The Market Value of Technological Spillovers

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First Version: September, 2025
This Version: September, 2026

ABSTRACT

Does the market price technological spillovers? If so, what determines the spillover value of innovation? I construct a patent-level measure of innovation's spillover value from peer firms' equity reactions to U.S. patent grants from 1926 to 2023. Around patent grants, peer firms in the patenting firms' industries earn higher three-day market-adjusted returns than firms outside the affected industries. Returns also increase with firms' technological similarity to the newly granted patents. The absolute magnitude of spillover value predicts forward citations. Private patent value is positively associated with spillover value for industry peers. Peer firms' spillover exposure predicts long-run output and employment growth conditional. Spillover effects on growth are stronger in more research intensive industries. Higher spillover exposure is associated with greater investment and acquisition expenditures, as well as increased inventive activity. Spillover pass-through varies with innovation characteristics, industry conditions, and the information environment. It is larger for breakthrough patents, process patents, and technologies in rapidly evolving fields, and weaker in industries with greater market power, tighter financial constraints and larger exposure to data. Measured pass-through is also stronger in larger industries and for patents issued by more actively traded firms, consistent with investor attention facilitating the recognition of external innovation opportunities in prices.

JEL Classification: G14, E32, O3, O4
Keywords: Patent, Innovation, Technology Spillover, Industrial Organization, Stock Returns, Event Study

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1 Introduction

An invention's value to its owner does not reveal what it is worth to other firms. New knowledge can expand their productive opportunities, while new products and stronger patent protection can erode their existing rents. The distinction matters for understanding innovation: the reward that motivates an invention and the opportunities it creates elsewhere accrue to different firms. These external effects are central to theories of innovation and growth (Lucas (1988); Romer (1990)), but measuring them requires examining how innovation affects peer firms as well as the innovator. This paper develops a market-based measure of innovation's external value and uses it to study how private rewards relate to gains and losses among other firms, and how those valuations anticipate peer firms' subsequent investment and growth.

The measure starts with a peer firm's own equity response to a patent grant. Kogan, Papanikolaou, Seru, and Stoffman (2017) (KPSS) infer a patent's private value from the patenting firm's equity response around the grant date. I extend their valuation framework to peer firms in the same three-digit SIC industry, using these firms' equity responses to measure spillover value for U.S. patents granted from 1926 through 2023. I infer a patent's value to peer firms from their market-adjusted returns over the three trading days beginning on the grant date. These responses reflect market assessments of the patent's economic implications for each peer, encompassing both technological opportunities and competitive displacement. An invention with high private value may benefit, harm, or have little effect on a particular peer. Peer-firm responses therefore provide information about the external effects of innovation that is not captured by the patenting firm's own return. For each patent grant, I cumulate the peer firm's market-adjusted return over a three-day window and apply Bayesian signal extraction to separate the patent-related component from idiosyncratic return noise. Event values are then assigned across contemporaneous patent grants.

I begin by examining how stock market reactions to patent grants differ across patenting firms, non-patenting firms in the same industries, and firms outside the affected industries. This comparison characterizes the distribution of returns around the events used to construct the measure. On the grant date, patenting firms outperform firms outside the affected industries by approximately 3.7 basis points, while the corresponding difference for industry peers is smaller and statistically insignificant. Over the three-day window, both patenting firms and their peers outperform other firms in market-adjusted returns, with differentials of approximately 2.8 and 2.5 basis points, respectively. I also sort firms into deciles based on their technological similarity to the newly granted patent. Firms in the highest similarity decile exhibit significantly stronger three-day returns than firms in

the lowest similarity decile, with a spread of approximately 10 basis points. This similarity gradient remains after controlling for firm characteristics, industry fixed effects, and date fixed effects. Subsequent patent citations provide complementary evidence about the information contained in external valuations. The absolute magnitude of external value predicts forward citations conditional on private patent value, whereas the coefficient on signed external value is statistically insignificant. Technologically important inventions can produce gains or losses elsewhere, so their importance need not translate into uniformly positive peer responses. The citation evidence indicates that the magnitude of the external valuation contains information about subsequent scientific recognition beyond the reward accruing to the patent owner. Together with the technological-exposure results, it supports interpreting peer valuations as capturing economically meaningful external effects of technological innovation.

Having established the economic content of the measure, I turn to a central question in the literature on innovation and growth: how much value does innovation create for other firms relative to the value captured by the innovator? Knowledge spillovers extend the benefits of innovation beyond its originator, while business stealing can reduce the value of competing firms (Bloom, Schankerman, and Van Reenen (2013)). I quantify the balance of these effects by examining the relation between net external value and private patent value. In sector-day regressions, an additional dollar of private patent value is associated with approximately \$0.20 of net equity value among listed firms in the same industry. This positive relation is robust to sector and sector-by-year fixed effects and to normalizing both values by sector market capitalization. The results suggest that greater private returns to innovation are accompanied by greater net external benefits within the observed peer group. These estimates capture external value reflected in peer firms' equity; consumer benefits and effects on private firms, future entrants, and firms outside the peer group remain beyond their coverage.

Do these valuations anticipate subsequent growth among peer firms? In innovation-based growth models, knowledge created by one firm can expand the productive opportunities of others and shape the allocation of economic activity across firms (Romer, 1990; Caballero and Jaffe, 1993; Klette and Kortum, 2004; Acemoglu, Akcigit, Alp, Bloom, and Kerr, 2018). I examine these implications by aggregating signed exposure to other firms' patent events to the receiving firm-year and relating it to subsequent output and employment growth. Controlling for firms' own patent value, initial output, capital, and employment, as well as sector and year fixed effects, spillover exposure positively predicts both outcomes across all one- through five-year horizons. A one-standard-deviation increase in exposure predicts approximately 2.1 log percentage points higher cumulative

output growth and 1.8 log percentage points higher cumulative employment growth over one year; the corresponding differences over five years are 5.0 and 4.6 log percentage points. Private patent value also predicts sustained output growth, but its employment association is smaller and statistically significant only at the two- and three-year horizons. Market-valued external innovation opportunities thus anticipate expansion in both production and employment beyond that predicted by firms' own patents.

What explains this growth? I examine three mechanisms that may connect knowledge spillover to growth. The first is knowledge diffusion and competition. Firms' incentives to invest in R&D depend in part on the extent to which innovation replaces existing profits (Arrow, 1962). Competitive pressure may encourage firms to learn from and adopt external discoveries, bringing forward their contribution to output and employment, while the same learning process can erode the innovator's advantage as rivals acquire and build on its knowledge. Consistent with this asymmetry, spillover exposure generally predicts stronger output growth in more R&D-intensive sectors, and its association with employment growth is stronger over two- to four-year horizons. By contrast, the relation between private patent value and employment growth is weaker in these sectors across all horizons. These findings are consistent with knowledge diffusion extending innovation's benefits beyond its originator, but do not separately identify competition's role in accelerating diffusion and eroding private advantages.

The second mechanism is investment and further invention. In a q-theoretic interpretation, external innovation that raises the expected profitability of additional capital increases marginal q and encourages investment (Hayashi, 1982). Consistent with this channel, a one-standard-deviation increase in annual spillover exposure predicts approximately 0.8–1.6 percentage points higher capital expenditure relative to lagged net property, plant, and equipment, as well as higher acquisition expenditure. Research capacity helps firms recognize and exploit outside knowledge (Cohen and Levinthal, 1989; Griffith, Redding, and Van Reenen, 2004). The one-year inventive-activity regressions show positive associations with spillover exposure. In both the main SIC3 specification and the TNIC classification, inventor and patent growth are positively associated with spillover exposure at the 5% level across all three specifications, including those controlling for investment opportunities and cash flow. Responses may differ across firms, since outside knowledge can substitute for internal research or capital even as it improves productive opportunities (Bernstein and Nadiri, 1989).

Finally, complementary patent-portfolio exercises distinguish the growth implications of technological opportunities from those of competitive displacement. Exposure based on technological similarity predicts expansion at several horizons, whereas exposure based

on the frontier of the patent portfolio, intended to capture competitive exposure, predicts lower output and employment growth. These contrasting associations connect the growth evidence to the distinction between technological spillovers and business stealing in Bloom, Schankerman, and Van Reenen (2013). They help distinguish the opposing forces underlying subsequent growth, complementing the signed valuation measure, which captures their net market-assessed effect.

There is large heterogeneity in innovation and growth dynamics of for different patents, firms and industries. What determines how much spillover value accompanies an innovation's private reward? I examine three dimensions: the knowledge embodied in an invention, the industry conditions governing firms' responses, and the information environment in which investors assess those responses. First is the patents' own characteristics. Conditional on private patent value, breakthrough patents generate roughly twice as much spillover value per dollar of private value as non-breakthrough patents. Process patents generate substantially more than product patents, and patents in rapidly evolving technological fields generate more than those in slower-moving fields. These patterns suggest that the importance, form, and technological setting of an invention help determine how widely its economic benefits extend.

Industry conditions also shape spillover pass-through. The relationship between private patent value and peer valuation is weaker in sectors with greater market power, consistent with protected incumbents having weaker incentives to respond to external innovation. This pattern connects the external valuation of innovation to the role of competition in shaping innovative incentives (Blundell, Griffith, and Van Reenen, 1999). Financial constraints also weaken the relationship, consistent with limited financing restricting adoption, complementary investment, or follow-on research. The role of financing connects to Matray (2021), who finds that capital availability amplifies local innovation spillovers. Whereas the growth analysis examines how firms subsequently adjust to external innovation, these results show how the economic environment is associated with the external value assessed at the grant date.

The information environment may also affect how external opportunities enter market valuations. Measured spillover pass-through is stronger in larger industries and for patents issued by more actively traded firms. These patterns are consistent with investor attention facilitating the incorporation of external patent news into peer valuations (Peng and Xiong, 2006), although industry size and trading activity are indirect attention proxies. Together with the evidence linking spillover valuations to subsequent investment, these findings raise the possibility that market attention contributes to the real effects of innovation through stock prices. The results connect the external valuation of innovation to both the economic

opportunities facing peer firms and the market's recognition of those opportunities.

Related Literature The paper contributes to the literature on measuring the economic value of innovation spillovers. Research beginning with Griliches (1979) studies how firms benefit from research conducted elsewhere. Jaffe (1986) constructs technology-weighted pools of external R&D and relates them to patenting, profits, and market value, while Bloom, Schankerman, and Van Reenen (2013) distinguish technological proximity from product-market proximity to separate knowledge spillovers from business stealing. These approaches establish that the effects of outside innovation depend on the relationship between the innovator and the receiving firm. A complementary literature uses financial markets to assess innovation's economic importance: Pakes (1985) studies the joint dynamics of research, patents, and stock returns, and Hall, Jaffe, and Trajtenberg (2005) relate firm value to research capital, patents, and citations. Earlier work also values effects beyond the patent owner. Austin (1993) and Austin (2000) examine owner and rival reactions to biotechnology patents, including dollar valuations and adjustments for partial anticipation; Patel and Ward (2011) distinguish favorable information conveyed by patent citations from an offsetting competitive component; and McGahan and Silverman (2006) relate incumbent value to outside innovation and complementary assets.

Like Kogan, Papanikolaou, Seru, and Stoffman (2017), this paper uses market-based measures of innovation value to examine subsequent firm growth. Whereas their measure captures the private value of patents to innovating firms, my measure captures the market-assessed net value of patent spillovers to peer firms using those firms' own stock market responses.[1] This distinction shifts the focus from growth and displacement associated with privately valuable innovation to peer firms' growth associated with the net value of external innovation. Higher annual spillover exposure predicts stronger output and employment growth, conditional on firms' own patent value and initial size. These findings complement the evidence on cost-reducing R&D spillovers in Bernstein and Nadiri (1989) and the technological spillovers identified by Bloom, Schankerman, and Van Reenen (2013). My analysis thus connects market-based spillover valuations to subsequent real outcomes.

The findings also relate to the literature on innovation, firm dynamics, and the sources of growth. Romer (1990) formalizes how nonrival knowledge supports subsequent innovation and production, while Caballero and Jaffe (1993) study knowledge spillovers and creative destruction, distinguishing the erosion of existing economic value from the obsolescence of useful knowledge. This distinction allows an innovation's private advantage to

[1] KPSS explicitly propose examining competitors' equity reactions as an extension in their article (p. 695, footnote 21).

diminish even as its knowledge continues to support economic activity elsewhere. Klette and Kortum (2004) connect firms' accumulated knowledge and research activity to innovation, expansion, and contraction; Lentz and Mortensen (2008) quantify growth and reallocation through heterogeneous firms' product innovation; and Acemoglu, Akcigit, Alp, Bloom, and Kerr (2018) emphasize the allocation of scarce research resources across firms. More recent work examines how knowledge diffusion between technological leaders and followers interacts with firms' innovation incentives (Akcigit and Ates, 2023). Empirical studies identify concrete channels through which these external opportunities reach other firms: Matray (2021) examines local spillovers from listed firms to nearby private firms, with evidence on inventor mobility, spin-outs, and financing; Moretti (2021) studies the productivity benefits of inventor clusters; and Giroud, Liu, and Mueller (2026) show how firms' plant networks transmit knowledge across locations. The ability to exploit these opportunities also depends on the recipient. Cohen and Levinthal (1989) explain how research develops both new knowledge and the capacity to absorb outside discoveries, and Griffith, Redding, and Van Reenen (2004) document roles for R&D in innovation and technological catch-up. I complement this literature by linking the market value of external patent news to receiving firms' subsequent output, employment, and inventive activity. Comparing these relationships with those associated with private patent value provides evidence on the different growth paths accompanying external opportunities and private rewards. The stronger productive-growth relationships in research-intensive sectors are consistent with knowledge diffusion extending innovation's benefits beyond its originator, and spillover exposure predicts further inventive activity under both industry definitions.

The investment results connect to the literature on firm value and capital accumulation. Hayashi (1982) links investment to the marginal value of capital, while Hall and Hayashi (1989) study how physical and research investment jointly respond to changes in profitability and technological opportunities. Bernstein and Nadiri (1989) estimate how recipients' production costs and investment respond to other firms' accumulated R&D capital, and Bernstein and Nadiri (1991) examine the interaction of research spillovers with production and investment decisions. In this approach, external research is an input whose benefits to recipients are inferred through a model of production and adjustment.

My analysis distinguishes research undertaken elsewhere from its net value to a particular recipient. I use each peer firm's own equity response to assess the consequences of external patent news, which depend on the firm's capabilities, existing assets, and competitive position. The same invention may save inputs for one firm, create opportunities for another to expand, and erode a third firm's profits. A favorable valuation need not imply greater investment: cost savings can raise firm value while reducing input demand. The

finding that higher recipient valuations predict greater capital expenditure and stronger output and employment growth therefore provides additional evidence about subsequent real adjustment. It connects the value of external innovation to the receiving firm's outcomes, rather than estimating the effect of a given increase in research conducted elsewhere.

Finally, the paper relates to research on information transmission across economically connected firms and the connection between financial prices and real decisions. Foster (1981) shows that earnings announcements convey information about other firms in the same industry, while subsequent research identifies more specific economic links through which information travels. Cohen and Frazzini (2008) document delayed price adjustment along customer–supplier relationships and connect customer returns to suppliers' subsequent operating performance. Lee, Sun, Wang, and Zhang (2019) find return predictability among technologically related firms and show that technology peer returns contain information about subsequent earnings. Lee, Shi, Sun, and Zhang (2024) document comovement in investment and innovation among production complementors and trace patent news, measured using patent owners' announcement returns, into peer firms' returns. These studies establish that understanding a firm's news requires recognizing its implications for other firms. Attention research examines how this recognition depends on information processing. Peng and Xiong (2006) study category learning, Veldkamp (2006) links information-production costs to common signals and price comovement, and Ben-Rephael, Da, and Israelsen (2017) connect institutional attention to more timely price adjustment. These mechanisms motivate examining how the information environment shapes the valuation of external innovation. A related literature asks whether information in prices subsequently influences corporate decisions. Bond, Edmans, and Goldstein (2012) organize the mechanisms connecting financial-market information to real activity; Chen, Goldstein, and Jiang (2007) examine investment sensitivity to prices and price informativeness; and Foucault and Frésard (2014) study managers' learning from peer firms' stock prices. Dessaint, Foucault, Frésard, and Matray (2019) and Yan (2024) further examine how noise in public valuations can affect investment decisions, including those of private firms. My analysis focuses on the receiving firm's own valuation response to external patent events. It uses this response to assign signed dollar values to external innovation and examines whether those values predict subsequent investment and growth. The attention analysis studies how the initial valuation response varies with the information environment. Together, these results connect the recognition of technological news across firms to the information in financial valuations about receiving firms' subsequent economic adjustment.

Section 2 constructs the spillover measure. Section 3 examines its economic content and its relation to private patent value. Section 4 examines how sector spillovers relate to

subsequent investment and long-run growth. Section 5 studies how innovation characteristics, industry conditions, and the information environment shape the pass-through from private patent value to sector spillovers. Section 6 concludes.

2 Construction of the Sector Spillover Measure

2.1 Conceptual Foundation

The goal is to isolate what the market believes a focal firm's innovation is worth to other firms from noise. This is conceptually distinct from the private value of the patent, which accrues to the innovator. A peer firm's stock reaction around a rival's patent grant combines patent-related valuation news with other return components; extracting the spillover component requires an explicit signal-extraction step. A positive value records an expected net gain to the peer firm, and a negative value records an expected net loss.

The spillover variable measures the external, market-based effects of firm-level innovation on technologically related peer firms. Specifically, it captures how the grant of a patent to one firm affects the market valuation of other firms operating in the same *3-digit SIC* sector.

As an illustration of a positive technological spillover, consider U.S. Patent 4,727,138, "Human Immune Interferon," granted to Genentech on February 23, 1988. The patent covered the recombinant production of human gamma interferon, a protein being developed to treat cancer, viral infections, and immune disorders. Biogen's stock appreciated by 7.0% over the three trading days beginning on the grant date, while the market declined by 0.8%; the corresponding cumulative idiosyncratic return was 7.5%. The increase added approximately $8.3 million to Biogen's market capitalization, and its trading volume on the grant date was about 4.5 times its preceding 20-day average. Genentech's gamma interferon was undergoing clinical testing as a cancer treatment, while Biogen had advanced its independently developed, gene-spliced gamma interferon to Phase III cancer trials in the United States and Europe.[2] Consistent with this evidence, Austin (2000) classifies Genentech and Biogen as rivals in the gamma-interferon research race and identifies this patent as one of the biotechnology grants reported in the *Wall Street Journal*. The firms' technological overlap is also evident in Biogen's opposition to Genentech's corresponding

[2]See Donna K. H. Walters, "Genentech Expects OK to Buy Out R&D Units," *Los Angeles Times*, December 30, 1986; and "Biogen Licenses IFN," *European Chemical News*, January 5/12, 1987, reprinted in United Nations Industrial Development Organization, *Genetic Engineering and Biotechnology Monitor*, no. 19 (1987), p. 38.

European human-immune-interferon patent.[3] Biogen's positive return is consistent with a technology-validation spillover: Genentech's patent grant may have increased investors' assessment of the potential of gamma interferon, raising the perceived value of Biogen's own program.

As a contrasting illustration of a negative competitive spillover, consider U.S. Patent 4,677,195, "Method for the Purification of Erythropoietin and Erythropoietin Compositions," granted to Genetics Institute on June 30, 1987. The patent covered purified erythropoietin (EPO), pharmaceutical compositions containing it, and a purification method, potentially constraining commercialization of Amgen's competing EPO program. Following the announcement on July 1, Amgen's stock fell by 17.0%, while Genetics Institute appreciated by 14.3% and the market declined by 0.2%. Over the three trading days beginning on the grant date, June 30–July 2, Amgen lost 15.0%, compared with a market decline of 0.6%; its cumulative idiosyncratic return was −14.5%. The grant raised the possibility that commercializing Amgen's EPO would require access to Genetics Institute's patent rights, potentially reducing Amgen's profits. Analysts discussed a possible cross-licensing agreement.[4] This pattern is consistent with a negative competitive spillover: stronger exclusionary rights for one firm reduced investors' assessment of the expected rents from a same-industry rival's competing development program.

2.2 Construction Procedure

Event Study Setup. Following Kogan, Papanikolaou, Seru, and Stoffman (2017), for each patent grant date t of a *focal firm* i, I compute cumulative idiosyncratic returns over the three-day window $[t, t+2]$ for all firms in the same sector $s(i)$, including i and its peers.

Noise and signal extraction. I treat a peer's observed return as the sum of a patent-related signal and return noise. Let i index a patenting firm, j a peer, s a sector, t a trading date, and $y(t)$ its calendar year. For an event with a single patenting firm, the three-day

[3] See European Patent Office, decision T 0223/92 (*HIF-Gamma/GENENTECH*), Board of Appeal 3.3.02, July 20, 1993.

[4] See "Amgen Stock Levels Out After Fall at News of Rival's Patent," *Los Angeles Times*, July 7, 1987. The opposing share-price movements are also attributed to the patent announcement in U.S. Congress, Office of Technology Assessment, *New Developments in Biotechnology: U.S. Investment in Biotechnology—Special Report*, OTA-BA-360 (July 1988), p. 181.

idiosyncratic return satisfies:

$$R_{j,t} = v_{j,i,t} + \varepsilon_{j,i,t}, \tag{1}$$

where $R_{j,t}$ is measured in decimal return units, $v_{j,i,t}$ is the component attributable to firm i's patent event, and $\varepsilon_{j,i,t}$ is unrelated return noise. The signal is a return component; multiplying its conditional expectation by the peer's market capitalization converts it into a dollar value. The allocation of a shared return signal across multiple same-day patentees is defined below.

Spillover Value for a Peer Firm

For a single-patentee event, the dollar spillover value assigned to peer j is:

$$SPV_{j,i,t} = \frac{\mathrm{E}[v_{j,i,t} \mid R_{j,t}]}{1 - \bar{\pi}} M_{j,t-1}, \tag{2}$$

where $M_{j,t-1}$ is the peer's market capitalization before the event and $\bar{\pi} = 0.57$ is the unconditional patent-approval probability from Carley, Hedge, and Marco (2015). The factor $(1 - \bar{\pi})^{-1}$ adjusts for anticipated approval. A positive value indicates a market-implied gain to the peer; a negative value indicates a loss. The contribution is zero when firm i has no grant on date t.

Assuming independent, mean-zero normal signal and noise components gives:

$$\begin{aligned} v_{j,i,t} \sim N(0, \sigma^2_{v,j,t}), \qquad \varepsilon_{j,i,t} \sim N(0, \sigma^2_{\varepsilon,j,t}), \\ \mathrm{E}[v_{j,i,t} \mid R_{j,t}] = \delta_{j,t} R_{j,t}, \qquad \delta_{j,t} = \frac{\sigma^2_{v,j,t}}{\sigma^2_{v,j,t} + \sigma^2_{\varepsilon,j,t}}, \end{aligned} \tag{3}$$

where σ^2_v and σ^2_ε are the signal and noise variances. The shrinkage factor $\delta_{j,t}$ lies between zero and one and gives more weight to returns when the signal accounts for a larger share of their variance.

Private Value for the Patenting Firm

For the patenting firm, I use the private-value construction of Kogan, Papanikolaou, Seru, and Stoffman (2017):

$$PPV_{i,t} = \frac{\mathrm{E}[v_{i,t} \mid R_{i,t}]}{1 - \bar{\pi}} M_{i,t-1}, \tag{4}$$

where $R_{i,t}$ is the patentee's three-day idiosyncratic return, $M_{i,t-1}$ is its pre-event market capitalization, and $v_{i,t}$ is the private patent-related return component. Private patent value is nonnegative under the assumed truncated-normal signal distribution:

$$v_{i,t} \sim N^{+}(0, \sigma^2_{v,i,t}), \qquad \varepsilon_{i,t} \sim N(0, \sigma^2_{\varepsilon,i,t}),$$
$$\mathrm{E}[v_{i,t} \mid R_{i,t}] = \delta_{i,t} R_{i,t} + \sqrt{\delta_{i,t}}\, \sigma_{\varepsilon,i,t} \frac{\phi(-\lambda_{i,t})}{1 - \Phi(-\lambda_{i,t})}, \tag{5}$$

where $\delta_{i,t} = \sigma^2_{v,i,t}/(\sigma^2_{v,i,t} + \sigma^2_{\varepsilon,i,t})$, $\lambda_{i,t} = \sqrt{\delta_{i,t}} R_{i,t}/\sigma_{\varepsilon,i,t}$, and ϕ and Φ are the standard normal density and distribution functions. N^{+} denotes truncation at zero. Unlike the private-value signal, the peer signal in Equation (3) permits negative effects.

In relation to KPSS It is useful to contrast this construction with the measures in Kogan, Papanikolaou, Seru, and Stoffman (2017). Their first measure corresponds directly to the private value of an innovation to the patenting firm, which I denote $PPV_{i,t}$ above. Their second measure aggregates the private values of other firms' innovations within the same industry and uses this as an indirect proxy for spillovers. Conceptually, this second measure answers a different question: if a competitor's innovation is valuable to that competitor, how does that relate to my subsequent outcomes?

The measure I propose differs in two respects. First, it is unconditional: it does not rely on competitors' private valuations, but directly captures the value of a competitor's patent to the focal firm through the peer firm's own stock market reaction. Second, it is conceptually closer to the definition of spillovers as external effects, i.e., changes in the valuation of others, rather than competitors' internal payoffs.

Same-day patent grants within a sector. When several firms receive patents on the same date, a peer's observed return reflects their combined news. I allocate its estimated aggregate signal across patentees in proportion to their private values:

$$SPV_{j,i,t} = \frac{PPV_{i,t}}{\sum_{i' \in I_{s,t}} PPV_{i',t}} \frac{\mathrm{E}[v_{j,t} \mid R_{j,t}]}{1 - \bar{\pi}} M_{j,t-1}, \tag{6}$$

where $I_{s,t}$ is the set of patenting firms in sector s on date t, and $v_{j,t}$ is peer j's aggregate patent-related return signal. The first ratio is the allocation weight of patentee i. This rule apportions a common peer response; it does not separately identify each patent's contribution from returns. Summing across eligible peers gives the event-level spillover attributed to firm i, $SPV_{i,s,t} = \sum_{j \in s,\, j \neq i} SPV_{j,i,t}$.

2.3 Aggregation for Empirical Analysis

The raw spillover value, $SPV_{j,i,t}$, represents a bilateral firm-to-firm shock. To map these micro-level reactions to the broader economic questions of this paper, I aggregate the measure to three distinct levels. First, the *patent level* averages peer reactions to validate whether the market's assessment correlates with the scientific impact (forward citations) of specific innovations. Second, the *sector-day level* aggregates all peer reactions to a cohort of patents, allowing a direct comparison between the total external spillover priced by the market and the innovators' private gains. Finally, the *peer firm-year level* accumulates a firm's total exposure to competitors' innovations over a year to test how external knowledge shocks predict long-run firm growth.

Patent level. For firm i's $N_{i,s,t}$ patents granted in sector s on date t, the assigned per-patent values are:

$$S^P_{i,s,t} = \frac{SPV_{i,s,t}}{N_{i,s,t}}, \qquad P^P_{i,s,t} = \frac{PPV_{i,t}}{N_{i,s,t}}, \tag{7}$$

where S^P is peer spillover and P^P is private value assigned to each patent on the same monetary scale. Each patent in the same firm-date event receives the same allocation. In the citation regressions, p identifies an individual patent and S^P_p and P^P_p denote these assigned values.

Sector-day level. Aggregate peer spillover and private patent value are:

$$S^S_{s,t} = \sum_{i \in I_{s,t}} \sum_{\substack{j \in s \\ j \neq i}} SPV_{j,i,t}, \qquad P^S_{s,t} = \sum_{i \in I_{s,t}} PPV_{i,t}, \tag{8}$$

where the sums cover all patentees and eligible peers in sector s on date t. The sector-day regressions use these dollar values or their scaled counterparts:

$$\widetilde{S}_{s,t} = \frac{S^S_{s,t}}{M_{s,t-1}}, \qquad \widetilde{P}_{s,t} = \frac{P^S_{s,t}}{M_{s,t-1}}, \tag{9}$$

where $M_{s,t-1}$ is lagged total sector market capitalization. A tilde denotes division by this common denominator; it does not denote standardization. Sector characteristics such as the Lerner index and HHI are not divided by market capitalization.

Peer firm-year level. For firm f and calendar year y, I aggregate peer exposure and own patent value as:

$$S^F_{f,y} = \sum_{t \in y} \sum_{\substack{i \in s(f) \\ i \neq f}} SPV_{f,i,t}, \qquad P^F_{f,y} = \sum_{t \in y} PPV_{f,t}, \tag{10}$$

where S^F accumulates the firm's exposure to other firms' patent events and P^F accumulates its own private patent value. The empirical annual panel supplies these measures to the investment and growth regressions. In those regressions, S^F and P^F denote the measures divided by their respective reference-sample standard deviations; they are not demeaned unless explicitly stated.

This measure provides a market-based, real-time estimate of how patents redistribute or create value within the same sector. By separating *private value* from *spillover effects* and aggregating across multiple levels, it captures distinct dimensions of innovation. At the *patent level*, the measure identifies exposure to spillovers by quantifying how peer firms react to a given innovation. At the *sector-day level*, it aggregates these reactions to compare the magnitude of spillovers with the private value generated by innovations within the same sector. At the *peer firm-year level*, it links cumulative spillover exposure to longer-run outcomes for peer firms, capturing the real effects of innovation on firm value and growth.

3 The Economic Content of Sector Spillover

The central question of this paper is whether financial markets actually price technological spillovers. The measure constructed in Section 2 provides a real-time, market-based framework to test this. However, before deploying this measure to answer broader economic questions, it is crucial to establish that these peer-firm stock reactions are indeed pricing genuine technological externalities, rather than merely reflecting transitory noise or generic industry shocks. To answer this fundamental question, this section conducts two distinct tests. First, I examine whether peer-firm stock returns vary systematically with their technological proximity to the innovator. Second, I investigate whether the magnitude of these market reactions predicts the future scientific impact of the underlying patents, as measured by forward citations.

3.1 Stock Returns around Patent Grants

How do stock returns around patent grants differ across innovators, their industry peers, and other firms? I begin by comparing these groups to characterize the distribution of market reactions around the events used to construct the spillover measure. The analysis distinguishes the response of patenting firms from that of non-patenting firms in the affected industries and examines how these differences vary with the event window and return benchmark.

I begin with a comparison of returns on patent grant dates. For each grant date, I form three mutually exclusive portfolios: patenting firms, non-patenting firms in the same three-digit SIC industries as the patentees (peers), and all remaining eligible firms (other firms). Firms receive lagged-market-capitalization weights within each group, while each event date receives equal weight. This design asks whether a dollar invested in patentees or their industry peers earns a different grant-day return from a dollar invested in firms outside the affected industries.

Figure 1 plots average one-day market-adjusted portfolio returns for the three groups across 4,973 patent grant dates over 1926–2023. Patentees earn an average excess return of 2.21 bp, compared with −0.54 bp for peers and −1.48 bp for other firms. Thus, patentees outperform the market on the grant date, while peers earn a higher average excess return than firms outside the affected industries. Internet Appendix Table IA.1 reports group-by-date regressions of one- and three-day raw returns with date fixed effects, other firms as the reference group, and year-clustered standard errors.

Table 2 broadens this comparison to one- and three-day windows and reports raw returns, market-adjusted excess returns, and CAPM, Fama–French three-factor, and Fama–French five-factor alphas. All entries are percentages per event window, with inference based on Newey–West standard errors using 20 lags. Over the one-day window, patentees, peers, and other firms earn raw returns of 0.0649%, 0.0374%, and 0.0280%. After subtracting the common market return, patentees earn 0.0221% and other firms lose 0.0148%, both significant at the 1% level, while peers earn an insignificant −0.0054%. Peers outperform other firms by 0.0094 percentage point, but this difference is not statistically significant. The one-day patenter-minus-other alphas are 0.0331 percentage point under the CAPM, 0.0235 under FF3, and 0.0200 under FF5, all significant at the 1% level. The corresponding peer-minus-other alphas are positive but statistically insignificant.

The three-day raw returns are 0.2129% for patentees, 0.2116% for peers, and 0.1873% for other firms. The corresponding excess returns are 0.0115%, 0.0084%, and −0.0162%. Relative to other firms, the three-day excess-return differentials are 0.0276 percentage point for patentees and 0.0246 percentage point for peers, both significant at the 5% level. After

factor adjustment, only the patenter-minus-other FF3 alpha is statistically significant. The remaining patenter and peer return differentials are positive but statistically insignificant.

These comparisons show a clear grant-day return differential for patentees and a smaller relative response among broad same-industry peers. The peer-minus-other difference is positive but insignificant over one day and becomes significant in market-adjusted returns over three days. These patterns are consistent with patenting firms benefiting from their patents and industry peers gradually receiving smaller gains from spillovers.

3.2 Technological Exposure and Stock Returns

Do firms with different patent portfolios exhibit different returns around patent grants? I compare non-patenting firms in the same three-digit SIC industry as a firm receiving a patent on that date, sorting them into deciles of a CPC4-based patent-portfolio score. Internet Appendix Section IA.1 documents the score, decile construction, and implementation discrepancies. The saved score uses grant-year information and is constant within firm-year when observed.

I then estimate the firm-day regression:

$$R^{(3)}_{f,s,t} = \sum_{d=1}^{10} \beta_d \, \mathrm{TSD}^{(d)}_{f,s,t} + \gamma' X_{f,s,t} + \lambda_t + \alpha_s + \varepsilon_{f,s,t}, \tag{11}$$

where $R^{(3)}_{f,s,t}$ is the three-day return in percent, and $\mathrm{TSD}^{(d)}_{f,s,t}$ indicates portfolio-score decile d. Firms with missing scores form the omitted group. All specifications control for lagged market capitalization and date effects; additional specifications include SIC3 effects and financial controls. Standard errors are clustered by date. Internet Appendix Table IA.2 gives the full specification.

Figure 2 plots the return differences associated with the portfolio-score deciles. Building on the baseline specification, Internet Appendix Table IA.2 reports the estimated coefficients from regressions of three-day returns on the portfolio-score deciles. Focusing first on the baseline specification with date fixed effects (Column 1), the coefficients exhibit a strong positive gradient, increasing from negative or near-zero values in the lower deciles to large positive values in the upper deciles. For example, relative to the baseline, firms in the top decile (D10) have a return difference of approximately 9.6 basis points over the three-day window, significant at the 1% level, while firms in the bottom decile (D1) earn −0.5 basis point. The estimated D10-minus-D1 coefficient difference that is long D10 and short D1 is therefore 10.1 basis points over the three-day window. The corresponding D10-minus-D1 spreads are 9.9, 9.2, and 9.8 basis points in Columns (2), (3), and (4),

respectively. These calculations describe the economic magnitude of the spread; Internet Appendix Table IA.2 does not separately report its standard error. The ninth decile (D9) earns about 12.5 basis points, so the decile pattern is strongly increasing overall but not perfectly monotonic at the top. These estimates describe return differences across the saved portfolio-score deciles.

Through columns (2) to (4), the results remain highly robust across more saturated specifications. The positive gradient across portfolio-score deciles persists, with D9 and D10 positive and significant at the 1% level throughout. D8 is positive in all three columns, significant at the 1% level in Column (2) and the 5% level in Column (3), and significant at the 5% level in Column (4). Firms in D1–D3 exhibit weak or negative responses. The positive D10-minus-D1 differences persist across the four specifications.

The score's construction limits the interpretation of these comparisons. As detailed in Internet Appendix Section IA.1, the saved measure weights firms' own annual patent values and uses current-year portfolio information. The reported associations therefore do not establish the response to a predetermined, event-specific measure of external patent shocks.

3.3 Patent-Level Sector Spillover and Patent Citations

I next examine whether the market-based spillover measure captures the scientific importance of the underlying innovation. To further validate the long-term economic content of the spillover measure, I examine its relationship with subsequent forward patent citations, a widely accepted proxy for an innovation's technological impact. If the aggregate peer response truly reflects how an innovation reshapes the technological landscape, patents that trigger larger market reassessments among peers should exert a stronger, lasting influence on future follow-on research.

The relation between the private and scientific value of innovation has long been debated in the innovation literature. A large body of work argues that forward patent citations are informative about innovation quality and economic importance. Hall, Jaffe, and Trajtenberg (2005), as well as Nicholas (2008), show that citation-weighted patent stocks are positively associated with firm value, using Tobin's Q regressions to link patent citations to the private value of innovation. Similarly, Harhoff, Narin, Scherer, and Vopel (1999) and Moser, Ohmstedt, and Rhode (2011) document a positive relation between patent citations and direct estimates of patent economic value in smaller samples. More recently, Kogan, Papanikolaou, Seru, and Stoffman (2017) also show that patents with larger market-value estimates subsequently receive more forward citations. However, the theoretical relation between patent citations and private patent value remains ambiguous. Abrams, Akcigit,

and Popadak (2013) challenge the earlier interpretation by proposing a model of defensive patenting. Using proprietary licensing-based estimates of patent value, they document an inverse-U relationship between citations and patent values, implying that highly cited patents are not always the most privately valuable. Given this ambiguity, peer-firm stock returns offer a valuable alternative perspective: testing whether the market's assessment of an innovation's external, sector-wide impact more robustly captures its scientific importance.

I examine whether both the direction and the magnitude of a patent's peer spillover predict its subsequent citations. The patent-level regression is:

$$\log(1 + C_p) = \alpha + \beta_S Z_{S,p} + \beta_A Z_{A,p} + \beta_P Z_{P,p} + \gamma' X_p + \eta_{c(p),y(p)} + \mathcal{F}_p + \varepsilon_p, \qquad (12)$$

where p indexes patents, C_p is the raw forward citation count, and $c(p)$ and $y(p)$ identify its technology class and grant year. $Z_{S,p} = S_p^P/\text{sd}(S^P)$ is signed spillover scaled by its sample standard deviation; $Z_{A,p} = |S_p^P|/\text{sd}(|S^P|)$ separately rescales its absolute magnitude; and $Z_{P,p} = P_p^P/\text{sd}(P^P)$ rescales private value. These three regressors are divided by standard deviations without demeaning. The coefficient β_A captures the association between spillover magnitude and $\log(1 + C_p)$ conditional on signed spillover and private value.

The control vector X_p adds log firm market capitalization in Column (2), return volatility in Column (3), and log sector market capitalization in Columns (4)–(5). Every specification includes technology-class-by-grant-year fixed effects $\eta_{c(p),y(p)}$. The additional term $\mathcal{F}_p$ represents sector effects in Column (4) and sector-by-year effects in Column (5), and is zero in the first three columns. Standard errors are clustered by technology class-year. The citation regressions use $\log(1+C_p)$; only the descriptive citation figure normalizes citations by their grant-year cohort mean.

Table 3 reports estimates from regressions of log one plus forward patent citations on the signed and absolute spillover measures. Across all specifications, the signed spillover term $Z_{S,p}$ is economically small and statistically insignificant, indicating that the direction of peer-firm market reaction is not systematically related to future citations. By contrast, the coefficient on the absolute spillover measure, $Z_{A,p}$, is positive and statistically significant at the 1% level in every specification, declining from 0.0263 in the baseline model in Column (1) to 0.0070 in the model with the full set of controls and sector-by-year fixed effects in Column (5). Since the absolute spillover is standardized, these coefficients describe changes in $\log(1 + C_p)$: a one-standard-deviation increase in spillover magnitude is associated with an approximately 0.7% to 2.63% increase in one plus forward citations, depending on the set of controls. This pattern is robust to adding sector fixed effects, sector-by-year

fixed effects, and controls for firm size, return volatility, and sector size. The fact that only the magnitude, not the sign, of spillover matters is consistent with the view that both strongly positive (value-enhancing) and strongly negative (business-stealing or defensive) innovations tend to be technologically important and thus attract more citations.

These results imply that *it is the size, not the sign, of the market reaction* that aligns most closely with future scientific recognition. Patents that trigger large market reassessments, whether they open new technological opportunities (creating large positive spillovers) or generate major technological disruptions (producing large negative spillovers), both tend to attract more follow-on citations. This is consistent with the dual mechanisms of positive technology spillovers and negative product-market rivalry identified in Bloom, Schankerman, and Van Reenen (2013).

Figure 3 illustrates the relationship nonparametrically. For each patent, I standardize signed spillover within grant year and compute $\log(1+C_p/\overline{C}_{y(p)})$, where $\overline{C}_{y(p)}$ is the cohort's mean citation count. Panel A forms 20 equal-frequency bins of signed standardized spillover across the pooled sample. Panel B forms 20 bins of its absolute value. The plotted means show relatively low citations near zero spillover and higher citations at large absolute spillovers, consistent with both positive and negative peer responses containing information about patent importance.

Taken together, these results show that forward citations and the magnitude of peer-firm spillovers capture distinct but closely related dimensions of a patent's broader impact. Citations trace the downstream scientific and technological reuse of an innovation, while spillover magnitude reflects investors' immediate assessment of its sector-wide economic consequences. The strong correlation between the two underscores their complementarity as indicators of social value. Importantly, the dominance of *magnitude* over *sign* highlights the dual nature of impactful patents: they may catalyze technological progress or create large disruption, yet in both cases leave a large footprint in the innovation landscape.

Finally, comparing this market-based spillover measure to the private value of innovation (Kogan, Papanikolaou, Seru, and Stoffman (2017)) provides a critical external validation. While P_p^P captures the financial reward appropriated by the innovating firm, the magnitude of the patent-level sector spillover, $\left|S_p^P\right|$, captures the broader economic reassessment by technologically related peers. The fact that $\left|S_p^P\right|$ strongly predicts forward citations—even after rigorously controlling for the innovation's private value—demonstrates that peer-firm reactions contain distinct and incremental information about a patent's scientific quality. This confirms that my measure is not merely a noisy proxy for the innovator's own success, but rather a robust, independent gauge of how profoundly an innovation alters the surrounding technological landscape.

Overall, the empirical evidence confirms that peer-firm stock reactions carry economically meaningful information rather than transitory market noise. As established earlier, these reactions are systematically aligned with firms' positions in the technology space, with their magnitude increasing alongside the degree of technological overlap. Furthermore, at the patent level, the aggregate peer reaction reliably predicts forward citations, tracking the true scientific impact of innovations. Having validated that financial markets do, in fact, actively and accurately price the real external effects of innovation at the micro level, I now turn to their aggregate economic magnitude. Specifically, the next section examines how the total market-priced spillover scales relative to the private returns of the innovators.

3.4 Innovation and Sector Spillover

The previous section established that financial markets systematically price the external effects of innovation into peer-firm valuations. Building on this micro-level evidence, this section turns to the aggregate economic magnitude of these priced externalities. The objective here is to quantify the proportionality between the value created for the broader sector and the value captured by the innovator. Specifically, how large is the total market-priced spillover relative to the private value of the underlying innovation?

I estimate the association between aggregate sector-day private value and peer spillover using dollar and scaled specifications:

$$\begin{aligned} S^S_{s,t} &= \alpha + \beta P^S_{s,t} + \gamma M_{s,t-1} + \mathcal{F}_{s,t} + \varepsilon_{s,t}, \\ \widetilde{S}_{s,t} &= \alpha + \beta \widetilde{P}_{s,t} + \mathcal{F}_{s,t} + \varepsilon_{s,t}, \end{aligned} \tag{13}$$

where S^S and P^S are the sector-day dollar aggregates in Equation (8), M is lagged sector market capitalization, and tildes denote division by M. The dollar specification includes sector capitalization as a control. The scaled specification uses sector capitalization as the regression weight. Within each three-column block of Table 4, $\mathcal{F}_{s,t}$ is zero in the first column, a sector fixed effect in the second, and a sector-by-year fixed effect in the third. Standard errors are clustered by sector-year. The coefficient β measures the association between private value and the value attributed to sector peers; it is not a causal estimate of total social value.

Table 4 shows that aggregate private patent value is positively associated with sector spillover, with all six coefficients significant at the 1% level. In the baseline specification reported in Column (1), a one-dollar increase in aggregate private patent value, $P^S_{s,t}$, is associated with a \$0.22 increase in aggregate sector spillover, $S^S_{s,t}$. The estimated coefficient

remains 0.22 when sector fixed effects are included in Column (2) and declines to 0.19 when sector-by-year fixed effects are included in Column (3). In the specifications reported in Columns (4)–(6), both measures are divided by lagged sector market capitalization to account for differences in sector size, and the estimated coefficients range from 0.21 to 0.22.

This result offers two critical layers of economic interpretation. First, the strong positive co-movement confirms that the aggregate external effect of innovation is systematically proportional to its private success: innovations that generate larger private rewards also tend to generate larger net spillovers for the sector. Second, the magnitude of the coefficient provides a market-based estimate of the external-to-private value wedge: for every dollar of wealth captured by the innovating firm, financial markets capitalize roughly an additional \$0.20 into the market value of technologically related sector peers.

This estimate provides an event-time counterpart to the literature on innovation externalities. Its direction is consistent with Bloom, Schankerman, and Van Reenen (2013)'s estimates, which separate technology spillovers from product-market rivalry using firm-level R&D exposure and production outcomes. The objects are not identical: their framework estimates real effects from low-frequency accounting data, whereas my estimate measures the value capitalized in publicly traded peers at the patent grant. The 20% ratio should therefore be interpreted as a market-implied external value among listed sector peers, not as a complete estimate of the patent's social value or evidence that every external effect is immediately incorporated into prices.

Finally, I repeat the sector-day analysis using the 300-industry TNIC classification of Hoberg and Phillips (2025). The underlying scope database permits multiple industry memberships; I assign each firm-year to the TNIC industry with its highest text loading to obtain mutually exclusive peer groups. These assignments can change across years, and the available classification data cover 1988–2023. Internet Appendix Table IA.3 reports spillover pass-through coefficients from 0.089 to 0.117, which are positive and significant at the 1% level in all six specifications. This implementation uses mutually exclusive 300-industry assignments from the scope text loadings rather than the original FIC-300 assignments or pairwise TNIC-3 links.

4 Sector Spillovers and Subsequent Firm Outcomes

Having established that financial markets price the external effects of innovation, I now examine whether these valuation responses predict subsequent firm growth. Innovation-based growth theory links knowledge spillovers to growth through further invention and expanded

production possibilities (Romer, 1990; Caballero and Jaffe, 1993; Klette and Kortum, 2004). For peer firms, external discoveries may create opportunities to improve production processes and develop new products, with implications for both output and labor demand. To the extent that peer firms' valuation responses reflect these opportunities, they should contain information about subsequent output and employment growth. I test this prediction first and examine how the relationship varies with sector research intensity. I then investigate whether spillover exposure also predicts further invention and the investment through which firms pursue these growth opportunities (Hayashi, 1982; Hall and Hayashi, 1989), examining inventive activity, capital investment, and acquisitions. Finally, building on the distinction between technology spillovers and product-market rivalry in Bloom, Schankerman, and Van Reenen (2013), I examine technological and product-market exposure separately to assess how knowledge diffusion and competitive displacement relate to subsequent firm growth.

A natural benchmark is Kogan, Papanikolaou, Seru, and Stoffman (2017), who use market-based measures of innovation to examine subsequent firm growth. As they emphasize, their patent valuation measures private rather than social value. Their measure of competitors' innovation therefore places greater weight on patents that generate larger private gains for their owners, emphasizing innovations with greater potential to displace competing firms. They find that this exposure predicts lower profits, output, and investment among competitors.[5] My measure instead weights external innovation by its market-assessed net value to the receiving firm, capturing both technological benefits and competitive losses. The different valuation perspectives help explain why their negative growth coefficients and my positive coefficients can coexist. KPSS also examine citation-weighted exposure to competitors' innovation and report generally nonnegative growth coefficients.[6] This alternative weighting emphasizes the scientific influence of patents rather than the private value appropriated by their owners, drawing on a literature that uses citations to measure the importance of innovations and trace their contribution to subsequent knowledge (Jaffe, Trajtenberg, and Henderson, 1993; Caballero and Jaffe, 1993; Hall, Jaffe, and Trajtenberg, 2005). Their citation-based results thus provide a closer parallel to my positive growth findings. The distinction is that citation weights reflect an innovation's broader scientific influence, whereas my measure assigns a market-based spillover value to a particular peer firm. My analysis therefore connects the value of external innovation to the subsequent growth of the firm receiving it. The growth regressions below therefore ask whether firms with more favorable market-assessed spillover exposure subsequently

[5]Table IV of Kogan, Papanikolaou, Seru, and Stoffman (2017).

[6]Tables V and VI of Kogan, Papanikolaou, Seru, and Stoffman (2017).

experience stronger output and employment growth.

4.1 Long-Run Output and Employment Growth

Table 1 reports summary statistics for the two principal panels used in the empirical analysis; all variables are defined in Appendix Table A.1. Panel A describes the firm-year sample. *Spillover* is the annual peer-firm exposure $S^F_{f,y}$ defined in Equation (10), which allocates the dollar value of same-sector patent spillovers to firm f while excluding its own patents. The variable exhibits substantial variation, with a mean of -0.27 and a standard deviation of 9.93. The 5th and 95th percentiles span from -5.76 to 4.55. *Output Growth* in the summary table is computed as the log difference in real firm-level gross output, where output is defined as sales plus the change in inventories (COMPUSTAT item `invt`), deflated using the Consumer Price Index (CPI). The variable displays considerable dispersion, with a mean of 5.56 and a standard deviation of 47.23, ranging from the 5th percentile of -45.23 to the 95th percentile of 57.67. *Employment Growth* is measured as the log difference in firm-level employment (COMPUSTAT item `emp`), and likewise shows high variability, with a mean of 4.64 and a standard deviation of 33.56, ranging from -29.85 to 44.77. Panel B describes the SIC3 sector-day sample underlying the sector-level pass-through tests. Raw sector spillover has a mean of $-\$3.28$ million and a standard deviation of \$2.67 billion. Patent events are sparse: only 4.43% of sector-days contain a patent event, so both the median and 95th percentile of sector private value are zero.

I estimate separate firm-year predictive regressions for output and employment:

$$\begin{aligned} G^{(\tau)}_{f,y} &= \beta_{S,\tau} S^F_{f,y-1} + \beta_{P,\tau} P^F_{f,y-1} + \gamma'_\tau X_{f,y-1} + \alpha_s + \lambda_y + \varepsilon^{(\tau)}_{f,y}, \\ G^{(\tau)}_{f,y} &= \log Y_{f,y+\tau-1} - \log Y_{f,y-1}, \qquad \tau = 1, \ldots, 5, \end{aligned} \tag{14}$$

where f indexes firms, y is the regression year, and Y is output or employment. Following the KPSS growth-window convention, τ denotes the number of elapsed years from the base year $y-1$ to the endpoint $y+\tau-1$. Thus, the one-year outcome ends in regression year y, and the five-year outcome ends in $y+4$. Exposure and controls are dated $y-1$. S^F and P^F are annual peer exposure and own private patent value, divided by their respective sample standard deviations, and X contains lagged log output, capital, and employment. The size controls remain in log units. Sector fixed effects α_s absorb persistent industry differences, and year effects λ_y absorb common annual conditions. The reported baseline output estimates use firm-year-clustered standard errors; employment estimates use sector-year clustering. The coefficient $\beta_{S,\tau}$ measures the association between a one-standard-deviation increase in base-year exposure and subsequent cumulative log growth,

conditional on own patent value and size.

Table 5 presents the regression results. Panel A shows a positive relationship between firm-year sector-spillover exposure and output growth. The spillover coefficient increases from 0.0214 over one year to 0.0496 over five years, and all five estimates are significant at the 1% level. A one-standard-deviation increase in annual exposure is therefore associated with approximately 2.1 log percentage points of additional cumulative output growth over one year and 5.0 over five years. The model's R^2 rises from 0.069 to 0.114. The larger coefficients at longer horizons are consistent with gradual knowledge diffusion, although horizon-specific samples and predictive regressions do not identify the timing of a causal effect.

Panel B uses employment growth as the dependent variable. The spillover coefficient rises from 0.0177 over one year to 0.0461 over five years; all five estimates are significant at the 1% level. These coefficients imply approximately 1.8 to 4.6 log percentage points of additional cumulative employment growth across the one- through five-year horizons. Figure 4 plots the five coefficients $\beta_{S,\tau}$ and their 95% confidence intervals for output (Panel A) and employment (Panel B), with elapsed years from the base year on the horizontal axis. Peer firms' valuations of external patent news predict subsequent output and employment growth, conditional on own patent value and the included controls. The estimates therefore relate growth to the net value of external innovation for the peer firm.

Internet Appendix Table IA.5 repeats the growth regressions using the TNIC industry classification of Hoberg and Phillips (2025). Output coefficients range from 0.019 to 0.057, while employment coefficients range from 0.017 to 0.047. All five estimates in each panel are significant at the 1% level. These results are robust to using an alternative industry classification. Overall, the market-based spillover measure predicts subsequent expansion in both output and employment beyond the predictive contribution of firms' own patent value, linking the valuation of external innovation to longer-run real outcomes.

4.2 Research Intensity

Sector R&D intensity characterizes the research environment in which peer firms operate. R&D may help firms absorb and build on external knowledge in addition to generating their own innovations (Cohen and Levinthal, 1989). Consistent with this complementarity, Jaffe (1986) finds that firms conducting more R&D benefit more from the research of technologically related firms. At the industry level, Griffith, Redding, and Van Reenen (2004) finds that R&D contributes to productivity growth through both innovation and technological catch-up. These findings motivate examining whether the association between spillover exposure and subsequent output and employment growth varies with sector R&D

intensity.

I allow both spillover exposure and own private patent value to interact with sector R&D intensity:

$$G_{f,y}^{(\tau)} = \beta_{S,\tau} S_{f,y-1}^{F} + \theta_{S,\tau} S_{f,y-1}^{F} \mathrm{RD}_{s,y-1} + \beta_{P,\tau} P_{f,y-1}^{F} + \theta_{P,\tau} P_{f,y-1}^{F} \mathrm{RD}_{s,y-1} + \gamma_{\tau}' X_{f,y-1} + \alpha_s + \lambda_y + \varepsilon_{f,y}^{(\tau)}, \tag{15}$$

where $G^{(\tau)}$ is the cumulative growth outcome in Equation (14), and $\mathrm{RD}_{s,y-1}$ is sector R&D expenditure divided by sector sales in the base year. Spillover, private value, and R&D intensity are each divided by their sample standard deviation before the interactions are formed. The size controls, sector effects, and year effects follow the baseline growth model. Standard errors are clustered by sector-year for both outcomes. The coefficient $\theta_{S,\tau}$ measures how the spillover-growth slope varies with R&D intensity, while $\theta_{P,\tau}$ permits a separate moderation of the own-patent-value slope.

Table 6 reports positive interactions between spillover exposure and sector R&D intensity at all five horizons. The output interactions are significant at the 5% level or better at one through four years; the employment interactions are significant at two through four years. This suggests that in high-R&D sectors—where technological activity is most intense—the growth effect of spillovers is approximately double that observed in lower-intensity industries. These results suggest that spillover exposure predicts stronger subsequent output and employment growth in more R&D-intensive sectors, where firms may be better equipped to absorb and build on external innovations.

4.3 Subsequent Investment and Inventive Activities

Investment provides a potential channel through which technology spillovers contribute to firm growth. External discoveries may create opportunities for peer firms to expand production or develop new products, but pursuing these opportunities may require additional physical capital, complementary assets, and inventive effort. I therefore examine whether the spillover exposure that predicts subsequent output and employment growth also predicts capital expenditure, acquisitions, and inventive activity.

The q theory of investment links capital expenditure to the marginal value of installed capital (Hayashi, 1982). External innovation may therefore encourage investment when it raises the expected return to additional capital. The empirical spillover measure captures a change in total peer firm value rather than marginal q. I examine whether this valuation response predicts subsequent capital expenditure by relating investment in year y to lagged

annual spillover exposure:

$$\frac{\text{CAPX}_{f,y}}{\text{PPENT}_{f,y-1}} = \alpha + \beta_S S^F_{f,y-1} + \beta_P P^F_{f,y-1} + \gamma' X_{f,y-1} + \mathcal{F}_{f,y} + \varepsilon_{f,y}, \tag{16}$$

where $\text{CAPX}_{f,y}$ is firm f's capital expenditure in year y and $\text{PPENT}_{f,y-1}$ is its lagged net property, plant, and equipment. S^F and P^F denote lagged annual peer exposure and own private patent value, scaled to unit variance. $X_{f,y-1}$ contains lagged log capital, output, and employment in every column. Columns (2)–(3) add lagged Tobin's Q and cash flow/assets; Column (3) also includes the leave-one-out SIC3-year average of lagged Tobin's Q.

The fixed-effect term $\mathcal{F}_{f,y}$ represents SIC3 and year effects in all three columns. All three columns use a common sample of 39,954 firm-years from 1963–2023 with consecutive fiscal-year ends. Standard errors are two-way clustered by firm and year. The coefficient β_S is the predicted change in the investment ratio per reference-sample standard deviation of prior-year spillover exposure.

Table 7 reports the results. The coefficient on lagged spillover exposure is positive in all three specifications, ranging from 0.0084 to 0.0160. All three estimates are statistically significant at the 1% level. A one-standard-deviation increase in exposure therefore predicts a change of roughly 0.84 to 1.60 percentage points in the capital-expenditure ratio. All specifications retain the growth regression's size controls; the additional controls capture own and peer investment opportunities.

The finding is consistent with peer firms' valuations anticipating improved investment opportunities. The patent-event signal may contain information about investment opportunities that these controls do not fully capture. They establish incremental predictive information about investment, conditional on own patent value, observed firm characteristics, and industry and year effects.

Firms may also pursue these growth opportunities by acquiring complementary assets and capabilities. Acquisitions can provide access to resources that help firms apply external discoveries or expand into related products. Prior research links acquisition activity to product-market complementarities (Hoberg and Phillips, 2010) and synergies from combining innovation capabilities (Bena and Li, 2014). I therefore examine whether spillover exposure predicts acquisition expenditure as another form of investment through which firms may realize the growth opportunities created by external innovation.

Table 8 examines acquisition expenditure, measured as Compustat AQC divided by lagged total assets, using the same controls and fixed effects as Table 7. The common sample contains 34,181 firm-years from 5,033 firms over 1971–2023, with reported zeros retained and missing or negative AQC excluded. Spillover coefficients are positive in all

three columns, ranging from 0.0011 to 0.0014, and are statistically significant at the 5% level in all three columns. A one-standard-deviation increase in spillover exposure is associated with approximately 0.11 to 0.14 percentage points higher acquisition expenditure relative to lagged assets. Spillover exposure positively predicts acquisition expenditure in Columns (1)–(3). By contrast, the coefficients on own private patent value are negative, indicating that higher own patent value is associated with lower subsequent acquisition expenditure.

Table 9 examines whether spillover exposure predicts inventive activity over the following year. The outcomes are annual changes in the log of one plus the number of active inventors in Panel A and granted patents in Panel B. The active inventor base captures participation in inventive activity, while patent counts capture one observable output of that activity. Column (1) controls for lagged private patent value, log capital, output, and employment. Column (2) adds lagged Tobin's Q and cash flow relative to assets, and Column (3) further includes the leave-one-out sector-year mean of lagged Q to account for peers' growth opportunities. Each panel uses a common sample across columns, with sector and year effects and standard errors clustered by firm and year. The coefficients on spillover exposure are positive and statistically significant at the 5% level in Columns (1)–(3) of both panels. In Column (3), the coefficient is 0.0062 for inventor growth in Panel A and 0.0048 for patent growth in Panel B, with corresponding p-values of 0.014 and 0.013.

Finally, I repeat the analyses using the TNIC industry classification of Hoberg and Phillips (2025). Internet Appendix Table IA.6 examines capital expenditure relative to lagged net property, plant, and equipment; Table IA.7 examines acquisition expenditure relative to lagged total assets; and Table IA.8 examines subsequent growth in the numbers of active inventors and granted patents. The results are generally consistent with the baseline findings: spillover exposure positively predicts all four outcomes.

The comparison with Bernstein and Nadiri (1989) clarifies the interpretation of the investment results. Their external R&D variable measures other firms' accumulated research capital, and their model estimates how that input changes recipients' costs and investment. My explanatory variable instead measures the market-assessed net value of external patent news to the recipient. These are different economic relationships: a given amount of external research need not create the same value for firms with different technological capabilities, and competitive exposure.

Taken together, these results show that higher spillover exposure predicts greater capital expenditure, acquisition expenditure, and subsequent growth in the number of active inventors and granted patents. The market-assessed value of external innovation thus contains information about peers' subsequent investment and inventive activity beyond their own patent value and the included controls. These patterns suggest that the growth

associated with spillover exposure is accompanied by investment in both productive and inventive resources.

4.4 Technological and Product-Market Exposure

The positive relation between spillover exposure and subsequent firm growth may mask opposing effects of external innovation. Bloom, Schankerman, and Van Reenen (2013) distinguish between positive technology spillovers and negative product-market rivalry effects. Following this distinction, I examine whether technological and product-market exposure predict different growth outcomes. I construct two firm-year exposure measures from patent-claim embeddings: *TechDiffusion* measures technological exposure, while *BusinessStealing* measures product-market exposure. Internet Appendix Section IA.2 describes their construction.

I replace $S^F_{f,y-1}$ in the baseline growth regression with each lagged exposure measure while retaining the firm's private patent value, size controls, sector and year fixed effects, and sector-year clustered standard errors. Internet Appendix Table IA.13 shows positive output coefficients at all five horizons. The one- and five-year coefficients are 0.020 and 0.063, respectively; the estimates are significant at the 5% level at one, four, and five years. The employment coefficient is close to zero and insignificant over one year, and positive thereafter; it is significant at the 5% level at three and four years and at the 10% level at five years. The positive longer-horizon associations are consistent with benefits from technologically related external innovation emerging over time.

Product-market exposure predicts lower subsequent growth at most horizons. Internet Appendix Table IA.14 reports output coefficients from -0.026 over one year to -0.093 over five years, significant at the 5% level in the first year and at the 1% level thereafter. The one-year employment estimate is essentially zero and insignificant. Employment coefficients are negative at two through five years, significant at the 1% level at two through four years and at the 10% level at five years. These patterns are consistent with competitive displacement.

Together, these results show that technological exposure predicts higher subsequent growth, whereas product-market exposure generally predicts lower growth. This contrast aligns with the opposing effects of technology spillovers and product-market rivalry documented by Bloom, Schankerman, and Van Reenen (2013), and helps interpret the baseline spillover measure as capturing both technological diffusion and business stealing effects.

5 Determinants of Technological Spillovers

What determines how much of an innovation's private value passes through to other firms in its sector? Having shown that the market prices sector spillovers and that these valuations forecast long-run growth, I examine three potential determinants: the knowledge embodied in an innovation, the industry conditions governing other firms' ability and incentives to respond, and investors' recognition of its implications for those firms. I study innovation characteristics in Subsection 5.1, industry frictions in Subsection 5.2, and investor attention in Subsection 5.3. These analyses characterize how market-valued spillovers vary with the innovation and its economic and information environment, conditional on private patent value.

Before examining these determinants, I assess whether the baseline relationship holds broadly across sectors. Internet Appendix Figure IA.1 and Table IA.9 report industry-specific estimates of the baseline scaled sector-day specification for the twelve Fama–French industries. The spillover coefficient is positive and statistically significant in eleven of the twelve industries; only Consumer Durables is insignificant. Excluding Utilities, the estimated coefficients range from 0.011 (Consumer Durables) to 0.87 (Finance), with most industries clustering between 0.11 and 0.48. Utilities is an outlier at 3.26, reflecting the sector's small aggregate market capitalization. The prevalence of positive, significant coefficients indicates that the baseline result extends beyond a small number of technology-intensive sectors.

5.1 Innovation Characteristics

I begin at the level of the innovation itself, examining whether the pass-through from an innovation's private value to its sector spillover differs across economically meaningful patent types. The premise is that patents are not homogeneous carriers of knowledge: they differ in how fundamental they are, in whether they improve a production process or a final product, and in how rapidly their underlying technology is changing. Each of these attributes plausibly governs how widely the knowledge a patent embodies diffuses to sector peers, and therefore how much of its private value is externalized. For each classification, I partition sector-day private value into attributed components and estimate:

$$\widetilde{S}_{s,t} = \alpha + \beta_1 \widetilde{P}^{(1)}_{s,t} + \beta_0 \widetilde{P}^{(0)}_{s,t} + \mathcal{F}_{s,t} + \varepsilon_{s,t}, \tag{17}$$

where $P^{(1)}$ and $P^{(0)}$ are the private values attributed to the two patent categories. Tildes denote division of sector spillover and each private-value component by lagged sector market capitalization $M_{s,t-1}$. For binary classifications, each firm-event's private value is allocated

according to the shares of classified patents in each category. For the process/product test, the allocation uses continuous process-claim and product-claim shares. The attributed values are then summed within sector-day; both components can be positive on the same date. Unclassified patents contribute to neither component, so coverage affects the population represented by the estimates.

The coefficients β_1 and β_0 describe the conditional pass-through associated with the two components. Table 10 reports the breakthrough, process/product, and RET splits in Columns (1)–(3), respectively. All three specifications include sector-by-year fixed effects. All specifications weight observations by lagged sector market capitalization $M_{s,t-1}$. Standard errors are clustered by sector-year.

Breakthrough patents. I first classify patents by whether they are breakthrough innovations, using the text-based measure of Kelly, Papanikolaou, Seru, and Taddy (2021). They score each patent by comparing its text to the patents filed before and after it: an important patent is one that is *distinct* from prior patents, marking it as novel, yet *similar* to the subsequent flow of patents, marking it as influential. A patent is flagged as a breakthrough if it lies in the top decile of this novelty-and-impact measure after residualizing on issue year, so that breakthroughs are identified consistently across cohorts. The flag is available for patents issued through 2010, and patents outside this window contribute to neither group. Because breakthroughs are precisely the innovations on which later research builds most heavily, they should embody the most broadly applicable knowledge and generate the largest spillovers. Column (1) of Table 10 confirms this. The pass-through coefficient is 0.3791 for breakthrough patents and 0.1875 for non-breakthrough patents. Innovations classified as breakthroughs thus generate roughly twice as much market-valued sector spillover per dollar of private value.

Process versus product patents. I next separate process from product patents. Following Bena and Simintzi (2025), the classification is built from the language of a patent's claims: a claim is a process claim when its preamble describes a method or process (for example, "a method for" or "a process for" followed by a gerund) rather than an apparatus or composition. For each patent I measure the share of its claims that are process claims and, in the binary version, label a patent a process patent when a majority of its claims are process claims; these patent-level shares are aggregated to the firm-event-day as in the other splits.

The distinction maps onto the embodied–disembodied view of innovation that Ma

(2025) applies to exactly this product/process split.[7] Product innovation is *embodied* in new vintages of capital: appropriating its value requires replacing the installed base, so it tends to displace incumbents and drive creative destruction (Kogan, Papanikolaou, Seru, and Stoffman (2017)). Process innovation is *disembodied*: it improves production methods and raises labour productivity, and is complementary to firms' existing investments, so peers can adopt it without scrapping their capital. Process innovation should therefore diffuse more readily across an industry and generate a larger *positive* spillover, while product innovation should transmit less because more of its private value is captured at rivals' expense. Consistent with this, Column (2) of Table 10 shows a markedly larger pass-through for process patents: the coefficient is 0.3658, compared with 0.1265 for product patents. Both coefficients are significant at the 1% level. Process innovation is disproportionately responsible for the sector spillover, consistent with its disembodied, complementary nature.

Rapidly evolving technologies. Finally, I compare patents in rapidly evolving technological areas with the rest, using the RETech measure of Bowen, Frésard, and Hoberg (2023), which gauges how quickly the technological vocabulary surrounding a patent is changing, so that a high value marks a patent embedded in a fast-moving, actively developing area of technology. A patent is classified as RET when its RETech score is above the within-year median, and the measure is available for patents issued between 1980 and 2010, which defines the sample for this split. Patents embedded in fast-moving technological fields are more likely to be relevant to the many peers innovating contemporaneously in the same space, so their grants should be more informative for sector valuations. Column (3) of Table 10 bears this out: the pass-through coefficient is 0.2844 for RET patents and 0.1450 for non-RET patents.

Taken together, the three splits show that the average sector spillover masks substantial heterogeneity along the dimension of patent quality and character. Breakthrough, process, and rapidly-evolving-technology patents each generate roughly twice to nearly three times the external valuation, per dollar of private value, of their more incremental, product-oriented, or slow-moving counterparts. The breakthrough and RET splits, both proxies for the fundamental importance of an innovation, likely capture overlapping variation; the process/product distinction is separate, isolating a diffusion channel that operates through

[7] See Ma (2025), pp. 24–25. The paper uses patent-claim text to separate product from process innovation and interprets process innovation as disembodied and "complementary to existing investments," whereas product innovation is "embodied in new vintages of capital" and may lead to greater creative destruction.

the *nature* of the innovation, embodied versus disembodied, rather than its magnitude.

5.2 Industry Frictions

Beyond the characteristics of the innovation itself, the sector environment may shape how strongly peer valuations respond. I consider three features of this environment: the market power its firms enjoy, the financial constraints they face, and the data intensity of their production.

Market Power. I examine whether spillover pass-through varies with the sector Lerner index. Using the accounting construction underlying the reported sector measure:

$$L_{i,y} = \frac{\text{Sales}_{i,y} - \text{COGS}_{i,y}}{\text{Sales}_{i,y}},$$
$$L_{s,y} = \sum_{i \in s} \omega_{i,s,y} L_{i,y}, \qquad \omega_{i,s,y} = \frac{\text{Sales}_{i,y}}{\sum_{j \in s} \text{Sales}_{j,y}}, \tag{18}$$

where $L_{i,y}$ is the firm gross operating margin, COGS is cost of goods sold, and $\omega_{i,s,y}$ is the sales share among firms with valid inputs. $L_{s,y}$ is a sales-weighted margin proxy for market power. It is distinct from the HHI measure of sales concentration.

The sector-day specification is:

$$\widetilde{S}_{s,t} = \alpha + \beta \widetilde{P}_{s,t} + \theta \widetilde{P}_{s,t} L_{s,y(t)} + \mathcal{F}_{s,t} + \varepsilon_{s,t}, \tag{19}$$

where $\widetilde{S}$ and $\widetilde{P}$ are peer spillover and private patent value divided by lagged sector market capitalization. The Lerner index remains in its original units. The fixed-effect term $\mathcal{F}_{s,t}$ comprises sector-by-year effects. Regressions are weighted by lagged sector market capitalization, and standard errors are clustered by sector-year. The marginal pass-through is $\beta + \theta L_{s,y(t)}$: β is the slope at a zero Lerner index, and θ measures how that slope varies with market power.

Column (1) of Table 11 reports these results. With sector-by-year fixed effects, the baseline coefficient on $\widetilde{P}_{s,t}$ is 0.2510, while the interaction coefficient on $\widetilde{P}_{s,t} L_{s,y(t)}$ is -0.1847; both are significant at the 1% level. This implies that in sectors with higher operating margins, the positive spillover associated with innovation is significantly attenuated, consistent with stronger business-stealing effects offsetting positive externalities.

To ensure robustness, I employ alternative measures of competition. As reported in Tables IA.4 and IA.10, the results remain consistent when using product market fluidity (Hoberg, Phillips, and Prabhala (2014)) and the Herfindahl–Hirschman Index (HHI). Taken

together, the evidence suggests that market power tilts the external impact of innovation toward rent redistribution rather than value-enhancing diffusion.

The negative interaction between private value and the Lerner index indicates that higher market power systematically attenuates the external valuation of innovation. This finding is highly consistent with the "escape-competition" regime of Aghion, Bloom, Blundell, Griffith, and Howitt (2005), albeit within the specific distributional context of the U.S. market. While Aghion, Bloom, Blundell, Griffith, and Howitt (2005) show that innovation in U.K. firms only begins to decline when the Lerner index drops below 0.05, the majority of U.S. public firms in my sample operate in a higher-markup environment, far to the left of this theoretical peak. Within this range, my results demonstrate that as competition increases (Lerner decreases), the market's propensity to price external spillovers rises significantly.

Financial Constraints. I next examine whether a sector's financial constraint moderates the pass-through, measuring constraint at the three-digit SIC sector-year level as the average across all firms in the sector, using two standard indices: the Whited-Wu (2006) index and the Kaplan-Zingales index (using the Lamont-Polk-Saa-Requejo 2001 coefficients). Column (2) of Table 11 reports the main specification with sector-by-year fixed effects. The interaction of private value with the sector's Whited-Wu index is negative and significant at the 5% level (-0.039 per standard deviation of sector constraint): private value transmits less to peers in more financially constrained sectors. As a robustness check, Table IA.11 repeats the test with the Kaplan-Zingales index; the interaction carries the same negative sign and magnitude (-0.039) but is only marginally significant (at the 10% level without fixed effects, and just short of it once sector-by-year fixed effects are included). The agreement in sign across the two indices supports a modest financial-constraint channel, while the weaker Kaplan-Zingales result is consistent with the well-known concern that its cash-flow and leverage components partly capture financial distress.

Data and Digital-Technology Orientation. Finally, I ask whether a sector's data intensity moderates the pass-through, proxying data intensity with cloud-computing adoption. The data-economy literature treats data as a nonrival productive input, while emphasizing that firms may restrict access to preserve their competitive advantage (Jones and Tonetti, 2020). Data can generate economic value through innovation, process optimization, and matching (Veldkamp and Chung, 2024). Cloud computing supplies infrastructure for storing, processing, and analyzing data (Farboodi and Veldkamp, 2023), making its adoption a plausible, though indirect, indicator of a sector's data intensity. I measure adop-

tion using the firm-level Cloud Computing hiring exposure of Kalyani, Bloom, Carvalho, Hassan, Lerner, and Tahoun (2025). The regression moderator is the sector-year mean of log one plus firm exposure, standardized across the estimation sample. Their measure is built from the share of a firm's job postings associated with the technology. Their audit across technologies finds that these postings overwhelmingly concern tasks that *use or produce* the technology, supporting its interpretation as a hiring-based proxy for adoption. Because postings measure open positions rather than completed hires, the measure captures demand for technology-related labor rather than directly observing realized adoption. The hiring-exposure series used here covers 2010–2019, so this test is restricted to that window, though at the sector-year level it still spans roughly half a million sector-day observations. Column (3) of Table 11 shows that, with sector-by-year fixed effects, the interaction is negative and significant at the 1% level (-0.0605 per standard deviation of sector data intensity): private value transmits less to peers in more data-intensive sectors. Proprietary data create barriers to benefiting from external innovation, weakening the transmission of private patent value to peer firms. This finding suggests that access to proprietary data may be necessary to benefit from external innovation, limiting spillovers to peer firms that lack such access.

5.3 Investor Attention

Investors must recognize a patent and its connection to another firm for the news to enter that firm's price. Attention can therefore affect the timing and composition of measured spillovers. Category learning motivates an industry-level dimension (Peng and Xiong (2006)), while evidence on retail purchases, information searches, and institutional news processing motivates a firm-level dimension (Barber and Odean (2008); Da, Engelberg, and Gao (2011); Ben-Rephael, Da, and Israelsen (2017)). The literature does not imply that greater attention must increase every event-window response: information may be incorporated before the grant, and attention may also create temporary buying pressure. I test whether pass-through differs with industry size and patentee turnover, two observable characteristics of the information environment.

Industry Salience. I first use the size of the three-digit SIC sector as an indirect proxy for industry salience. Category-learning models motivate a distinction between industry and firm information (Peng and Xiong (2006)). Huang, Huang, and Lin (2019) use lottery-induced distraction to show that attention allocation changes return comovement; that design does not directly establish that larger sectors receive more patent-specific attention.

Sector size may also capture information production or economic connectivity, and it can mechanically increase the dollar value of peer reactions. I therefore scale both sector spillover and private value by sector market capitalization, center and scale log sector market capitalization, include its level directly, and estimate

$$\widetilde{S}_{s,t} = \alpha + \beta \widetilde{P}_{s,t} + \theta \widetilde{P}_{s,t} Z_{s,t} + \delta Z_{s,t} + \mathcal{F}_{s,t} + \varepsilon_{s,t}, \tag{20}$$

where $\widetilde{S}$ and $\widetilde{P}$ are scaled sector spillover and private value. $Z_{s,t}$ is log lagged sector market capitalization, demeaned using sector capitalization weights over the complete-case sector-day sample before singleton removal and divided by its unweighted full-panel standard deviation. It enters both directly and interacted with private value. The fixed-effect term $\mathcal{F}_{s,t}$ comprises sector-by-year effects. The regression uses sector capitalization weights and sector-year-clustered standard errors.

The marginal pass-through is $\beta + \theta Z_{s,t}$. Because the size measure is centered using sector capitalization weights, β describes an industry at the capitalization-weighted mean of log size and θ is the change in pass-through associated with a one-standard-deviation increase in log size.

Column (1) of Table 12 shows that it does. The interaction between private value and industry size is positive and significant at the 5% level with sector-by-year fixed effects. Its coefficient is 0.0614 per standard deviation of industry size. The pass-through is approximately 0.205 for an industry at the capitalization-weighted mean of log size and rises to about 0.267 for an industry one standard deviation larger. The result is therefore not a mechanical consequence of summing the returns of more or larger peer firms: the dependent variable and private value are already scaled by sector capitalization, and the level of industry size is separately controlled for.

I interpret this pattern as evidence consistent with an industry-attention channel. Innovations released into economically prominent sectors appear to be incorporated more strongly into peer valuations within the event window. This interpretation is not unique, however. Large sectors may also possess richer information environments, denser economic linkages, or a broader investor base. The result establishes that industry size moderates measured pass-through, while the firm-level test below provides a complementary proxy.

Patenting-Firm Salience. I next use the innovator's share turnover, defined as mean daily trading volume divided by shares outstanding during the calendar year, as an indirect firm-level salience proxy. The supporting attention measures differ across studies: attention-grabbing events attract retail purchases (Barber and Odean (2008)), retail search can predict temporary price pressure (Da, Engelberg, and Gao (2011)), preannouncement

search can reduce the subsequent earnings response (Drake, Roulstone, and Thornock (2012)), and institutional news attention is associated with more timely permanent adjustment (Ben-Rephael, Da, and Israelsen (2017)). Annual turnover can reflect liquidity, disagreement, and information arrival as well as attention. I partition sector-day private value into patents issued by firms in the top decile of the within-year turnover distribution and patents issued by all remaining firms. As in the industry-salience test, spillover and private value are scaled by sector market capitalization.

Column (2) of Table 12 shows larger estimated pass-through for patents issued by high-turnover firms. With sector-by-year fixed effects, the coefficient is 0.346 for the top-turnover group and 0.206 for the remaining firms; both are significant at the 1% level. Internet Appendix Table IA.12 replaces the top-decile split with an above- versus below-median comparison. The corresponding coefficients are 0.250 and 0.188 in the sector-by-year specification. These point estimates describe the contrast; significance of each coefficient does not establish significance of their difference.

Taken together, the industry-size interaction and firm-turnover split show larger estimated pass-through in more prominent sectors and around more actively traded patentees. The patterns are consistent with differences in recognition of external patent news. Research using media interruptions establishes a related role for information dissemination (Peress (2014)), but the proxies here do not isolate an attention shock. The results help characterize when the market registers external innovation value, while leaving open how much of the variation reflects attention, economic connections, or other features of the information environment.

6 Conclusion

This paper develops a market-based measure of external innovation value from peer firms' equity reactions to patent grants. The framework combines signed peer firm valuations with signal extraction, common-scale aggregation, and technological validation. Peer returns vary with technological similarity, and the absolute magnitude of external value predicts forward citations conditional on private patent value. The evidence supports the technological content of the measure and the usefulness of observing firms outside the patent owner.

The measure supports applications to classical questions in innovation and growth. At the sector-day level, each dollar of private patent value is associated with approximately \$0.20 in net value among publicly traded firms in the same three-digit SIC industry. This estimate provides a benchmark for comparing value capitalized by observed peers with the

innovator's private reward.

The external value associated with a given private reward varies with the innovation and the peer firm's economic environment. Breakthrough and process patents, and patents in rapidly evolving fields, generate greater measured pass-through. Pass-through is weaker in sectors with greater market power and tighter financial constraints. These results connect external innovation value to incentives and the capacity to undertake complementary adjustment. Industry size and patentee turnover are also associated with measured pass-through, consistent with differences in recognition of patent news in financial markets.

Aggregation to the peer firm-year connects the initial valuation to subsequent capital expenditure and productive growth. Spillover exposure predicts investment and approximately 2.1–5.0 log percentage points of additional cumulative output growth and 1.8–4.6 log percentage points of employment growth across the one- through five-year horizons. Growth associations are stronger in research-intensive sectors at several horizons. The one-year inventor and patent growth estimates are positive and significant at the 5% level under both SIC3 and TNIC across all three specifications, including those with investment-opportunity and cash-flow controls. Technological exposure predicts expansion at several horizons, while product-market exposure predicts lower output growth and lower employment growth beyond the first year.

Together, the findings connect the market valuation of external innovation to the subsequent investment and growth of peer firms. They provide a measurement framework for studying how innovation's benefits and losses are distributed and how firms adjust to opportunities created elsewhere.

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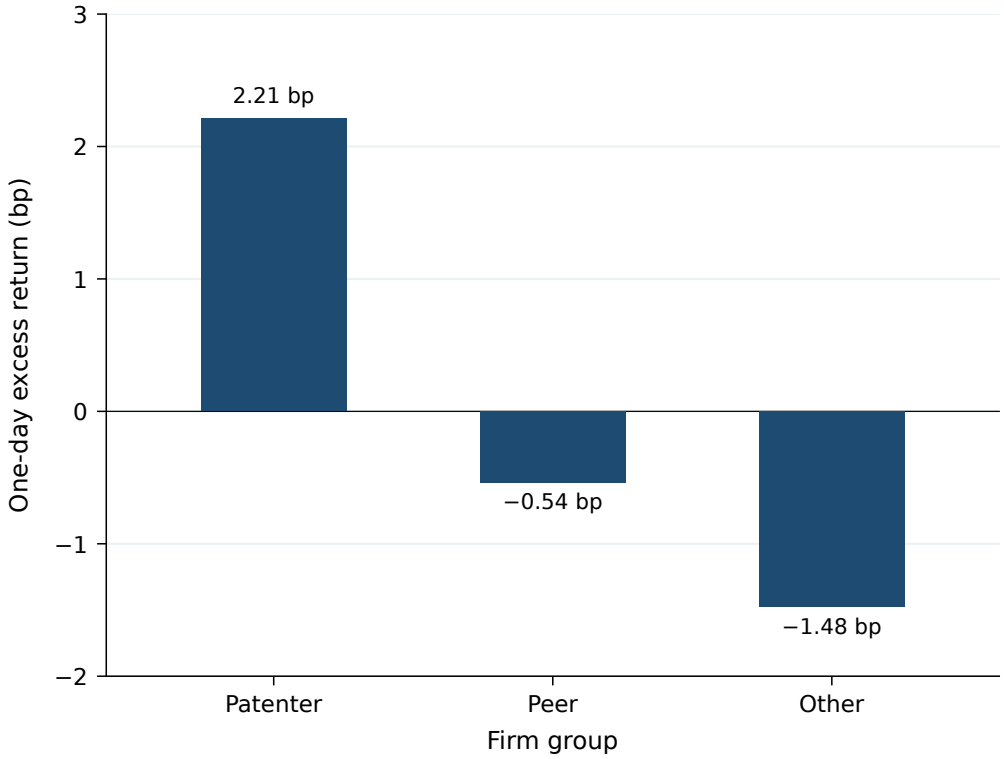


Figure 1: Excess returns on patent grant dates

Bars show average one-day excess returns, in basis points (bp), for three mutually exclusive groups on patent grant dates. Excess return is the firm's raw return minus the market return. Patentees are firms receiving patents; peers are non-patenting firms in the same SIC3 industries; other firms are all remaining eligible firms. Returns receive lagged-market-capitalization weights within each group on each grant date, and the group portfolio returns are then averaged with equal weight across dates. The sample covers 4,973 patent grant dates over 1926–2023.

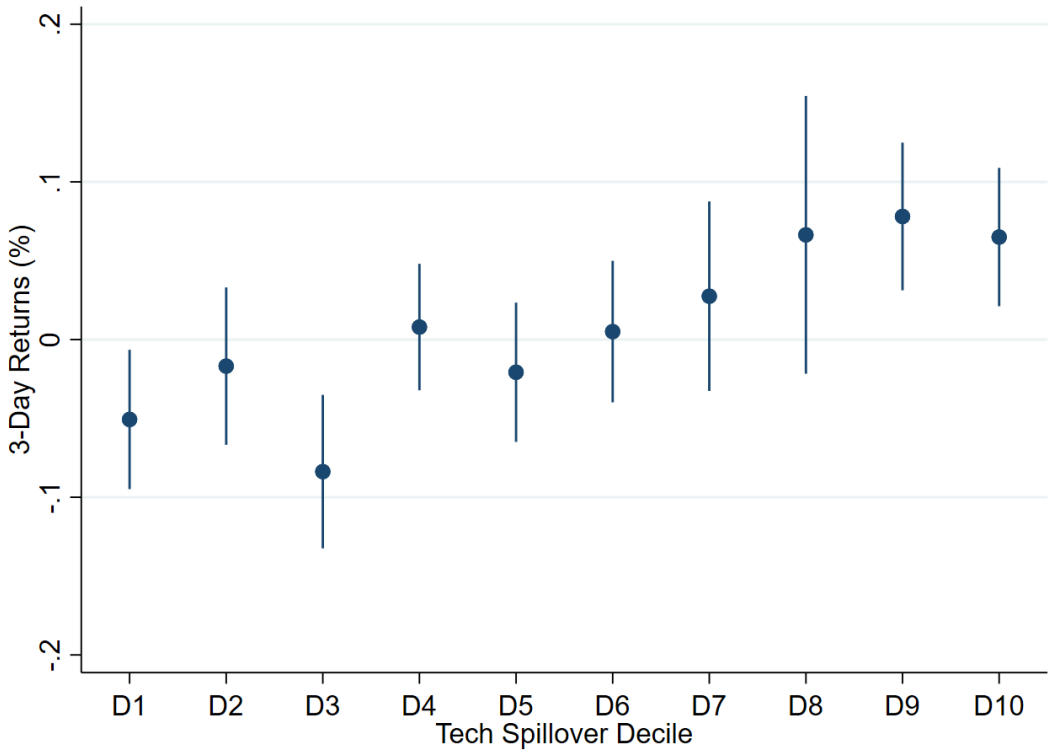
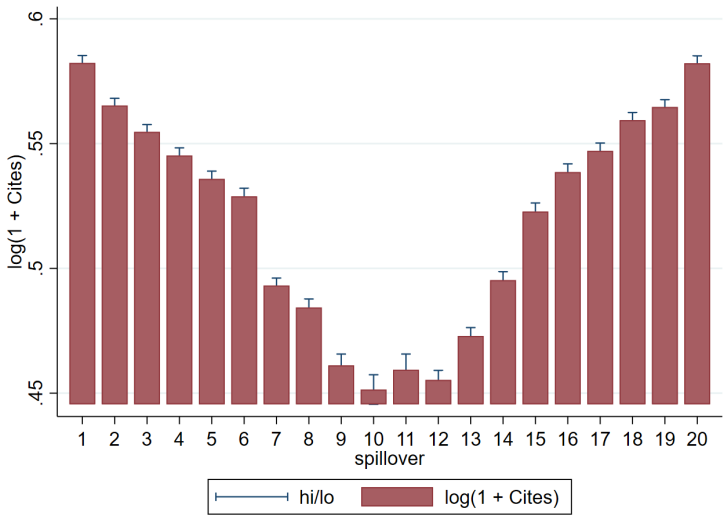


Figure 2: Technology similarity and peer stock returns

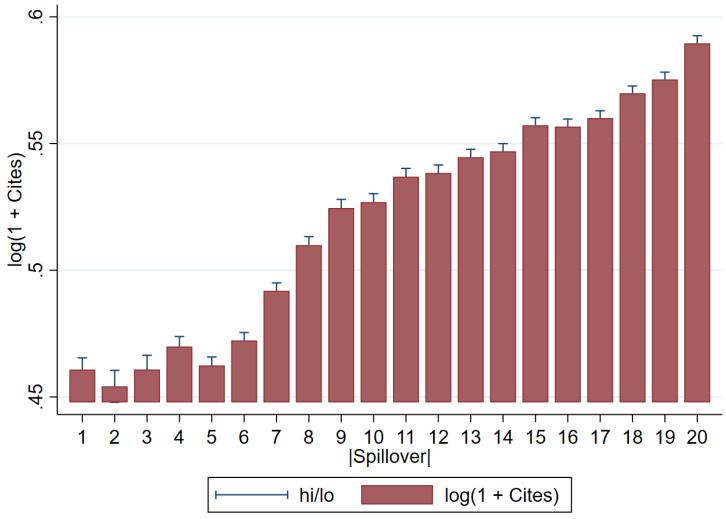
This figure plots technology-exposure decile coefficients from:

$$R^{(3)}_{f,s,t} = \sum_{d=1}^{10} \beta_d \, \mathrm{TSD}^{(d)}_{f,s,t} + \gamma' X_{f,s,t} + \alpha_s + \lambda_t + \varepsilon_{f,s,t},$$

where $R^{(3)}$ is the three-day stock return in percent, and $TSD^{(d)}$ indicates a pooled decile of the yearly standardized CPC4 portfolio score. Internet Appendix Section IA.1 documents the score and its implementation discrepancies. The sample contains non-patenting firms in the same SIC3 industry as a firm receiving a patent on date t; firms with missing scores form the omitted group. Estimates are from Column (4) of Internet Appendix Table IA.2. Controls include lagged market capitalization, book-to-market, profitability, earnings per share, return on equity, free cash flow, and investment. α_s and λ_t denote SIC3 and date fixed effects. Points show return differences in percentage points; bars show 95% confidence intervals based on date-clustered standard errors. The unit of observation is the firm-day. The sample covers 1952–2023.



Panel A: Signed spillover



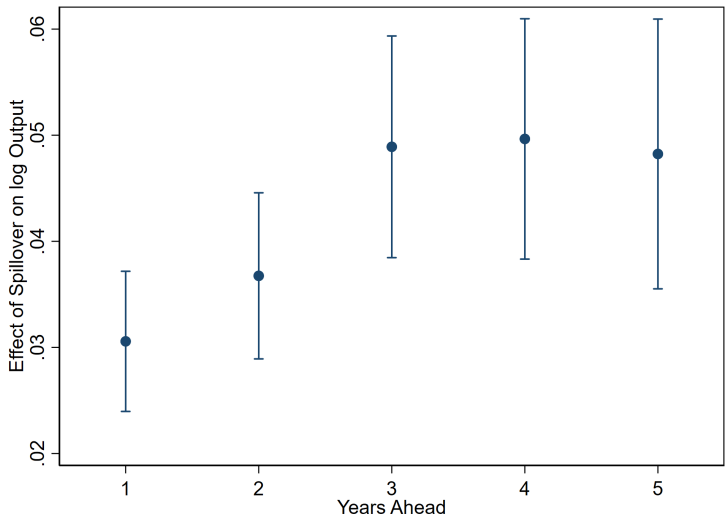
Panel B: Spillover magnitude

Figure 3: Patent-level sector spillover and forward citations

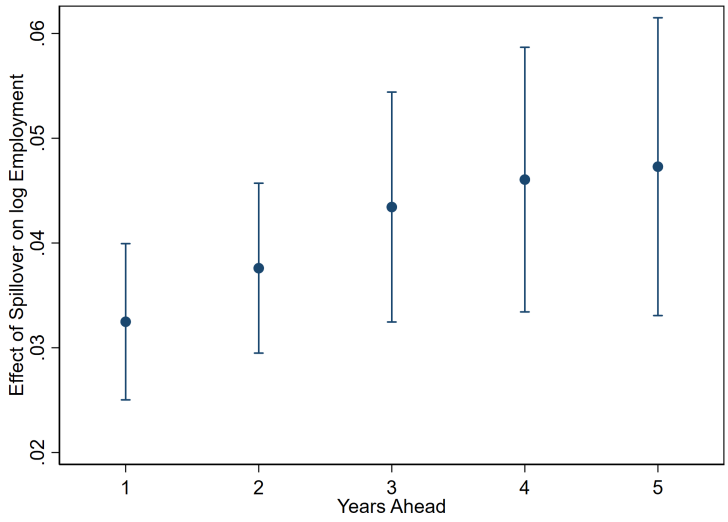
This figure reports average citation outcomes across bins of patent-level spillover. The plotting variables are:

$$z_p = \frac{S_p^P - \overline{S}_{y(p)}^P}{\mathrm{sd}_{y(p)}(S^P)}, \qquad c_p = \log\left(1 + \frac{C_p}{\overline{C}_{y(p)}}\right),$$

where C_p is the forward citation count and the bars and standard deviation in the formula refer to the patent's grant-year cohort. Panel A sorts the pooled sample into 20 equal-frequency bins of signed standardized spillover z_p. Panel B sorts it into 20 bins of $|z_p|$. The horizontal axis reports the bin rank; bar heights report mean c_p. Whiskers in both panels show 95% confidence intervals computed from the within-bin standard error of the mean. Cohort adjustment is used for this figure, whereas Table 3 uses $\log(1 + C_p)$. The patent sample covers 1926–2023.



Panel A: Output growth



Panel B: Employment growth

Figure 4: Sector spillover and long-run growth

This figure plots the spillover coefficients from the firm-year regressions:

$$G_{f,y}^{(\tau)} = \beta_{S,\tau} S_{f,y-1}^{F} + \beta_{P,\tau} P_{f,y-1}^{F} + \gamma_{\tau}' X_{f,y-1} + \alpha_s + \lambda_y + \varepsilon_{f,y}^{(\tau)},$$

where $G_{f,y}^{(\tau)} = \log Y_{f,y+\tau-1} - \log Y_{f,y-1}$ is cumulative log output growth in Panel A and employment growth in Panel B. The horizontal axis reports elapsed years from the base year $y-1$: $\tau = 1, \ldots, 5$ denotes one through five years. Spillover S^F and own private value P^F are measured in the base year and scaled to unit variance. X contains lagged log output, capital, and employment; α_s and λ_y denote sector and year effects. Points show $\beta_{S,\tau}$ in log units. Bars show 95% confidence intervals, using firm-year clustering for output and sector-year clustering for employment. At the one-year horizon, regression years run from 1952 through 2023; the last usable year moves back by one in each subsequent horizon and is 2019 at the five-year horizon.

Table 1: Summary statistics

This table reports summary statistics for the two principal estimation panels. Panel A describes firm-year observations from 1950 through 2024. *Spillover* (S^F) is a firm's annual exposure to other firms' patent grants, and *Private value* (P^F) is the value of its own patents. *Output growth* and *Employment growth* are one-year log changes multiplied by 100. *R&D intensity* is sector R&D expenditure divided by sector sales. Panel B describes SIC3 sector-day observations from 1926–2023. S^S and P^S are sector peer spillover and private patent value; their scaled counterparts divide these measures by lagged sector market capitalization. The *Lerner index* is the sector's operating margin. Panel B statistics are unweighted, although the scaled regressions use lagged sector-market-capitalization weights. Columns report nonmissing observations, mean, standard deviation, and the 5th, 50th, and 95th percentiles. Statistics precede regression-specific standardization. Variable definitions and sources appear in Appendix Table A.1.

	Observations	Mean	SD	P5	Median	P95
Panel A: Firm-year sample						
Spillover (S^F)	203,832	−0.266	9.933	−5.761	−0.020	4.549
Private value (P^F)	203,832	151.328	1,454.811	0.000	0.000	226.497
Output growth (%)	152,427	5.556	47.225	−45.231	4.791	57.674
Employment growth (%)	93,700	4.645	33.559	−29.849	2.575	44.765
R&D intensity	203,377	0.019	0.057	0.000	0.005	0.075
Panel B: SIC3 sector-day sample						
Sector spillover (S^S)	6,326,427	−3.283	2,670.391	−428.353	−0.052	427.426
Sector private value (P^S)	6,326,427	0.460	908.035	0.000	0.000	0.000
Scaled sector spillover ($\widetilde{S}$)	6,326,427	0.000153	0.039037	−0.046201	−0.000610	0.047956
Scaled sector private value ($\widetilde{P}$)	6,326,427	0.000002	0.003210	0.000000	0.000000	0.000000
Sector market capitalization	6,326,427	30,311.340	201,304.521	9.102	970.482	103,835.270
Lerner index	3,189,460	0.308	0.142	0.119	0.288	0.565

Table 2: Patent-issuance-window returns, excess returns, and factor alphas

This table reports raw returns, market-adjusted excess returns, and factor alphas for patentees, non-patenting SIC3 peers, and other firms, together with patenter-minus-other and peer-minus-other spreads. Excess return is each firm's return minus the contemporaneous total Fama–French market return; Panel B compounds these daily differences over three sessions as $\prod_{\tau=0}^{2}[1 + (r_{f,t+\tau} - r_{m,t+\tau})] - 1$, matching the construction of the paper's spillover measure. Factor alphas are estimated from:

$$r^{RF}_{g,t,w} = \alpha_{g,w} + \boldsymbol{\beta}'_{g,w} F_{t,w} + \varepsilon_{g,t,w},$$

where g indexes a portfolio or spread, t is a grant date, and w is the event window. For a portfolio, r^{RF} is its return less the risk-free return; for a zero-cost spread, it is the return difference. F contains the CAPM, Fama–French three-factor, or Fama–French five-factor returns over the same window. Firms receive lagged-market-capitalization weights within each group, and grant dates receive equal weight. Panel A uses the grant date; Panel B compounds raw returns over that date and the next two trading sessions. Entries are percentages per window. Parentheses contain Newey–West t-statistics using 20 actual trading-session lags. The sample covers 1926–2023.

	Raw return	Excess return	CAPM alpha	FF3 alpha	FF5 alpha
Panel A: One day					
Patenter	0.0649	0.0221	0.0215	0.0139	0.0111
	(4.21)	(5.73)	(5.56)	(3.89)	(3.04)
Peer	0.0374	-0.0054	-0.0072	-0.0007	-0.0061
	(2.29)	(-1.24)	(-1.73)	(-0.17)	(-1.80)
Other	0.0280	-0.0148	-0.0116	-0.0096	-0.0089
	(2.01)	(-4.18)	(-3.52)	(-2.81)	(-2.43)
Patenter − Other	0.0369	0.0369	0.0331	0.0235	0.0200
	(5.65)	(5.65)	(5.16)	(3.74)	(3.08)
Peer − Other	0.0094	0.0094	0.0043	0.0089	0.0028
	(1.51)	(1.51)	(0.76)	(1.42)	(0.56)
Panel B: Three days					
Patenter	0.2129	0.0115	0.0129	0.0136	0.0070
	(8.39)	(1.75)	(1.98)	(2.35)	(1.04)
Peer	0.2116	0.0084	-0.0033	-0.0031	-0.0035
	(7.56)	(1.19)	(-0.48)	(-0.46)	(-0.54)
Other	0.1873	-0.0162	-0.0040	-0.0055	-0.0137
	(7.54)	(-2.46)	(-0.60)	(-0.89)	(-1.83)
Patenter − Other	0.0255	0.0276	0.0169	0.0190	0.0207
	(2.19)	(2.37)	(1.43)	(1.80)	(1.63)
Peer − Other	0.0243	0.0246	0.0007	0.0024	0.0102
	(2.20)	(2.23)	(0.07)	(0.23)	(1.00)

Table 3: Patent-level sector spillover and forward citations

This table examines whether the direction and magnitude of peer spillovers predict forward patent citations. The specification is:

$$\log(1 + C_p) = \alpha + \beta_S Z_{S,p} + \beta_A Z_{A,p} + \beta_P Z_{P,p} + \gamma' X_p + \eta_{c(p),y(p)} + \mathcal{F}_p + \varepsilon_p,$$

where p indexes patents and C_p is the forward citation count. $Z_{S,p}$, $Z_{A,p}$, and $Z_{P,p}$ denote *Patent-level sector spillover*, *Absolute patent-level sector spillover*, and *Private value*, each divided by its own sample standard deviation. X_p adds log firm market capitalization in Column (2), return volatility in Column (3), and log sector market capitalization in Columns (4)–(5). All columns include technology-class-by-grant-year fixed effects $\eta_{c(p),y(p)}$; $\mathcal{F}_p$ adds sector fixed effects in Column (4) and sector-by-year fixed effects in Column (5). The dependent variable uses raw citation counts; cohort normalization is used only in Figure 3. Regressions are estimated at the patent level using patents granted from 1926 through 2023. Standard errors are clustered by technology class-year and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Citations	(2) Citations	(3) Citations	(4) Citations	(5) Citations
Spillover	0.0015	0.0013	0.0011	0.0008	0.0006
	(0.0019)	(0.0018)	(0.0017)	(0.0017)	(0.0017)
$\|Spillover\|$	0.0263***	0.0213***	0.0187***	0.0120***	0.0070***
	(0.0025)	(0.0024)	(0.0022)	(0.0022)	(0.0023)
PrivateValue	0.0444***	0.0322***	0.0258***	0.0220***	0.0196***
	(0.0026)	(0.0024)	(0.0022)	(0.0022)	(0.0023)
FirmSize		0.0161***	0.0297***	0.0300***	0.0309***
		(0.0007)	(0.0008)	(0.0009)	(0.0010)
Volatility			6.0661***	5.5312***	5.2885***
			(0.1881)	(0.1915)	(0.2020)
SectorSize				-0.0140***	-0.0072
				(0.0019)	(0.0081)
Observations	1672508	1672508	1672508	1672484	1670971
R^2	0.382	0.383	0.385	0.391	0.398
Tech × Year FE	Yes	Yes	Yes	Yes	Yes
Sector FE	No	No	No	Yes	No
Sector × Year FE	No	No	No	No	Yes

Table 4: Innovation and sector spillover

This table examines the relation between aggregate private patent value and peer spillover using the common specification:

$$S_{s,t} = \alpha + \beta P_{s,t} + \gamma M_{s,t-1} + \mathcal{F}_{s,t} + \varepsilon_{s,t},$$

where S and P denote aggregate peer spillover and private patent value, respectively, and M is lagged sector market capitalization. Columns (1)–(3) use the level measures and include M as a control. Columns (4)–(6) divide both measures by M, omit the capitalization control ($\gamma = 0$), and weight observations by M. Within each block, $\mathcal{F}_{s,t}$ denotes no fixed effects, sector fixed effects, and sector-by-year fixed effects, respectively. Regressions are estimated at the SIC3 sector-day level. The sample covers 1926–2023. Standard errors are clustered by sector-year and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Spillover	Spillover	Spillover	SpilloverS	SpilloverS	SpilloverS
PrivateValue	0.2212***	0.2209***	0.1904***			
	(0.0243)	(0.0243)	(0.0265)			
SectorSize	-0.0003	-0.0003	-0.0126***			
	(0.0002)	(0.0002)	(0.0022)			
PrivateValueS				0.2242***	0.2236***	0.2134***
				(0.0136)	(0.0137)	(0.0137)
Observations	6326427	6326427	6326424	6326427	6326427	6326424
R^2	0.006	0.006	0.029	0.003	0.004	0.016
Sector FE	No	Yes	No	No	Yes	No
Sector × Year FE	No	No	Yes	No	No	Yes

Table 5: Sector spillover and long-run growth

This table examines whether annual spillover exposure predicts subsequent firm growth. A separate regression is estimated for each outcome and lead:

$$G_{f,y}^{(\tau)} = \beta_{S,\tau} S_{f,y-1}^{F} + \beta_{P,\tau} P_{f,y-1}^{F} + \gamma_{\tau}' X_{f,y-1} + \alpha_s + \lambda_y + \varepsilon_{f,y}^{(\tau)},$$

where $G_{f,y}^{(\tau)} = \log Y_{f,y+\tau-1} - \log Y_{f,y-1}$ is cumulative log growth in output (Panel A) or employment (Panel B). Columns (1)–(5) report horizons $\tau = 1, \ldots, 5$, corresponding to one through five years from the base year $y-1$. *Spillover* (S^F) and *Private value* (P^F) are annual peer exposure and own patent value, divided by their sample standard deviations. $X_{f,y-1}$ contains lagged log output, log capital, and log employment. α_s and λ_y denote sector and year fixed effects. Regressions are estimated at the firm-year level. Standard errors are clustered by firm-year for output and by sector-year for employment, and are reported in parentheses. In Column (1), regression years run from 1952 through 2023; the last usable year moves back by one in each subsequent horizon and is 2019 in Column (5). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Panel A: Output growth					
Spillover	0.0214***	0.0306***	0.0367***	0.0489***	0.0496***
	(0.0021)	(0.0034)	(0.0040)	(0.0053)	(0.0058)
Private value	0.0138***	0.0227***	0.0319***	0.0416***	0.0483***
	(0.0025)	(0.0037)	(0.0050)	(0.0059)	(0.0070)
Observations	81,610	75,096	70,622	67,011	63,875
R^2	0.069	0.084	0.094	0.105	0.114
Panel B: Employment growth					
Spillover	0.0177***	0.0325***	0.0376***	0.0434***	0.0461***
	(0.0021)	(0.0038)	(0.0041)	(0.0056)	(0.0064)
Private value	0.0027	0.0068**	0.0097**	0.0094	0.0062
	(0.0020)	(0.0031)	(0.0045)	(0.0059)	(0.0072)
Observations	75,286	67,022	61,396	56,354	52,031
R^2	0.042	0.065	0.085	0.099	0.112
Controls	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table 6: R&D intensity, sector spillover, and long-run growth

This table examines whether the relation between patent exposure and subsequent growth varies with sector R&D intensity:

$$G_{f,y}^{(\tau)} = \beta_{S,\tau} S_{f,y-1}^{F} + \theta_{S,\tau} S_{f,y-1}^{F} \mathrm{RD}_{s,y-1} + \beta_{P,\tau} P_{f,y-1}^{F} + \theta_{P,\tau} P_{f,y-1}^{F} \mathrm{RD}_{s,y-1} + \gamma_{\tau}' X_{f,y-1} + \alpha_s + \lambda_y + \varepsilon_{f,y}^{(\tau)},$$

where $G_{f,y}^{(\tau)} = \log Y_{f,y+\tau-1} - \log Y_{f,y-1}$ is cumulative log growth in output (Panel A) or employment (Panel B). Columns (1)–(5) report horizons $\tau = 1, \ldots, 5$, corresponding to one through five years from the base year $y-1$. *Spillover* (S^F), *Private value* (P^F), and *R&D intensity* (RD) are divided by their respective sample standard deviations before forming the interactions. R&D intensity is total sector R&D expenditure divided by sector sales. The specification includes interactions of R&D intensity with both spillover and own private value. $X_{f,y-1}$ contains lagged log output, log capital, and log employment. α_s and λ_y denote sector and year fixed effects. Regressions are estimated at the firm-year level. In Column (1), regression years run from 1952 through 2023; the last usable year moves back by one in each subsequent horizon and is 2019 in Column (5). Standard errors are clustered by sector-year and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Panel A: Output growth					
Spillover	0.0178***	0.0234***	0.0275***	0.0339***	0.0438***
	(0.0024)	(0.0042)	(0.0050)	(0.0070)	(0.0073)
Spillover × R&D	0.0111**	0.0225***	0.0283***	0.0466**	0.0172
	(0.0050)	(0.0081)	(0.0104)	(0.0190)	(0.0189)
Private value	0.0149***	0.0250***	0.0408***	0.0516***	0.0572***
	(0.0037)	(0.0059)	(0.0093)	(0.0109)	(0.0120)
Private value × R&D	-0.0012	-0.0033	-0.0114	-0.0126	-0.0102
	(0.0055)	(0.0090)	(0.0140)	(0.0165)	(0.0168)
Observations	81,610	75,096	70,622	67,011	63,875
R^2	0.070	0.084	0.094	0.105	0.114
Panel B: Employment growth					
Spillover	0.0165***	0.0277***	0.0290***	0.0323***	0.0420***
	(0.0021)	(0.0041)	(0.0046)	(0.0058)	(0.0076)
Spillover × R&D	0.0031	0.0150**	0.0272***	0.0352***	0.0121
	(0.0039)	(0.0066)	(0.0103)	(0.0129)	(0.0184)
Private value	0.0089***	0.0179***	0.0285***	0.0306***	0.0244***
	(0.0031)	(0.0046)	(0.0062)	(0.0074)	(0.0091)
Private value × R&D	-0.0093***	-0.0176***	-0.0265***	-0.0297***	-0.0246**
	(0.0035)	(0.0061)	(0.0084)	(0.0090)	(0.0101)
Observations	75,286	67,022	61,396	56,354	52,031
R^2	0.042	0.065	0.086	0.099	0.112
Controls	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table 7: Sector spillover and subsequent investment

This table examines whether prior-year spillover exposure predicts capital investment. The specification is:

$$\frac{\text{CAPX}_{f,y}}{\text{PPENT}_{f,y-1}} = \alpha + \beta_S S^F_{f,y-1} + \beta_P P^F_{f,y-1} + \gamma' X_{f,y-1} + \mathcal{F}_{f,y} + \varepsilon_{f,y},$$

where *Investment* is capital expenditure divided by lagged net property, plant, and equipment. *Spillover* sums the firm's grant-window dollar exposure on Tuesday grant dates when another firm in the same SIC3 industry receives a patent and the recipient receives none; annual firm totals are winsorized within year at the 1st and 99th percentiles. *Private value* is own annual patent value. Both measures are divided by their standard deviations in the investment reference sample before the peer-Q screen and singleton removal (41,098 firm-years); the spillover standard deviation is \$5.2244 million. All three columns control for lagged log capital, output, and employment. Columns (2)–(3) additionally include lagged Tobin's Q and cash flow/assets; Column (3) also includes the leave-one-out SIC3-year mean of lagged Tobin's Q, computed before the complete-case screen. $\mathcal{F}_{f,y}$ comprises SIC3 and year effects in all three columns. All regressors are dated $y-1$. The sample covers 1963–2023. Standard errors are two-way clustered by firm and year and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Spillover	0.0160***	0.0087***	0.0084***
	(0.0037)	(0.0022)	(0.0021)
Private value	0.0133***	0.0072***	0.0071***
	(0.0028)	(0.0027)	(0.0027)
Q		0.0485***	0.0478***
		(0.0074)	(0.0074)
Peer Q			0.0224***
			(0.0060)
Cash flow		0.1797***	0.1775***
		(0.0569)	(0.0560)
Observations	39,954	39,954	39,954
R^2	0.1288	0.1641	0.1649
Control	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 8: Sector spillover and subsequent acquisitions

This table relates acquisition expenditure to prior-year spillover exposure:

$$\frac{\text{AQC}_{f,y}}{\text{AT}_{f,y-1}} = \alpha + \beta_S S^F_{f,y-1} + \beta_P P^F_{f,y-1} + \gamma' X_{f,y-1} + \mathcal{F}_{f,y} + \varepsilon_{f,y},$$

where the outcome is acquisition expenditure (Compustat AQC) divided by lagged total assets (AT). The ratio is winsorized within fiscal year at the 1st and 99th percentiles before matching. Reported zeros are retained; missing or negative AQC is excluded. *Spillover* and *Private value* follow the construction and standardization in Table 7. All three columns control for lagged log capital, output, and employment. Columns (2)–(3) additionally include lagged Tobin's Q and cash flow/assets; Column (3) also includes the leave-one-out SIC3-year mean of lagged Tobin's Q, computed before the complete-case screen. $\mathcal{F}_{f,y}$ comprises SIC3 and year effects in all three columns. All regressors are dated $y-1$. The sample covers 1971–2023. Standard errors are two-way clustered by firm and year and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Spillover	0.0014**	0.0011**	0.0011**
	(0.0005)	(0.0005)	(0.0005)
Private value	-0.0004	-0.0006**	-0.0006**
	(0.0003)	(0.0003)	(0.0003)
Q		0.0017***	0.0016***
		(0.0004)	(0.0004)
Peer Q			0.0025**
			(0.0012)
Cash flow		0.0152***	0.0150***
		(0.0027)	(0.0027)
Observations	34,181	34,181	34,181
R^2	0.0584	0.0598	0.0601
Control	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 9: Sector spillover and subsequent inventive activity

This table relates one-year inventive growth to prior-year spillover exposure, using the control specifications in Table 8:

$$G^Z_{f,y} = \alpha + \beta_S S^F_{f,y-1} + \beta_P P^F_{f,y-1} + \gamma' X_{f,y-1} + \alpha_s + \lambda_y + \varepsilon^Z_{f,y},$$

where $G^Z_{f,y} = Z_{f,y} - Z_{f,y-1}$. Panel A uses $Z = \log(1 + \text{inventors})$, counting distinct active PatentsView inventor IDs on the firm's KPSS-linked grants; Panel B uses $Z = \log(1 + \text{patents})$, counting distinct KPSS-linked grants. Observed zeros are retained; unobserved firm-years are not filled. Inventor counts are missing if any grant lacks an inventor link. *Spillover* and *Private value* follow the construction and standardization in Table 7, before outcome-specific sample selection. All columns control for lagged log capital, output, and employment. Columns (2)–(3) add lagged Tobin's Q and cash flow/assets; Column (3) adds leave-one-out SIC3-year mean lagged Q, computed before complete-case selection. All regressors are dated $y - 1$; SIC3 and year effects are included. Within each panel, columns use the same complete-case sample after fixed-effect singleton removal. Current and lagged accounting dates must be in December, 350–380 days apart; acquisition and investment outcome availability are not required. Outcome years are 1977–2023 in Panel A and 1963–2023 in Panel B. Standard errors in parentheses are two-way clustered by firm and year (47 and 61 year clusters, respectively), with the estimator's positive-semidefinite covariance adjustment. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)
Panel A: Inventor growth			
Spillover	0.0069***	0.0061**	0.0062**
	(0.0025)	(0.0024)	(0.0024)
Private value	-0.0003	-0.0009	-0.0009
	(0.0020)	(0.0021)	(0.0021)
Q		0.0047***	0.0049***
		(0.0006)	(0.0006)
Peer Q			-0.0049
			(0.0050)
Cash flow		0.0267**	0.0272***
		(0.0101)	(0.0101)
Observations	32,102	32,102	32,102
R^2	0.0119	0.0122	0.0122
Panel B: Patent growth			
Spillover	0.0056***	0.0047**	0.0048**
	(0.0020)	(0.0019)	(0.0019)
Private value	-0.0010	-0.0017	-0.0017
	(0.0024)	(0.0025)	(0.0025)
Q		0.0058***	0.0059***
		(0.0008)	(0.0008)
Peer Q			-0.0050
			(0.0041)
Cash flow		0.0362***	0.0367***
		(0.0087)	(0.0087)
Observations	40,519	40,519	40,519
R^2	0.0152	0.0157	0.0158
Control	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 10: Innovation characteristics and sector spillover

This table compares spillover pass-through across three classifications of patent value:

$$\widetilde{S}_{s,t} = \alpha + \beta_1 \widetilde{P}^{(1)}_{s,t} + \beta_0 \widetilde{P}^{(0)}_{s,t} + \mathcal{F}_{s,t} + \varepsilon_{s,t},$$

where S^S is aggregate peer spillover and a tilde denotes division by lagged sector market capitalization M. Each column estimates a separate regression using two attributed private-value components, $P^{(1)}$ and $P^{(0)}$. Column (1) compares breakthrough and non-breakthrough patents; breakthroughs are in the top decile of the issue-year-adjusted novelty-and-impact measure of Kelly, Papanikolaou, Seru, and Taddy (2021). Column (2) allocates private value using continuous process-claim and product-claim shares following Bena and Simintzi (2025). Column (3) compares patents with RETech scores above the within-grant-year median (RET) with the remaining classified patents (non-RET), using Bowen, Frésard, and Hoberg (2023). Components are formed at patenting-firm events and summed within sector-days; both components may be positive on the same date, and unclassified patents enter neither component. All regressions use SIC3 sector-day observations, weight them by M, and include sector-by-year fixed effects $\mathcal{F}_{s,t}$. Columns (1)–(2) use the 1926–2023 panel; breakthrough classifications cover grants through 2010 and process/product classifications cover 1976–2021. Column (3) uses the 1980–2010 sample. Standard errors are clustered by sector-year and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Breakthrough	(2) Process/product	(3) RET
Private value: breakthrough	0.3791***		
	(0.0601)		
Private value: non-breakthrough	0.1875***		
	(0.0181)		
Private value: process		0.3658***	
		(0.0321)	
Private value: product		0.1265***	
		(0.0168)	
Private value: RET			0.2844***
			(0.0309)
Private value: non-RET			0.1450***
			(0.0214)
Observations	6,326,424	6,326,424	2,795,376
R^2	0.015	0.016	0.017
Sector × Year FE	Yes	Yes	Yes

Table 11: Industry conditions and sector spillover

This table examines how market power, financial constraints, and data intensity moderate spillover pass-through. Each column estimates a separate regression:

$$\widetilde{S}_{s,t} = \alpha + \beta \widetilde{P}_{s,t} + \theta \widetilde{P}_{s,t} Z_{s,y(t)} + \mathcal{F}_{s,t} + \varepsilon_{s,t},$$

where $\widetilde{S}_{s,t} = S^S_{s,t}/M_{s,t-1}$ is aggregate peer spillover divided by lagged sector market capitalization, and $\widetilde{P}_{s,t} = P^S_{s,t}/M_{s,t-1}$ is aggregate private patent value divided by the same denominator. In Column (1), $Z_{s,y(t)}$ is the sales-weighted sector Lerner index, assigned to each date in calendar year $y(t)$ and retained in its original units. In Column (2), $Z_{s,y(t)}$ is the standardized sector-year mean of firm-level Whited–Wu indices; higher values indicate tighter financial constraints. In Column (3), $Z_{s,y(t)}$ is the standardized sector-year mean of $\log(1 + \textit{Cloud share})$, where *Cloud share* measures firm job postings associated with cloud-computing technology using Kalyani, Bloom, Carvalho, Hassan, Lerner, and Tahoun (2025). Marginal pass-through is $\beta + \theta Z_{s,y(t)}$. The interaction coefficient θ measures the change in pass-through per unit of the Lerner index in Column (1) and per standard deviation of the moderator in Columns (2)–(3). All regressions use SIC3 sector-day observations, weight them by lagged sector market capitalization, and include sector-by-year fixed effects $\mathcal{F}_{s,t}$. Samples are restricted to observations with the corresponding moderator and cover 1950–2023 in Column (1), 1951–2021 in Column (2), and 2010–2019 in Column (3). Standard errors are clustered by sector-year and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Market power	(2) Financial constraints	(3) Data intensity
Private value	0.2510***	0.2165***	0.2646***
	(0.0334)	(0.0151)	(0.0209)
Private value × Lerner index	-0.1847***		
	(0.0669)		
Private value × Whited–Wu index		-0.0390**	
		(0.0162)	
Private value × Cloud exposure			-0.0605***
			(0.0106)
Observations	3,219,754	3,569,332	515,715
R^2	0.016	0.016	0.015
Sector × Year FE	Yes	Yes	Yes

Table 12: Industry salience, patenting-firm liquidity, and sector spillover

This table examines whether spillover pass-through varies with industry salience and patenting-firm liquidity. Each column estimates a separate regression of the form:

$$\widetilde{S}_{s,t} = \alpha + \boldsymbol{\beta}'\mathbf{X}_{s,t} + \mathcal{F}_{s,t} + \varepsilon_{s,t},$$

where $\widetilde{S}_{s,t} = S^S_{s,t}/M_{s,t-1}$ is aggregate peer spillover divided by lagged sector market capitalization, and $\widetilde{P}_{s,t} = P^S_{s,t}/M_{s,t-1}$ is aggregate private patent value divided by the same denominator. In Column (1), the regressor vector $\mathbf{X}_{s,t}$ contains $\widetilde{P}_{s,t}$, $\widetilde{P}_{s,t}Z_{s,t}$, and $Z_{s,t}$. *Industry size* ($Z_{s,t}$) is log lagged SIC3 market capitalization, demeaned using lagged sector capitalization weights over the complete-case sector-day sample before singleton removal and divided by its unweighted full-panel standard deviation. The private-value coefficient measures pass-through at the capitalization-weighted mean of log size; the interaction coefficient measures its change per standard deviation of industry size. In Column (2), $\mathbf{X}_{s,t}$ contains $\widetilde{P}^H$ and $\widetilde{P}^L$, the private-value components attributed to high- and low-turnover patentees, divided by lagged sector market capitalization. *Turnover*, mean daily trading volume divided by shares outstanding within firm-year, is the liquidity proxy. High-turnover firms are in the top 10% of the within-year distribution; low-turnover firms are in the remaining 90%. Components are summed across patenting firms within each sector-day, which can contain both groups; patentees without turnover data enter neither component. Both regressions use SIC3 sector-day observations from 1926–2023, weight them by lagged sector market capitalization, and include sector-by-year fixed effects $\mathcal{F}_{s,t}$. Standard errors are clustered by sector-year and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Industry salience	(2) Patenting-firm liquidity
Private value	0.2053***	
	(0.0144)	
Private value × Industry size	0.0614**	
	(0.0251)	
Industry size	-0.0260***	
	(0.0017)	
Private value: high-turnover patentees		0.3462***
		(0.0608)
Private value: low-turnover patentees		0.2059***
		(0.0136)
Observations	6,326,424	6,326,424
R^2	0.021	0.016
Sector × Year FE	Yes	Yes

A Appendix

Table A.1: Variable definitions

Variable	Definition	Source
Panel A: Spillover measures		
S_p^P (*Patent-level sector spillover*)	Signed sum of eligible non-patenting firms' grant-date market-value reactions in patent p's SIC3 sector. Citation regressions scale by the sample standard deviation; the figure standardizes within grant year.	CRSP; KPSS
$S_{f,y}^F$ (*Spillover*)	Annual sum of spillovers allocated to firm f from other firms' patent grants; own-patent events are excluded. Regressions scale by the sample standard deviation.	CRSP; KPSS
$S_{s,t}^S$ (*Spillover*)	Sum of spillovers allocated to eligible sector peers on date t, as in Equation (8).	CRSP
$\widetilde{S}_{s,t}$ (*SpilloverS*)	$S_{s,t}^S$ divided by lagged sector market capitalization.	CRSP
$TSD^{(d)}$	Decile d of firm-day technology exposure, based on CPC4 patent-value shocks and the firm's historical patent shares. Exposure is standardized within year; missing exposure is the omitted group.	USPTO; KPSS
TechDiffusion	Exposure from technology-claim embeddings and the firm's prior-year patent centroid, scaled by its sample standard deviation. Construction and patent weights are defined in Internet Appendix Section IA.2.	USPTO; KPSS
BusinessStealing	Exposure from product-claim embeddings and a max-pooled representation of the firm's prior-year patents, scaled by its sample standard deviation. See Internet Appendix Section IA.2.	USPTO; KPSS
Panel B: Private patent value		
P_p^P (*Patent private value*)	Patent p's value to its owner, inferred from the owner's idiosyncratic grant-window return following Kogan, Papanikolaou, Seru, and Stoffman (2017). Patent-level regressions scale by the sample standard deviation.	CRSP; KPSS
$P_{f,y}^F$ (*PrivateValue*)	Annual sum of firm f's own private patent values following Kogan, Papanikolaou, Seru, and Stoffman (2017), scaled by the sample standard deviation in regressions.	CRSP; KPSS
$P_{s,t}^S$ (*PrivateValue*)	Sum of private patent values across patentees in sector s on date t.	CRSP; KPSS
$\widetilde{P}_{s,t}$ (*PrivateValueS*)	$P_{s,t}^S$ divided by lagged sector market capitalization.	CRSP; KPSS
Panel C: Outcome variables		
Three-day return ($R_{f,s,t}^{(3)}$)	Firm f's compounded return over the grant date and next two trading sessions; multiplied by 100 in technology-exposure regressions.	CRSP
Output growth	$\log Y_{f,y+\tau-1} - \log Y_{f,y-1}$ for $\tau = 1, \ldots, 5$. Summary statistics use 100 times one-year log growth. Winsorized annually at the 1st/99th percentiles; Y is defined in Panel G.	Compustat; BLS
Employment growth	$\log H_{f,y+\tau-1} - \log H_{f,y-1}$ for $\tau = 1, \ldots, 5$. Summary statistics use 100 times one-year log growth. Winsorized annually at the 1st/99th percentiles; H is `emp`.	Compustat
$\log(1 + C_p)$ (*Citations*)	Log of one plus raw forward citations. The figure instead uses $\log(1 + C_p/\overline{C}_{y(p)})$, where $\overline{C}_{y(p)}$ is the grant-year mean.	KPSS; USPTO
Investment	Capital expenditure (`capx`) divided by lagged net property, plant, and equipment (`ppent`).	Compustat
Acquisition expenditure	Acquisition expenditure (`aqc`) divided by lagged assets (`at`); zeros are retained and the ratio is winsorized annually at the 1st/99th percentiles.	Compustat
Inventor growth	$\log(1 + \text{inventors}_{f,y}) - \log(1 + \text{inventors}_{f,y-1})$; one-year growth in distinct active disambiguated inventors on firm patents.	PatentsView; KPSS
Patent growth	$\log(1 + \text{patents}_{f,y}) - \log(1 + \text{patents}_{f,y-1})$; one-year growth in distinct KPSS-linked grants.	KPSS

Variable	Definition	Source
Panel D: Sector-level controls		
SectorSize	Lagged total market capitalization of SIC3-sector firms.	CRSP
Lerner ($L_{s,y}$)	Sector sales-weighted mean of (Sales − COGS)/Sales.	Compustat
RD intensity	Total R&D expenditure divided by total sales within SIC3 sector-year.	Compustat
Industry size	Log SIC3 market capitalization, weighted-mean centered and scaled by its full-panel standard deviation before interaction with private value.	CRSP
HHI	Sum of squared firm sales shares within sector-year; higher values indicate greater concentration.	Compustat
Fluidity	Sector-year mean product-market fluidity, centered using lagged sector-market-capitalization weights.	Hoberg–Phillips
WW	Sector-year mean Whited–Wu index, standardized over the estimation sample; higher values indicate tighter financial constraints.	Compustat
KZ	Sector-year mean Kaplan–Zingales index, standardized over the estimation sample; higher values indicate tighter measured financial constraints.	Compustat
Cloud	Sector-year mean of $\log(1 + \textit{Cloud share})$, standardized over the sample; *Cloud share* is the cloud-technology share of a firm's job postings.	Bloom et al.
Panel E: Firm-level controls		
Firm size	Log market capitalization in citation regressions; lagged market capitalization in firm-day return regressions.	CRSP
Return volatility	Volatility of the patent owner's stock return in citation regressions.	CRSP
$\log Y$ (*log output*)	Log real gross output, defined in Panel G.	Compustat
$\log K$ (*log capital*)	Log gross PPE (`ppegt`) deflated by the capital-goods price index. Investment expenditure is scaled by lagged net PPE (`ppent`).	Compustat
$\log H$ (*log employment*)	Log employment (`emp`).	Compustat
Tobin's Q	Market value of assets divided by book assets, dated $y - 1$ in investment, acquisition, and one-year inventive-activity regressions.	CRSP; Compustat
Peer Q	Leave-one-out sector-year mean of lagged Tobin's Q, computed before the complete-case screen.	CRSP; Compustat
Cash flow/assets	Operating cash flow divided by total assets, dated $y - 1$.	Compustat
Turnover	Firm-year mean daily volume divided by shares outstanding; also used to form high- and low-turnover groups.	CRSP
Panel F: Patent classifications		
Breakthrough	Indicator for patents in the top decile of issue-year-adjusted novelty and impact.	Kelly et al.
Process/Product shares	Shares of classified claims associated with processes and products; the sector-day shares need not be mutually exclusive.	Bena–Simintzi
RET/Non-RET	RET indicates a RETech score above the grant-year median; Non-RET contains the remaining classified patents.	Bowen et al.
Panel G: Compustat data items		
Sales (`sale`)	Net sales (revenues), used in output, the Lerner index, and R&D intensity.	Compustat
COGS (`cogs`)	Cost of goods sold, used in the Lerner index.	Compustat
SGA (`xsga`)	Selling, general, and administrative expenses; not deducted in the reported Lerner proxy.	Compustat
Output (`sale` + Δ`invt`)	Real gross output: sales plus the change in inventories, deflated by the CPI.	Compustat; BLS
Employment (`emp`)	Number of employees, in thousands.	Compustat

Internet Appendix

IA.1 Construction of the CPC4 Portfolio Score

This section documents the CPC4-based portfolio score underlying the decile regressions in Section 3.2. The saved implementation yields a firm-year score observed on a subset of patent-grant dates. Two implementation discrepancies matter: the portfolio includes current-year information, and the aggregation uses the firm's annual class-specific patent value rather than the class-level value of patents granted on the event date. The following construction describes the measure used by the reported estimates.

The classification routine links KPSS patents to CPC records by patent number, retains the first available CPC entry for each patent, and takes its first four characters as the CPC4 class. Patents without a usable CPC4 class do not enter the class aggregates. Within each firm-year, I sum nominal private patent values by CPC4 class and retain at most ten classes with the largest annual values. Let $\mathcal{C}_{f,y}$ be this retained set and $V_{f,c,y}$ the annual nominal value in a retained firm-class-year row. For notation, set $V_{f,c,y} = 0$ when that row is absent.

The rolling value and corresponding share are

$$H_{f,c,y} = \sum_{\ell=0}^{4} V_{f,c,y-\ell}, \qquad \omega_{f,c,y} = \frac{H_{f,c,y}}{\sum_{k\in\mathcal{C}_{f,y}} H_{f,k,y}}, \qquad c \in \mathcal{C}_{f,y}.$$

The window is $y-4$ through y, including the grant year. The top-ten restriction is applied separately in each year before taking rolling sums. Shares are calculated only for classes retained in year y: a class present in earlier years but absent from $\mathcal{C}_{f,y}$ is not carried forward.

Separately, the paper aggregates nominal patent values by CPC4 class and grant date across all industries. Let $\mathcal{D}_{c,y}$ be the set of dates represented for class c in year y, and $n_{c,y} = |\mathcal{D}_{c,y}|$. Joining these records to the portfolio creates one row per retained firm-class and matching class grant date. Both inputs use the same variable name for nominal patent value, and the join retains the value from the firm-class input. Each joined row therefore contributes $\omega_{f,c,y}V_{f,c,y}$, not the share multiplied by the daily class aggregate. The code then sums by firm and year, giving

$$T^{\text{saved}}_{f,y} = \sum_{c\in\mathcal{C}_{f,y}} n_{c,y}\,\omega_{f,c,y}\,V_{f,c,y}. \tag{21}$$

This score is repeated on dates in $\bigcup_{c\in\mathcal{C}_{f,y}} \mathcal{D}_{c,y}$; other firm-dates remain unmatched. The daily class aggregates determine matching dates and their counts, but their value magni-

tudes do not enter the saved score. There is no own-patent subtraction in this construction. A zero share denominator produces missing class contributions, which the summation routine treats as zero. A reconstruction from the saved class inputs reproduces all 91,349 firm-year scores to numerical precision; the 4,166,429 saved firm-date observations have no within-firm-year variation. The saved exposure file covers 1926–2022.

For the return analysis, I merge the score into a panel of firms observed on dates with at least one KPSS patent grant and remove firms receiving their own grant on that date. Unmatched scores remain missing. Within each calendar year, I subtract the mean score and divide by its sample standard deviation, using nonmissing observations in this broader panel. These moments weight firm-date observations equally, so a firm-year with more matched dates enters more often. I then assign nonmissing standardized scores to ten pooled quantile groups across years, before restricting the sample to industry peers or excluding observations for missing regression controls. The cutoffs are not recomputed within each year or within the peer sample. Observations with missing standardized scores receive zero for all ten decile indicators and form the reference group; they are not assigned to the lowest decile or assumed to have zero economic exposure.

The reported regressions retain non-patenting firms in the same SIC3 industry as at least one patent recipient on the event date, with each firm-date counted once. Peer membership requires a grant, including a grant with zero recorded value, and excludes unknown industry codes. All columns include lagged market capitalization and date fixed effects. Columns (2) and (4) add SIC3 effects; Columns (3) and (4) add book-to-market, gross and operating profitability, earnings per share, return on equity, free cash flow, and investment. Standard errors are clustered by date. Figure 2 displays Column (4).

Accordingly, the estimates compare returns across an annual patent-portfolio score, not a lagged portfolio-weighted event shock. Implementing the latter would require portfolio shares fixed before the grant year, an explicitly identified daily class-value variable, and aggregation by firm-date. The deciles and return regressions would then need to be reestimated. The reported estimates are retained here, with these discrepancies made explicit.

IA.2 Machine Learning Methodology

This section describes the construction of the technological and product-market exposure measures used in Section 4.4. I use patent claims to represent the content of inventions in a common numerical space, then compare newly granted patents with a firm's existing patent portfolio. The procedure has three components: classifying claims as technology or product claims, embedding their text with a pretrained language model, and aggregating the resulting similarities into annual firm-level exposure. The reported measures use a

one-year patent history and enter the output and employment regressions with a one-year lag.

I begin with the annual USPTO patent-claim files distributed through PatentsView. The text unit is an individual claim, and the procedure uses both independent and dependent claims. Claims are identified by patent number and claim sequence; observations without the identifiers needed to assign a patent, year, or sequence are excluded before embedding. Each claim is assigned to one of two categories using ordered keyword rules. The classification first examines the claim's preamble, ending at a transition such as "comprising," "including," "consisting," "characterized by," or "wherein," or at an earlier colon. Product indicators include "apparatus," "system," "device," "composition," and "compound"; technology indicators include "method," "process," "procedure," "software," and "algorithm." Product indicators receive priority when both groups occur in the text being searched. If the preamble contains no recognized indicator, the same rules are applied to the full claim. Claims with no recognized indicator are assigned to the product category. This classification describes the language of the claim; the subsequent embedding step supplies the learned representation of its content.

I encode the full text of each claim with the pretrained `Qwen3-Embedding-0.6B` model of Zhang, Li, Long, Zhang, Lin, Yang, Xie, Yang, Liu, Lin, Huang, and Zhou (2025), which produces a 1,024-dimensional vector. I apply the same encoder to both claim categories, without additional training on patent values, stock returns, or firm growth. Within each patent, I take the arithmetic mean of the claim vectors separately for technology and product claims. Let $\mathcal{C}_p^k$ denote the claims of patent p assigned to category $k \in \{T, P\}$, and let $h(c)$ be the vector returned by the encoder. The patent-category representation is

$$e_p^k = \begin{cases} |\mathcal{C}_p^k|^{-1} \sum_{c \in \mathcal{C}_p^k} h(c), & |\mathcal{C}_p^k| > 0, \\ 0, & |\mathcal{C}_p^k| = 0. \end{cases}$$

Thus, a patent containing both types of claims has two representations, while a missing claim category receives a zero vector. The reported specifications retain these patent-category means without principal-component reduction or additional normalization before constructing the firm portfolio.

I link patents to the private-value data of Kogan, Papanikolaou, Seru, and Stoffman (2017) by patent number. This link supplies the public firm's PERMNO identifier and the inflation-adjusted patent value, `xi_real`. Historical portfolios require an observed PERMNO and retain one observation per firm–patent pair. For exposure in year t, let $\mathcal{H}_{f,t-1}$ contain firm f's patents granted in the preceding calendar year. The technolog-

ical representation is the normalized centroid of their technology vectors. The product representation is the normalized coordinatewise maximum of their product vectors:

$$a^T_{f,t-1} = \mathcal{N}\left(\frac{1}{|\mathcal{H}_{f,t-1}|}\sum_{p\in\mathcal{H}_{f,t-1}} e^T_p\right), \qquad a^P_{f,t-1} = \mathcal{N}\left(\max_{p\in\mathcal{H}_{f,t-1}} e^P_p\right).$$

Here, $\mathcal{N}(v) = v/\|v\|_2$ for a nonzero vector, $\mathcal{N}(0) = 0$, and the maximum is taken separately in each coordinate. Each historical patent enters the centroid equally; neither portfolio representation weights historical patents by private value. The centroid summarizes the average technological content of the firm's recent inventions. Max pooling retains the largest value in each product-vector coordinate and provides a different summary of the portfolio's product-related content.

For each patent granted in year t, I calculate its inner product with the corresponding firm representation, replace negative inner products with zero, and cube the result:

$$w^k_{fp,t} = \left[\max\left\{(e^k_p)' a^k_{f,t-1}, 0\right\}\right]^3, \qquad k \in \{T, P\}.$$

The cube increases the relative weight of larger positive scores. The firm representation has unit length when nonzero, but the current patent-category mean retains its original length. Accordingly, the score incorporates both the direction and the magnitude of the patent representation: for nonzero vectors it equals $\|e^k_p\|_2^3$ times the positive part of cosine similarity cubed. This distinction matters because averaging claim vectors generally produces patent vectors of different lengths.

I aggregate these scores over the current year's patent file. Let $\mathcal{P}_t$ denote its patents, and let $\mathcal{O}_{f,t} \subseteq \mathcal{P}_t$ denote patents linked to firm f by PERMNO. The patent weight v_p equals the numerical inflation-adjusted value `xi_real` as stored in KPSS, without rescaling, when observed; a missing value receives a weight of one in that same numerical scale. The current-year file retains patents without a KPSS match, so these patents contribute with unit weight and cannot be assigned to a firm's own-patent subtraction without a PERMNO link. The annual measures are

$$E^k_{f,t} = \max\left\{\sum_{p\in\mathcal{P}_t} v_p w^k_{fp,t} - \sum_{p\in\mathcal{O}_{f,t}} v_p w^k_{fp,t},\, 0\right\}, \qquad k \in \{T, P\}.$$

I call E^T *TechDiffusion* and E^P *BusinessStealing*. Both measures remove patents linked to the focal firm and truncate net exposure at zero. The comparison set spans the current patent file rather than a single SIC industry. The construction uses observed patent values

with a unit-weight fallback; it does not estimate missing patent values with the language model.

I merge these annual measures with the firm accounting panel by PERMNO and year. In the regressions, each lagged exposure and the firm's own annual private patent value are divided by their respective sample standard deviations, without subtracting their means. The standard deviations are calculated from the nonmissing lagged variables in the merged panel before horizon-specific regression exclusions. I replace $S^F_{f,y-1}$ in Equation (14) with the standardized $E^k_{f,y-1}$ and estimate the specification separately for each exposure and outcome, retaining lagged log output, log capital, and log employment, sector and year fixed effects, and standard errors clustered by sector–year. For regression year y and horizon τ, growth is measured from $y-1$ to $y+\tau-1$, and the exposure is $E^k_{f,y-1}$. Its firm portfolio therefore uses patents from $y-2$, while the new patents being compared are granted in $y-1$.

Internet Appendix Tables IA.13 and IA.14 report horizons of one through five years. The one-year regression sample covers 1981–2023; the final regression year falls to 2019 at the five-year horizon. The number of usable observations varies with the outcome and horizon. The two exposure measures describe different dimensions of patent-text proximity, and their coefficients measure conditional associations with subsequent growth. They do not separately identify a causal knowledge-diffusion effect or a causal business-stealing effect. The historical patent windows precede the growth outcomes, but the pretrained encoder is applied retrospectively; this construction is not a test using language models available at each historical date.

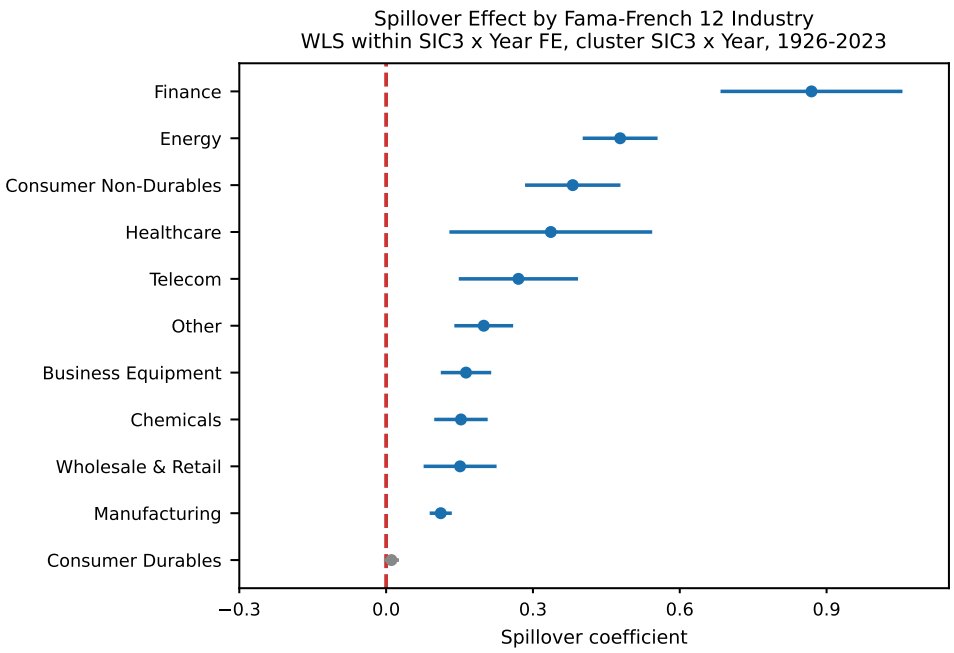


Figure IA.1: Sector spillover by Fama–French industry

This figure reports the private-value coefficient estimated separately within each Fama–French 12 industry:

$$\widetilde{S}_{s,t} = \beta_k \widetilde{P}_{s,t} + \alpha_{s,y(t)} + \varepsilon_{s,t}, \qquad s \in k,$$

where $\widetilde{S}$ and $\widetilde{P}$ are sector spillover and private patent value divided by lagged sector market capitalization, and $\alpha_{s,y(t)}$ denotes SIC3-by-year fixed effects. Regressions use sector-day observations weighted by lagged sector market capitalization. SIC3 sectors are assigned to Fama–French industries using their centroid four-digit SIC code. Points report β_k; bars show 95% confidence intervals based on sector-year-clustered standard errors. The dashed line marks zero. Utilities, with an estimate of 3.26, is omitted to preserve the display scale. The sample covers 1926–2023.

Table IA.1: Patenter and peer return differences around patent grants

This table reports group portfolio return differences relative to other firms from:

$$r_{g,t}^{(h)} = \beta_{\text{Pat}}^{(h)} \mathbf{1}\{g = \text{Pat}\} + \beta_{\text{Peer}}^{(h)} \mathbf{1}\{g = \text{Peer}\} + \lambda_t^{(h)} + \varepsilon_{g,t}^{(h)},$$

where $r_{g,t}^{(h)}$ is the raw portfolio return, in percent, for group g over h trading days beginning on patent grant date t. Column (1) uses one-day returns; Column (2) compounds each firm's raw returns over the grant date and the next two trading sessions before portfolio aggregation. Patentees are firms receiving patents; peers are non-patenting firms in the same SIC3 industries; all remaining eligible firms form the omitted group. Firms with complete returns for the relevant window receive lagged-market-capitalization weights within each group and grant date. Each column is estimated separately with date fixed effects $\lambda_t^{(h)}$ and equal weights across group-date observations. Both columns cover the same grant dates over 1926–2023. Coefficients and standard errors are in percentage points. Standard errors are clustered by calendar year and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) One-day raw return	(2) Three-day raw return
Patenter	0.0369***	0.0255*
	(0.0071)	(0.0131)
Peer	0.0094	0.0243**
	(0.0075)	(0.0111)
Observations	14,919	14,919
Grant dates	4,973	4,973
Date FE	Yes	Yes
Year clusters	98	98

Table IA.2: Technology similarity and peer stock returns

This table examines whether peer stock returns vary with patent-based technology exposure. The specification is:

$$R^{(3)}_{f,s,t} = \sum_{d=1}^{10} \beta_d \, \mathrm{TSD}^{(d)}_{f,s,t} + \gamma' X_{f,s,t} + \lambda_t + \alpha_s + \varepsilon_{f,s,t},$$

where $R^{(3)}_{f,s,t}$ is the three-day stock return, in percent, of firm f in sector s beginning on date t. The sample consists of non-patenting firms in the same SIC3 industry as a patent recipient on that date, with each firm-date counted once. $TSD^{(d)}$ is a pooled decile of the yearly standardized CPC4 portfolio score, with cutoffs retained from the broader non-patenting sample. Section IA.1 documents the score and implementation discrepancies. Firms with missing standardized scores form the omitted group. Lagged market capitalization is included throughout; Columns (3)–(4) additionally control for book-to-market, gross and operating profitability, earnings per share, return on equity, free cash flow, and investment. All columns include date fixed effects λ_t; Columns (2) and (4) also include SIC3 fixed effects α_s. Regressions are estimated at the firm-day level. Columns (1)–(2) cover 1926–2023; Columns (3)–(4) cover 1952–2023. Standard errors are clustered by date and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Ret_3D	(2) Ret_3D	(3) Ret_3D	(4) Ret_3D
D1	-0.0050	-0.0107	-0.0068	-0.0282
	(0.0159)	(0.0159)	(0.0275)	(0.0276)
D2	-0.0006	-0.0110	-0.0012	-0.0244
	(0.0267)	(0.0256)	(0.0303)	(0.0289)
D3	-0.0575*	-0.0669**	-0.0633**	-0.0869***
	(0.0322)	(0.0288)	(0.0290)	(0.0273)
D4	0.0331	0.0211	0.0111	-0.0116
	(0.0236)	(0.0221)	(0.0236)	(0.0225)
D5	0.0334	0.0190	-0.0060	-0.0302
	(0.0250)	(0.0233)	(0.0258)	(0.0241)
D6	0.0458*	0.0326	0.0289	0.0076
	(0.0239)	(0.0226)	(0.0254)	(0.0244)
D7	0.0278	0.0152	0.0439	0.0241
	(0.0320)	(0.0301)	(0.0327)	(0.0307)
D8	0.1401***	0.1301***	0.1059**	0.0899**
	(0.0370)	(0.0355)	(0.0431)	(0.0410)
D9	0.1255***	0.1187***	0.1057***	0.0944***
	(0.0294)	(0.0282)	(0.0305)	(0.0295)
D10	0.0962***	0.0883***	0.0853***	0.0701***
	(0.0228)	(0.0221)	(0.0262)	(0.0254)
Sector FE	No	Yes	No	Yes
Date FE	Yes	Yes	Yes	Yes
Control	No	No	Yes	Yes
N	9,167,888	9,167,879	6,204,070	6,204,064
R^2	0.0668	0.0669	0.0680	0.0681

Table IA.3: Innovation and sector spillover: TNIC industry classification

This table repeats the sector-day spillover regressions using the 300-industry TNIC classification of Hoberg and Phillips (2025). Each firm-year is assigned to the TNIC industry with its highest text loading:

$$S_{s,t} = \alpha + \beta P_{s,t} + \gamma M_{s,t-1} + \mathcal{F}_{s,t} + \varepsilon_{s,t},$$

where S and P denote aggregate peer spillover and private patent value, respectively, and M is lagged sector market capitalization. Columns (1)–(3) use the level measures and include M as a control. Columns (4)–(6) divide both measures by M, omit the capitalization control ($\gamma = 0$), and weight observations by M. Within each block, $\mathcal{F}_{s,t}$ denotes no fixed effects, sector fixed effects, and sector-by-year fixed effects, respectively. Regressions are estimated at the TNIC industry-day level. The sample covers 1988–2023. Standard errors are clustered by sector-year and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Spillover	Spillover	Spillover	SpilloverS	SpilloverS	SpilloverS
PrivateValue	0.1140***	0.1137***	0.0890***			
	(0.0237)	(0.0238)	(0.0241)			
SectorSize	-0.0000	-0.0001	-0.0177***			
	(0.0002)	(0.0002)	(0.0021)			
PrivateValueS				0.1168***	0.1158***	0.1073***
				(0.0089)	(0.0090)	(0.0090)
Observations	2664158	2664158	2664158	2664158	2664158	2664158
R^2	0.002	0.002	0.023	0.001	0.002	0.014
Sector FE	No	Yes	No	No	Yes	No
Sector × Year FE	No	No	Yes	No	No	Yes

Table IA.4: Product-market fluidity and sector spillover: TNIC industry classification

This table examines whether product-market fluidity moderates spillover pass-through within TNIC industries:

$$\widetilde{S}_{s,t} = \alpha + \beta \widetilde{P}_{s,t} + \theta \widetilde{P}_{s,t} \text{Fluidity}_{s,y(t)} + \mathcal{F}_{s,t} + \varepsilon_{s,t},$$

where $\widetilde{S}_{s,t} = S^S_{s,t}/M_{s,t-1}$ is aggregate peer spillover divided by lagged sector market capitalization, and $\widetilde{P}_{s,t} = P^S_{s,t}/M_{s,t-1}$ is aggregate private patent value divided by the same denominator. $\text{Fluidity}_{s,y(t)}$ is the sector average of the product-market fluidity measure of Hoberg, Phillips, and Prabhala (2014), demeaned using lagged sector market capitalization as weights; higher fluidity indicates greater product-market competitive pressure. Sectors follow the 300-industry TNIC classification of Hoberg and Phillips (2025), with each firm-year assigned to the TNIC industry with its highest text loading. The moderator is not divided by market capitalization. $\mathcal{F}_{s,t}$ denotes the fixed effects: none in Column (1), sector in Column (2), and sector-by-year in Column (3). Regressions are estimated at the sector-day level and weighted by lagged sector market capitalization. Standard errors are clustered by sector-year and reported in parentheses. The sample covers 1989–2023. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	SpilloverS	SpilloverS	SpilloverS
PrivateValueS	0.1233***	0.1223***	0.1137***
	(0.0095)	(0.0096)	(0.0096)
PrivateValueS × Fluidity	0.0265***	0.0266***	0.0262***
	(0.0045)	(0.0045)	(0.0045)
Observations	2589780	2589780	2589780
R^2	0.002	0.002	0.014
Sector FE	No	Yes	No
Sector × Year FE	No	No	Yes

Table IA.5: Sector spillover and long-run growth: TNIC industry classification

This table repeats the firm-year growth regressions using the 300-industry TNIC classification of Hoberg and Phillips (2025), with each firm-year assigned to the TNIC industry with its highest text loading:

$$G_{f,y}^{(\tau)} = \beta_{S,\tau} S_{f,y-1}^{F} + \beta_{P,\tau} P_{f,y-1}^{F} + \gamma_{\tau}' X_{f,y-1} + \alpha_s + \lambda_y + \varepsilon_{f,y}^{(\tau)},$$

where $G_{f,y}^{(\tau)} = \log Y_{f,y+\tau-1} - \log Y_{f,y-1}$ is cumulative log growth in output (Panel A) or employment (Panel B). Columns (1)–(5) report horizons $\tau = 1, \ldots, 5$, corresponding to one through five years from the base year $y-1$. *Spillover* (S^F) is annual exposure to other firms' patents within the same TNIC industry; *Private value* (P^F) is the firm's own annual patent value. Both measures are scaled to unit variance. $X_{f,y-1}$ contains lagged log output, log capital, and log employment. α_s and λ_y denote sector and year fixed effects. Regressions are estimated at the firm-year level. Standard errors are clustered by firm-year for output and by TNIC industry-year for employment, and are reported in parentheses. Regression years run from 1990 through 2023 in Column (1); the last usable year moves back by one in each subsequent horizon and is 2019 in Column (5). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Panel A: Output growth					
Spillover	0.0194***	0.0318***	0.0376***	0.0465***	0.0570***
	(0.0036)	(0.0054)	(0.0078)	(0.0088)	(0.0102)
Private value	0.0218***	0.0343***	0.0542***	0.0710***	0.0807***
	(0.0049)	(0.0074)	(0.0096)	(0.0110)	(0.0130)
Observations	25,141	20,726	18,124	16,199	14,625
R^2	0.083	0.101	0.119	0.138	0.146
Panel B: Employment growth					
Spillover	0.0173***	0.0414***	0.0354***	0.0405***	0.0474***
	(0.0036)	(0.0065)	(0.0075)	(0.0087)	(0.0124)
Private value	0.0092*	0.0235***	0.0366***	0.0471***	0.0593***
	(0.0050)	(0.0082)	(0.0103)	(0.0130)	(0.0181)
Observations	21,692	16,710	13,876	11,354	9,286
R^2	0.047	0.078	0.116	0.143	0.177
Controls	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table IA.6: Sector spillover and subsequent investment: TNIC industry classification

This table repeats the three specifications in Table 7 using the 300-industry TNIC classification of Hoberg and Phillips (2025). Each firm-year is assigned to the TNIC industry with its highest text loading:

$$\frac{\text{CAPX}_{f,y}}{\text{PPENT}_{f,y-1}} = \alpha + \beta_S S^F_{f,y-1} + \beta_P P^F_{f,y-1} + \gamma' X_{f,y-1} + \mathcal{F}_{f,y} + \varepsilon_{f,y}.$$

Investment is capital expenditure divided by lagged net property, plant, and equipment. *Spillover* is annual exposure to other firms' patents within the same TNIC industry; *Private value* is the firm's own annual patent value. Patent measures use common standard deviations from the complete-case reference sample before singleton removal. All three columns control for lagged log capital, output, and employment. Columns (2)–(3) additionally include lagged Tobin's Q and cash flow/assets; Column (3) also includes the leave-one-out TNIC industry-year mean of lagged Tobin's Q, computed before the complete-case screen. $\mathcal{F}_{f,y}$ comprises TNIC industry and year effects in all three columns. All regressors are dated $y-1$. The sample covers 1990–2023. Standard errors are two-way clustered by firm and year (34 year clusters), with the estimator's positive-semidefinite covariance adjustment when required, and are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Spillover	0.0166**	0.0068*	0.0064*
	(0.0063)	(0.0037)	(0.0037)
Private value	0.0190***	0.0067	0.0070
	(0.0052)	(0.0041)	(0.0041)
Q		0.0698***	0.0694***
		(0.0049)	(0.0049)
Peer Q			0.0091*
			(0.0049)
Cash flow		0.0499	0.0490
		(0.0529)	(0.0531)
Observations	14,197	14,197	14,197
R^2	0.1468	0.1987	0.1990
Control	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table IA.7: Sector spillover and subsequent acquisitions: TNIC industry classification

This table repeats the three specifications in Table 8 using the 300-industry TNIC classification of Hoberg and Phillips (2025). Each firm-year is assigned to the TNIC industry with its highest text loading:

$$\frac{\text{AQC}_{f,y}}{\text{AT}_{f,y-1}} = \alpha + \beta_S S^F_{f,y-1} + \beta_P P^F_{f,y-1} + \gamma' X_{f,y-1} + \mathcal{F}_{f,y} + \varepsilon_{f,y}.$$

The outcome is acquisition expenditure (Compustat AQC) divided by lagged total assets (AT), winsorized within fiscal year at the 1st and 99th percentiles before matching, as in Table 8. Reported zeros are retained; missing or negative AQC is excluded. *Spillover* is annual exposure to other firms' patents within the same TNIC industry; *Private value* is the firm's own annual patent value. Patent measures use the same standard deviations as in Internet Appendix Table IA.6. All three columns control for lagged log capital, output, and employment. Columns (2)–(3) additionally include lagged Tobin's Q and cash flow/assets; Column (3) also includes the leave-one-out TNIC industry-year mean of lagged Tobin's Q, computed before the complete-case screen. $\mathcal{F}_{f,y}$ comprises TNIC industry and year effects in all three columns. All regressors are dated $y-1$. The sample covers 1990–2023. Standard errors are two-way clustered by firm and year (34 year clusters) and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Spillover	0.0031***	0.0028***	0.0028***
	(0.0009)	(0.0009)	(0.0009)
Private value	-0.0019*	-0.0022**	-0.0022**
	(0.0010)	(0.0010)	(0.0010)
Q		0.0025***	0.0025***
		(0.0008)	(0.0008)
Peer Q			0.0002
			(0.0004)
Cash flow		0.0155***	0.0154***
		(0.0043)	(0.0043)
Observations	13,241	13,241	13,241
R^2	0.0743	0.0762	0.0762
Control	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table IA.8: Sector spillover and subsequent inventive activity: TNIC industry classification

This table repeats the one-year inventive-growth specifications in Table 9 using the 300-industry TNIC classification of Hoberg and Phillips (2025). Firm-years are assigned to their highest-loading text industry:

$$G^Z_{f,y} = \alpha + \beta_S S^F_{f,y-1} + \beta_P P^F_{f,y-1} + \gamma' X_{f,y-1} + \alpha_s + \lambda_y + \varepsilon^Z_{f,y},$$

where $G^Z_{f,y} = Z_{f,y} - Z_{f,y-1}$. Panel A uses $Z = \log(1 + \text{inventors})$, counting distinct active PatentsView inventor IDs on the firm's KPSS-linked grants; Panel B uses $Z = \log(1 + \text{patents})$, counting distinct KPSS-linked grants. Observed zeros are retained; unobserved firm-years are not filled. Inventor counts are missing if any grant lacks an inventor link. *Spillover* is annual within-TNIC peer exposure; *Private value* is own annual patent value. Both use the accounting-panel standard deviations from Internet Appendix Table IA.6, before outcome-specific selection. All columns control for lagged log capital, output, and employment. Columns (2)–(3) add lagged Tobin's Q and cash flow/assets; Column (3) adds leave-one-out TNIC-year mean lagged Q, computed before complete-case selection. All regressors are dated $y-1$; TNIC industry and year effects are included. Within each panel, columns use the same complete-case sample after fixed-effect singleton removal. December accounting-date alignment and outcome coverage follow Table 9; acquisition and investment outcome availability are not required. Both panels cover outcome years 1990–2023. Standard errors in parentheses are two-way clustered by firm and year (34 year clusters), with the estimator's positive-semidefinite covariance adjustment. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)
Panel A: Inventor growth			
Spillover	0.0135**	0.0125**	0.0127**
	(0.0054)	(0.0051)	(0.0052)
Private value	-0.0053	-0.0063	-0.0064
	(0.0038)	(0.0038)	(0.0038)
Q		0.0063***	0.0065***
		(0.0018)	(0.0019)
Peer Q			-0.0045
			(0.0058)
Cash flow		0.0332*	0.0336*
		(0.0186)	(0.0186)
Observations	14,329	14,329	14,329
R^2	0.0254	0.0259	0.0259
Panel B: Patent growth			
Spillover	0.0113**	0.0103**	0.0105**
	(0.0046)	(0.0042)	(0.0043)
Private value	-0.0061*	-0.0070*	-0.0071*
	(0.0036)	(0.0035)	(0.0035)
Q		0.0057***	0.0059***
		(0.0011)	(0.0012)
Peer Q			-0.0032
			(0.0040)
Cash flow		0.0339**	0.0342**
		(0.0147)	(0.0147)
Observations	14,402	14,402	14,402
R^2	0.0278	0.0285	0.0286
Control	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table IA.9: Sector spillover by Fama–French industry

This table reports the private-value coefficient estimated separately within each Fama–French 12 industry:

$$\widetilde{S}_{s,t} = \beta_k \widetilde{P}_{s,t} + \alpha_{s,y(t)} + \varepsilon_{s,t}, \qquad s \in k,$$

where $\widetilde{S}$ and $\widetilde{P}$ are sector spillover and private patent value divided by lagged sector market capitalization, and $\alpha_{s,y(t)}$ denotes SIC3-by-year fixed effects. Regressions use sector-day observations weighted by lagged sector market capitalization. SIC3 sectors are assigned to Fama–French industries using their centroid four-digit SIC code. Standard errors are clustered by SIC3 sector-year. The sample covers 1926–2023.

Industry	Coefficient	Std. error	95% CI	Observations	Clusters
Consumer Non-Durables	0.3813	0.0479	[0.2874, 0.4752]	942,146	3,774
Consumer Durables	0.0108	0.0060	[−0.0010, 0.0227]	167,132	653
Manufacturing	0.1116	0.0097	[0.0926, 0.1306]	1,270,647	4,986
Energy	0.4782	0.0372	[0.4053, 0.5511]	125,523	494
Chemicals	0.1529	0.0260	[0.1019, 0.2039]	165,853	638
Business Equipment	0.1632	0.0244	[0.1153, 0.2111]	149,838	579
Telecom	0.2703	0.0603	[0.1521, 0.3885]	118,945	462
Utilities	3.2560	0.5854	[2.1087, 4.4034]	93,382	359
Wholesale & Retail	0.1511	0.0362	[0.0802, 0.2221]	1,056,099	4,246
Healthcare	0.3365	0.1039	[0.1329, 0.5401]	97,654	403
Finance	0.8691	0.0930	[0.6869, 1.0514]	549,261	2,214
Other	0.1995	0.0288	[0.1430, 0.2560]	1,589,947	6,561

Table IA.10: Market concentration and sector spillover

This table examines whether sector concentration moderates spillover pass-through:

$$\widetilde{S}_{s,t} = \alpha + \beta \widetilde{P}_{s,t} + \theta \widetilde{P}_{s,t} \text{HHI}_{s,y(t)} + \mathcal{F}_{s,t} + \varepsilon_{s,t},$$

where $\widetilde{S}_{s,t} = S^S_{s,t}/M_{s,t-1}$ is aggregate peer spillover divided by lagged sector market capitalization, and $\widetilde{P}_{s,t} = P^S_{s,t}/M_{s,t-1}$ is aggregate private patent value divided by the same denominator. $\text{HHI}_{s,y(t)}$ is the sector Herfindahl–Hirschman Index of firms' sales shares. Higher values indicate greater concentration. HHI is not divided by market capitalization. The marginal pass-through is $\beta + \theta \text{HHI}_{s,y(t)}$. $\mathcal{F}_{s,t}$ denotes the fixed effects: none in Column (1), sector in Column (2), and sector-by-year in Column (3). Regressions are estimated at the sector-day level and weighted by lagged sector market capitalization. Standard errors are clustered by sector-year and reported in parentheses. The sample is restricted to sector-years with a nonmissing HHI and covers 1950–2023. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	SpilloverS	SpilloverS	SpilloverS
PrivateValueS	0.2893***	0.2887***	0.2765***
	(0.0205)	(0.0206)	(0.0207)
PrivateValueS × HHI	-0.3141***	-0.3138***	-0.3063***
	(0.0394)	(0.0395)	(0.0396)
Observations	3928083	3928083	3928083
R^2	0.004	0.004	0.017
Sector FE	No	Yes	No
Sector × Year FE	No	No	Yes

Table IA.11: Financial constraints and sector spillover: Kaplan–Zingales index

This table repeats the financial-constraint test using the Kaplan–Zingales index:

$$\widetilde{S}_{s,t} = \alpha + \beta \widetilde{P}_{s,t} + \theta \widetilde{P}_{s,t} \mathrm{KZ}_{s,y(t)} + \mathcal{F}_{s,t} + \varepsilon_{s,t},$$

where $\widetilde{S}_{s,t} = S^S_{s,t}/M_{s,t-1}$ is aggregate peer spillover divided by lagged sector market capitalization, and $\widetilde{P}_{s,t} = P^S_{s,t}/M_{s,t-1}$ is aggregate private patent value divided by the same denominator. $\mathrm{KZ}_{s,y(t)}$ is the standardized sector-year mean of firm-level Kaplan–Zingales indices computed with the Lamont–Polk–Saa-Requejo coefficients. Higher values indicate greater measured financial constraints. The interaction coefficient θ measures the change in pass-through per standard deviation of the sector index. $\mathcal{F}_{s,t}$ denotes the fixed effects: none in Column (1), sector in Column (2), and sector-by-year in Column (3). Regressions are estimated at the sector-day level and weighted by lagged sector market capitalization. Standard errors are clustered by sector-year and reported in parentheses. The sample is restricted to sector-years with a nonmissing Kaplan–Zingales measure and covers 1961–2021. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	SpilloverS	SpilloverS	SpilloverS
PrivateValueS	0.2223***	0.2216***	0.2127***
	(0.0142)	(0.0142)	(0.0143)
PrivateValueS × KZ	-0.0399*	-0.0394*	-0.0389
	(0.0238)	(0.0239)	(0.0237)
Observations	3221807	3221807	3221807
R^2	0.004	0.004	0.016
Sector FE	No	Yes	No
Sector × Year FE	No	No	Yes

Table IA.12: Patenting-firm liquidity and sector spillover: Median split

This table examines whether spillover pass-through differs with turnover-based liquidity of the patenting firm:

$$\widetilde{S}_{s,t} = \alpha + \beta_H \widetilde{P}^H_{s,t} + \beta_L \widetilde{P}^L_{s,t} + \mathcal{F}_{s,t} + \varepsilon_{s,t},$$

where $\widetilde{S}$ is aggregate peer spillover divided by lagged sector market capitalization. $\widetilde{P}^H$ and $\widetilde{P}^L$ are private-value components attributed to high- and low-turnover patentees, divided by the same denominator. *Turnover*, mean daily trading volume divided by shares outstanding within firm-year, is used as the liquidity proxy. High-turnover firms are above the within-year median; low-turnover firms are at or below the median. The components are summed across patenting firms within each sector-day, which can contain both groups. Patentees without turnover data contribute to neither component. $\mathcal{F}_{s,t}$ denotes the fixed effects: none in Column (1), sector in Column (2), and sector-by-year in Column (3). Regressions use the 1926–2023 sector-day panel. Observations are weighted by lagged sector market capitalization. Standard errors are clustered by sector-year and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	SpilloverS	SpilloverS	SpilloverS
PrivateValueS × HighLiq	0.2631***	0.2626***	0.2504***
	(0.0234)	(0.0236)	(0.0239)
PrivateValueS × LowLiq	0.1978***	0.1972***	0.1883***
	(0.0161)	(0.0161)	(0.0161)
Observations	6326427	6326427	6326424
R^2	0.003	0.004	0.016
Sector FE	No	Yes	No
Sector × Year FE	No	No	Yes

Table IA.13: Technology diffusion and long-run growth

This table examines whether patent-embedding exposure predicts subsequent firm growth:

$$G_{f,y}^{(\tau)} = \beta_{E,\tau}\text{TechDiffusion}_{f,y-1} + \beta_{P,\tau}P_{f,y-1}^{F} + \gamma_{\tau}'X_{f,y-1} + \alpha_s + \lambda_y + \varepsilon_{f,y}^{(\tau)},$$

where $G_{f,y}^{(\tau)} = \log Y_{f,y+\tau-1} - \log Y_{f,y-1}$ is cumulative log growth in output (Panel A) or employment (Panel B). Columns (1)–(5) report horizons $\tau = 1, \ldots, 5$, corresponding to one through five years from the base year $y-1$. *TechDiffusion* uses technology-claim embeddings and a normalized centroid of the firm's prior-year patent portfolio. It aggregates positive inner products cubed, weighted by real private patent value when observed and one otherwise, removes patents linked to the focal firm, and truncates net exposure at zero. Internet Appendix Section IA.2 gives the construction. Exposure and the firm's own annual private patent value P^F are divided by their sample standard deviations. $X_{f,y-1}$ contains lagged log output, log capital, and log employment. α_s and λ_y denote sector and year fixed effects. Regressions are estimated at the firm-year level. Regression years run from 1981 through 2023 in Column (1); the last usable year moves back by one in each subsequent horizon and is 2019 in Column (5). Standard errors are clustered by sector-year and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Panel A: Output growth					
TechDiffusion	0.0204**	0.0160	0.0293	0.0426**	0.0626**
	(0.0099)	(0.0146)	(0.0203)	(0.0212)	(0.0265)
Private value	0.0102***	0.0178***	0.0203***	0.0211***	0.0191**
	(0.0027)	(0.0043)	(0.0060)	(0.0076)	(0.0090)
Observations	15,870	14,097	13,088	12,303	11,580
R^2	0.089	0.103	0.113	0.122	0.135
Panel B: Employment growth					
TechDiffusion	-0.0029	0.0125	0.0312**	0.0383**	0.0441*
	(0.0067)	(0.0108)	(0.0144)	(0.0187)	(0.0257)
Private value	0.0022	0.0031	0.0045	0.0000	-0.0041
	(0.0020)	(0.0034)	(0.0048)	(0.0064)	(0.0084)
Observations	14,635	12,631	11,538	10,449	9,511
R^2	0.060	0.083	0.107	0.127	0.148
Controls	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table IA.14: Product-market exposure and long-run growth

This table examines whether patent-embedding exposure predicts subsequent firm growth:

$$G_{f,y}^{(\tau)} = \beta_{E,\tau}\text{BusinessStealing}_{f,y-1} + \beta_{P,\tau}P_{f,y-1}^{F} + \gamma_{\tau}'X_{f,y-1} + \alpha_s + \lambda_y + \varepsilon_{f,y}^{(\tau)},$$

where $G_{f,y}^{(\tau)} = \log Y_{f,y+\tau-1} - \log Y_{f,y-1}$ is cumulative log growth in output (Panel A) or employment (Panel B). Columns (1)–(5) report horizons $\tau = 1, \ldots, 5$, corresponding to one through five years from the base year $y-1$. *BusinessStealing* uses product-claim embeddings and a normalized, max-pooled representation of the firm's prior-year patent portfolio. It aggregates positive inner products cubed, weighted by real private patent value when observed and one otherwise, removes patents linked to the focal firm, and truncates net exposure at zero. Internet Appendix Section IA.2 gives the construction. Exposure and the firm's own annual private patent value P^F are divided by their sample standard deviations. $X_{f,y-1}$ contains lagged log output, log capital, and log employment. α_s and λ_y denote sector and year fixed effects. Regressions are estimated at the firm-year level. Regression years run from 1981 through 2023 in Column (1); the last usable year moves back by one in each subsequent horizon and is 2019 in Column (5). Standard errors are clustered by sector-year and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Panel A: Output growth					
BusinessStealing	-0.0264**	-0.0438***	-0.0593***	-0.0810***	-0.0927***
	(0.0113)	(0.0117)	(0.0169)	(0.0197)	(0.0260)
Private value	0.0098***	0.0151***	0.0176***	0.0172**	0.0165*
	(0.0029)	(0.0043)	(0.0063)	(0.0080)	(0.0093)
Observations	15,870	14,097	13,088	12,303	11,580
R^2	0.090	0.105	0.114	0.124	0.137
Panel B: Employment growth					
BusinessStealing	0.0001	-0.0297***	-0.0384***	-0.0516***	-0.0435*
	(0.0067)	(0.0107)	(0.0132)	(0.0170)	(0.0236)
Private value	0.0019	0.0020	0.0044	-0.0004	-0.0030
	(0.0020)	(0.0034)	(0.0049)	(0.0064)	(0.0082)
Observations	14,635	12,631	11,538	10,449	9,511
R^2	0.060	0.083	0.107	0.128	0.148
Controls	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes