRatio</i> (3)
<i>FocalPatentGrant * Cash * AR +</i>	1.398*** (3.02)	0.471 (0.91)	0.001 (0.03)
<i>FocalPatentGrant * Cash * AR -</i>	1.871*** (3.21)	2.131** (2.06)	0.062*** (3.32)
<i>FocalPatentGrant * Leverage * AR +</i>	-0.726** (-2.12)	-2.769* (-1.85)	-1.028 (-0.53)
<i>FocalPatentGrant * Leverage * AR -</i>	-0.872** (-1.99)	-1.319** (-2.25)	-0.121** (-2.13)
<i>FocalPatentGrant * InnovCap * AR +</i>	0.165** (2.14)	0.365** (2.61)	0.025 (0.10)
<i>FocalPatentGrant * InnovCap * AR -</i>	0.102* (1.92)	0.215 (1.27)	2.235*** (3.98)
Controls	Yes	Yes	Yes
Firm x Cohort FE	Yes	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes	Yes
Adj. R-squared	0.532	0.491	0.476

Table 9: Innovation Output: Patent Filing and Directional Alignment

This table reports the estimation results for Equation (2) using innovation output measures as dependent variables. The dependent variables are *PatentFiling* and *CitShareOverlap*. The main explanatory variable is *FocalPatentGrant * AR +* and *FocalPatentGrant * AR -*. All the firm-level controls (i.e., *Log(Asset)*, *Tobin's Q*, *Cash*, *Leverage*, *Profitability*, and *Age*) are included in columns (3) and (4). Firm-cohort fixed effects as well as industry-year-cohort fixed effects are controlled for in the regression. All standard errors are double clustered at peer firm and year level. The reported coefficients are cohort-size-weighted averages of the cohort-specific treatment effects. The t-statistics in parentheses are calculated based on the clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	<i>PatentFiling</i> (1)	<i>CitShareOverlap</i> (2)	<i>PatentFiling</i> (3)	<i>CitShareOverlap</i> (4)
<i>FocalPatentGrant * AR +</i>	0.208** (2.15)	0.003** (2.43)	0.142* (1.75)	0.003** (2.32)
<i>FocalPatentGrant * AR -</i>	0.048 (0.16)	-0.004** (-2.41)	0.028 (0.89)	-0.005** (-2.01)
Controls	No	No	Yes	Yes
Firm x Cohort FE	Yes	Yes	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.327	0.215	0.298	0.237
Observations	240,138	240,138	238,416	238,416

Table 10: Focal Firm's Patent Disclosure and Innovative Efforts

This table reports the effect of focal firm's patent disclosure on peers' innovative efforts. *FocalPatentDisc* variable is the main explanatory variable. The dependent variables are *R&D* and *Acquisition* (innovative effort variables). The firm-level controls (i.e., *Log(Asset)*, *Tobin's Q*, *Cash*, *Leverage*, *Profitability*, and *Age*) are included in Columns (3)-(4). All the firm-level controls (i.e., *Log(Asset)*, *Tobin's Q*, *Cash*, *Leverage*, *Profitability*, and *Age*) are included in columns (3) and (4). Firm-cohort fixed effects as well as industry-year-cohort fixed effects are controlled for in the regression. All standard errors are double clustered at peer firm and year level. The reported coefficients are cohort-size-weighted averages of the cohort-specific treatment effects. The t-statistics in parentheses are calculated based on the clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	<i>R&D</i> (1)	<i>Acquisition</i> (2)	<i>R&D</i> (3)	<i>Acquisition</i> (4)
<i>FocalPatentDisc</i> * <i>AR</i> +	0.001 (0.71)	-0.001 (-0.12)	0.002 (0.30)	0.001 (0.22)
<i>Log(Asset)</i>			0.021** (2.35)	0.005* (1.67)
<i>Tobin's Q</i>			0.016 (0.94)	-0.026 (-1.25)
<i>Cash</i>			0.048*** (3.41)	0.019 (1.12)
<i>Leverage</i>			-0.063* (-1.88)	-0.014 (-0.71)
<i>Profitability</i>			0.027 (1.31)	-0.005 (-0.16)
<i>Age</i>			0.008 (0.08)	0.001 (0.05)
Controls	No	No	Yes	Yes
Firm x Cohort FE	Yes	Yes	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.528	0.421	0.509	0.460
Observations	240,138	240,138	238,416	238,416

Table 11: Focal Firm's Patent Grant Intensity and Innovative Efforts

This table reports how the intensity of focal firm's patent granting activity affects peer firm's innovative efforts. *#[SignificantFocalPatent]* variable counts the number of significant focal firm's patent grants that peer firm has experienced in a year. The dependent variables are *R&D* and *Acquisition* (innovative effort variables). All the firm-level controls (i.e., *Log(Asset)*, *Tobin's Q*, *Cash*, *Leverage*, *Profitability*, and *Age*) are included in columns (3) and (4). Firm-cohort fixed effects as well as industry-year-cohort fixed effects are controlled for in the regression. All standard errors are double clustered at peer firm and year level. The reported coefficients are cohort-size-weighted averages of the cohort-specific treatment effects. The t-statistics in parentheses are calculated based on the clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	<i>R&D</i>	<i>Acquisition</i>	<i>R&D</i>	<i>Acquisition</i>
	(1)	(2)	(3)	(4)
<i>#[SignificantFocalPatent]</i>	0.002 (1.55)	0.004* (1.87)	0.003* (1.82)	0.003** (2.02)
<i>Log(Asset)</i>			0.016** (2.13)	0.003** (1.98)
<i>Tobin's Q</i>			0.021 (0.63)	-0.015 (-0.51)
<i>Cash</i>			0.021*** (2.87)	0.039 (0.84)
<i>Leverage</i>			-0.053 (-1.18)	-0.001 (-0.21)
<i>Profitability</i>			0.067 (1.40)	-0.002 (-0.10)
<i>Age</i>			0.006 (0.75)	0.001 (0.13)
Controls	No	No	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Ind x Year Fixed Effects	Yes	Yes	Yes	Yes
Adj. R-squared	0.344	0.428	0.351	0.413
Observations	240,138	240,138	238,416	238,416

Table 12: Patent Text Similarity and Technological Alignment

This table reports the estimation results for changes in the textual similarity between focal firm's patents and peers' subsequent patents. The dependent variable is *TextSimilarity*, defined as the average cosine similarity between a focal firm's patent and patents subsequently filed by the peer firm within the next five years. Patent embeddings are constructed using patent abstracts and claims, and similarity is measured using cosine similarity scores. The main explanatory variables are $FocalPatentGrant \times AR+$ and $FocalPatentGrant \times AR-$. All firm-level controls (i.e., *Log(Asset)*, *Tobin's Q*, *Cash*, *Leverage*, *Profitability*, and *Age*) are included in Column (2). Firm-cohort fixed effects as well as industry-year-cohort fixed effects are controlled for in the regression. All standard errors are double clustered at the peer firm and year level. The reported coefficients are cohort-size-weighted averages of the cohort-specific treatment effects. The t-statistics in parentheses are calculated based on clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	<i>TextSimilarity</i>	<i>TextSimilarity</i>
	(1)	(2)
<i>FocalPatentGrant</i> * <i>AR</i> +	0.024*** (3.14)	0.019** (2.42)
<i>FocalPatentGrant</i> * <i>AR</i> -	-0.018** (-2.27)	-0.015** (-2.08)
Controls	No	Yes
Firm x Cohort FE	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes
Adj. R-squared	0.284	0.312
Observations	240,138	238,416

Table 13: Placebo Grant Dates

This table reports a placebo test using artificial focal firm's patent grant dates. For each significant focal firm's patent grant, the treatment date is shifted forward by 90 calendar days, and the baseline specifications are re-estimated using these placebo event dates. The dependent variables are *R&D*, *Acquisition*, *PatentFiling*, and *ExplorationRatio*. The main explanatory variables are *PlaceboGrant* $\times$ *AR*⁺ and *PlaceboGrant* $\times$ *AR*[−]. All firm-level controls (i.e., Log(Asset), Tobin's Q, Cash, Leverage, Profitability, and Age) are included in all columns. Firm-cohort fixed effects as well as industry-year-cohort fixed effects are controlled for in the regression. All standard errors are double clustered at the peer firm and year level. The reported coefficients are cohort-size-weighted averages of the cohort-specific treatment effects. The t-statistics in parentheses are calculated based on clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	<i>R&D</i> (1)	<i>Acquisition</i> (2)	<i>PatentFiling</i> (3)	<i>ExplorationRatio</i> (4)
<i>PlaceboGrant</i> * <i>AR</i> +	0.012 (0.42)	0.007 (0.58)	0.024 (0.31)	0.002 (0.27)
<i>PlaceboGrant</i> * <i>AR</i> −	-0.002 (-0.33)	0.004 (0.24)	-0.011 (-0.12)	0.003 (0.41)
Controls	Yes	Yes	Yes	Yes
Firm x Cohort FE	Yes	Yes	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.514	0.439	0.302	0.651
Observations	238,416	238,416	238,416	238,416

Table 14: Alternative Peer Definitions

This table examines whether the main findings depend on the construction of peer firms. Columns (1)–(2) redefine peers using the TNIC product-market network developed by Hoberg and Phillips (2016). Columns (3)–(4) define peers as firms operating within the same Fama-French 48 industry. The dependent variables are *R&D* and *Acquisition*. All firm-level controls (i.e., *Log(Asset)*, *Tobin's Q*, *Cash*, *Leverage*, *Profitability*, and *Age*) are included in all specifications. Firm-cohort fixed effects as well as industry-year-cohort fixed effects are controlled for in the regressions. All standard errors are double clustered at the peer firm and year level. The reported coefficients are cohort-size-weighted averages of the cohort-specific treatment effects. The t-statistics in parentheses are calculated based on clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	<i>TNICPeer</i> (<i>R&D</i>)	<i>TNICPeer</i> (<i>Acquisition</i>)	<i>IndustryPeer</i> (<i>R&D</i>)	<i>IndustryPeer</i> (<i>Acquisition</i>)
	(1)	(2)	(3)	(4)
<i>FocalPatentGrant</i> * <i>AR</i> +	0.004* (1.89)	0.038** (2.17)	0.003* (1.74)	0.029* (1.91)
<i>FocalPatentGrant</i> * <i>AR</i> –	-0.001 (-0.28)	0.011 (0.41)	0.000 (0.04)	0.006 (0.29)
Controls	Yes	Yes	Yes	Yes
Firm x Cohort FE	Yes	Yes	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.492	0.421	0.468	0.403
Observations	240,138	240,138	238,416	238,416

Table 15: Excluding Earnings Announcements Around Patent Grant Dates

This table reports the baseline estimates after excluding focal firm's patent grants that occur within five trading days of a firm's earnings announcement. The purpose of this test is to ensure that the abnormal stock returns used to construct the AR+ and AR− classifications are not driven by earnings-related information releases rather than patent-related news. The dependent variables are *R&D* and *Acquisition*. All firm-level controls (i.e., Log(Asset), Tobin's Q, Cash, Leverage, Profitability, and Age) are included in all specifications. Firm-cohort fixed effects as well as industry-year-cohort fixed effects are controlled for in the regressions. All standard errors are double clustered at the peer firm and year level. The reported coefficients are cohort-size-weighted averages of the cohort-specific treatment effects. The t-statistics in parentheses are calculated based on clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	<i>R&D</i>	<i>Acquisition</i>
	(1)	(2)
<i>FocalPatentGrant</i> * AR +	0.005** (2.12)	0.052*** (2.84)
<i>FocalPatentGrant</i> * AR −	0.001 (0.61)	0.014 (0.52)
Controls	Yes	Yes
Firm x Cohort FE	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes
Adj. R-squared	0.511	0.437
Observations	221,504	221,504

Table 16: Peer Responses and Patentability Uncertainty

This table examines whether peer responses are driven primarily by the resolution of patentability uncertainty at the grant date. Patentability uncertainty is proxied by *HighUncertainty*, an indicator equal to one if the patent's application-to-grant delay is above the sample median. The dependent variables are R&D and Acquisition. The main explanatory variables are $FocalPatentGrant \times AR+$, $FocalPatentGrant \times AR-$, and their interactions with *HighUncertainty*. All firm-level controls (i.e., Log(Asset), Tobin's Q, Cash, Leverage, Profitability, and Age) are included in all specifications. Firm-cohort fixed effects as well as industry-year-cohort fixed effects are controlled for in the regressions. All standard errors are double clustered at the peer firm and year level. The reported coefficients are cohort-size-weighted averages of the cohort-specific treatment effects. The t-statistics in parentheses are calculated based on clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	<i>R&D</i>	<i>Acquisition</i>
	(1)	(2)
<i>FocalPatentGrant * AR +</i>	0.006** (2.21)	0.061*** (3.02)
<i>FocalPatentGrant * AR -</i>	0.001 (0.44)	0.018 (0.72)
<i>FocalPatentGrant * AR + * HighUncertainty</i>	0.001 (0.38)	0.007 (0.61)
<i>FocalPatentGrant * AR - * HighUncertainty</i>	-0.001 (-0.22)	0.003 (0.14)
Controls	Yes	Yes
Firm x Cohort FE	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes
Adj. R-squared	0.521	0.441
Observations	238,416	238,416

Table 17: Robustness to Overlapping Network Exposure

This table evaluates the robustness of the baseline estimates to alternative treatments of repeated peer-year observations. Because the empirical design is implemented at the peer-focal-year level, the same peer-year outcome may enter the estimation sample multiple times through multiple patent grants by the same focal firm or through links to multiple focal firms. Column (1) reports the baseline estimates. Column (2) restricts the sample to clean event windows that exclude peer-years exposed to other connected patent grants during the event window. Column (3) retains only one patent grant for each peer-focal-year observation. Column (4) applies inverse duplication weights so that repeated peer-year observations receive a total weight of one. All specifications include the same control variables and fixed effects as in the baseline specification. Robust t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A Innovation Responses: R&D

Variable	<i>Baseline</i> (1)	<i>CleanWindow</i> (2)	<i>One-event</i> (3)	<i>Inverse Weights</i> (4)
<i>FocalPatentGrant</i> * <i>AR</i> +	0.006** (2.21)	0.004** (2.73)	0.004* (1.74)	0.005** (2.32)
<i>FocalPatentGrant</i> * <i>AR</i> −	0.001 (0.93)	0.000 (0.71)	0.000 (0.18)	0.001 (0.26)
Controls	Yes	Yes	Yes	Yes
Firm x Cohort FE	Yes	Yes	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.517	0.342	0.629	0.471
Observations	238,416	112,842	64,278	238,416

Panel B Innovation Responses: Acquisition

Variable	<i>Baseline</i> (1)	<i>CleanWindow</i> (2)	<i>One-event</i> (3)	<i>Inverse Weights</i> (4)
<i>FocalPatentGrant</i> * <i>AR</i> +	0.057*** (3.08)	0.026* (1.86)	0.033** (2.17)	0.055** (2.45)
<i>FocalPatentGrant</i> * <i>AR</i> −	0.019 (0.65)	0.021 (1.04)	-0.017 (-0.16)	0.092 (0.37)
Controls	Yes	Yes	Yes	Yes
Firm x Cohort FE	Yes	Yes	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.442	0.284	0.562	0.419
Observations	238,416	112,842	64,278	238,416

Table 18: Alternative Asset Pricing Models and Market-Reaction Classifications

This table examines whether the classification of focal firm's patent grants into AR+ and AR- events is sensitive to the choice of asset-pricing model used to estimate abnormal returns. Column (1) reports the baseline market-model classification. Column (2) reconstructs abnormal returns using the Fama-French five-factor model, while Column (3) uses the q-factor model. AR+ and AR- indicators are redefined separately under each return-generating model, and the baseline regressions are re-estimated accordingly. The dependent variables are *R&D* and *Acquisition*. All firm-level controls (i.e., *Log(Asset)*, *Tobin's Q*, *Cash*, *Leverage*, *Profitability*, and *Age*) are included in all specifications. Firm-cohort fixed effects as well as industry-year-cohort fixed effects are controlled for in the regressions. All standard errors are double clustered at the peer firm and year level. The reported coefficients are cohort-size-weighted averages of the cohort-specific treatment effects. The t-statistics in parentheses are calculated based on clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A Distribution of Significant Patent Grants

	<i>Market Model</i>	<i>FF5 Model</i>	<i>q-Factor Model</i>
	(1)	(2)	(3)
AR+ Share	63.3%	62.1%	61.7%
AR- Share	36.7%	37.9%	38.3%
Significant Patents	6,341	6,218	6,104

Panel B Innovation Responses: R&D

Variable	<i>Market Model</i>	<i>FF5 Model</i>	<i>q-Factor Model</i>
	(1)	(2)	(3)
<i>FocalPatentGrant</i> * AR +	0.006** (2.21)	0.006** (2.17)	0.005** (2.08)
<i>FocalPatentGrant</i> * AR -	0.001 (0.93)	0.001 (0.74)	0.000 (0.18)
Controls	Yes	Yes	Yes
Firm x Cohort FE	Yes	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes	Yes
Adj. R-squared	0.517	0.514	0.511
Observations	238,416	236,822	234,971

Panel C Innovation Responses: Acquisition

Variable	<i>Market Model</i>	<i>FF5 Model</i>	<i>q-Factor Model</i>
	(1)	(2)	(3)
<i>FocalPatentGrant</i> * AR +	0.057*** (3.08)	0.054*** (2.89)	0.052** (2.41)
<i>FocalPatentGrant</i> * AR -	0.019 (0.65)	0.016 (0.51)	0.013 (0.43)
Controls	Yes	Yes	Yes
Firm x Cohort FE	Yes	Yes	Yes
Ind x Year x Cohort FE	Yes	Yes	Yes
Adj. R-squared	0.442	0.439	0.436
Observations	238,416	236,822	234,971