Technical Hiring under Navigable Patent Congestion: Evidence from Chinese Listed Firms[1]

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Abstract

As patent landscapes become more congested, the innovation problem can shift from funding additional R&D to finding feasible technical paths around existing claims. This paper studies whether pre-period technical hiring orientation conditions firms' invention-filing response to rising patent congestion in inherited technology fields. We combine Chinese listed-firm recruitment records, firm-technology-field patent-thicket data, patent outcomes, annual-report text, output-persistence measures, productivity data, and controls from 2016 to 2023. Patent congestion is measured with a triangular-blocking thicket index based on patent citation networks. We interact firms' 2016-2017 technical hiring orientation with leave-one-out congestion growth across inherited fields. Firms with stronger pre-period technical hiring orientation file more invention applications when exposed to subsequent congestion growth. The estimate remains positive after firm-specific trends and one-year pre-period windows, and it is stronger when congestion growth is residualized against field-level activity proxies. Mechanism-related evidence indicates that this association is not driven by generic R&D expansion or broad workforce growth; annual-report text responses are concentrated in technical-search and intellectual-property-navigation language. The association is concentrated in instrument manufacturing and technical-repair source fields where the exposure design has empirical leverage. Boundary evidence is mixed for the primary application outcome but stronger for supplemental output-persistence and efficiency measures. The findings support a scoped technology-management claim: technical hiring orientation is associated with stronger invention filing under congestion growth, while the navigable-congestion boundary is clearer for supplemental margins.

Keywords: technical hiring; patent congestion; invention-filing continuation; technology management; patent thickets; constrained search

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1. Introduction

Firms can respond to crowded patent landscapes in different ways. Some abandon or defer projects when prior claims accumulate; others continue by redesigning components, recombining technical paths, and navigating freedom-to-operate constraints. The difference is not only legal. It depends on whether the firm has enough technical problem-solving orientation to convert blocking claims into feasible design alternatives.

This paper asks whether a firm's pre-period technical hiring orientation shapes how it responds when the technology fields in which it was already active become more congested. The mechanism is constrained technological navigation. Patent congestion raises the cost of freedom-to-operate interpretation, design-around work, recombination, and project redirection. Technical personnel matter because those responses require engineering judgment as well as legal awareness. A patent lawyer can warn that a claim is blocking; engineers must decide whether the product architecture can be changed without losing technical feasibility.

Patent-thicket research provides one side of the argument. Shapiro (2001) frames dense overlapping rights as a navigation problem involving cross-licenses, patent pools, and standard setting. Hall and Ziedonis (2001) and Ziedonis (2004) show that fragmented technology-rights environments change firms' patenting strategies. Cockburn and MacGarvie (2011) connect software patenting to entry conditions, while Galasso and Schankerman (2015) and Williams (2017) show that patent rights can affect follow-on research and cumulative innovation. Research on patent-thicket incidence also links thicket growth to technological opportunities and complexity (von Graevenitz, Wagner, and Harhoff, 2013). These studies explain why patent environments affect average innovation and market outcomes. They say less about which internal organizational inputs help firms respond when congestion rises.

Human-capital and technology-search research provides the other side. Almeida and Kogut (1999) and Song, Almeida, and Wu (2003) show that engineers and hiring can transfer technological knowledge across firms and locations. Hatch and Dyer (2004) and Campbell, Coff, and Kryscynski (2012) emphasize that human capital can be a source of firm heterogeneity. Cohen and Levinthal (1990) highlight the role of prior knowledge in recognizing and using external knowledge. Fleming (2001) and Katila and Ahuja (2002) show why technological search depends on recombination and the balance between familiar and novel knowledge. These studies explain why technical labor can matter. They do not specify when its marginal value should rise.

We study the interaction between these two margins. The closest competing papers establish that patent thickets shape innovation environments and that technical hiring can transfer knowledge. The question is whether pre-period technical hiring orientation conditions the firm's response to an external rise in patent congestion. The contribution is therefore not "technical hiring increases innovation" or "patent thickets reduce innovation." It is that technical hiring becomes a congestion-contingent input whose value depends on whether the firm's inherited patent landscape still permits internal design-around search.

The empirical setting is Chinese listed firms from 2016 to 2023. China is useful for this question for three reasons. First, patenting expanded rapidly, so many technology fields experienced large changes in congestion over a short period. Hu and Jefferson (2009) and Li (2012) show that China's patenting boom reflected not only R&D growth but also institutional incentives and changes in patent-law enforcement. This is why we distinguish invention-filing continuation from patent-quality claims. Second, China grants invention, utility-model, and design patents, allowing us to focus on invention applications while treating broader patenting

activity as a diagnostic rather than a direct quality measure. Third, the data link online recruitment records, listed-firm patent outcomes, patent-thicket exposure, and annual-report text, making it possible to observe both a managerial input and the patent environment that managers must navigate.

Patent congestion is measured using a listed-firm patent-thicket dataset based on Zhang and Long (2024). The underlying index follows the triangular-blocking approach of von Graevenitz, Wagner, and Harhoff (2011). A triangular blocking relationship arises when three firms in the same technology field hold patent portfolios connected through mutual citation relationships, creating a network of potential blocking positions. Field-level thicket density equals the number of triangular blocking triples divided by patent applications, multiplied by 1,000. The measure is therefore not a simple patent-volume proxy; it captures networked blocking density relative to field patenting activity.

The main design uses inherited exposure to external congestion growth. It combines each firm's 2015 technology-field exposure with subsequent leave-one-out field-year congestion growth, excluding the focal firm from the field-year component. The empirical design follows exposure-design logic (Autor, Dorn, and Hanson, 2013; Borusyak, Hull, and Jaravel, 2022), but we do not require the 2015 shares to be random. The identifying variation comes from changes in patent congestion across inherited technology fields after removing the focal firm's own contribution and conditioning on firm fixed effects, industry-year fixed effects, province-year fixed effects, and listed-firm controls.

The baseline evidence uses 2016-2017 average technical hiring orientation as the pre-period firm characteristic. In the post-2018 sample, the interaction between pre-period technical hiring orientation and leave-one-out congestion growth predicts more invention applications. The

coefficient is 0.0540 in the baseline specification and remains positive after adding firm-specific linear trends. One-year pre-period windows based on 2016 alone and 2017 alone also produce positive estimates. A residualized congestion-growth measure, which removes year effects and field-level activity proxies before constructing firm exposure, produces a larger positive estimate for invention applications. The median post-2018 firm-year has 11 future invention applications, so the baseline magnitude is economically moderate.

The result should be read as an invention-filing continuation margin, not as a patent-quality claim. Invention grants, authorization conversion, innovation efficiency, and productivity do not show the same stable pattern. A growth-weighted innovation-output persistence measure is positive in the baseline specification but becomes small after firm trends. These results narrow our claim: pre-period technical hiring orientation is associated with firms' ability to keep invention activity moving when inherited technological paths become more congested.

Mechanism-related evidence narrows this interpretation. The interaction does not predict higher R&D spending, R&D intensity, technical employee stock, or broad employment expansion. Annual-report text responses are concentrated in technical-search language and a change measure of intellectual-property-navigation language; the other text categories are mostly null. This evidence points to constrained search as the most direct observed channel, even though the underlying patent-level steps are not directly observed. We therefore use exposure-based language rather than causal language about hiring.

The central theoretical boundary is navigable congestion. Technical hiring is valuable when blocking problems can still be solved through internal technical search. If inherited congestion is already very dense, the binding constraint may shift from technical problem solving to external access through licensing, patent pools, alliances, acquisitions, or legal

settlement. The data provide mixed support for this boundary. The high-congestion tercile is not statistically weaker for the primary invention-application outcome, but supplemental output-persistence and innovation-efficiency measures show weaker responses under high inherited congestion. The technology-management implication is still useful: managers should not treat technical hiring as uniformly valuable in every crowded patent market. Its value depends on whether the patent landscape creates solvable design-around problems.

2. Institutional Background and Measurement

2.1 Patent Congestion in China

China's patent system is a useful but demanding setting for studying patent congestion. The country experienced a rapid rise in patenting, supported by R&D growth, market expansion, institutional incentives, and changes in patent-law enforcement. Hu and Jefferson (2009) document that China's patent surge cannot be explained by R&D alone; foreign investment, legal changes, and ownership reform also contributed. Li (2012) similarly emphasizes that institutional forces shaped Chinese patenting. For this paper, that background has two implications. First, patent counts must be interpreted carefully because they can reflect strategic filing and policy incentives as well as technological output. Second, rising congestion can be empirically informative because it changes the constraints that firms face in inherited technology fields.

The sample period from 2016 to 2023 comes after China's patenting expansion had already created dense portfolios in many listed-firm technology fields. Invention patents are more demanding than utility-model and design patents because they require substantive examination. For that reason, the main outcome is invention applications, interpreted as continuation of inventive activity rather than patent quality. Utility-model and design

applications are used only in supplemental structure tests. We avoid claiming that more applications necessarily indicate more valuable innovation.

The setting is also suited to technology-management research because organizational response can be observed. Listed firms disclose annual reports, job postings reveal hiring orientation, and patent-thicket exposure can be mapped to technology fields. This allows us to connect three pieces that are often studied separately: the external patent-rights environment, the firm's technical labor demand, and subsequent innovation activity.

2.2 Patent-Thicket Density

The patent-congestion measure comes from the listed-firm patent-thicket dataset based on Zhang and Long (2024). The source study measures thickets using triangular blocking relationships in patent citation networks. The logic follows von Graevenitz et al. (2011): in a technology field, three firms form a triangular blocking relationship when their patent portfolios are mutually connected through citation relationships that can create blocking positions for one another. Related work uses this approach to study the incidence and growth of patent thickets across technology areas (von Graevenitz et al., 2013).

Field-level patent-thicket density is defined as:

$$\text{Thicket}_{k,t}=\frac{\text{Triples}_{k,t}}{\text{Applications}_{k,t}}\times 1000,$$

where $\text{Thicket}_{k,t}$ is the number of triangular blocking relationships in technology field k and year t. $\text{Applications}_{k,t}$ is the number of patent applications in that field-year. Dividing by applications reduces the risk that the index merely captures patenting volume. The construct is still a citation-network proxy. It does not observe every licensing negotiation, threat of litigation, claim scope, or private settlement.

The firm-technology-field dataset reports patent-thicket density for listed firms across technology fields and years. The main exposure combines pre-period firm-field exposure with subsequent field-year thicket growth. Diagnostic checks show that within major technology fields, firm-field component series are close to proportional over time, consistent with a fixed firm-field exposure component multiplied by a common field-year congestion component. The main specification uses a leave-one-out version to reduce reflection from the focal firm's own current patenting.

2.3 Technical Hiring Orientation

Technical hiring is measured from online recruitment postings. A posting is classified as technical when its title, category, or job content refers to R&D, engineering, software, algorithms, semiconductor, testing, laboratory, process, materials, automation, machinery, electrical, biotechnology, pharmaceutical, or related technical work. Appendix Table B1 reports the classification rules. The main pre-period variable is the firm's average log number of core technical postings in 2016-2017.

This is a hiring-flow measure, not a realized hiring stock and not a direct measure of capability. We therefore call it technical hiring orientation. The label is deliberately narrower than technical capability. Validation checks are consistent with the orientation interpretation: log technical postings correlate positively with technical employee stock, R&D spending, invention applications, invention grants, innovation-output persistence, and innovation-efficiency measures. These correlations do not make the variable exogenous; they show that the posting measure is aligned with observable technology orientation rather than being only a recruitment-platform artifact.

3. Conceptual Framework and Hypotheses

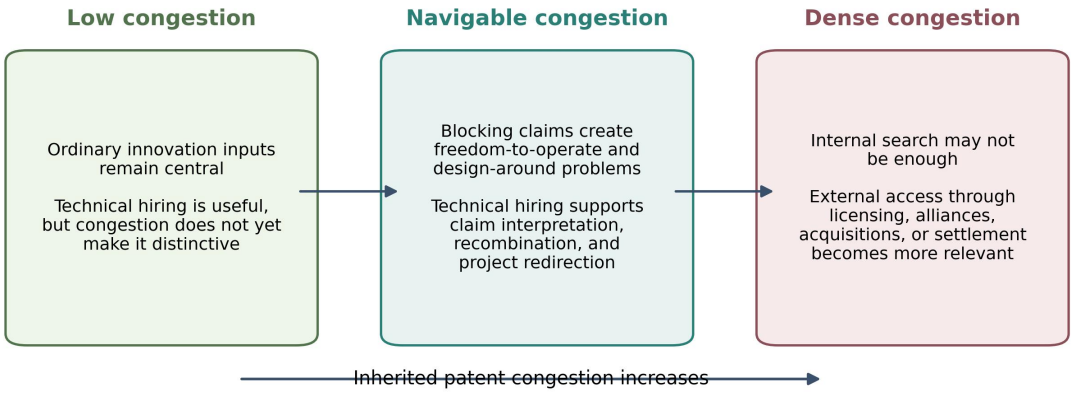
Patent congestion changes the firm's innovation-search problem. Under low congestion, the binding constraint is often ordinary innovation input: project funding, R&D effort, or available ideas. Under moderate congestion, the binding constraint shifts toward constrained technical navigation. Firms must interpret prior claims, assess freedom to operate, redesign components, and recombine existing technical paths. Under very dense congestion, internal technical search may no longer be enough. The firm may need external access strategies such as licensing, patent pools, alliances, acquisitions, or legal settlement.

Figure 1 summarizes the three-region framework. Technical personnel help firms absorb and interpret external technical information, a logic consistent with Cohen and Levinthal's (1990) absorptive-capacity argument. They also help recombine components when the original project path becomes blocked, which connects the argument to technological-search and recombination research (Fleming, 2001). Finally, they can judge whether a design-around requires a change in component architecture rather than a simple incremental adjustment, a problem related to architectural innovation (Henderson and Clark, 1990). Technical hiring orientation therefore matters most when patent congestion turns innovation into a constrained navigation problem that can still be solved inside the firm.

Figure 1. Conceptual Framework

Notes: The framework maps the firm's innovation-search problem into three congestion regions. Under low congestion the binding constraint is ordinary innovation input; under moderate, navigable congestion it shifts to constrained technical navigation, where technical hiring orientation is most valuable; under very dense congestion internal design-around search may be displaced by external access strategies such as licensing, patent pools, alliances, acquisitions, or settlement. Technical personnel support absorption of external technical information (Cohen and Levinthal, 1990), recombination of blocked component paths (Fleming, 2001), and judgment of whether a design-around requires architectural rather than incremental change (Henderson and Clark, 1990).

Patent congestion changes the marginal value of technical hiring by turning innovation into constrained technical navigation.



The main observable margin is invention-filing continuation. If technical hiring helps firms convert blocking constraints into feasible design alternatives, technically oriented firms should be less likely to stop filing invention applications when inherited fields become more congested. The prediction is about continuation of formal inventive activity, not about immediate patent quality. Grants may respond with lags, and grant counts depend on examination processes. Productivity may not move because it reflects many noninnovation forces. This outcome hierarchy also follows patent-data measurement cautions: patent variables are useful but should not be treated as interchangeable measures of innovation value (Lerner and Seru, 2022).

Hypothesis 1. Firms with stronger pre-period technical hiring orientation file more invention applications when their inherited technology fields experience patent-congestion growth.

The mechanism should appear in organizational language as well as in patent counts. If technically oriented firms respond through constrained search, they should discuss technical search, new technical paths, R&D problem solving, and intellectual-property navigation more

intensively after congestion rises. The most direct text prediction concerns technical-search and IP-navigation language. Design-around language, product language, originality, reconfiguration, and collaboration are more indirect because annual reports may not describe the engineering path by which a claim was avoided. Annual-report text cannot prove that patent-level technology-path reallocation occurred. It can, however, help distinguish a technical-search response from generic expansion in R&D spending or total employment.

Mechanism prediction. Firms with stronger pre-period technical hiring orientation increase technical-search and intellectual-property-navigation language when inherited technology fields experience patent-congestion growth.

The boundary condition follows directly from the three-region framework. Technical hiring appears particularly relevant when inherited congestion is navigable: high enough to create blocking problems but not so dense that internal design-around search is dominated by external access strategies. In the empirical implementation, navigable congestion refers to firms in the low and middle terciles of inherited 2016 congestion. High inherited congestion is the top tercile. A significantly negative high-tercile effect is not required for the theory. The positive association should be concentrated in the low and middle terciles and become statistically indistinguishable from zero in the high tercile.

Boundary Prediction. Technical hiring orientation should be less useful when inherited congestion is already dense enough that internal design-around search is likely to be displaced by external access strategies. Because this boundary may appear differently across filing, persistence, and efficiency margins, the evidence is interpreted as scope evidence rather than as a primary hypothesis test.

The timing implication is auxiliary. If technical hiring helps firms redirect constrained search, the response should be stronger after congestion rises than before it. Because the shock is continuous and serially correlated, lead-lag estimates are reported as timing diagnostics rather than a formal event-study or parallel-trends design.

4. Data and Empirical Design

4.1 Sample and Data Sources

The main panel covers Chinese listed firms from 2016 to 2023. It links online recruitment data, firm-technology-field patent-thicket exposure, patent applications and grants, annual-report text, innovation input-output-efficiency variables, total factor productivity, and listed-firm controls. The broad analysis panel contains 30,748 firm-year observations for 5,256 firms. The main predetermined-hiring tests use post-2018 outcomes for firms with 2016-2017 recruitment data.

The recruitment data report online job postings for listed firms and their affiliates. Postings are classified into technical and nontechnical categories using job-title, job-category, and job-content rules summarized in the appendix. The patent-thicket data provide field-year triangular-blocking density and firm-field exposure. The patent outcome data report listed-firm patent applications and grants by patent type. Annual-report text measures are constructed from term counts in firm annual reports scaled by report length. Control variables include firm size, leverage, profitability, growth, Tobin's Q, state ownership, firm age, board independence, ownership concentration, pay, capital intensity, regulation status, cash flow, and other listed-firm characteristics. The Internet Appendix gives the full variable list.

4.2 Outcomes and Mechanism Measures

The primary outcome is invention applications, measured as $\log(1 + InventionApplications_{i,t+1})$ the firm-year count at $t+1$. This variable is interpreted as invention-filing continuation. It is the best-aligned outcome for the central claim because invention applications are the point at which firms continue or stop formal inventive activity after facing congestion.

Invention grants are reported as a secondary outcome. They are informative but less immediate because grants depend on examination timing and may correspond to applications filed earlier. Patent authorization conversion is not treated as a quality measure in the main text for the same reason.

We also report a supplemental growth-weighted innovation-output persistence measure from the innovation-sustainability dataset. The source variable is:

$$OIP_{i,t} = \frac{OIN_{i,t}}{OIN1_{i,t}} \times OIN_{i,t},$$

where $OIN_{i,t}$ is the two-year sum of innovation output in t−1 and t, and $OIN1_{i,t}$ is the two-year sum in t−2and t−1. The regression uses log(1+OIP). Because this formula combines recent output level with recent growth, it is labeled growth-weighted output persistence rather than environmental sustainability or patent quality.

Innovation-efficiency variables and total factor productivity are outside the core claim. InnoEff1 equals patent output divided by log(1+R&D). InnoEff2 uses a weighted patent-output index before dividing by log(1+R&D). These variables are useful diagnostics, but the denominator creates a mechanical link to innovation inputs. TFP is reported only as an economic implication..

The mechanism proxy comes from annual-report text. Terms are grouped into technical-search language, design-around language, intellectual-property navigation language,

reconfiguration language, product language, originality language, and collaboration language.

Appendix Table C1 reports the dictionary. The main text mechanism is the inverse-hyperbolic-sine of technical-search terms per 10,000 annual-report words. The dictionary is intentionally broad and is interpreted as disclosed search orientation rather than direct design-around behavior. Text-based innovation measures can capture dimensions of innovation not visible in patent counts (Bellstam, Bhagat, and Cookson, 2021), but the measure used here remains supportive evidence. It does not observe patent-level IPC reallocation, claim-level redesign, licensing negotiations, or litigation.

4.3 Empirical Specification

The main regression is:

$$Y_{i,t+1}=\beta \text{TechHire}_{i,2016-2017}\times\Delta\text{Congestion}_{i,t}^{LOO}+\gamma\Delta\text{Congestion}_{i,t}^{LOO}+X_{i,t}'\theta+\alpha_i+\lambda_{\text{industry},t}+\pi_{\text{province},t}+\varepsilon_{i,t}.$$

$\text{TechHire}_{i,2016-2017}$is the firm's pre-period technical hiring orientation. $\Delta\text{Congestion}_{i,t}^{LOO}$ is leave-one-out growth in inherited technology-field patent congestion. The fixed effects absorb permanent firm differences, industry-year shocks, and province-year shocks. Firm-specific linear trends are reported as a conservative robustness check because they absorb heterogeneous pre-existing growth paths.

The design is an inherited-exposure design. The 2015 technology-field exposure structure is predetermined relative to post-2018 congestion growth, but it is not assumed to be random. The design relies on field-year congestion growth being plausibly external to the focal firm after excluding the firm from the field-year component and conditioning on fixed effects and controls.

We therefore use conditional-exposure language rather than claiming that technical hiring causes innovation. Standard errors are clustered by firm in the main tables. The appendix reports two-way firm-year clustering, dominant-technology-field clustering, field-shock permutation

diagnostics, and dominant-field leverage tests (Cameron, Gelbach, and Miller, 2011; Petersen, 2009). The permutation diagnostics and leverage tests are sensitivity checks; they also identify the scope of the empirical design.

5. Results

5.1 Patent-Congestion Exposure

Patent-congestion exposure varies substantially across firms and years. In the 2015-2024 exposure panel, the median leave-one-out exposure is 2,909 and the 90th percentile is 8,761. The median log growth in exposure is 0.284. Firms are exposed to an average of 12.7 inherited technology fields. The most congested fields include construction-related engineering, computer and communication-related fields, and other complex technology domains. This field composition is a reminder that the measure captures citation-network blocking density in the Chinese patent system, not only the canonical semiconductor or telecom examples from the U.S. literature.

Table 1 reports descriptive statistics for the main variables. The source firm-field components are close to proportional over time within major technology fields. This supports the interpretation that the data combine fixed firm-field exposure with common field-year congestion evolution. The leave-one-out measure is highly correlated with the direct source exposure growth measure, with a correlation of 0.979. Leave-one-out construction reduces reflection from the focal firm's current patenting, but it does not by itself remove all field-level policy or technology-opportunity concerns.

Table 1. Descriptive Statistics

Variable	N	Mean	SD	P25	Median	P75
Log technical postings	30,748	3.154	1.984	1.609	3.332	4.654
Log nontechnical postings	30,748	1.969	1.669	0.000	1.792	3.178
Log LOO congestion exposure	21,427	7.928	1.034	7.423	8.113	8.692

Variable	N	Mean	SD	P25	Median	P75
Technical hiring x congestion	21,427	-0.106	0.988	-0.496	-0.054	0.269
Future invention applications	30,693	2.409	1.630	1.099	2.398	3.434
Future invention grants	30,693	1.723	1.452	0.693	1.609	2.639
Innovation efficiency	23,034	0.169	0.080	0.121	0.179	0.225
Output persistence	20,118	4.270	1.603	3.295	4.339	5.295
TFP, OP	30,006	6.806	0.892	6.189	6.689	7.306

Notes: LOO denotes leave-one-out. Future outcomes are measured at t+1. Output persistence is the log of the growth-weighted innovation-output persistence measure described in the text. The interaction is standardized in the regression sample.

5.2 Main Evidence: Invention-Filing Continuation

Table 2 reports the main results. Firms with stronger 2016-2017 technical hiring orientation file more invention applications when patent congestion grows in their inherited technology fields. The coefficient on $TechHire_{2016-2017} \times \Delta Congestion^{LOO}$ is 0.0540 and significant at the 5 percent level. With firm-specific linear trends, the coefficient is 0.0968 and significant at the 10 percent level. The nontechnical-hiring interaction is small and statistically insignificant in the same specifications.

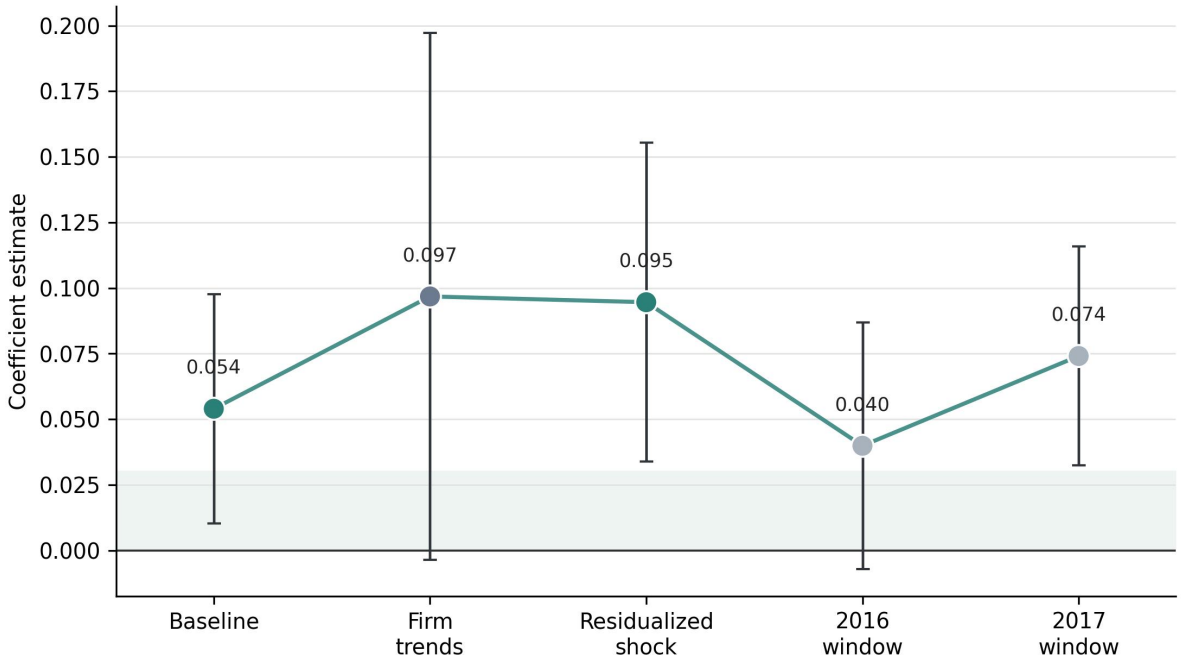
Table 2. Main Exposure-Based Results

Outcome	Fixed effects	N	Firms	Tech x congestion	Tech SE	Nontech x congestion	Nontech SE
Invention applications	Firm FE, industry-year FE, province-year FE	12,781	2,411	0.0540**	(0.0223)	-0.0120	(0.0224)
Invention applications + firm trends	Firm FE, industry-year FE, province-year FE, firm trend	12,781	2,411	0.0968*	(0.0512)	-0.0315	(0.0506)
Invention grants	Firm FE, industry-year FE, province-year FE	12,781	2,411	-0.0278	(0.0219)	0.0271	(0.0226)
Invention grants + firm trends	Firm FE, industry-year FE, province-year FE, firm trend	12,781	2,411	0.1258**	(0.0598)	-0.0884	(0.0569)
Output persistence, supplemental	Firm FE, industry-year FE, province-year FE	10,053	2,329	0.0850**	(0.0385)	-0.0059	(0.0383)
Output persistence + firm trends	Firm FE, industry-year FE, province-year FE, firm trend	10,053	2,329	0.0256	(0.0751)	0.0329	(0.0754)

Notes: The coefficient of interest is pre-period technical hiring orientation x leave-one-out patent-congestion growth. Pre-period hiring is measured over 2016-2017. Standard errors are clustered by firm. *, **, and *** denote 10%, 5%, and 1% significance. Output persistence is supplemental and is not treated as the primary outcome.

Figure 2 visualizes the main estimate and alternative timing specifications. The result is robust to feasible alternative pre-period windows within the available recruitment panel. Using 2016 alone gives a coefficient of 0.0399; using 2017 alone gives a coefficient of 0.0741. The recruitment panel begins in 2016, so earlier pre-period windows cannot be tested with the current data. A residualized congestion-growth measure also supports the application result. After residualizing field-level congestion growth against year effects, active-firm growth, and changes in zero-density shares, the pre-period technical-hiring interaction is 0.0946 and significant at the 1 percent level. This test does not eliminate all technology-opportunity concerns, but it reduces the risk that the result is only field-level patenting expansion.

Figure 2. Invention-Filing Continuation



Notes: The figure plots the coefficient on pre-period technical hiring orientation interacted with leave-one-out patent-congestion growth, with log(1 + future invention applications) as the outcome, across the baseline specification and alternative pre-period and shock definitions (2016-only and 2017-only hiring windows and residualized congestion growth). Points are point estimates and bars are 95 percent confidence intervals based on standard errors clustered by firm. All specifications include firm, industry-year, and province-year fixed effects and listed-firm controls. Pre-period hiring is measured over 2016-2017 unless the window is stated otherwise.

Invention grants are less stable. The baseline grant coefficient is negative and insignificant, while the firm-trend specification is positive and significant. Current technical hiring interacted with congestion is significantly negative for invention grants in the same-year hiring specification. This is consistent with authorization lags and with the possibility that current hiring partly reflects a response to difficult or delayed projects. The evidence is therefore strongest for invention-filing continuation, not for immediate grant conversion or patent quality.

5.3 Dominant-Field Leverage

Table 3 reports dominant-field leverage diagnostics. The main estimate is not evenly distributed across all source technology fields. Firms whose dominant inherited exposure is O81, C43, or C40 account for a large share of the identifying sample. In the post-2018 regression sample, 24.2 percent of firms have dominant exposure to O81, 22.7 percent to C43, and 4.6 percent to C40. The patent-thicket source labels this column as technology field, but the observed codes match the two-digit structure of China's GB/T 4754 industry classification (National Bureau of Statistics of China, 2017). We therefore report the codes with descriptive GB/T labels: O81 is repair of motor vehicles, electronic products, and daily products; C43 is metal-products, machinery and equipment repair; and C40 is instrument manufacturing. These labels are used to identify the empirical source fields, not to reinterpret the measure as an IPC technology class.

Table 3. Leverage, Alternative Shock, and Timing Diagnostics

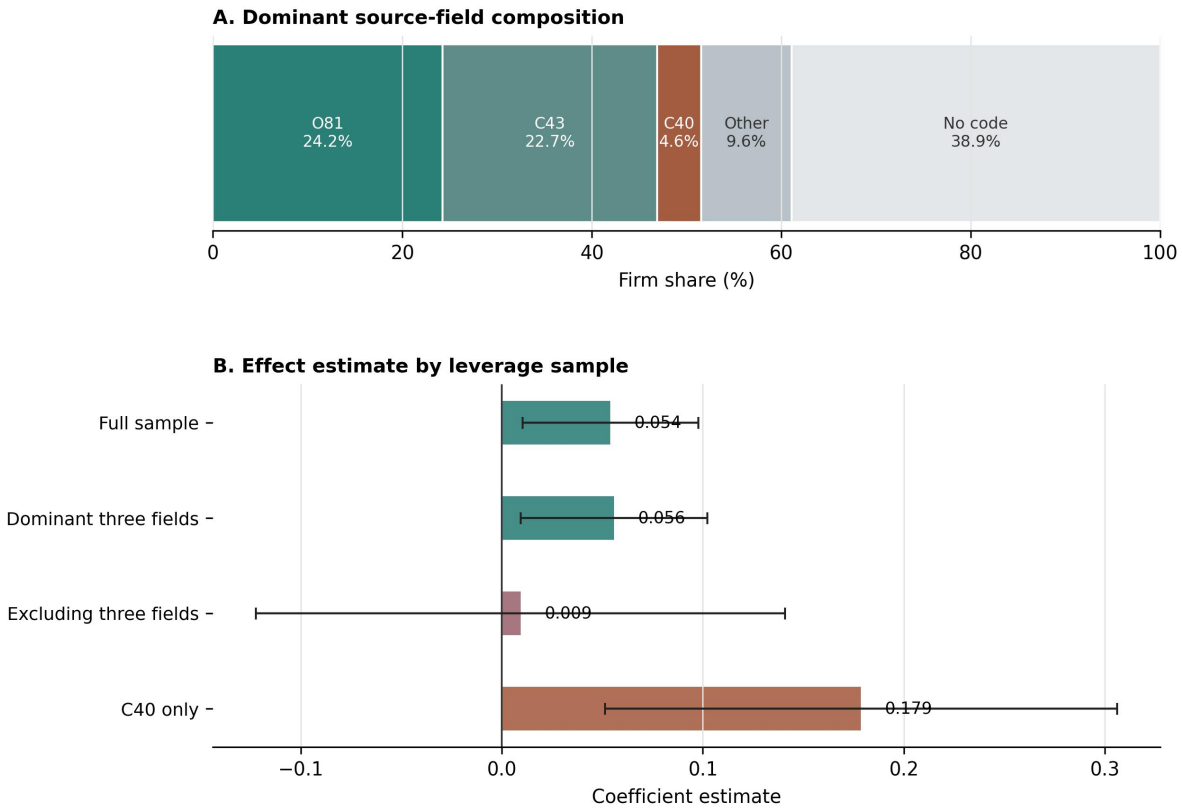
Panel	Check	N	Firms	Estimate	SE
Field leverage	Dominant O81/C43/C40 fields	10,972	2,054	0.0558**	(0.0237)
Field leverage	Exclude O81/C43/C40 fields	1,809	357	0.0093	(0.0672)
Alternative shock	Residualized congestion	12,781	2,411	0.0946***	(0.0310)
Pre-period window	2016 technical hiring only	10,584	2,017	0.0399*	(0.0240)
Pre-period window	2017 technical hiring only	12,372	2,320	0.0741***	(0.0213)

Current hiring	Current hiring x congestion, grants	18,276	3,108	-0.0307**	(0.0155)

Notes: All rows use log(1 + future invention applications) except the current-hiring grant row. The source labels O81/C43/C40 as technology-field codes; the codes match GB/T 4754 labels for repair services, equipment repair, and instrument manufacturing. The residualized-congestion row uses field-level congestion growth residualized against year effects and field activity proxies before constructing firm exposure.

Figure 3 summarizes this leverage pattern. In the dominant-O81/C43/C40 subsample, the invention-application coefficient is 0.0558 and significant at the 5 percent level. Excluding all three dominant fields reduces the coefficient to 0.0093 with a standard error of 0.0672. Within the three fields, C40 shows the strongest standalone estimate. This pattern narrows the empirical scope. The evidence is strongest in source fields where triangular-blocking congestion has sufficient variation and sample leverage; it should not be interpreted as a uniform effect across all technology domains.

Figure 3. Dominant-Field Leverage



Notes: The figure plots the coefficient on pre-period technical hiring orientation interacted with leave-one-out congestion growth, with log(1 + future invention applications) as the outcome, in the subsample whose dominant inherited exposure is GB/T field O81, C43, or C40 and in the sample that excludes these three fields. Points are point estimates and bars are 95 percent confidence

intervals based on standard errors clustered by firm. All specifications include firm, industry-year, and province-year fixed effects and listed-firm controls. O81, C43, and C40 denote repair services, equipment repair, and instrument manufacturing under GB/T 4754.

5.4 Alternative Hiring Measures and Selection Checks

Pre-period technical hiring orientation is also measured as the share of technical postings among core postings. This addresses the concern that the log number of technical postings mainly captures firm expansion. The interaction between pre-period technical hiring share and congestion growth is positive for invention applications. The coefficient is 0.0222 in the baseline specification and weakens after adding firm-specific trends. This pattern supports the technical-orientation interpretation while confirming that the cleanest evidence comes from the log technical-posting measure.

Lagged annual technical hiring does not produce stable results for the main outcomes. Annual hiring variation is noisy and should not be interpreted as a clean predetermined firm characteristic. Current technical hiring produces mixed evidence: it is positive for some output-persistence and efficiency variables, but negative for invention grants. These estimates are not used as the causal core because current hiring may be part of the firm's response to congestion.

5.5 What the Main Result Is Not

A remaining concern is that technical hiring merely proxies for unobserved R&D expansion. Table 4 shows otherwise. Pre-period technical hiring orientation does not predict higher R&D spending after congestion growth. The coefficients for future R&D spending, R&D-to-assets, R&D-to-sales, and innovation-input persistence are small or negative.

Table 4. Mechanism and Text-Category Checks

Panel	Outcome	N	Firms	Pre-tech x congestion	SE
Input exclusion	R&D spending, t+1	12,486	2,376	0.0053	(0.0140)
Input exclusion	R&D-to-sales, t+1	10,363	2,377	-0.0029***	(0.0010)
Input exclusion	Technical employee stock, t+2	10,265	2,361	-0.0376*	(0.0216)
Input exclusion	Total employment, t+2	10,268	2,361	-0.0259**	(0.0109)
Text category	Technical-search language, t+1	12,788	2,411	0.0653***	(0.0230)

Panel	Outcome	N	Firms	Pre-tech x congestion	SE
Text category	Design-around language, t+1	12,788	2,411	0.0253	(0.0234)
Text category	IP-navigation level, t+1	12,788	2,411	0.0288	(0.0220)
Text category	IP-navigation language increase	12,788	2,411	0.0282**	(0.0140)
Text category	Reconfiguration language, t+1	12,788	2,411	-0.0058	(0.0237)
Text category	Originality language, t+1	12,788	2,411	-0.0235	(0.0206)
Text category	Product language, t+1	12,788	2,411	-0.0097	(0.0209)
Text category	Collaboration language, t+1	12,788	2,411	0.0088	(0.0151)

Notes: Input-exclusion rows test whether the primary result reflects higher R&D spending or broad employment expansion. Text rows report all main one-year annual-report categories plus the IP-navigation change measure. Text evidence is supportive only and does not observe patent-level technology-path reallocation.

The result is also not broad employment expansion. The interaction does not predict future technical employee stock, and it is negative for total employment at the two-year horizon. This is consistent with the constrained-navigation interpretation: technically oriented firms continue invention activity without parallel expansion in R&D inputs or total employment.

A second concern is strategic patenting. In the Chinese setting, more patent applications can reflect subsidies, disclosure incentives, defensive filing, or claim staking rather than higher patent value. The evidence is therefore interpreted as an invention-filing continuation result. The response is strongest for technical hiring rather than nontechnical hiring, survives controls for pre-period R&D spending and technical employee stock, and is accompanied by annual-report language about technical search and intellectual-property navigation. Grants do not move robustly, so we do not claim that the main result represents higher patent quality.

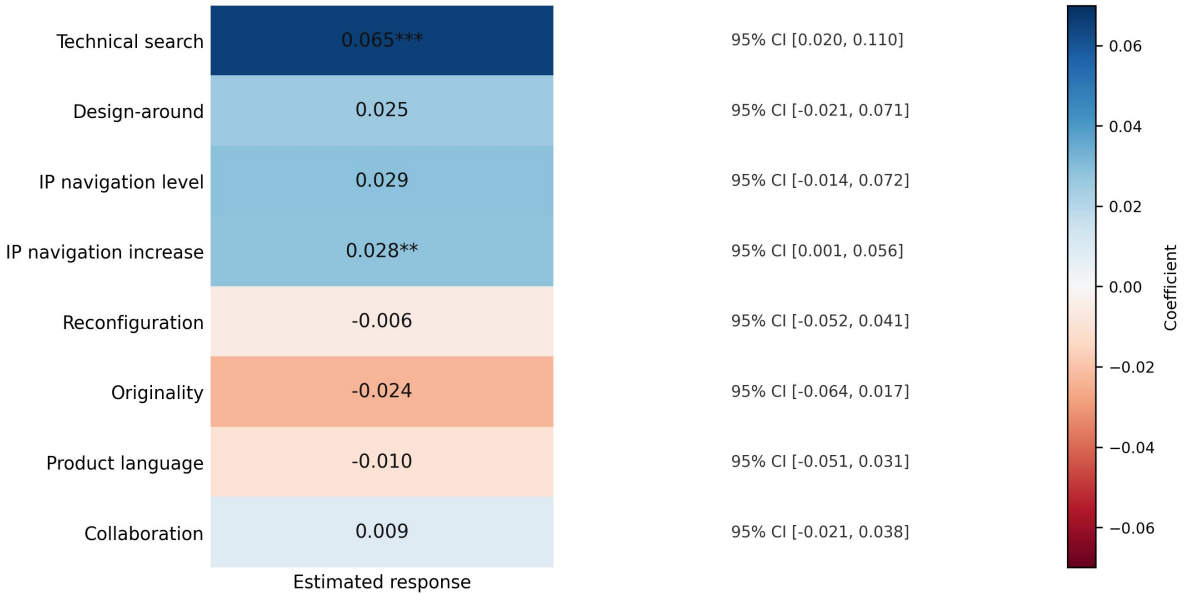
Patent-structure tests point to a continuation margin. At the two-year horizon, pre-period technical hiring orientation predicts more total patent applications, invention applications, utility-model applications, and design applications, but not robustly more grants. This is consistent with firms keeping projects and patenting activity moving under congestion. It is not enough to prove design-around success or patent value.

5.6 Text-Based Mechanism Evidence

Table 4 reports all annual-report text categories rather than only the significant ones. Of the seven level measures at the one-year horizon, only technical-search language responds robustly. The coefficient is 0.0653 and significant at the 1 percent level. Design-around, IP-navigation level, reconfiguration, originality, product-language, and collaboration measures are not significantly positive. A change specification for IP-navigation language is positive and significant, with a coefficient of 0.0282.

Figure 4 displays the full set of text-category estimates. Technical-search language is the broadest disclosed language for constrained navigation, while design-around behavior may occur inside project work without appearing directly in annual reports. The text results support a technical-search response and some IP-navigation language change; they do not establish IPC reallocation, claim redesign, licensing, or a complete design-around mechanism.

Figure 4. Annual-Report Text Categories



Notes: The figure plots the coefficient on pre-period technical hiring orientation interacted with leave-one-out congestion growth for each annual-report text category at the t+1 horizon, corresponding to the text-category rows of Table 4. Outcomes are inverse-hyperbolic-sine transformations of category term counts per 10,000 report words. Points are point estimates and bars are 95 percent confidence intervals based on standard errors clustered by firm. All specifications include firm, industry-year, and province-year fixed effects and listed-firm controls.

5.7 Navigable Congestion as Boundary Condition

Table 5 reports boundary tests. The tercile split suggests an inverted-U pattern for the primary application outcome: the middle tercile has the largest coefficient, while the low and high terciles are positive but insignificant. Formal pooled tests do not show that the high-congestion coefficient is significantly weaker for invention applications. The high-versus-low/middle interaction is 0.0007, and the continuous inherited-congestion moderation coefficient is 0.0069.

Table 5. Boundary Evidence by Inherited Congestion

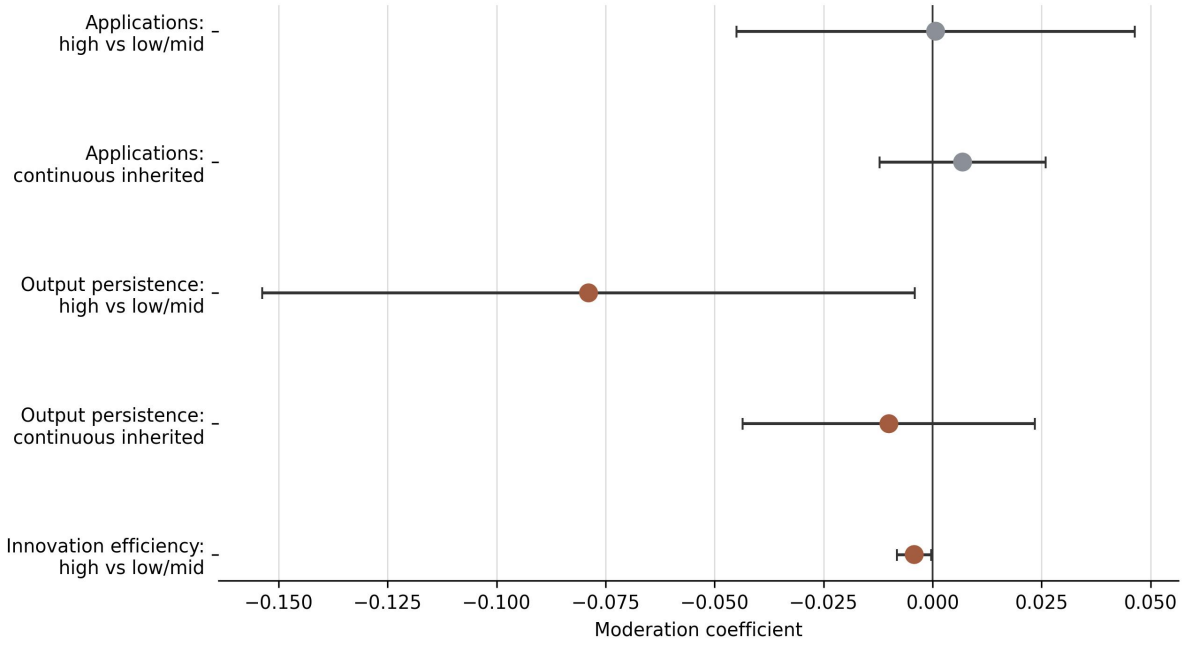
Panel	Outcome	Test	N	Firms	Estimate	SE
Tercile split	Invention applications	Low inherited congestion	3,484	673	0.0553	(0.0457)
Tercile split	Invention applications	Middle inherited congestion	3,502	669	0.0853*	(0.0468)
Tercile split	Invention applications	High inherited congestion	3,598	675	0.0400	(0.0450)
Tercile split	Output persistence, supplemental	Low inherited congestion	2,686	644	0.1392*	(0.0838)
Tercile split	Output persistence, supplemental	Middle inherited congestion	2,753	646	0.1795**	(0.0820)
Tercile split	Output persistence, supplemental	High inherited congestion	2,841	652	-0.0285	(0.0780)
Formal moderation	Invention applications	High x pre-tech x congestion	10,584	2,017	0.0007	(0.0233)
Formal moderation	Invention applications	Continuous inherited x pre-tech x congestion	10,584	2,017	0.0069	(0.0097)
Formal moderation	Output persistence, supplemental	High x pre-tech x congestion	8,280	1,942	-0.0789**	(0.0382)
Formal moderation	Innovation efficiency, supplemental	High x pre-tech x congestion	8,308	1,947	-0.0042**	(0.0020)

Notes: Inherited congestion is measured using 2016 exposure. Tercile rows report separate coefficients. Formal moderation rows test whether the coefficient differs under high or continuous inherited congestion. The primary application outcome does not show a significant high-congestion moderation; supplemental output-persistence and efficiency measures do.

Figure 5 reports the formal boundary estimates. The boundary evidence is stronger for supplemental outcomes. For output persistence, the high-congestion interaction is -0.0789 and significant at the 5 percent level in the high-versus-low/middle specification. Innovation efficiency shows a similar negative high-congestion interaction. These results support the

navigable-congestion idea for persistence and efficiency, but not as a statistically established boundary for the primary invention-application outcome.

Figure 5. Formal Boundary Tests



Notes: The figure plots the high-inherited-congestion moderation coefficients, the high-congestion indicator interacted with pre-period technical hiring orientation and congestion growth, for the primary and supplemental outcomes, corresponding to the formal-moderation rows of Table 5. Inherited congestion is measured with 2016 exposure. Points are point estimates and bars are 95 percent confidence intervals based on standard errors clustered by firm. All specifications include firm, industry-year, and province-year fixed effects and listed-firm controls.

The appropriate interpretation is therefore narrower than a strong boundary confirmation. Technical hiring orientation is associated with invention-filing continuation under congestion growth. The evidence that this association weakens in dense inherited congestion is suggestive for supplemental outcomes and not established for the primary outcome.

5.8 Supplemental Outcomes and Timing Diagnostics

Innovation-efficiency results are weaker in the preferred leave-one-out predetermined-hiring design. They become more positive in the direct-exposure robustness, but that specification does not isolate the focal firm from the field-year component. Accordingly, innovation efficiency is reported as a supplemental outcome.

The growth-weighted output-persistence measure is positive in the baseline specification, but the estimate becomes small and statistically insignificant after firm-specific trends. TFP results do not support a productivity claim. These variables are useful for assessing scope conditions, but they do not carry the main argument.

Lead-lag estimates are reported as timing diagnostics in the appendix. They are consistent with delayed response for some outcomes, especially output persistence, but we do not treat them as formal parallel-trends evidence because congestion growth is continuous and serially correlated.

6. Discussion and Conclusion

The findings recast technical hiring as a congestion-contingent input. Technical hiring orientation is associated with a stronger invention-filing continuation margin when a firm's inherited technology fields become more congested. This claim is narrower than saying that technical hiring generally improves innovation, but it fits the evidence more closely.

For technology-management research, we connect human-capital input to the external patent landscape. Technical workers matter because congestion changes the task. The firm must interpret blocking claims, search for feasible design alternatives, and decide whether to redirect projects. The clearest evidence is on formal invention filing, while output-persistence and efficiency evidence provides more tentative support for the navigable-congestion boundary.

For patent-thicket research, we add firm heterogeneity to a literature that often studies average effects of fragmented rights. Patent congestion does not affect all firms in the same way. Firms enter congestion shocks with different labor orientations, and those orientations shape whether the firm continues invention filing. The evidence does not show that technical hiring

eliminates thickets or raises patent quality. It shows that technical hiring orientation conditions the continuation margin in the main congested source fields observed in the data.

For managers, the implication is not to hire more technical workers in every crowded technology market. The implication is to match technical hiring with the firm's patent landscape. Where congestion creates solvable search and design-around problems, technical hiring can support internal navigation. Where congestion is very dense, managers may need licensing, patent pools, alliances, acquisitions, or legal settlement rather than relying on technical hiring alone. The current data support this boundary more clearly for supplemental persistence and efficiency outcomes than for invention applications.

The interpretation is bounded by four measurement limits. Recruitment postings are not realized hires. Citation-based congestion does not observe every legal or licensing constraint. Field-level congestion growth may still reflect policy or technology-opportunity changes. The empirical leverage is concentrated in instrument manufacturing and technical-repair source fields, indicating a scoped setting where design adjustment and equipment reconfiguration are more plausible. Future work could combine inventor mobility, patent-claim text, patent transactions, and licensing data to observe design-around behavior directly.

Our central claim is therefore specific: pre-period technical hiring orientation conditions firms' invention-filing response to inherited patent congestion, especially in the main congested source fields where the exposure design has empirical leverage.

References

Almeida, P., & Kogut, B. 1999. Localization of knowledge and the mobility of engineers in regional networks. Management Science, 45(7): 905-917. https://doi.org/10.1287/mnsc.45.7.905

Autor, D. H., Dorn, D., & Hanson, G. H. 2013. The China syndrome: Local labor market effects of import competition in the United States. American Economic Review, 103(6): 2121-2168. https://doi.org/10.1257/aer.103.6.2121

Bellstam, G., Bhagat, S., & Cookson, J. A. 2021. A text-based analysis of corporate innovation. Management Science, 67(7): 4004-4031. https://doi.org/10.1287/mnsc.2020.3682

Borusyak, K., Hull, P., & Jaravel, X. 2022. Quasi-experimental shift-share research designs. Review of Economic Studies, 89(1): 181-213. https://doi.org/10.1093/restud/rdab030

Cameron, A. C., Gelbach, J. B., & Miller, D. L. 2011. Robust inference with multiway clustering. Journal of Business & Economic Statistics, 29(2): 238-249. https://doi.org/10.1198/jbes.2010.07136

Campbell, B. A., Coff, R., & Kryscynski, D. 2012. Rethinking sustained competitive advantage from human capital. Academy of Management Review, 37(3): 376-395. https://doi.org/10.5465/amr.2010.0276

Cockburn, I. M., & MacGarvie, M. J. 2011. Entry and patenting in the software industry. Management Science, 57(5): 915-933. https://doi.org/10.1287/mnsc.1110.1321

Cohen, W. M., & Levinthal, D. A. 1990. Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly, 35(1): 128-152. https://doi.org/10.2307/2393553

Fleming, L. 2001. Recombinant uncertainty in technological search. Management Science, 47(1): 117-132. https://doi.org/10.1287/mnsc.47.1.117.10671

Galasso, A., & Schankerman, M. 2015. Patents and cumulative innovation: Causal evidence from the courts. Quarterly Journal of Economics, 130(1): 317-369. https://doi.org/10.1093/qje/qju029

Hall, B. H., & Ziedonis, R. H. 2001. The patent paradox revisited: An empirical study of patenting in the U.S. semiconductor industry, 1979-1995. RAND Journal of Economics, 32(1): 101-128.

Hatch, N. W., & Dyer, J. H. 2004. Human capital and learning as a source of sustainable competitive advantage. Strategic Management Journal, 25(12): 1155-1178. https://doi.org/10.1002/smj.421

Henderson, R. M., & Clark, K. B. 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. Administrative Science Quarterly, 35(1): 9-30. https://doi.org/10.2307/2393549

Hu, A. G., & Jefferson, G. H. 2009. A great wall of patents: What is behind China's recent patent explosion? Journal of Development Economics, 90(1): 57-68. https://doi.org/10.1016/j.jdeveco.2008.11.004

Katila, R., & Ahuja, G. 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. Academy of Management Journal, 45(6): 1183-1194. https://doi.org/10.2307/3069433

Lerner, J., & Seru, A. 2022. The use and misuse of patent data: Issues for finance and beyond. Review of Financial Studies, 35(6): 2667-2704. https://doi.org/10.1093/rfs/hhab084

Li, X. 2012. Behind the recent surge of Chinese patenting: An institutional view. Research Policy, 41(1): 236-249. https://doi.org/10.1016/j.respol.2011.07.003

National Bureau of Statistics of China. 2017. Industrial classification for national economic activities (GB/T 4754-2017). Beijing: Standards Press of China.

Petersen, M. A. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. Review of Financial Studies, 22(1): 435-480. https://doi.org/10.1093/rfs/hhn053

Shapiro, C. 2001. Navigating the patent thicket: Cross licenses, patent pools, and standard setting. In A. B. Jaffe, J. Lerner, & S. Stern (Eds.), Innovation Policy and the Economy, Vol. 1: 119-150. MIT Press.

Song, J., Almeida, P., & Wu, G. 2003. Learning-by-hiring: When is mobility more likely to facilitate interfirm knowledge transfer? Management Science, 49(4): 351-365. https://doi.org/10.1287/mnsc.49.4.351.14429

von Graevenitz, G., Wagner, S., & Harhoff, D. 2011. How to measure patent thickets: A novel approach. Economics Letters, 111(1): 6-9. https://doi.org/10.1016/j.econlet.2010.12.005

von Graevenitz, G., Wagner, S., & Harhoff, D. 2013. Incidence and growth of patent thickets: The impact of technological opportunities and complexity. Journal of Industrial Economics, 61(3): 521-563. https://doi.org/10.1111/joie.12032

Williams, H. L. 2017. How do patents affect research investments? Annual Review of Economics, 9: 441-469. https://doi.org/10.1146/annurev-economics-110216-100959

Zhang, M., & Long, X. 2024. Patent thicket: Impetus or barrier in technological innovation? Journal of Financial Research, 527(5): 169-187.

Ziedonis, R. H. 2004. Don't fence me in: Fragmented markets for technology and the patent acquisition strategies of firms. Management Science, 50(6): 804-820. https://doi.org/10.1287/mnsc.1040.0208

Internet Appendix

Technical Hiring under Navigable Patent Congestion: Evidence from Chinese Listed Firms

Appendix Table A1. Variable Definitions

Variable	Definition
Pre-period technical hiring orientation	Average log(1 + core technical recruitment postings) over 2016-2017.
LOO congestion growth	Annual growth in leave-one-out inherited patent-congestion exposure.
Technical-search text	asinh of annual-report technical-search terms per 10,000 words.

Notes: Full variable definitions are in Appendix A of the markdown appendix. The manuscript uses pre-period technical hiring orientation rather than current hiring as the central conditioning variable.

Appendix Table B1. Recruitment Classification Rules

Category	Rule
Technical postings	R&D, engineering, software, algorithms, testing, lab, process, materials, automation, machinery, electrical, semiconductor, biotech, pharmaceutical.
Nontechnical postings	Core postings not classified as technical.

Notes: Recruitment categories are based on job title, category, and job-content keywords. Nontechnical hiring is used as a placebo orientation measure.

Appendix Table C1. Annual-Report Text Dictionary

Text group	Terms included
Technical search	new technology; new process; new material; develop; technical problem solving; new path; invention; intellectual property
IP navigation	intellectual property; invention
Reconfiguration	change; update; new model; iteration; reform; new business; replace old with new

Notes: Text variables are normalized by annual-report word count and transformed with inverse hyperbolic sine. These variables proxy disclosed technical-search and IP-navigation activity; they are not patent-level reallocation measures.

Appendix Table F1. Main Evidence

Specification	Tech × Δcong.	Nontech × Δcong.	Δcong. (LOO)	N	Firms	R^2
Invention applications (t+1) — Baseline	0.0540** (0.0223)	-0.0120 (0.0224)	-0.0186 (0.0492)	12781	2411	0.058
Invention applications (t+1) — + Firm trends	0.0968* (0.0512)	-0.0315 (0.0506)	-0.0175 (0.0572)	12781	2411	0.015
Invention applications (t+1) — Lagged hiring	0.0177 (0.0167)	0.003 (0.0174)	-0.0019 (0.0385)	16239	3049	0.070
Invention applications (t+1) — Current hiring	0.0193 (0.0156)	0.0000 (0.0155)	0.0002 (0.0271)	18276	3108	0.081
Invention grants (t+1) — Baseline	-0.0278 (0.0219)	0.0271 (0.0226)	0.0828* (0.0477)	12781	2411	0.043
Invention grants (t+1) — + Firm trends	0.1258** (0.0598)	-0.0884 (0.0569)	0.0760 (0.0657)	12781	2411	0.008

Specification	Tech × Δcong.	Nontech × Δcong.	Δcong. (LOO)	N	Firms	R^2
Invention grants (t+1) — Lagged hiring	-0.0109 (0.0165)	-0.003 (0.0174)	0.0690* (0.0374)	16239	3049	0.049
Invention grants (t+1) — Current hiring	-0.0307** (0.0155)	0.0049 (0.0147)	0.0389 (0.0278)	18276	3108	0.055
Output persistence (t+1) — Baseline	0.0850** (0.0385)	-0.0059 (0.0383)	-0.1030 (0.0732)	10053	2329	0.042
Output persistence (t+1) — + Firm trends	0.0256 (0.0751)	0.0329 (0.0754)	-0.0446 (0.0942)	10053	2329	0.018
Output persistence (t+1) — Lagged hiring	0.0418 (0.0316)	0.0158 (0.0296)	-0.0967 (0.0658)	12748	2874	0.046
Output persistence (t+1) — Current hiring	0.0672*** (0.0254)	0.0043 (0.0273)	-0.0445 (0.0500)	14352	2900	0.053

*Notes: This table reports compact main specifications. Standard errors are clustered by firm unless otherwise indicated in the specification label. All models include firm, industry-year, and province-year fixed effects, with firm-specific linear trends where the specification is labeled "+ Firm trends." Firm-clustered standard errors are in parentheses; *, **, and *** denote 10%, 5%, and 1% significance.*

Appendix Table G1. Text Mechanism

Specification	Tech × Δcong.	Nontech × Δcong.	Δcong. (LOO)	N	Firms	R^2
Technical-search language (t+1)	0.0653*** (0.0230)	-0.0500** (0.0227)	-0.0604 (0.0545)	12788	2411	0.011
Design-around language (t+1)	0.0253 (0.0234)	-0.0119 (0.0225)	-0.0428 (0.0566)	12788	2411	0.009
IP-navigation language (t+1)	0.0288 (0.0220)	-0.0146 (0.0207)	0.0349 (0.0455)	12788	2411	0.005
Reconfiguration language (t+1)	-0.0058 (0.0237)	0.0012 (0.0232)	0.0172 (0.0631)	12788	2411	0.005
Originality language (t+1)	-0.0235 (0.0206)	0.0012 (0.0205)	-0.0254 (0.0506)	12788	2411	0.010
Product language (t+1)	-0.0097 (0.0209)	-0.0117 (0.0211)	-0.0315 (0.0579)	12788	2411	0.009
Collaboration language (t+1)	0.0088 (0.0151)	0.0047 (0.0150)	0.0779** (0.0361)	12788	2411	0.006
Technical-search (log) (t+1)	0.0143 (0.0156)	-0.0108 (0.0154)	-0.0441 (0.0371)	12788	2411	0.018
Design-around (log) (t+1)	-0.0088 (0.0144)	0.0080 (0.0139)	-0.0314 (0.0342)	12788	2411	0.012
IP-navigation (log) (t+1)	-0.0054 (0.0141)	0.0053 (0.0134)	0.0233 (0.0292)	12788	2411	0.007
Technical-search language (t+2)	0.0657** (0.0268)	-0.0465* (0.0260)	-0.0879 (0.0561)	10488	2394	0.007
Design-around language (t+2)	0.0311 (0.0280)	-0.0175 (0.0263)	-0.0399 (0.0565)	10488	2394	0.004
Reconfiguration language (t+2)	0.0109 (0.0311)	-0.0155 (0.0300)	-0.0104 (0.0612)	10488	2394	0.005
Δ Technical-search language	0.0128 (0.0164)	-0.0173 (0.0160)	-0.0552 (0.0497)	12788	2411	0.004
Δ Design-around language	0.0211 (0.0166)	-0.0209 (0.0163)	0.0221 (0.0549)	12788	2411	0.003
Δ IP-navigation language	0.0282** (0.0140)	-0.0291** (0.0137)	0.0069 (0.0401)	12788	2411	0.003
Δ Reconfiguration language	0.0191 (0.0187)	-0.0066 (0.0180)	0.0134 (0.0588)	12788	2411	0.003
Δ Technical-search (log)	0.0166 (0.0105)	-0.0198* (0.0103)	-0.0126 (0.0319)	12788	2411	0.004
Δ² Technical-search language	0.0214 (0.0400)	-0.0282 (0.0383)	-0.1034 (0.0782)	10488	2394	0.005
Δ² Design-around language	0.0483 (0.0399)	-0.0522 (0.0388)	0.0222 (0.0771)	10488	2394	0.005
Δ² Reconfiguration language	0.0538 (0.0439)	-0.0269 (0.0418)	-0.0336 (0.0896)	10488	2394	0.006

Specification	Tech × Δcong.	Nontech × Δcong.	Δcong. (LOO)	N	Firms	R^2
Technical-search language (t+1) — + Firm trends	0.0559 (0.0580)	-0.0766 (0.0565)	-0.1293* (0.0701)	12788	2411	0.009
Design-around language (t+1) — + Firm trends	0.0742 (0.0577)	-0.0928 (0.0567)	-0.0583 (0.0717)	12788	2411	0.009
Reconfiguration language (t+1) — + Firm trends	0.0940 (0.0627)	-0.0778 (0.0602)	0.0176 (0.0810)	12788	2411	0.007

*Notes: The text mechanism is supportive evidence. Significant coefficients indicate more technical-search or IP-navigation language after congestion growth, not proven IPC-level design-around behavior. All models include firm, industry-year, and province-year fixed effects, with firm-specific linear trends where the specification is labeled "+ Firm trends." Firm-clustered standard errors are in parentheses; *, **, and *** denote 10%, 5%, and 1% significance.*

Appendix Table H1. Boundary Conditions

Specification	Tech × Δcong.	Nontech × Δcong.	Δcong. (LOO)	N	Firms	R^2
Invention applications (t+1) — Low tercile	0.0553 (0.0457)	-0.0388 (0.0451)	0.0319 (0.0687)	3484	673	0.062
Invention applications (t+1) — Mid tercile	0.0853* (0.0468)	-0.0557 (0.0471)	0.0224 (0.1919)	3502	669	0.082
Invention applications (t+1) — High tercile	0.0400 (0.0450)	0.0223 (0.0441)	-0.1434 (0.4387)	3598	675	0.086
Invention applications (t+1) — Excl. O81	0.0617** (0.0298)	-0.0230 (0.0305)	0.0019 (0.0570)	7515	1433	0.060
Invention applications (t+1) — Excl. C43	0.0454* (0.0267)	-0.0095 (0.0268)	-0.0273 (0.0531)	7991	1503	0.063
Invention applications (t+1) — Excl. C40	0.0432* (0.0235)	0.0059 (0.0231)	-0.0354 (0.0523)	11865	2243	0.060
Invention applications (t+1) — Excl. top-3	0.0093 (0.0672)	-0.0018 (0.0667)	0.0136 (0.0713)	1809	357	0.100
Output persistence (t+1) — Low tercile	0.1392* (0.0838)	-0.0804 (0.0815)	-0.1065 (0.1085)	2686	644	0.037
Output persistence (t+1) — Mid tercile	0.1795** (0.0820)	-0.0672 (0.0798)	-0.0589 (0.2651)	2753	646	0.069
Output persistence (t+1) — High tercile	-0.0285 (0.0780)	0.0543 (0.0766)	-0.7818 (0.6042)	2841	652	0.063
Output persistence (t+1) — Excl. O81	0.1548*** (0.0505)	-0.0377 (0.0512)	-0.0480 (0.0863)	5888	1383	0.047
Output persistence (t+1) — Excl. C43	0.0650 (0.0468)	-0.0151 (0.0471)	-0.0875 (0.0799)	6252	1443	0.049
Output persistence (t+1) — Excl. C40	0.0796* (0.0407)	0.0006 (0.0400)	-0.0955 (0.0752)	9332	2167	0.043
Output persistence (t+1) — Excl. top-3	0.5012*** (0.1191)	-0.3977*** (0.1186)	0.0653 (0.1153)	1366	335	0.112
Innovation efficiency (t+1) — Low tercile	0.0071* (0.0039)	-0.0030 (0.0038)	0.0014 (0.0057)	2711	646	0.049
Innovation efficiency (t+1) — Mid tercile	0.0063 (0.0043)	0.0015 (0.0043)	-0.0160 (0.0157)	2755	648	0.064
Innovation efficiency (t+1) — High tercile	-0.0042 (0.0038)	0.0058 (0.0038)	-0.0273 (0.0286)	2842	653	0.046

Specification	Tech × Δcong.	Nontech × Δcong.	Δcong. (LOO)	N	Firms	R^2
Innovation efficiency (t+1) — Excl. O81	0.0058** (0.0026)	0.0005 (0.0026)	0.0016 (0.0045)	5920	1388	0.036

*Notes: Boundary tests split firms by inherited congestion terciles and exclude dominant technology fields as stress tests. Small-sample exclusion tests should be read cautiously. All models include firm, industry-year, and province-year fixed effects, with firm-specific linear trends where the specification is labeled "+ Firm trends." Firm-clustered standard errors are in parentheses; *, **, and *** denote 10%, 5%, and 1% significance.*

Appendix Table I1. Lead-Lag Diagnostics

Specification	Tech × Δcong.	Nontech × Δcong.	Δcong. (LOO)	N	Firms	R^2
Innovation efficiency (t−2)	-0.0020 (0.0034)	-0.0001 (0.0034)	0.0086 (0.0074)	7242	2065	0.053
Innovation efficiency (t−1)	0.0004 (0.0030)	0.0028 (0.0029)	-0.0046 (0.0057)	7242	2065	0.036
Innovation efficiency (t)	0.0043 (0.0029)	-0.0013 (0.0028)	0.0009 (0.0054)	7242	2065	0.042
Innovation efficiency (t+1)	0.0064** (0.0030)	-0.0024 (0.0030)	0.0001 (0.0052)	7242	2065	0.030
Innovation efficiency (t+2)	0.0063** (0.0031)	0.0014 (0.0032)	0.0033 (0.0067)	7242	2065	0.019
Innovation efficiency (t−2) — + Firm trends	0.0000 (0.0064)	0.0027 (0.0063)	0.0203*** (0.0069)	7242	2065	0.045
Innovation efficiency (t−1) — + Firm trends	0.0024 (0.0063)	0.0012 (0.0060)	-0.0072 (0.0075)	7242	2065	0.019
Innovation efficiency (t) — + Firm trends	0.0000 (0.0060)	-0.0018 (0.0059)	-0.0017 (0.0074)	7242	2065	0.016
Innovation efficiency (t+1) — + Firm trends	0.0036 (0.0054)	-0.0005 (0.0055)	-0.0068 (0.0070)	7242	2065	0.018
Innovation efficiency (t+2) — + Firm trends	-0.0026 (0.0052)	0.0061 (0.0051)	0.0127* (0.0074)	7242	2065	0.011
Innovation efficiency (2) (t−2)	-0.0013 (0.0039)	-0.0013 (0.0040)	0.0063 (0.0080)	7242	2065	0.056
Innovation efficiency (2) (t−1)	0.0008 (0.0034)	0.0032 (0.0033)	-0.0035 (0.0066)	7242	2065	0.032
Innovation efficiency (2) (t)	0.0053 (0.0033)	-0.0012 (0.0032)	0.0008 (0.0066)	7242	2065	0.036
Innovation efficiency (2) (t+1)	0.0063* (0.0035)	-0.0024 (0.0034)	-0.0001 (0.0059)	7242	2065	0.026
Innovation efficiency (2) (t+2)	0.0058 (0.0037)	0.0017 (0.0037)	0.0042 (0.0074)	7242	2065	0.018
Innovation efficiency (2) (t−2) — + Firm trends	0.0024 (0.0074)	0.0015 (0.0072)	0.0196** (0.0083)	7242	2065	0.053
Innovation efficiency (2) (t−1) — + Firm trends	0.0010 (0.0074)	0.0025 (0.0070)	-0.0042 (0.0087)	7242	2065	0.017
Innovation efficiency (2) (t) — + Firm trends	0.0013 (0.0070)	-0.0025 (0.0067)	-0.0041 (0.0083)	7242	2065	0.015
Innovation efficiency (2) (t+1) — + Firm trends	0.0024 (0.0063)	0.0002 (0.0062)	-0.0067 (0.0081)	7242	2065	0.016
Innovation efficiency (2) (t+2) — + Firm trends	-0.0028 (0.0059)	0.0057 (0.0058)	0.0122 (0.0090)	7242	2065	0.012
Output persistence (t−2)	0.0503 (0.0787)	0.0033 (0.0778)	0.2113 (0.1780)	5963	1994	0.032
Output persistence (t−1)	0.0143 (0.0811)	0.0125 (0.0805)	-0.1161 (0.1271)	5963	1994	0.041
Output persistence (t)	-0.0287 (0.0743)	0.0065 (0.0751)	0.0359 (0.1574)	5963	1994	0.062
Output persistence (t+1)	0.1183 (0.0723)	-0.0338 (0.0702)	0.0858 (0.1205)	5963	1994	0.048

Specification	Tech × Δcong.	Nontech × Δcong.	Δcong. (LOO)	N	Firms	R^2
Output persistence (t+2)	0.2321*** (0.0774)	-0.0455 (0.0775)	0.0321 (0.1439)	5963	1994	0.036
Output persistence (t−2) — + Firm trends	-0.1108 (0.1443)	0.0753 (0.1496)	0.2626 (0.1863)	5963	1994	0.024
Output persistence (t−1) — + Firm trends	-0.1240 (0.1491)	0.0713 (0.1493)	-0.1632 (0.1947)	5963	1994	0.023
Output persistence (t) — + Firm trends	0.0625 (0.1415)	-0.0344 (0.1423)	-0.0812 (0.1631)	5963	1994	0.042
Output persistence (t+1) — + Firm trends	0.0845 (0.1357)	0.0280 (0.1343)	0.0131 (0.2006)	5963	1994	0.027
Output persistence (t+2) — + Firm trends	0.2482** (0.1229)	-0.1319 (0.1206)	0.0112 (0.1472)	5963	1994	0.032

*Notes: Lead-lag coefficients are timing diagnostics for continuous congestion growth. They should not be interpreted as a canonical staggered event-study test. All models include firm, industry-year, and province-year fixed effects, with firm-specific linear trends where the specification is labeled "+ Firm trends." Firm-clustered standard errors are in parentheses; *, **, and *** denote 10%, 5%, and 1% significance.*

Appendix Table J1. Field-Shock Permutation

Outcome	Observed β	Perm. mean	Perm. SD	p (two-sided)	p (right tail)	Reps
Invention applications (t+1)	0.0540	0.0323	0.0200	0.14	0.14	199
Output persistence (t+1)	0.0850	0.0491	0.0463	0.2	0.2	199

Notes: The permutation randomly reassigns field-level congestion paths across technology fields. Right-tail p-values summarize how often randomized shocks produce coefficients as large as the observed estimate.

Appendix Table K1. Dominant-Field Leverage

Specification	Tech × Δcong.	Nontech × Δcong.	Δcong. (LOO)	N	Firms	R^2
Full sample	0.0540** (0.0223)	-0.0120 (0.0224)	-0.0186 (0.0492)	12781	2411	0.058
O81 only	0.0317 (0.0337)	0.0074 (0.0326)	0.3835 (0.3802)	5266	978	0.068
C43 only	0.0370 (0.0359)	0.0270 (0.0362)	-0.0919 (0.1959)	4790	908	0.065
C40 only	0.1787*** (0.0650)	-0.1181* (0.0687)	0.2755 (0.1973)	916	168	0.177
Top-3 only	0.0558** (0.0237)	-0.0148 (0.0238)	0.0253 (0.0806)	10972	2054	0.059
Excl. top-3	0.0093 (0.0672)	-0.0018 (0.0667)	0.0136 (0.0713)	1809	357	0.100

*Notes: O81, C43, and C40 are source technology-field codes. The non-top-three row shows how much the main estimate changes outside those fields. All models include firm, industry-year, and province-year fixed effects, with firm-specific linear trends where the specification is labeled "+ Firm trends." Firm-clustered standard errors are in parentheses; *, **, and *** denote 10%, 5%, and 1% significance.*

Appendix Table L1. Formal Boundary Tests

Specification	Tech × Δcong.	× Mid	× High	× Cont.	Nontech × Δcong.	N	R^2
Invention applications (t+1) — High vs low/mid	0.0577** (0.0279)		0.0007 (0.0233)		-0.017 (0.0262)	10584	0.062
Invention applications (t+1) — Mid+high vs low	0.0591* (0.0309)	-0.0028 (0.0278)	-0.0008 (0.0275)		-0.0169 (0.0262)	10584	0.062

Specification	Tech × Δcong.	× Mid	× High	× Cont.	Nontech × Δcong.	N	R^2
Invention applications (t+1) — Continuous	0.0579** (0.0260)			0.0069 (0.0097)	-0.0169 (0.0261)	10584	0.062
Output persistence (t+1) — High vs low/mid	0.1079** (0.0501)		-0.0789** (0.0382)		-0.0049 (0.0450)	8280	0.042
Output persistence (t+1) — Mid+high vs low	0.1005* (0.0551)	0.0153 (0.0479)	-0.0710 (0.0442)		-0.0053 (0.0449)	8280	0.042
Output persistence (t+1) — Continuous	0.0750 (0.0465)			-0.01 (0.0171)	-0.0028 (0.0450)	8280	0.041
Innovation efficiency (t+1) — High vs low/mid	0.0039 (0.0025)		-0.0042** (0.0020)		0.002 (0.0023)	8308	0.032
Innovation efficiency (t+1) — Mid+high vs low	0.0036 (0.0027)	0.0007 (0.0025)	-0.0039* (0.0023)		0.002 (0.0023)	8308	0.032
Innovation efficiency (t+1) — Continuous	0.0022 (0.0023)			-0.0004 (0.0010)	0.0021 (0.0023)	8308	0.031

*Notes: Formal moderation rows test whether high or continuous inherited congestion changes the pre-period technical-hiring interaction. All models include firm, industry-year, and province-year fixed effects, with firm-specific linear trends where the specification is labeled "+ Firm trends." Firm-clustered standard errors are in parentheses; *, **, and *** denote 10%, 5%, and 1% significance.*

Appendix Table M1. Alternative Pre-Period Windows

Specification	Tech × Δcong.	Nontech × Δcong.	Δcong. (LOO)	N	Firms	R^2
Invention applications (t+1) — 2016 window	0.0399* (0.0240)	0.0021 (0.0233)	-0.0131 (0.0575)	10584	2017	0.062
Invention grants (t+1) — 2016 window	-0.0003 (0.0234)	-0.0026 (0.0233)	0.0498 (0.0535)	10584	2017	0.041
Invention applications (t+1) — 2017 window	0.0741*** (0.0213)	-0.0263 (0.0218)	-0.0269 (0.0502)	12372	2320	0.062
Invention grants (t+1) — 2017 window	-0.0198 (0.0209)	0.0162 (0.0218)	0.0867* (0.0482)	12372	2320	0.044

*Notes: Recruitment data begin in 2016. These checks therefore compare 2016-only and 2017-only pre-period measures with the 2016-2017 average. All models include firm, industry-year, and province-year fixed effects, with firm-specific linear trends where the specification is labeled "+ Firm trends." Firm-clustered standard errors are in parentheses; *, **, and *** denote 10%, 5%, and 1% significance.*

Appendix Table N1. All Text Categories

Specification	Tech × Δcong.	Nontech × Δcong.	Δcong. (LOO)	N	Firms	R^2
Technical-search language (t+1)	0.0653*** (0.0230)	-0.0500** (0.0227)	-0.0604 (0.0545)	12788	2411	0.011
Technical-search language (t+1) — + Firm trends	0.0559 (0.0580)	-0.0766 (0.0565)	-0.1293* (0.0701)	12788	2411	0.009
Design-around language (t+1) — + Firm trends	0.0742 (0.0577)	-0.0928 (0.0567)	-0.0583 (0.0717)	12788	2411	0.009
Design-around language (t+1)	0.0253 (0.0234)	-0.0119 (0.0225)	-0.0428 (0.0566)	12788	2411	0.009
IP-navigation language (t+1)	0.0288 (0.0220)	-0.0146 (0.0207)	0.0349 (0.0455)	12788	2411	0.005
Reconfiguration language (t+1) — + Firm trends	0.0940 (0.0627)	-0.0778 (0.0602)	0.0176 (0.0810)	12788	2411	0.007
Reconfiguration language (t+1)	-0.0058 (0.0237)	0.0012 (0.0232)	0.0172 (0.0631)	12788	2411	0.005
Originality language (t+1)	-0.0235 (0.0206)	0.0012 (0.0205)	-0.0254 (0.0506)	12788	2411	0.010

Specification	Tech × Δcong.	Nontech × Δcong.	Δcong. (LOO)	N	Firms	R^2
Product language (t+1)	-0.0097 (0.0209)	-0.0117 (0.0211)	-0.0315 (0.0579)	12788	2411	0.009
Collaboration language (t+1)	0.0088 (0.0151)	0.0047 (0.0150)	0.0779** (0.0361)	12788	2411	0.006
Δ IP-navigation language	0.0282** (0.0140)	-0.0291** (0.0137)	0.0069 (0.0401)	12788	2411	0.003

*Notes: This table reports all main text categories, not only significant categories. All models include firm, industry-year, and province-year fixed effects, with firm-specific linear trends where the specification is labeled "+ Firm trends." Firm-clustered standard errors are in parentheses; *, **, and *** denote 10%, 5%, and 1% significance.*

Appendix Table N2. Residualized Congestion

Specification	Tech × Δcong.	Nontech × Δcong.	Δcong. (LOO)	N	Firms	R^2
Invention applications (t+1)	0.0946*** (0.0310)	-0.0643** (0.0314)	0.0042 (0.0286)	12781	2411	0.057
Invention grants (t+1)	0.0307 (0.0323)	-0.0270 (0.0328)	0.0681** (0.0282)	12781	2411	0.043
Output persistence (t+1)	0.0327 (0.0423)	-0.0137 (0.0423)	-0.0716* (0.0410)	10053	2329	0.039

*Notes: Field-level congestion growth is residualized against year effects and field activity proxies before constructing firm exposure. All models include firm, industry-year, and province-year fixed effects, with firm-specific linear trends where the specification is labeled "+ Firm trends." Firm-clustered standard errors are in parentheses; *, **, and *** denote 10%, 5%, and 1% significance.*