Technology Obsolescence and Transportation Infrastructure in China*

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Abstract

The rapid expansion of China's HSR network since the mid-2000s represents one of the most significant infrastructure investments in modern history, fundamentally reshaping the economic geography of the country by shortening travel times and integrating previously isolated regional economies. From an evolutionary economics perspective, this market integration may accelerate creative destruction: intensified inter-regional competition and expanded knowledge flows could simultaneously raise the quality threshold for viable innovations and hasten the lapse of marginal ones. To examine this hypothesis, this study first integrates spatial extension into Pakes (1986) 's canonical patent renewal framework to theoretically identify potential channels of the influence. There are four possible channels through which a national transportation network impact the obsolescence of technologies: market access expansion, knowledge-frontier exposure, multi-market discovery, and competitive crowding. To test the relationship empirically, it employs a comprehensive dataset of invention and utility patents applied between 2002 and 2019, and adopt robust Difference-in-Differences (DiD) estimators at the city level and semi-parametric Cox proportional hazards models at the patent level. Doubly-robust difference-in-differences estimates show that HSR connection reduces lapsed invention patent counts by 18.9 percent and lapsed utility model counts by 14.5 percent at the city level. Patent-level Cox proportional hazards models reveal that the aggregate renewal-promoting result for invention patents conceals a compositional shift: legacy patents face an elevated lapse hazard of 10.6 percent, while patents filed after HSR connection face a reduced hazard of 22 percent. No such tension arises for utility models, whose lapse hazards fall uniformly across all cohorts.

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These findings establish that large-scale infrastructure investment shapes not only the level but also the quality composition of a region's innovative activity, accelerating the exit of marginal technologies while sustaining a stronger residual portfolio.
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1 Introduction

The Schumpeterian engine of economic growth runs on both creation and destruction. A rich empirical literature has documented how transportation infrastructure, agglomeration, and knowledge spillovers stimulate the arrival of new technologies. Yet the destruction side of the theory has received far less attention. A few empirical studies examine the obsolescence and retirement of existing technologies. In the Pakes and Schankerman (1979) framework, a patent lapses the moment its expected future returns fall below the annual renewal fee, making lapse a direct revealed-preference measure of economic obsolescence. This paper asks how improvements in transportation connectivity affect the obsolescence risk of existing technologies.

I exploit China's high-speed railway (HSR) network as a source of quasi-experimental variation in intercity connectivity. The staggered opening of HSR stations across more than 200 prefecture-level cities generates plausibly exogenous and temporally dispersed shifts in market access, opportunities for knowledge diffusion, and competitive exposure. The outcome of interest is patent lapse, measured at both the city level (aggregate lapse counts and lapse-to-stock ratios) and the individual patent level (survival time). The analysis will use China's unique patent system, which comprises two distinct patent types: invention patents, which protect radical, knowledge-intensive innovations with broad technological scope, versus utility models, which protect incremental, product-specific innovations with closer ties to local manufacturing.

To guide the empirical analysis, I develop a spatial extension of the PAKES and SIMPSON (1989)–Bessen (2008) patent renewal framework. The baseline model treats renewal as a financial option: the patentee maintains a patent whenever the expected continuation value exceeds the statutory fee. The spatial extension introduces inter-regional transportation accessibility as a determinant of this value through four channels that a transportation improvement activates simultaneously. *Channel 1 (Market Access)* raises initial rents of patents by expanding the accessible consumer market. *Channel 2 (Knowledge Spillovers)*

accelerates the patentee's awareness of the technological frontier, hastening the obsolescence of technologies that fall below it. *Channel 3 (Multi-market Discovery)* opens new application domains for existing patents, extending their economic lives. *Channel 4 (Competitive Crowding)* multiplies HSR-enabled rivals from distant cities, compressing market shares and eroding continuation values. The theory's central prediction is a threshold result: the net effect of HSR connectivity on patent renewal depends on a patent-specific commercial viability threshold determined by the relative strength of these four channels. Above the threshold, Channels 1 and 3 dominate and connectivity prolongs patent life; below it, Channels 2 and 4 dominate and connectivity accelerates obsolescence.

Recognizing the staggered rollout of the HSR connection, the city-level analysis employs difference-in-differences estimators robust to such design, including doubly-robust (Callaway & Sant'Anna, 2021) and a Sun–Abraham (L. Sun & Abraham, 2021) interaction-weighted design to handle staggered treatment timing, with a Goodman-Bacon (Goodman-Bacon, 2021) decomposition revealing that standard two-way fixed effects (TWFE) estimates are contaminated to some extent. The patent-level analysis focuses on the firm patents and estimates Cox proportional hazards models for three subsamples: all firm patents, patents from HSR cities (i.e., those eventually connected to the HSR network by the end of the study period), and legacy patents filed prior to HSR connection. Together, the city- and patent-level designs identify the aggregate net effect and the within-city compositional forces that underlie it.

The city-level DRDID estimates document a robust net renewal-promoting effect. HSR connection reduces the count of lapsed invention patents by 18.9% for all applicants and 26.8% for firm applicants; the corresponding reductions for utility models are 14.5% and 19.0%. These findings are confirmed by the Sun–Abraham style estimator and remain robust to the inclusion of alternative transport modes (road and air passenger volumes) and an intangible information exchange channel (the internet connection), ruling out a general connectivity confound.

Nonetheless, the patent-level analysis reveals a tension between opposing forces. Full-sample Cox estimates indicate that HSR connectivity increases the average hazard of lapse for invention patents by 5.1%, which appears to contradict the city-level finding. The cohort-stratified analysis resolves the contradiction: invention patents filed *after* HSR connection in eventually-treated cities face a 22% *lower* lapse hazard, whereas legacy patents filed *before* HSR connection face a 10.6% *higher* one. This asymmetry reflects the threshold mechanism directly: post-HSR patents are selected on the basis of improved market-access expectations (above the threshold), whereas legacy patents are exposed to heightened competition and knowledge obsolescence from newly reachable rivals (below the threshold). The aggregate city-level reduction in lapse counts occurs because the expanding stock of survivable post-HSR patents, which face lower hazard rates, dominates the accelerated culling of the pre-HSR portfolio. For utility models, no such tension exists: lapse hazards are uniform across all subsamples and patent cohorts, confirming that incremental innovations respond primarily to the market-access channel, regardless of vintage.

The mechanism channels are confirmed by patent-level heterogeneity results. GDP- and population-based market access (Channel 1) reduce the lapse hazard for both patent types in all subsamples. The collaboration interaction (Channel 3 proxy) shows that collaborative patents benefit the most from HSR connectivity in eventually-treated cities — invention patents filed after HSR connection by collaborative applicants face a 34% reduction in lapse hazard. Competition from HSR-reachable external rivals (Channel 4) raises the lapse hazard of legacy invention patents by 1% per 1% increase in competitor count, while the same competitive exposure *lowers* the lapse hazard of utility models, consistent with the view that a denser product market signals commercial opportunity for incremental innovations rather than technological substitution. The HHI gap results reveal a further asymmetry: for legacy invention patents, a locally sheltered market raises lapse risk (firms in historically concentrated local markets have weaker incentives to sustain frontier technologies), while for legacy utility models, local market concentration reduces lapse risk (incumbents derive

genuine maintenance value from their dominant local position). HSR connectivity moderates both effects, partially integrating sheltered local markets into the national competitive landscape.

This paper makes three contributions to the literature. First, it develops a spatial patent renewal model that proposes four channels through which transportation connectivity affects technology obsolescence, bridging the quantitative spatial economics literature (Akcigit & Melitz, 2022; Allen & Arkolakis, 2025) and the empirical patent valuation literature (Bessen, 2008; Pakes, 1986). Second, it provides the first large-scale causal evidence that transportation infrastructure shapes the rate of technology obsolescence, extending the HSR-and-innovation literature, which has focused almost exclusively on the creation of new patents, to the under-studied destruction side of the Schumpeterian process. Third, it documents a novel asymmetry in the obsolescence response to market integration between radical and incremental innovations: incremental innovations experience uniform renewal promotion, whereas radical innovations undergo selective portfolio recomposition. This distinction has direct implications for understanding how infrastructure investment shapes not only the level but also the quality composition of a region's innovative activity.

The rest of this study is organised as follows. Section 2 reviews the literature on transportation and innovation and on patent renewal as a measure of technology value. Section 3 develops the spatial patent renewal framework and derives the four-channel threshold prediction. Section 4 describes the data and empirical strategies. Section 5 characterises the spatial and temporal patterns of technology obsolescence in China. Section 6.1 presents the city-level difference-in-differences results and event studies. Section 6.2 reports the patent-level Cox proportional hazards analysis, including the reconciliation of city- and patent-level evidence. Section 7 interprets the results through the lens of the theoretical channels, positions the findings relative to the existing literature, and derives policy implications. Section 8 concludes.

2 Literature Review

2.1 Innovation, technology development and infrastructure

The influence of transportation infrastructure on innovation has attracted growing interest from the academic community, both theoretically and empirically. Innovation being brought to the center of economic theories (Romer, 1990; Solow, 1956), and space and location being crucial aspects of economic activities (Krugman, 1991), have paved the way for a theoretical foundation to understand the relationship between transportation and innovation.

Existing empirical studies have examined the influence of transportation infrastructure on innovation activities from different perspectives. In recent decades, the rapid expansion of high-speed rail networks, particularly in China, has provided a quasi-experimental setting to study how reduced travel times could potentially influence the flow of knowledge and therefore innovation.

Innovation capacity. A significant portion of the literature focuses on innovation at the city level, examining whether connection to an HSR network benefits innovation performance at the city or firm level.

Both Lu et al. (2022) and Fan and Xu (2022) investigated the impact of HSR on innovation using a panel of 285 cities in China from early 2000s to 2016. They used a composite measurement for city-level innovation performance, the FIND index published by Fudan University. Lu et al. (2022) adopted a DiD specification and a spatial panel model. Their results showed that HSR significantly improves urban innovation. Regarding mechanisms, the authors found that HSR stimulates the agglomeration of innovation factors, including population and investment, which in turn boost innovation. Besides, their spatial analysis, with a weight matrix made of binary indicators suggesting whether two cities are connected within the HSR network, revealed that HSR facilitates knowledge dissemination and technology spillovers among connected cities. In terms of heterogeneity, they found that HSR had a significant positive effect on prefecture-level cities and cities with lower levels of science and

education resources, suggesting a convergence effect. However, the impact was not significant for core cities or those with already high levels of science and education. They found no significant geographic heterogeneity between the eastern and central-western regions.

Fan and Xu (2022) used two key independent variables: a dummy variable indicating HSR opening and a variable for HSR service intensity, measured as train frequency. Based on PSM-DID models, the authors found that both HSR opening and service intensity significantly improved innovation. They highlighted two main mechanisms: urban specialization and the acceleration of population mobility, though they didn't estimate the effect empirically. Their heterogeneity analysis offered nuanced insights. They found that the effects were more remarkable in peripheral and small cities compared to central cities, which aligns with Lu et al. (2022)'s findings. Furthermore, for cities located far from central hubs, HSR had a stronger positive impact, whereas for cities very close to central hubs, the service intensity mattered more than just the connection itself. They also noted that service industries and private enterprises benefited more than other sectors.

Focusing on a specific type of innovation, Huang and Wang (2020) explored the effect of HSR on green innovation efficiency. Their study covered 108 cities in the Yangtze River Economic Belt of China from 2005 to 2016. They constructed the green innovation efficiency measurement using by combining inputs like labor, capital, and energy, and outputs like GDP, patents, and pollution. The key independent variable was an HSR opening dummy. They found that HSR significantly improved green innovation efficiency by approximately 11.3 percent. The authors identified innovation factor mobility as the primary mechanism. Based on a classic three-step model, they argued that HSR facilitates the flow of talent, which leads to technological advancement and structural upgrading. Their heterogeneity analysis first revealed a dynamic effect where the benefits followed an inverted U shape over time, peaking around the sixth year. Spatially, they found that the positive effect decayed with distance from the HSR station to the city center. The effects were significant for large cities but not for megacities or small cities.

Du et al. (2020) also analyzed the impact of HSR on urban innovation performance using a dataset of 287 Chinese cities from 2008 to 2016. They measured the outcome variable using the number of patent applications per unit of labor. Their key independent variable was access to the HSR network. They employed a DID method to estimate the causal effects. Their results indicated a robust positive relationship between HSR access and innovation performance. The authors highlighted urban specialization and the agglomeration of knowledge-intensive industries as key mechanisms. They also noted that high population mobility enhanced these effects. Regarding heterogeneity, they observed a quasi U-shaped relationship with city size. Specifically, the benefits were greater for large and small cities compared to medium-sized cities. They also found that the positive effects were stronger in cities with a higher concentration of knowledge-intensive industries.

Focusing on the city level, D. Sun et al. (2021) examined how HSR spurs innovation in China using data from 2005 to 2015. Their outcome variable was the natural logarithm of patent applications at the city level. They also categorized patents into collaborative versus independent, complex versus discrete, and radical versus incremental. The key independent variable was a binary variable for HSR connection. Using a DID strategy, they found that HSR connection significantly increases the number of patents. Regarding the mechanism, the authors argued that HSR reduces travel costs, which facilitates the flow of tacit knowledge and face to face interaction. This interaction is crucial for sharing complex ideas. Their heterogeneity analysis revealed that HSR benefits collaborative innovation more than independent innovation. Furthermore, radical innovations (invention patents) and industries with complex technologies benefit more from HSR than incremental innovations or discrete technologies.

Hou (2022) focused on the Electronic Information (EI) industry in 75 innovative pilot cities in China. The study used data from 2013 and 2015 to explain outcomes in the 2016 to 2018 period to take into account the time needed from R&D input to output. The outcome variable was the count of invention patents in the EI sector. The key independent

variable was inter-city accessibility via HSR network, calculated at different time thresholds (2 hours, 3.6 hours, 4.8 hours). The author used a Knowledge Production Function (KPF) framework estimated via Generalized Method of Moments (GMM), with historical courier routes as an instrument for modern-time HSR connections. The results showed that intercity accessibility mattered more for innovation than local proximity to an HSR station. The mechanism identified was that HSR provided access to external innovation factors such as universities, human capital, and markets. Regarding heterogeneity, the study found that large cities, with a population of 1 to 3 million, benefited most from this inter-city access, whereas megacities (with a population exceeding 5 million) showed signs of potential negative impacts on scientific workers due to brain drain.

Tang et al. (2021) provided a perspective on externalities. They analyzed Chinese city panel data from 2003 to 2016. Their outcome variable was urban innovation performance, measured by the number of patents per 10,000 people. They employed a propensity score matching DID model and a spatial econometric model. The key results showed that HSR significantly improves urban innovation performance. Regarding the mechanism, the authors decomposed the effect into agglomeration externalities and network externalities. They found that while HSR promotes the concentration of factors (agglomeration), the network externalities, manifested as the centrality of cities in the patent transfer network, generated by inter-city economic linkages, have a stronger impact on innovation. In terms of heterogeneity, the improvement was more obvious in economically developed eastern regions and large cities. This suggests that while HSR improves overall performance, it may widen the innovation gap between regions.

Guo et al. (2021) examined the impact of executive diversity on corporate innovation using data on Chinese listed firms from 2007 to 2016. Their outcome variables were R&D investment (input) and the number of patents granted (output). They also constructed a Blau index for executive diversity based on education, age, gender, tenure, and experience. Their key independent variable was the HSR opening in the firm's city. By combining a

DID specification with an IV constructed from a straight line strategy, they found that firms from HSR cities had higher executive diversity than those in non-HSR cities, and this diversity positively drove corporate innovation. The mechanism proposed was that HSR reduced travel time, allowing firms to attract a broader pool of diverse executive talent from distant locations. Their heterogeneity analysis indicated that the impact was magnified for firms in competitive industries, regions with low marketization, or regions with poor initial transportation infrastructure.

X. Zhang et al. (2020) investigated how geographic proximity affects corporate innovation using evidence from A-share listed firms in China. Their study period covered the years 2006 to 2017. The authors constructed their outcome variables using three measures: the natural logarithm of R&D expenditure, the natural logarithm of patent counts, and patents granted per unit of R&D expenditure to proxy innovation efficiency. They used a propensity score matching DID method and an instrumental variable approach based on city altitude and steel prices to address endogeneity. The key results showed that HSR construction promotes corporate innovation in terms of inputs, outputs, and efficiency. Regarding the mechanism, the authors found that HSR facilitates information flows and improves monitoring capabilities. This occurs by reducing financing constraints, strengthening talent flows, and increasing institutional investor site visits. In terms of heterogeneity, the study found that the positive effect is more prominent for private firms, small firms, and firms located in areas with a higher degree of property right protection.

Innovation collaboration. Another strand of literature goes beyond singular city output to examine how HSR influences collaboration between firms and regions. These studies often use city pair data or firm-level data to trace knowledge flows and collaborations.

Hanley et al. (2022) provided a detailed analysis of collaborative innovation using a large enterprise census in China from 2005 to 2015. Their outcome variables included the total number of collaborative patents between cities, the extensive margin (number of partnerships), the intensive margin (patents per partnership), and patent citations. Their key inde-

pendent variables were a dummy for HSR connection and a continuous variable measuring travel time saved. They combined DID estimation with an instrumental variable (IV) based on the 1934 railway network to address endogeneity. They found that HSR stations significantly increased the number of collaborative patents and partnerships at the city level. Besides, they also found that at the city pair level, the reduced travel time induced by HSR connection increased collaborative patent numbers, partnership numbers, and also the number of patents per partnership. The heterogeneity analysis further showed that the effects were more significant for the western region of China, the service sector, and domestic private enterprises. A heterogeneous effect across space also exists, where HSR was most effective for collaborations within a distance of 200 kilometers.

Inoue et al. (2017) offered evidence from Japan, focusing on the opening of the Nagano Shinkansen line. Their study period covered 1993 to 2008, focusing on the 1997 opening. They measured innovation using patent applications, citations per patent, and impacts per patent at the establishment level. Their key independent variable was a treatment dummy based on proximity to new stations (within a 30 km radius from Nagano Shinkansen line stations) interacted with a post treatment time dummy. They found that establishments along the new line significantly increased both the quantity and quality of their innovation. The authors identified two distinct mechanisms: collaboration, which relies on tacit knowledge and face-to-face interaction, and patent citations, which represent codified knowledge flows from Tokyo.

Gao and Zheng (2020) utilized a unique dataset of three waves of innovation surveys (2006, 2010, 2014) from manufacturing firms in the Yangtze River Delta and Pearl River Delta in China. They targeted "above-scale" manufacturing firms, i.e., those with sales incomes of above 5 million RMB before 2011 and 20 million RMB thereafter. Their outcome variables were binary indicators for the existence of product innovation, process innovation, and the scope of innovation. The key independent variable was the HSR connection status of the county. They employed a DID method combined with an IV approach using a straight

line strategy, which constructed a hypothetical HSR network based on the shortest distance between large cities. Their results showed that HSR promoted firm innovation, particularly the scope of innovation and new product development. They identified three specific mechanisms: HSR aroused entrepreneurs' recognition of the importance of innovation, opened new sources for innovation (such as cooperation with colleges and usage of internal R&D inputs), and created market size effects that encouraged marketing and branding. In terms of heterogeneity, they found the effects were stronger for firms in the Yangtze River Delta (specifically Zhejiang province) than in the Pearl River Delta and that the benefits increased over time.

Wang et al. (2022) examined whether HSR stimulates cross-city technological innovation collaboration, using data from 2000 to 2016 in China. The outcome variable was the intensity of cross-city R&D collaboration, defined as the number of co-developed patents involving inventors from different cities. They also combined the DID model with an instrumental variable based on the 1961 railway network. The key results showed that HSR services significantly increase the number of co-developed patents. Regarding the mechanism, the paper highlighted that reduced travel time facilitates face-to-face interaction, which is essential for sharing knowledge. In terms of heterogeneity, the study found that megacities benefit the most. Secondary cities also benefit, but primarily through their connections to megacities. The effect decays as travel time increases, with the strongest effects seen within short travel times.

Providing a long-term perspective from Japan, Komikado et al. (2021) investigated the link between accessibility and regional innovation. Using data between 1981 and 2014 and deriving from a regional knowledge productivity function, they studies if HSR station existence and HSR-induced accessibility made any changes to the number of patent applications per employee. The key results showed that the existence of HSR stations has a positive and significant association with knowledge productivity. Regarding the mechanism, the authors suggested that HSR facilitates employee communication and face-to-face interaction, which

are vital for knowledge spillover. In terms of heterogeneity, they found a significant interaction effect: HSR stations had a positive association with innovation primarily in regions with lower effective density (peripheral areas), suggesting HSR can help smaller regions overcome disadvantages. They also found that the agglomeration of the finance industry positively associates with innovation.

Impact mechanisms. Several consistent mechanisms emerge from the literature review regarding how HSR exerts influence on innovation.

First, factor mobility and agglomeration are dominant channels through which HSR influences innovation. Lu et al. (2022), Huang and Wang (2020), Du et al. (2020) and Li et al. (2022) all emphasize that HSR allows for the physical movement of innovation inputs, specifically high-skilled labor and capital, across connected cities. This mobility leads to agglomeration economies where firms and talent cluster in favored environments, fostering a fertile environment for innovation. The influence of HSR on labor movement and talent flows has also been examined and verified by other empirical studies, such as Dong et al. (2020), DU and PENG (2017), and X. Zhang et al. (2020). HSR connection reduces the search cost of migrants and expands destination options. The increased labor flow could influence technology flow in two ways: migrants bring knowledge about new technologies from their origin to the destination cities; new talents increase the absorptive capability of destination cities for new knowledge and technologies

Second, face-to-face interaction and knowledge spillovers are also critical. Hanley et al. (2022), Inoue et al. (2017), and Bhatt and Kato (2021) argue that while information and communication technology facilitate the exchange of codified knowledge, tacit knowledge still requires personal interaction. HSR reduces the cost of travel, enabling frequent meetings, collaborative research, and participation in academic conferences.

Third, access to external resources plays a vital role. Hou (2022) and Gao and Zheng (2020) highlight that HSR allows firms in smaller or peripheral cities to access resources located in major hubs, such as universities, research institutes, and specialized producer

services. This access allows firms to innovate without necessarily being located in a mega city.

Fourth, organizational changes within firms drive innovation. Guo et al. (2021) provide a novel mechanism showing that HSR allows firms to hire a more diverse executive team from a wider geographic area. This diversity in leadership brings different perspectives that enhance corporate creativity and innovation strategy. Gao and Zheng (2020) also showed that HSR increased the awareness of entrepreneurs towards innovation.

Finally, market size effects are crucial for innovation output, based on findings by Gao and Zheng (2020). By connecting to a larger market via HSR, firms are incentivized to improve products and processes to compete effectively and satisfy a broader customer base.

Research gaps. Despite a surging amount of emprical studies that examine the influence of HSR on innovation activies and performance in different contexts, current studies ignore the influence of transportation infrastructure on a dynamic process of innovation activities: what role does increased inter-regional accessibility play in the story of the creative destruction, where existing technologies are outdated by the new ones? An exception is a Chinese study by Yu et al. (2019), which studied the infleunce of HSR openning on the number of invalid patents between 2008 and 2013. I expand the study period to 2002 and 2019, explicitly focus on the patent lapse due to annual payment and investigate the potential channels. This question is crucial to understand the full picture of how transportation infrastructure shapes the technology development and economic growth, given the importance of obsolescence in the Schumpeterian growth model (Aghion et al., 2014). The next section reviews existing studies concerning technology obsolescence and measurement.

2.2 Technology Obsolescence and Technology life cycle

While technology obsolescence is a crucial building block in the Schumpeterian growth model, it has received relatively fewer attention from empirical research compared to its counterpart, creation of new technologies. Technology lifecycle evolves from emergence to maturity,

and finally to obsolescence. The "obsolescence" stage is not merely the end of a cycle but a measurable rate of decay that varies by industry and is driven by the arrival of rival innovations and the exhaustion of technological opportunity. Existing literature has used patent data to quantify and identify different stages of the technology lifecycle. For instance, Lin et al. (2021) utilized patent application and applicant data to quantitatively identify the distinct stages of a technology life cycle based on the technological entropy of patent distributions. Huang et al. (2021) and Huang et al. (2022) introduce a dynamic perspective using patent citation networks. Huang et al. (2021) propose a framework for identifying technology evolution pathways by analyzing the connectivity and modularity of citation networks. Huang et al. (2022) refine this by explicitly modeling the technology life cycle based on the structural evolution of these networks. Based on a dataset of 387 US patents, Haupt et al. (2007) combined multiple indicators of patents, such as backward citations, claim counts, and examination duration, to distinguish technology life cycle stages.

Patent renewal as an economic indicator. In particular, patent renewal data has been widely used in the literature as a proxy for measuring technology obsolescence and the private value of innovations.

The foundational framework for using patent renewals as an economic indicator is established by Pakes and Schankerman (1979) and Pakes (1986). The core premise is that a patent holder must pay periodic renewal fees to keep a patent in force. Rational agents will only pay these fees if the expected future returns (i.e., current benefit from patent rights plus the future value of patent renewal option) exceed the cost of renewal. Therefore, a patent that is renewed is revealed to be more valuable than the renewal fee, while a lapsed patent is revealed to be worth less. Pakes and Schankerman (1979) use this logic to estimate the rate of obsolescence of knowledge capital. They find that the rate of decay in appropriable revenues from knowledge is significantly higher than the physical depreciation of capital. This high decay rate is driven by the difficulty of appropriating benefits and the displacement of old innovations by new ones. It has paved the way for subsequent studies to use patent renewal

data as a proxy for technology obsolescence and innovation value, such as G. Zhang et al. (2014) and Gupeng and Xiangdong (2012) for China, Bessen (2008) and Hughes (2024) for the US, Baudry and Dumont (2006), Deng (2011) and Deng (2007) for the EU, Danish et al. (2020) for India, and Lanjouw et al. (1998) for multiple regions.

Determinants of patent renewal behavior. Existing studies have identified several key factors that influence patent renewal decisions, including internal factors related to patent characteristics and external factors related to market and technological environment.

Deng (2011) develops a dynamic stochastic model to examine the joint decision of patent application and renewal. Estimating the model with an EPO dataset for pharmaceutical and electronics patents applied for between 1980 and 1985, the results show that these decisions are correlated: high-value inventions are filed in more countries and renewed for longer periods. However, there also exists a paradox: pharmaceutical patents have larger families but shorter lives compared to electronics patents. This suggests that "value" has different dimensions—initial returns vs. longevity. Pharmaceutical patents have high initial returns but become obsolete quickly, whereas electronics patents may have lower initial returns but longer strategic value.

Using a dataset of granted priority patents from five major source countries covering the period from 1982 to 2012, Kabore and Park (2019) studied if family size, that is, the number of countries in which a patent is filed, influences patent lifespan. The authors argued that inventors tend to seek wider international coverage for patents they deem more valuable. The key results show that the GDP weighted family size increases the patent life, with a higher prediction accuracy compared to alternative measurements, such as simple family size or forward citations.

Maurseth and Svensson (2020) proposes a nuanced view of patent citations. Conventionally, forward citations are usually viewed as indicators of quality and knowledge spillovers, correlating with higher value and therefore longer patent life. However, using Norway patent data from 1980 to 1994 and citation data from the European Patent Office from 1979 to

1996. The research showed that while citations across technology fields correlate with longer survival, citations within the same technology field correlate with shorter survival. On one hand, citations can indicate a technological breakthrough and high quality, which implies a positive relationship with patent survival. On the other hand, citations may represent knowledge spillovers to competitors. This supports the creative destruction hypothesis.

Liu (2014) shifts the focus from the patent document to the inventors. Using patents granted between 1990 and 2004 to 284 public pharmaceutical firms in the US, the research found that patents created by "star inventors" and larger, geographically dispersed teams are significantly more likely to be renewed at the fourth year. The positive impact of star inventors on patent renewal is attributed to the tacit knowledge and legitimacy they bring. Their presence signals high quality and legitimacy to the firm's decision-makers, who must decide which patents to maintain under conditions of uncertainty. As for the impact of the co-inventor number, larger teams allow for the pooling of complementary knowledge. Furthermore, knowledge created by a larger team is more "socially embedded" within the firm. This makes the knowledge harder for competitors to appropriate, even when attrition happens, and therefore increases the firm's ability to protect the value of the patent. The strength of cross-location collaboration allows the firm to recombine unique, location-specific knowledge. It also makes the invention team harder for competitors to "poach" in its entirety, thereby strengthening the firm's ability to protect the patent's private value.

Liu et al. (2008) drew upon evolutionary economics to propose that innovations are often cumulative and path-dependent and challenged the common assumption in existing literature that a firm's patents are independent assets. They investigated the impact of interrelatedness among a firm's patents on patent renewal decisions, using pharmaceutical and biotechnology patents granted between 1990 and 1993 in the US. The authors introduced the concept of "internal sequential innovations", defined as a sequence of innovations that build upon the same underlying technological path. Unlike stand-alone innovations, these patents are mutually dependent; they define and extend a specific existing technology. The results showed

that being part of a patent sequence significantly increases the likelihood of a patent being renewed, and firms that maintain a larger percentage of internal sequential innovations tend to renew a higher percentage of their patents.

Lee and Sohn (2017) investigated whether military technologies with applicability in both military and civilian sectors, defined as "dual-use" capabilities by the authors, are more valuable than those strictly limited to military use. The authors use patent renewal data as a proxy for technology value. The authors analyzed military patents granted by the USPTO between 1976 and 2014, specifically those classified under IPC codes F41 (Weapons) and F42 (Ammunition). They measured the "dual-use" capabilities of these patents with three indexes: (1) whether the patent contains IPC codes other than F41/F42, indicating direct applicability in civilian sectors; (2) the degree centrality of the IPC co-occurrence network to reflect the convergence with other technology fields; (3) and the ratio of forward citations coming from civilian sectors versus total forward citations. Using logistic regression, the study found that the military patents that included non-military (civilian) IPC codes were significantly more likely to be renewed, and similarly, patents that converged with many different fields were also more likely to be renewed.

Other than the internal characteristics of patents, the intellectual property system, the external market, and the technological environment also influence patent renewal decisions.

Thompson (2017) empirically investigated patentee sensitivity to renewal fees. Using a dataset covering 46 countries over the period 1980–2013, the study employed multiple models, including logit regression, Poisson regression, and Cox proportional hazard model, to estimate the impact of renewal fee changes on patent renewal behavior. The analysis revealed statistically significant yet small changes in patent renewal rates in response to fee adjustments. The average elasticity is estimated to be around 0.10 (10%). This means that a 10% increase in fees results in only a 1% decrease in the likelihood of renewal. Nonetheless, while sensitivity is low at average fee levels, patentees become increasingly sensitive as the total fee burden rises.

The impact mechanism of patent fees might be complicated by the sequential innovations and the firm's portfolio management strategy. Kim (2015) investigated how firms manage their patent portfolios regarding sequential inventions. Firms do not view patents in isolation, but manage them as bundles of sequential inventions. If inventions are complements, a firm is more likely to renew older patents to protect the value of newer ones. If they are substitutes, a new invention might cannibalize the old one, leading to the abandonment of the earlier patent. Using a database of US patents filed between 1981 and 1991 and renewed up to 1996, the research studies how application fees and renewal fees influence the renewal decisions of sequential patents. As expected, a higher renewal fee reduces the likelihood of renewal. However, it also found evidence that higher filing fees lower the renewal probability of existing patents. It supports a theory that sequential inventions within a firm are largely complementary: firms are less likely to maintain old patents if they cannot afford (or choose not) to patent the new inventions that add value to the portfolio.

Bosworth and Jobome (2003) investigated the impact of market competition on patent renewal behavior. The authors utilize a dataset of United Kingdom patent renewal information, covering patent cohorts granted from 1950 to 1975, with renewal data extending through 1991. The study constructed a hazard rate for each patent cohort at each year, and investigated how it responded to subsequent granted patents, which proxied the market competition faced by the patent. The analysis found that competition from subsequent patents tended to increase the hazard rate. Additionally, the study also finds that higher renewal fees led to higher hazard rates.

3 Theory and Mechanisms

The decision to renew a patent is a financial option exercise. At each anniversary date, the patentee pays a statutory fee to maintain the right to monopoly rents for one additional period, or allows the patent to lapse permanently. Since Pakes (1986), the revealed-preference

content of this binary choice has served as the primary empirical strategy for inferring the distribution of patent values from observed renewal survival curves. Subsequent contributions enriched the framework with litigation risk (Lanjouw et al., 1998), international portfolio decisions (Deng, 2011), heterogeneous patent-specific depreciation (Bessen, 2008; Hughes, 2024), Schumpeterian obsolescence (Aghion & Howitt, 1992), and oligopolistic market structure (G. Zhang et al., 2014).

A dimension consistently absent from this literature is space. Existing models treat the patentee as a representative agent operating in a single, frictionless market. In practice, patentees occupy geographically differentiated locations, sell into markets at varying transport costs, absorb knowledge from spatially dispersed research communities, and compete with imitators whose entry cost depends on the transportation network connecting their home region to the patentee's market. The quantitative spatial economics literature, in particular Allen and Arkolakis (2025), Akcigit and Melitz (2022), Berkes et al. (2025), and Cai et al. (2022), has established that transportation infrastructure systematically reorganizes trade, knowledge diffusion, and the geography of innovation. The patent renewal decision sits at the intersection of the two streams of literature.

This section builds a spatial patent renewal model by grafting four channels onto the Pakes (1986) and Bessen (2008) backbone. The key task of this section is to identify the spatial renewal threshold: the minimum Cournot-adjusted rent at which renewal is optimal. A transportation improvement, modeled as an increase in location n's market access $\mathcal{A}_n$, shifts this threshold through each channel simultaneously. I derive first-order conditions that characterize the direction and relative magnitude of each channel, clarify which channels are complementary and which are opposing, and identify the conditions under which the net effect on renewal propensity is positive or negative.

3.1 The Baseline Aspatial Framework

Consider a discrete-time model indexed by patent age $t = 0, 1, \ldots, T$, where T is the statutory maximum patent life. A patent is applied at $t = 0$. The following setting is applied to cater to the reality: at the beginning of each subsequent period $t \geq 1$, the patentee decides whether to pay a non-refundable renewal fee $c_t > 0$ to maintain the patent for one additional period, or to allow it to lapse permanently; lapsing is irreversible, therefore once abandoned, the patent cannot be reinstated.

Let $R_t \geq 0$ denote the per-period monopoly rent accruing to the patent at age t. The patentee's problem generates a value function $V(t, R_t)$ satisfying the Pakes (1986) Bellman equation:

$$V(t, R_t) = \max\{0,\ R_t - c_t + \beta\ \mathbb{E}_t[V(t+1, R_{t+1})]\}\,, \tag{1}$$

where c_t is the renewal cost, $\mathbb{E}_t[V(t+1, R_{t+1})]$ is the expected rent from the future $t+1$ if the patentees choose to maintain the patents at t, and $\beta \in (0, 1)$ is the discount factor and the expectation is taken over the stochastic transition of R_t.

Following Pakes (1986), the rent R_t follows a first-order Markov process:

$$R_{t+1} = \begin{cases} 0 & \text{with probability } 1 - \vartheta, \\ \tilde{R}_{t+1} \sim F(\cdot \mid R_t) & \text{with probability } \vartheta, \end{cases} \tag{2}$$

where $1-\vartheta$ is the per-period probability that the innovation is rendered permanently obsolete by a superior competing technology, and $F(\cdot \mid R_t)$ is the conditional distribution of positive rents given survival and current rent level R_t. The initial rent R_0 is drawn from a lognormal distribution, $\ln R_0 \sim \mathcal{N}(\mu, \sigma^2)$, which generates the right-skewed patent value distributions documented universally in the empirical literature (Bessen, 2008; Hughes, 2024; Pakes, 1986).

Define the continuation value. Using eq. (2) and the fact that $V(t+1, 0) = 0$ (a patent

with zero rent is never worth renewing):

$$W(t, R_t) \;\equiv\; \beta\, \mathbb{E}_t[V(t+1, R_{t+1})] \;=\; \beta\, \vartheta\, \mathbb{E}\Big[V(t+1, \tilde{R}_{t+1}) \mid R_t\Big], \tag{3}$$

where the second equality expands the mixture in (2): with probability $1-\vartheta$ the patent is obsolete and contributes zero value, so only the survival event matters. The Bellman equation (1) implies a *renewal threshold* $\bar{R}_t$ such that the patentee renews if and only if $R_t \geq \bar{R}_t$:

$$R_t \;\geq\; \bar{R}_t \;\equiv\; c_t - W(t, R_t). \tag{4}$$

The threshold is decreasing in W: a higher expected future value lowers $\bar{R}_t$ and broadens the set of rent realisations for which renewal is optimal. That suggests that a patent holder might be willing to maintain a patent with a lower current rent if the option value of future renewal is high.

For tractability, I adopt the Bessen (2008) parameterization as the special case of the Pakes max process. Under this approximation, the rent follows deterministic exponential decay:

$$R_t \;=\; R_0\, e^{-d\, t}, \qquad d > 0, \tag{5}$$

where the composite decay rate d absorbs both technological depreciation and obsolescence risk. In Pakes (1986), the two are structurally distinct: obsolescence is a sudden, permanent drop to zero with probability $1-\vartheta$ each period, while depreciation is a gradual erosion of a positive rent. The composite representation is exact under the linearisation $V(t+1, r) \approx r$ that this paper maintains throughout: since $\mathbb{E}[R_{t+1} \mid R_t] = \vartheta\, e^{-d}\, R_t$ and linearity makes the continuation value reduce to $\beta\vartheta e^{-d} R_t$, the two parameters ϑ and d enter only through their product $\tilde{\rho} = \vartheta e^{-d}$ and are not separately identified from renewal decisions alone. The patentee renews at age t iff $R_0\, e^{-d\, t} \geq \bar{R}_t$.

The rent R_t in the baseline model is the sufficient statistic for the renewal decision. The four spatial mechanisms developed below shift the renewal decision by modifying: (a) the

initial rent level R_0; (b) the carry-forward rate $\rho = e^{-d}$; (c) the option value embedded in the continuation value $W(t, R_t)$ via multi-market discovery; or (d) the mapping between monopoly rents and the patentee's effective income via competitive market structure.

3.2 Spatial Environment

The economy consists of N discrete locations indexed by $n, m \in \mathcal{N} = \{1, ..., N\}$. Bilateral trade between any two locations is subject to iceberg trade costs $\tau_{nm} \geq 1$, with $\tau_{nn} = 1$. The cost τ_{nm} captures all transport frictions: shipping costs, time-in-transit, and logistics barriers. A transportation improvement between n and m is modelled as a reduction in τ_{nm}.

Definition 1 (Market Access) *The* market access *of location n is:*

$$\mathcal{A}_n \equiv \sum_{m \in \mathcal{N}} \tau_{nm}^{-\theta} Y_m, \tag{6}$$

where Y_m is total income (expenditure) at location m and $\theta > 1$ is the trade elasticity. $\mathcal{A}_n$ is strictly decreasing in each bilateral cost τ_{nm} for $m \neq n$.

Definition 2 (Knowledge Access) *The* knowledge access *of location n is:*

$$K_n \equiv \sum_{m \in \mathcal{N}} \tau_{nm}^{-\delta} \phi_m, \tag{7}$$

where $\phi_m \geq 0$ is the R&D intensity (R&D input or density of active innovators) at location m and $\delta > 0$ governs the spatial decay of knowledge spillovers.

Both $\mathcal{A}_n$ and K_n are decreasing in bilateral trade costs but weight destination characteristics differently: $\mathcal{A}_n$ weights demand (income Y_m) while K_n weights supply-side technological activity (ϕ_m). A transportation improvement raises both simultaneously, but the magnitudes could differ by the economic composition of the surrounding region.

To aggregate bilateral cost reductions into a scalar measure, I define the transportation accessibility index:

$$\mathcal{T}_n \equiv \ln \mathcal{A}_n = \ln\left(\sum_{m\in\mathcal{N}} \tau_{nm}^{-\theta} Y_m\right). \tag{8}$$

A transportation improvement, mainly HSR as a railway upgrade in this study, is modelled as an increase in $\mathcal{T}_n$. Because $d\mathcal{A}_n = \mathcal{A}_n\, d\mathcal{T}_n$, derivatives with respect to $\mathcal{T}_n$ and $\mathcal{A}_n$ are related by the factor $\mathcal{A}_n$. All mechanisms in Section 3.5 are expressed as derivatives with respect to both $\mathcal{T}_n$ and $\mathcal{A}_n$ to maintain comparability with the empirical spatial literature.

3.3 Four Spatial Channels

The four channels through which the spatial environment enters the patent renewal decision differ in both their theoretical lineage and the margin of the Bellman equation on which they act. Channel 1 is a product-market expansion effect rooted in the constant elasticity of substitution (CES) monopolistic-competition framework of Allen and Arkolakis (2025): better market access raises the initial condition $R^{\mathrm{M}}_{i,n,0}$ of the rent process. Channel 2 is Schumpeterian: following Aghion and Howitt (1992), the rivals here are innovators who displace the technology itself, shrinking the carry-forward factor $\rho_{i,n}$ and acting on the state transition of the Bellman equation. Channel 3 is an option-value mechanism: the patentee's multi-market search increases the identification chance of new applications in new markets, raising the continuation value. Channel 4 is a Marshallian oligopoly competition following G. Zhang et al. (2014): the rivals are producers who share the same product market, compressing the flow payoff each period. Channels 2 and 4 are both forms of competitive pressure, but they act on different objects: Channel 2 erodes the asset by making the underlying technology obsolete faster, while Channel 4 taxes the income stream from it each period without displacing the technology. A patent can exhibit strong Schumpeterian obsolescence with negligible product-market rivalry, or face intense Cournot competition with a technology that remains fully relevant.

3.3.1 Channel 1: Market Access and Initial Rent Level

In a standard CES monopolistic competition framework (Allen & Arkolakis, 2025), a patentee at location n holds a patent on an innovation with quality index $q_i > 0$. Serving market m at delivered price $\tau_{nm} p_i$ generates profit:

$$\pi_{i,n,m} \;=\; \frac{1}{\sigma}\left(\frac{\tau_{nm}^{-1}\, p_i^{-1}}{P_m}\right)^{\sigma-1} Y_m, \tag{9}$$

where $\sigma > 1$ is the elasticity of substitution and P_m is the CES price index at m. Summing over all locations and absorbing equilibrium price-index terms into the constant $\kappa > 0$, the initial per-period monopoly rent is:

$$R^{\mathrm{M}}_{i,n,0} \;=\; \kappa\, q_i \sum_{m\in\mathcal{N}} \tau_{nm}^{1-\sigma} Y_m \;=\; \kappa\, q_i\, \mathcal{A}_n, \tag{10}$$

where the last equality uses $\theta = \sigma - 1$ in Definition 1.

Assumption 1 *The initial rent satisfies $R^{\mathrm{M}}_{i,n,0} = \kappa\, q_i\, \mathcal{A}_n$, where $\kappa > 0$ is a technology-class constant and $q_i > 0$ is a patent quality index with $\ln q_i \sim \mathcal{N}(\mu_q, \sigma_q^2)$.*

The Akcigit and Melitz (2022) framework reinforces this channel: in a quality-ladder trade model, the expected value of an innovation equals monopoly profit times effective market size, and trade liberalization raises that product by expanding the market accessible to successful innovators. Exporting and international patenting are strategic complements under this mechanism (Deng, 2011): a firm with better transportation access has stronger incentives to both export and to maintain multi-jurisdiction patent protection.

3.3.2 Channel 2: Knowledge Spillovers and the Depreciation Rate

In Aghion and Howitt (1992), the arrival rate of creative destruction equals the Poisson intensity of R&D effort directed at the incumbent technology. A patentee at a well-connected

location faces faster inward diffusion of competing innovations: knowledge of superior technologies travels more cheaply across a well-integrated network, raising the effective rate at which the incumbent innovation is displaced. Berkes et al. (2025) document that technological waves propagate along transportation links, with well-connected locations adopting new technologies several years ahead of isolated ones. This channel borrows structure by Hughes (2024):

Assumption 2 *The patent-specific depreciation rate is affine in knowledge access:*

$$d_{in} \;=\; d_i^0 + \gamma_d \, K_n, \qquad \gamma_d > 0, \tag{11}$$

where $d_i^0 > 0$ is the baseline technology-field depreciation rate and K_n is defined in (7)*.*

Under Assumptions 1–2, the per-period carry-forward factor in the Pakes max process is:

$$\rho_{in} \;\equiv\; e^{-d_{in}} \;=\; e^{-(d_i^0 + \gamma_d K_n)}. \tag{12}$$

The initial condition is $R^{\mathrm{M}}_{in0} = \kappa \, q_i \, \mathcal{A}_n$. In the cross-sectional approximation where no new application ever dominates the carry-forward (i.e., the Bessen special case), the rent at age t follows the deterministic path $\rho_{in}^t R^{\mathrm{M}}_{in0} = \kappa \, q_i \, \mathcal{A}_n \, e^{-(d_i^0 + \gamma_d K_n)\, t}$.

Remark 1 *Knowledge access $K_n = \sum_{m \in \mathcal{N}} \tau_{nm}^{-\delta} \phi_m$ embeds two structurally distinct components: the* access component $\tau_{nm}^{-\delta}$*, which co-moves with market access $\mathcal{A}_n$ when transportation improves, and the* supply component ϕ_m*, the R&D intensity at location m. These respond to different policy levers: an R&D subsidy that raises ϕ_m in neighboring regions increases K_n, accelerating depreciation through Channel 2, without affecting $\mathcal{A}_n$ or the competitor count m_n. Channels 2 and 4 therefore have distinct identifying variation: cross-sectional differences in innovation-environment intensity (e.g. proximity to universities or public research laboratories) shift Schumpeterian obsolescence independently of Cournot competitive pressure.*

3.3.3 Channel 3: Multi-Market Discovery and the Continuation Value

Channel 3 specifies the conditional distribution $F(\cdot \mid R_t)$ from eq. (2). The rent at age $t+1$, conditional on surviving the obsolescence shock, is the maximum of two quantities: the depreciated carry-forward of the current application and a freshly drawn new application discovered through experimentation:

$$R^{\mathrm{M}}_{in,t+1} \;=\; \max(\rho_{in}\, R^{\mathrm{M}}_{int},\; z_{t+1})\,, \tag{13}$$

where $\rho_{in} = e^{-d_{in}} \in (0,1)$ is the location-specific carry-forward factor from Channel 2 (eq. (12)), and z_{t+1} is an independent draw from a fixed distribution $G(\cdot)$ representing the profit potential of the best new use of the technology discovered this period. The max operator is economically substantive: the patentee adopts the new application if and only if it dominates the depreciated incumbent. The discovery of new applications and the quality of the invention are therefore the same economic phenomenon viewed from different angles: a patent that repeatedly yields high z draws is more likely to be perceived as high-quality.

Transportation enters this structure through the breadth of the search space. Without geographic connectivity, the patentee can only experiment locally and in the near neighborhood. With access to M_n distinct markets, the patentee runs M_n experiments per period and adopts the best application found across all of them.

Assumption 3 *(a) The rent process follows the Pakes (1986) max structure in* (13)*, with* $z^m_{t+1} \overset{iid}{\sim} G(\cdot)$ *independently across markets* m *and periods.*

(b) The patentee draws one application candidate from each accessible market $m \in \mathcal{M}_n \equiv \{m : \tau_{nm} \le \bar{\tau}\}$ *per period and adopts the best:*

$$z^{(M_n)}_{t+1} \;\equiv\; \max_{m \in \mathcal{M}_n}\; z^m_{t+1}. \tag{14}$$

(c) The number of accessible markets is $M_n \equiv |\mathcal{M}_n|$*, weakly increasing in* $\mathcal{A}_n$*.*

Under Assumption 3(b), the effective new-application draw is the first-order statistic of M_n independent draws. Its distribution is:

$$\Pr\big(z_{t+1}^{(M_n)} \leq z\big) \;=\; G(z)^{M_n}. \tag{15}$$

Since $G(z) \in [0,1]$, the function $G(z)^{M_n}$ is non-increasing in M_n for every z: the distribution of $z^{(M_n)}$ first-order stochastically dominates G for all $M_n > 1$. More accessible markets raise the expected best application discovered each period.

The spatial rent process and continuation value are now updated to be:

$$R_{in,t+1}^{\mathrm{M}} \;=\; \max\big(\rho_{in}\, R_{int}^{\mathrm{M}},\; z_{t+1}^{(M_n)}\big)\,, \tag{16}$$

$$W_{in}(t, R_{int}^{\mathrm{M}}) \;=\; \beta\,\vartheta\;\mathbb{E}\big[V_{in}\big(t+1,\, \max\big(\rho_{in}\, R_{int}^{\mathrm{M}},\; z^{(M_n)}\big)\big)\big]\,. \tag{17}$$

For tractability, I approximate $V_{in}(t+1, r) \approx r$, which is exact when the patent is always renewed and is standard practice in the quantitative renewal literature (Pakes, 1986). Under this approximation, and using the survival-function representation of the expectation of a non-negative random variable:

$$W_{in}(t, R_{int}^{\mathrm{M}}) \;\approx\; \beta\,\vartheta\left[\rho_{in}\, R_{int}^{\mathrm{M}} + \int_{\rho_{in} R_{int}^{\mathrm{M}}}^{\infty} \big[1 - G(z)^{M_n}\big]\, dz\right]. \tag{18}$$

The first term is the guaranteed carry-forward; the second term is the discovery premium, or the expected gain from finding a new application that exceeds the depreciated existing one.

3.3.4 Channel 4: Market Integration and Competitive Crowding

Transportation integration expands not only the patentee's own market access but also the access of competing firms to the patentee's market. In an oligopolistic product market, the effective number of competitors at location n increases with market integration.

Assumption 4 *The number of Cournot competitors in the product market at location n is affine in market access:*

$$m_n \;=\; m_0 + \alpha_m \, \mathcal{A}_n, \qquad \alpha_m > 0. \tag{19}$$

Under m_n-firm Cournot competition with linear demand, following G. Zhang et al. (2014), the per-period profit accruing to the patentee is:

$$R^{\mathrm{C}}_{int} \;=\; \frac{4}{(m_n+1)^2}\, R^{\mathrm{M}}_{int}, \tag{20}$$

where R^{M}_{int} is the current state variable of the Pakes max process with initial condition $R^{\mathrm{M}}_{in0} = \kappa \, q_i \, \mathcal{A}_n$ and carry-forward factor $\rho_{in} = e^{-d_{in}}$.

The expression $4/(m_n+1)^2$ is the ratio of per-firm Cournot profit to monopoly profit under symmetric linear demand with m_n competitors (total of $m_n + 1$ firms), with normalisation $(a-c)^2/4$. As market integration raises m_n, this ratio falls monotonically:

$$\frac{\partial}{\partial m_n}\left(\frac{4}{(m_n+1)^2}\right) = -\frac{8}{(m_n+1)^3} < 0. \tag{21}$$

Remark 2 *Channels 1 and 4 operate in opposite directions. Channel 1 says that better transportation grows the* total *market pie. Channel 4 says that better transportation also brings more competitors, shrinking each firm's* slice. *The net effect on the patentee's per-period rent depends on whether market expansion outpaces competitive entry, a condition characterised formally in Section 3.5.*

3.4 The Integrated Spatial Renewal Model

Combining Assumptions 1–4, the patent renewal problem for patentee i at location n is:

$$\boxed{V_{in}(t, R^{\mathrm{M}}_{int}) \;=\; \max\!\big\{0,\; R^{\mathrm{C}}_{int} - c_t + \beta\,\vartheta\;\mathbb{E}\big[V_{in}\big(t+1,\, \max\big(\rho_{in}\, R^{\mathrm{M}}_{int},\, z^{(M_n)}\big)\big)\big]\big\}\,,} \tag{22}$$

where the state variable is the current rent R^{M}_{int}, which the patentee observes directly, and the Cournot-adjusted flow rent is:

$$R^{\mathrm{C}}_{int} \;=\; \frac{4}{(m_n+1)^2}\, R^{\mathrm{M}}_{int}, \tag{23}$$

with $m_n = m_0 + \alpha_m \mathcal{A}_n$ and $\rho_{in} = e^{-(d_i^0 + \gamma_d K_n)}$. The max process in (16) governs how R^{M}_{int} evolves; eq. (23) applies the Cournot market-structure adjustment to obtain the period flow payoff.

The patent is renewed at age t iff $R^{\mathrm{C}}_{int} \geq \bar{R}_{int}$, where the *spatial renewal threshold* is:

$$\bar{R}_{int} \;\equiv\; c_t - \beta\,\vartheta\;\mathbb{E}\big[V_{in}\big(t+1, \max\big(\rho_{in}\, R^{\mathrm{M}}_{int},\, z^{(M_n)}\big)\big)\big]\,, \tag{24}$$

equivalently written as:

$$\bar{R}_{int} \;=\; c_t - W_{in}(t, R^{\mathrm{M}}_{int}), \tag{25}$$

where W_{in} is the continuation value from (17). The threshold is decreasing in the continuation value: a higher expected best-discovery next period lowers $\bar{R}_{int}$ and broadens the set of current rent realisations for which renewal is optimal.

Proposition 1 (Discovery Premium) *Under Assumption 3, the continuation value $W_{in}(t, R^{\mathrm{M}}_{int})$ satisfies:*

(i) $W_{in} > \beta\,\vartheta\, V_{in}(t+1, \rho_{in}\, R^{\mathrm{M}}_{int})$ whenever G has positive support above $\rho_{in} R^{\mathrm{M}}_{int}$ (the discovery premium is strictly positive);

(ii) W_{in} is strictly increasing in M_n (the continuation value rises with the number of accessible markets).

Remark 3 *Proposition 1(ii) shows that the option embedded in the continuation value operates through the order statistics of the search process. Transportation expands the number*

of experiments M_n, shifts the distribution of the best new application to the right by first-order stochastic dominance, and thereby raises the continuation value and lowers the renewal threshold. Unlike the competitive-crowding and depreciation channels, the discovery channel unambiguously promotes renewal.

3.5 Mechanisms: How Transportation Impacts Patent Renewal

I now derive the first-order conditions characterising each channel's contribution to patent value and the renewal threshold. The master chain-rule decomposition of the total effect of a transportation improvement $d\mathcal{T}_n > 0$ (equivalently, $d\mathcal{A}_n = \mathcal{A}_n\, d\mathcal{T}_n > 0$) on patent value is:

$$\begin{aligned}\frac{dV_{in}}{d\mathcal{T}_n} \;=\; & \underbrace{\frac{\partial V_{in}}{\partial R^{\mathrm{C}}_{int}} \cdot \frac{\partial R^{\mathrm{C}}_{int}}{\partial \mathcal{A}_n} \cdot \mathcal{A}_n}_{\text{Channel 1: market access}} + \underbrace{\frac{\partial V_{in}}{\partial \rho_{in}} \cdot \frac{\partial \rho_{in}}{\partial K_n} \cdot \frac{\partial K_n}{\partial \mathcal{A}_n} \cdot \mathcal{A}_n}_{\text{Channel 2: carry-forward decay}} \\ & + \underbrace{\frac{\partial W_{in}}{\partial M_n} \cdot \frac{\partial M_n}{\partial \mathcal{A}_n} \cdot \mathcal{A}_n}_{\text{Channel 3: discovery}} + \underbrace{\frac{\partial V_{in}}{\partial m_n} \cdot \frac{\partial m_n}{\partial \mathcal{A}_n} \cdot \mathcal{A}_n}_{\text{Channel 4: competition}}\,. \end{aligned} \tag{26}$$

Each term is now characterised in turn.

3.5.1 Channel 1: Market Access Raises the Initial Rent Level

First-order condition with respect to $\mathcal{A}_n$. From (23), holding m_n and ρ_{in} fixed (isolating the direct rent-scale effect) and using the Bessen approximation $R^{\mathrm{M}}_{int} \approx \kappa q_i \mathcal{A}_n e^{-d_{in}t}$:

$$\left.\frac{\partial R^{\mathrm{C}}_{int}}{\partial \mathcal{A}_n}\right|_{\text{Ch.1}} \;=\; \frac{4}{(m_n+1)^2}\,\kappa\, q_i\, e^{-d_{in}t} \;>\; 0. \tag{27}$$

The Cournot rent is strictly increasing in market access. A unit increase in $\mathcal{A}_n$ raises each period's rent proportionally, which raises the present value of the rent stream and lowers the

renewal threshold:

$$\left.\frac{\partial V_{in}}{\partial \mathcal{A}_n}\right|_{\text{Ch.1}} = \frac{\partial V_{in}}{\partial R^{\text{C}}_{int}} \cdot \left.\frac{\partial R^{\text{C}}_{int}}{\partial \mathcal{A}_n}\right|_{\text{Ch.1}} > 0. \tag{28}$$

Effect on the renewal threshold.

$$\left.\frac{\partial \bar{R}_{int}}{\partial \mathcal{A}_n}\right|_{\text{Ch.1}} = -\frac{\partial W_R}{\partial \mathcal{A}_n} < 0. \tag{29}$$

Higher market access raises future expected rents, raises the continuation value W_R, and thereby *lowers* the renewal threshold — making renewal optimal over a wider set of current rent realisations.

Transportation link.

$$\left.\frac{dV_{in}}{d\mathcal{T}_n}\right|_{\text{Ch.1}} = \frac{\partial V_{in}}{\partial R^{\text{C}}_{int}} \cdot \frac{\partial R^{\text{C}}_{int}}{\partial \mathcal{A}_n} \cdot \mathcal{A}_n > 0. \tag{30}$$

Better transportation raises patent value and renewal propensity through the market access channel.

3.5.2 Channel 2: Knowledge Spillovers Shrink the Carry-Forward

First-order condition with respect to ρ_{in}. From eq. (12), a higher carry-forward factor raises the guaranteed component of the continuation value:

$$\frac{\partial W_{in}}{\partial \rho_{in}} = \beta\,\vartheta\,R^{\text{M}}_{int} > 0 \qquad \Longrightarrow \qquad \frac{\partial V_{in}}{\partial \rho_{in}} > 0. \tag{31}$$

Patent value is strictly increasing in the carry-forward factor: a larger ρ_{in} preserves more of the existing application's value each period.

First-order condition with respect to K_n. From Assumption 2 and eq. (12):

$$\frac{\partial \rho_{in}}{\partial K_n} \;=\; -\gamma_d \, e^{-(d_i^0 + \gamma_d K_n)} \;=\; -\gamma_d \, \rho_{in} \;<\; 0. \tag{32}$$

Higher knowledge access raises d_{in}, which lowers ρ_{in}.

First-order condition with respect to $\mathcal{A}_n$. For proportional improvements ($\delta = \theta$, $\phi_m \propto Y_m$):

$$\frac{\partial K_n}{\partial \mathcal{A}_n} \;=\; \frac{K_n}{\mathcal{A}_n} \;>\; 0. \tag{33}$$

Effect on the renewal threshold.

$$\left.\frac{\partial \bar{R}_{int}}{\partial \mathcal{A}_n}\right|_{\text{Ch.2}} \;=\; -\frac{\partial W_{in}}{\partial \rho_{in}} \cdot (-\gamma_d \, \rho_{in}) \cdot \frac{K_n}{\mathcal{A}_n} \;>\; 0. \tag{34}$$

Higher market access raises K_n, shrinks ρ_{in}, reduces the carry-forward and continuation value, and *raises* the renewal threshold.

Transportation link.

$$\left.\frac{dV_{in}}{d\mathcal{T}_n}\right|_{\text{Ch.2}} \;=\; \frac{\partial V_{in}}{\partial \rho_{in}} \cdot (-\gamma_d \, \rho_{in}) \cdot K_n \;<\; 0. \tag{35}$$

Better transportation accelerates knowledge diffusion, shrinks the carry-forward factor ρ_{in}, and reduces patent value and renewal propensity through the Schumpeterian obsolescence channel.

3.5.3 Channel 3: Multi-Market Discovery Raises the Continuation Value

First-order condition with respect to M_n. From Proposition 1(ii):

$$\frac{\partial W_{in}}{\partial M_n} \;=\; -\beta \, \vartheta \int_{\rho_{in} R_{int}^{\mathrm{M}}}^{\infty} G(z)^{M_n} \ln G(z) \, dz \;>\; 0. \tag{36}$$

The continuation value is strictly increasing in the number of accessible markets. Each additional market provides one more independent candidate application draw; the best among M_n draws first-order stochastically dominates the best among $M_n - 1$ draws, thereby raising the expected maximum and consequently the expected future rent stream.

First-order condition with respect to $\mathcal{A}_n$. From Assumption 3(c):

$$\frac{\partial M_n}{\partial \mathcal{A}_n} > 0. \tag{37}$$

Effect on the renewal threshold. From (25):

$$\frac{\partial \bar{R}_{int}}{\partial M_n} = -\frac{\partial W_{in}}{\partial M_n} < 0. \tag{38}$$

More accessible markets raise the continuation value, which lowers the renewal threshold and makes renewal optimal over a wider set of current rent realisations. This is the direct analogue of Channel 1: just as Channel 1 raises the current rent through market access, Channel 3 raises the *future* rent through the option of discovering better applications in a broader geographic search space.

Transportation link.

$$\left.\frac{dV_{in}}{d\mathcal{T}_n}\right|_{\text{Ch.3}} = \frac{\partial W_{in}}{\partial M_n} \cdot \frac{\partial M_n}{\partial \mathcal{A}_n} \cdot \mathcal{A}_n > 0. \tag{39}$$

Better transportation expands the geographic search space for new profit applications, raises the expected best application discovered each period through an order-statistics effect, raises the continuation value, and lowers the renewal threshold. Channel 3 unambiguously promotes renewal.

3.5.4 Channel 4: Competitive Crowding Reduces Per-Patent Profit

First-order condition with respect to m_n. From Assumption 4:

$$\frac{\partial R^{\mathrm{C}}_{int}}{\partial m_n} \;=\; -\frac{8}{(m_n+1)^3}\, R^{\mathrm{M}}_{int} \;<\; 0. \tag{40}$$

Per-patent Cournot profit is strictly decreasing in the number of competitors.

First-order condition with respect to $\mathcal{A}_n$. From Assumption 4:

$$\frac{\partial m_n}{\partial \mathcal{A}_n} \;=\; \alpha_m \;>\; 0. \tag{41}$$

Net rent effect: Channels 1 and 4 combined. The combined effect of $\mathcal{A}_n$ on Cournot profit isolates the market-expansion effect (Channel 1) from the competitive-crowding effect (Channel 4):

$$\frac{\partial R^{\mathrm{C}}_{int}}{\partial \mathcal{A}_n}\Big|_{\text{Ch.1+4}} \;=\; R^{\mathrm{M}}_{int} \cdot \frac{4}{(m_n+1)^2} \cdot \left[\frac{1}{\mathcal{A}_n} - \frac{2\,\alpha_m}{m_n+1}\right]. \tag{42}$$

The sign of (42) is positive iff $m_n + 1 > 2\,\alpha_m\,\mathcal{A}_n$, i.e., the total number of firms exceeds twice the marginal entry induced by a unit transportation improvement. In competitive markets (m_n large), the market-expansion effect dominates; in concentrated markets with elastic competitive entry (α_m large), the crowding effect dominates.

Effect on the renewal threshold.

$$\frac{\partial \bar{R}_{int}}{\partial \mathcal{A}_n}\bigg|_{\text{Ch.4}} \;=\; -\frac{\partial W_R}{\partial m_n} \cdot \alpha_m \;>\; 0. \tag{43}$$

Market integration raises the effective number of competitors, lowers per-patent future rents, reduces W_R, and raises the renewal threshold.

Transportation link.

$$\left.\frac{dV_{in}}{d\mathcal{T}_n}\right|_{\text{Ch.4}} = \frac{\partial V_{in}}{\partial m_n} \cdot \alpha_m \cdot \mathcal{A}_n < 0. \tag{44}$$

Better transportation attracts additional Cournot competitors into the patentee's market, reducing per-patent rents and lowering renewal propensity through the competitive crowding channel.

3.6 Composite Effect: Net Impact on Renewal Propensity

Assembling all four channels from (26):

$$\begin{aligned}\frac{dV_{in}}{d\mathcal{T}_n} = &\underbrace{\frac{\partial V_{in}}{\partial R^{\text{C}}_{int}} \cdot \frac{\partial R^{\text{C}}_{int}}{\partial \mathcal{A}_n} \cdot \mathcal{A}_n}_{(+)\text{ market access}} + \underbrace{\frac{\partial V_{in}}{\partial \rho_{in}} \cdot \frac{\partial \rho_{in}}{\partial K_n} \cdot \frac{\partial K_n}{\partial \mathcal{A}_n} \cdot \mathcal{A}_n}_{(-)\text{ carry-forward decay}} \\ &+ \underbrace{\frac{\partial W_{in}}{\partial M_n} \cdot \frac{\partial M_n}{\partial \mathcal{A}_n} \cdot \mathcal{A}_n}_{(+)\text{ discovery}} + \underbrace{\frac{\partial V_{in}}{\partial m_n} \cdot \alpha_m \cdot \mathcal{A}_n}_{(-)\text{ competition}}.\end{aligned} \tag{45}$$

Proposition 2 (Net Effect of Transportation on Renewal) *Channels 1 and 3 (market access and discovery) both unambiguously promote renewal: $dV_{in}/d\mathcal{T}_n|_{\text{Ch.1}} > 0$ and $dV_{in}/d\mathcal{T}_n|_{\text{Ch.3}} > 0$. Channels 2 and 4 (depreciation and competition) unambiguously oppose renewal. Define the net renewal-opposing sensitivity:*

$$\Gamma_n \equiv \gamma_d \frac{K_n}{\mathcal{A}_n} + \frac{2\,\alpha_m}{m_n + 1}. \tag{46}$$

There exists a threshold current rent $\bar{R}^*(\Gamma_n, M_n)$ such that:

(i) For $R^{\text{M}}_{int} > \bar{R}^*$: renewal-promoting channels dominate, $dV_{in}/d\mathcal{T}_n > 0$, and transportation raises renewal propensity.

(ii) For $R^{\text{M}}_{int} < \bar{R}^*$: depreciation and competition channels dominate, $dV_{in}/d\mathcal{T}_n < 0$, and transportation accelerates lapsing.

(iii) $\bar{R}^*$ *is increasing in* Γ_n *and decreasing in* $\partial W_{in}/\partial M_n$*: locations with stronger discovery potential (responsive* M_n*) or weaker opposing forces (low* Γ_n*) exhibit net renewal promotion over a larger portion of the patent value distribution.*

Summary of mechanisms. Table 1 collects the four channels, their structural parameters, the direction of the first-order condition, and the sign of the transportation effect on the renewal threshold.

4 Empirical analysis

4.1 Data

This study has combined different datasets, including patent data, patent citation data, high-speed railway data, firm registration database, national tax survey data, and city statistics data.

Patsnap and Incopat Patent Data. The patent system in China differentiates three types of patents: invention patent, utility patent, and design patent. Design patent focuses on the appliance and aesthetic aspect of products, while invention and utility patents require technological innovation and improvement. Therefore, this study focuses on invention and utility patents. The patent data are sourced from Patsnap and Incopat mainly between June and July 2024, with a minority of data collected in early 2025. I target all inventions and utility patents applied for before the end of 2023 and already published during the time of data collection. The database provides key information about each patent filed with the China National Intellectual Property Administration (CNIPA), including application/publication number, applicant/assignee names, first applicant/assignee address, patent type (i.e., invention or utility), application/publication dates, last legal status, and patent classification. Patents are geocoded to prefecture-level cities based on the address of the first applicant listed on the patent record as the address information of other applicants are

usually unavailable unless they are listed as the single applicant or the first applicant for other patents.

Table 2 shows the comparison between invention patents and utility models based on the Patent Law of the People's Republic of China (2000 Amendment). It shows that the two types of patents differ significantly in terms of protection term, requirements, and examination procedure, with the invention patents receiving a longer protection, yet being much harder to be granted, compared with the utility patents. It also reflects in the 1 that the growth trend of utility patents is much faster than that of invention patents.

To ensure data comprehensiveness, I compare the collected dataset with several official data sources. CNIPA periodically publishes an authority file containing a comprehensive list of publication numbers for all invention and utility patents applied to the office. The latest released authority file by the time of this study includes all patent records published between September 10, 1985, and December 31, 2024 (China National Intellectual Property Administration, 2025). The comparison shows that my dataset includes all the inventions and utility patents applied for before December 31, 2023, and published before December 31, 2024. I also collected patent application counts by different patent types and different applicant countries (CN applicants vs. non-CN applicants) over the year from the "Patent Search and Analysis" system provided by CNIPA. I narrowed the search range to all patents applied to the CNIPA office and published by June 31st, 2024, which corresponds to the earliest data collection time of my dataset. I searched for the number of applications filed for the two types of patents and by different applicants (domestic vs. foreign). Figure 1 visualizes the annual patent application number between 1985 and 2023, where the search results from the "Patent Search and Analysis" system are indicated as the yellow dashed lines and the blue and red lines represent a summary of the analysis dataset. The first thing to notice is the high overlap of the application trend between the analysis dataset and the CNIPA dataset, which suggests that my dataset not only complies with the total application count but also accurately identifies the application year, patent type, and applicant country

of each patent over the year. Nonetheless, one might notice at a second look that there exists an obvious deviation in domestic utility patent counts in 2023. Our data is slightly higher than the CNIPA source. It suggests that my Patsnap dataset includes some 2023 utility patents published after July 1st 2024. It could be explained by the relatively long data collection time and the relatively short time lag between application and publication for utility patents.

Despite the establishment of the patent system in the mid-1980s, the application number remains relatively low between 1985 and 2000. During this period, the country was undergoing significant reform and had just begun efforts to encourage greater innovation and technological activity. China joined the World Intellectual Property Organization (WIPO) in 1980, and the Paris Convention for the Protection of Industrial Property in 1985 when its patent law came into effect. In 1994 it became part of the global Patent Cooperation Treaty (PCT), integrating into the global IP system. In the 1990s, China was negotiating WTO entry. The TRIPS Agreement set IP standards that China had to meet, prompting legal changes and government efforts for innovation and intellectual property protection.

The amendment of patent law in 2000 has further strengthened intellectual property protection to prepare China for joining the WTO in 2001, since which both domestic and foreign patents began to climb in the application numbers. China's 2001 WTO accession was a turning point. The 2000 amendment of the Patent Law codified TRIPS compliance, and after 2001 Chinese firms began prioritizing innovation. In 2008, China also announced a National IP Strategy, signaling a stable policy commitment to IP as part of an innovation-driven economy. During this decade, the State Intellectual Property Office (replaced by the CNIPA in 2018) modernized its examination process, raised patentability standards, and encouraged domestic firms to patent.

Between 2010 and 2020, the yearly numbers skyrocketed, especially those of domestic applicants. Successive Five-Year Plans and "Made in China 2025" emphasized home-grown technology, biotech, AI, green tech, etc. The government launched mass R&D programs, such

as national laboratories and high-tech industry funds, and encouraged firms to develop core technologies. Patent filings continued their rapid rise under these conditions. At the same time, the priority of the patent system was shifting from increasing quantity to enhancing innovative quality. CNIPA began campaigns to curb abnormal or irregular patents. Beijing, Shanghai, and Guangzhou specialized IP courts opened in 2014, followed by IP tribunals around China.

After 2020, the application count for utility patents has dropped sharply, and the increasing trend of invention patent applications was also halted and fluctuated around 1.5 million yearly. There might be multiple possible reasons. First and foremost, it might be attributed to the right truncation problem: not all applications applied for in this period are published by the time of data collection. Second, Covid-19 pandemic has struck the world unexpectedly, causing major hurdles to research and development activities and also the patent system. Hence, the patent application drop might be due to the negative impact of Covid-19 pandemic and related restriction policies. Third, the negative effects of the rising trade tensions between China and the US might start to manifest. While the trade friction prompted China to double down on tech self-reliance (e.g., dual-circulation strategy from 2019), it inevitably imposed an undesired impact on talent mobility and knowledge diffusion, disrupting innovation activities. Finally, it could also be the result of a decade-long effort of shifting focus from sheer quantity to innovative quality.

Over the long term, it's observed that among foreign applications, invention patents dominate compared to utility patents. In contrast, domestic applicants file more utility patents, instead of invention patents.

Figure 2 shows the annual application trend decomposed by the nature of patent applicants. The data reveals a dramatic transformation in the composition of Chinese innovation, characterized by the explosive growth of corporate patenting and the divergence between high-value inventions and utility models.

The most striking feature across both charts is the exponential rise of Firms (orange line)

as the dominant engine of patent production, based on the primary Y-axis of both plots. For the first two decades (1985–2005), firm applications remained low in both invention patents (2a) and utility patents (2b), hovering near zero alongside other groups. However, starting around 2005, coinciding with China's accession to the WTO and subsequent indigenous innovation policies, firm applications began a steep ascent. By 2015, firms had decisively decoupled from other groups, becoming the undisputed leaders in invention applications. The dominance of firms is even more pronounced for the utility patents. The volume of utility patent applications from firms skyrocketed after 2010, reaching peaks far exceeding invention patents. This reflects a "quantity-heavy" strategy often employed by Chinese manufacturing firms to protect incremental improvements and design tweaks rapidly. The secondary Y-axis (right side) tracks the Percentage of Firm Patents, offering a normalized view of this dominance. In the early years (between 1985 and 1995), firms accounted for a minority share (around 25%) of applications, indicating that early Chinese innovation was driven largely by individuals or state institutes. A structural break occurs around 2000. From this point onward, the firm's share climbs steadily, eventually exceeding 75% for both patent types by the end of the period. This suggests a shift from individual or academic institutes to more commercial-oriented, corporate R&D.

Universities and Research Institutes (green line) show steady but much more gradual growth. For invention patents, they maintain a solid second place, reflecting their role in fundamental research. Their growth is more or less linear rather than exponential, suggesting potential issues of capacity constraints (e.g., number of researchers) and a lack of motivation to seek protection for commercialization, which firms usually do not face. On the other hand, for utility patents, their participation is notably lower. This aligns with academic incentives: universities prioritize high-novelty invention patents for academic prestige and ranking, whereas utility models offer less academic credit.

Finally, Individual Applicants (blue line) exhibit a volatile and distinct trajectory, particularly in Utility Patents. While the number of invention patents per individual application

grew until roughly the late 2010s, it has since declined sharply. This drop is likely a response to policy changes by a series of national policies aimed at curbing "junk patents", reducing subsidies for low-quality individual applications, and the Covid-19 pandemic.

The growing gap between the number of firm-applied patents and others underscores the industrialization of innovation. Particularly, the gap is getting significantly wider for utility patents, suggesting that they are no longer the domain of the "garage inventor" but are strategic tools for mass-manufacturing enterprises.

High Speed Railway Data. The high-speed railway data was collected from Wikipedia, including station coordinates, construction/open date, and design/operation speed. The dataset is then cross-checked with Davis et al. (2025)'s database. Figure 3 maps the spatial distribution of high-speed railway stations across China. High-speed railway lines are defined as: (1) railway lines with an operation speed of at least 250 km/h, represented as red dots in Figure 3; (2) or intercity passenger-dedicated lines running at 200 km/h or above, represented as green dots in Figure 3.

City Statistics Data. The city-level data are drawn from China's City Statistics Yearbooks, published yearly by the National Bureau of Statistics of China. The dataset includes key socio-economic indicators for all prefecture-level cities in China, including GDP, population, industrial structure, FDI inflow, R&D expenditure, number of R&D personnel, education level, etc. It provides macro-level measurements of city economic development and innovation capacity.

4.2 Impact of Transportation Infrastructure: City Level

To understand the causal influence of transportation connection to technology obsolescence, the analysis first recovers the average treatment effect on the treated (ATT) at the city level. The ATT answers the question: What is the average causal effect of HSR connection on technology obsolescence among cities connected in the HSR network? As A. Baker et al. (2025) shows, under certain assumptions, including no anticipation, (conditional) parallel

trend and common support assumptions, the Difference-in-Differences (DiD) design yields the sample estimates for the ATT parameter. Equation 47 demonstrates the group-time average treatment effect for staggered intervention effect:

$$ATT(g,t) = \mathbb{E}[Y_{i,t}(g) - Y_{i,t}(\infty)|G_i = g] \tag{47}$$

where i denotes an individual city and t denotes time, which is the year in this study. G is a set of treatment happening times, indexed by g. $Y_{i,t}(g)$ is the potential outcome variable for individual city i at year t if the treatment happens at year g, and $Y_{i,t}(\infty)$ is the potential outcome variable if treatment never happens, i.e., the city belongs to the control group. $ATT(g,t)$ measures the treatment effect of the policy at year t for all cities treated at year g.

Equation 48 aggregates the group-time average treatment effect.

$$ATT_{agg} = \sum_{g,t} w_{g,t} ATT(g,t) \tag{48}$$

Given the staggered roll-out of HSR connection, I consider three estimators for the ATT parameter: Two-Way Fixed-Effect (TWFE) estimator, doubly robust estimator and interaction weighted estimator (A. C. Baker et al., 2022). The baseline model adopts the TWFE Difference-in-Differences specification, as shown in equation 49.

$$y_{i,t} = \beta_0 + \beta_1^{TWFE} HSR_{i,t} + X_{i,t}B + \eta_i + \theta_t + \xi_i\theta_t + \epsilon \tag{49}$$

$y_{i,t}$ is measurement for technology obsolescence. This study mainly uses the number of lapsed patents to measure technology obsolescence. η_i and θ_t denote city and year fixed effects, respectively, and $\xi_i\theta_t$ controls for the interaction between province and year fixed effects. $HSR_{i,t}$ is the independent variable of interest, equal to one if unit i is connected to the national HSR network in time t. The model also includes a list of city-level covariates

$X_{i,t}$ to control for other factors that may affect technology obsolescence, such as economic development, education level, research input, and intellectual property protection, etc. β_1^{TWFE} is the TWFE coefficient.

Nonetheless, recent developments in DiD research design show that the TWFE estimator is prone to mis-specification and bias under staggered policy intervention. As discussed by Goodman-Bacon (2021), the TWFE estimator includes "forbidden comparison", where the later-treated group is compared with the earlier-treater group. Besides, L. Sun and Abraham (2021) also shows that simple TWFE estimation could be biased if there is treatment effect heterogeneity. Last but not least, Caetano and Callaway (2024) shows that when the parallel trend assumptions require covariates to hold, the TWFE estimator includes mis-specification bias terms, and the complexity increases when there are multiple periods. The high-speed railway station inauguration across China is clearly a staggered policy treatment, where different cities have the station open at different times. Therefore, the analysis considers several DiD estimators that are more robust to the staggered roll-out and treatment effect heterogeneity.

The first one is the doubly robust estimator (DRDID), or known as CSDID as it's proposed by Callaway and Sant'Anna (2021). This approach generalizes the DiD framework to multiple time periods by estimating group-time average treatment effects, denoted as $ATT(g,t)$. As A. Baker et al. (2025) explains, this method views the complex staggered design as an aggregation of all possible 2×2 DiD comparisons between the treatment and control groups. The estimator proceeds in two steps: first identifying the group-time specific effects, and then aggregating them into summary measures.

The identification of $ATT(g,t)$ under the DRDID framework relies on a conditional parallel trends assumption, which naturally extends to the case of unconditional parallel trends. Specifically, for a group g treated at time g, the estimator compares the evolution of outcomes between period t and the period prior to treatment $g-1$, against a valid control group. The estimator for a specific group-time cell is given by:

$$\widehat{ATT}(g,t) = \mathbb{E}_n \left[\left(\frac{G_g}{\mathbb{E}_n[G_g]} - \frac{\frac{p_g(X_{IPW})C}{1-p_g(X_{IPW})}}{\mathbb{E}_n\left[\frac{p_g(X_{IPW})C}{1-p_g(X_{IPW})}\right]} \right) (Y_t - Y_{g-1} - m_{g,t}(X)) \right] \tag{50}$$

where G_g is an indicator for being in the group treated at time g, C is an indicator for the control group, $p_g(X_{IPW})$ is the propensity score of being in group g conditional on covariates X_{IPW}, and $m_{g,t}(X)$ is the outcome regression model for the evolution of untreated potential outcomes. The covariates X used in the outcome regression model could differ from the X_{IPW} used in the inverse-probability weighting estimation. This estimator is termed "doubly robust" because, as noted by Sant'Anna and Zhao (2020) and reinforced by A. Baker et al. (2025), the estimator remains consistent if either the propensity score model or the outcome regression model is correctly specified. Therefore, this property makes DRDID particularly suitable for this study, as it allows for flexible control of covariates without relying on the strict linearity assumptions inherent in standard TWFE specifications.

Regarding the choice of control group, there are several parallel trend assumptions given different choices of control groups, specifically distinguishing between "never-treated" units and "not-yet-treated" units. A. Baker et al. (2025) outline two primary assumptions corresponding to distinct control groups: the "never-treated" and the "not-yet-treated." Under the "never-treated" specification, the parallel trends assumption requires that, conditional on covariates, the average evolution of untreated potential outcomes for the treated group g is identical to that of units that never experience the intervention. Formally, this is expressed as:

$$\mathbb{E}[Y_t(0) - Y_{g-1}(0)|G = g, X] = \mathbb{E}[Y_t(0) - Y_{g-1}(0)|G = \infty, X] \tag{51}$$

where $G = \infty$ denotes the never-treated cohort. The parallel trend assumption under Eq. 51 has the advantage of avoiding compositional changes in the control group over time. Alternatively, the "not-yet-treated" specification assumes parallel trends hold between the treated group g and units that have not yet received treatment by time t. This assumption

is defined as:

$$\mathbb{E}[Y_t(0) - Y_{g-1}(0)|G = g, X] = \mathbb{E}[Y_t(0) - Y_{g-1}(0)|G = g', X] \tag{52}$$

where g' indicates groups untreated by period t. Eq. 52 leverages a larger pool of control units, enhancing statistical power and comparability.

While using never-treated units avoids compositional changes in the control group, in the context of HSR expansion in China, the "never-treated" group may include geographically isolated or economically distinct cities, potentially violating the parallel trends assumption. Moreover, the ambitious expansion of the railway network has reached most prefectural cities in China by the end of the study period (2019), leaving few "never treated" city-level samples in our study. Conversely, the "not-yet-treated" group maximizes the sample size and comparability. Therefore, this study adopts the "not-yet-treated" units as the control group. The group-time average treatment effect on the treated, $ATT(g,t)$, using the not-yet-treated units as the control group, is identified as:

$$ATT(g,t) = \mathbb{E}[Y_t - Y_{g-1}|G = g, X] - \mathbb{E}[Y_t - Y_{g-1}|G > \max g, t, X] \tag{53}$$

where Y_t is the observed outcome at time t, while Y_{g-1} is the outcome in the period prior to treatment for group g, and $G > \max g, t$ restricts the control group to units that have not received treatment by period t. This is essentially a 2×2 difference-in-differences setup, using the two sets of observations (treatment group g and the not-yet-treated group by the time t) and two periods (pre-treatment period $g-1$ and post-treatment period t) to identify the treatment effect for group g at time t.

The final one is the estimator proposed by L. Sun and Abraham (2021) (hereafter, SA). This estimator addresses the "contamination" bias in dynamic TWFE specifications where treatment effects from other periods or cohorts affect the coefficient of interest. To correct this, the SA estimator employs an interaction-weighted specification that explicitly allows

for cohort-specific treatment effects. The fundamental building block of this approach is a cohort-specific DID estimator, denoted as $\hat{\delta}_{e,\ell}$, which estimates the cohort-specific ATE on the treated ($CATT_{e,\ell}$) for a specific cohort e at relative time period ℓ:

$$\hat{\delta}_{e,\ell} = \frac{\mathbb{E}_N[(Y_{i,e+\ell} - Y_{i,s}) \cdot \mathbf{1}\{E_i = e\}]}{\mathbb{E}_N[\mathbf{1}\{E_i = e\}]} - \frac{\mathbb{E}_N[(Y_{i,e+\ell} - Y_{i,s}) \cdot \mathbf{1}\{E_i \in C\}]}{\mathbb{E}_N[\mathbf{1}\{E_i \in C\}]} \tag{54}$$

where $Y_{i,t}$ is the outcome, E_i is the initial treatment time, and s is a pre-treatment reference period (typically $e-1$). A crucial distinction of the SA approach regarding the control group C is their handling of settings without a never-treated group. If never-treated units exist ($E_i = \infty$), the control group is set to $C = \{\infty\}$. However, if all units are eventually treated, they utilize the *last-treated cohort* as the control group, setting $C = \{\max\{E_i\}\}$, and restrict the estimation sample to periods prior to the treatment of this control cohort.

To implement this estimator efficiently, L. Sun and Abraham (2021) recommends estimating a linear TWFE specification that fully interacts relative period indicators with cohort indicators, as follows:

$$Y_{i,t} = \alpha_i + \lambda_t + \sum_{e \notin C} \sum_{\ell \neq -1} \delta_{e,\ell}(\mathbf{1}\{E_i = e\} \cdot D_{i,t}^{\ell}) + \epsilon_{i,t} \tag{55}$$

where $D_{i,t}^{\ell} = \mathbf{1}\{t - E_i = \ell\}$ indicates being ℓ periods away from initial treatment. This interacted regression yields consistent estimates of the underlying $CATT_{e,\ell}$ parameters under parallel trends and no anticipation assumptions.

The final Interaction-Weighted (IW) estimator, $\hat{\nu}_{\ell}$, is obtained by aggregating these cohort-specific estimates. Unlike the implicit, often negative weights of the standard TWFE estimator, the IW estimator explicitly weights each $\hat{\delta}_{e,\ell}$ by the sample share of cohort e in the relevant period:

$$\hat{\nu}_{\ell} = \sum_{e} \hat{\delta}_{e,\ell} \cdot \widehat{Pr}\{E_i = e \mid E_i \in [-\ell, T - \ell]\} \tag{56}$$

By construction, this method ensures that the estimated dynamic effect for relative period ℓ is a convex average of the underlying treatment effects from that specific period only. As A. Baker et al. (2025) observe, this approach "avoids the 'variance-weighting' feature of OLS" present in standard TWFE, ensuring that the estimated aggregate effect is a proper convex combination of the underlying heterogeneous effects.

Comparing these estimators to the baseline TWFE model reveals significant advantages in terms of robustness. The standard TWFE model, as shown in equation 49, relies on the assumption of homogeneous treatment effects or specific variance-weighted conditions to recover the ATT. In contrast, both DRDID and SA estimators explicitly avoid these forbidden comparisons. DRDID offers superior flexibility in handling covariates through its doubly robust nature. The SA estimator provides a regression-based alternative that is computationally efficient and familiar in interpretation, while still robust to effect heterogeneity across cohorts. By implementing both DRDID and SA, this study ensures that the estimated impact of HSR on technology obsolescence is not an artifact of restrictive econometric assumptions or weighting failures. When the results of the two estimators differ, the results might prefer the DRDID estimates, given their usage of the propensity score to re-weight the control group.

In a similar spirit, to investigate the validity of the parallel trends assumption and the dynamic effect, I implement the event-study design with different estimators: TWFE, DRDID and SA. As the SA estimator has already incorporated the event-study design in its framework, I only need to implement the TWFE and DRDID event-study specifications. The TWFE event-study specification is defined as:

$$y_{i,t} = \beta_0 + \sum_{e=-K, e\neq -1}^{L} \beta_e^{TWFE} \mathbb{1}\{t - G_i = e\} + \eta_i + \theta_t + \epsilon_{i,t} \tag{57}$$

where $\mathbb{1}\{t - G_i = e\}$ is an indicator variable equal to one if city i is e periods away from HSR connection. The coefficients β_e^{TWFE} capture the dynamic treatment effects relative to the reference period $e = -1$. However, as L. Sun and Abraham (2021) demonstrate, un-

der treatment effect heterogeneity, these coefficients are prone to "cross-lag contamination," where the coefficient β_e "may be contaminated by treatment effects at relative time $e' \neq e$." Consequently, pre-trend coefficients ($e < -1$) may appear statistically significant even if parallel trends hold, or post-treatment effects may be biased.

To address these limitations, the CSDID estimator aggregates the group-time average treatment effects, $ATT(g,t)$, into event-time parameters. The event-study parameter $\theta_{es}(e)$ for relative time e is calculated as a weighted average of $ATT(g,t)$ across all groups g such that $t - g = e$:

$$\theta_{es}(e) = \sum_{g \in \mathcal{G}} w_{g,e} \widehat{ATT}_{dr}(g, g+e) \tag{58}$$

where $w_{g,e}$ represents the weights proportional to the group size, ensuring that the parameter represents the average effect on the treated population at that specific event time. When estimating the dynamic effects, it allows for two types of base period, namely adaptive base (short difference) vs common base (long difference) (A. Baker et al., 2025; StataCorp, 2025). When the adaptive base is adopted, the comparison base period for time t after the treatment is still $t_0 = g - 1$, the period right before the treatment; for time t before treatment, the base period is set to be the period immediately preceding the period, i.e., $t_0 = t - 1$. When a common base is adopted, the base period for all event times is fixed to be the period right before treatment, i.e., $t_0 = g - 1$, same as the case of TWFE and SA estimators. The choice between adaptive and common base periods can influence the interpretation of the dynamic effects, with adaptive bases capturing more immediate changes around the treatment time, while common bases provide a long-term reference point across all event times. The following sections will report the results given a common base period as the main results to be compatible with the other two estimators.

Tables 3, 4, and 5 present summary statistics for variables used in the city-level analysis across three samples: the full analytical sample, the HSR-connected subsample, and the pre-connection or never-connected subsample. Outcomes include annual patent applications,

grants, and lapses (in counts), and the patent lapse ratio (lapses as a percentage of the active patent stock at the beginning of the year). The two subsamples reveal substantial pre-existing differences between HSR-connected and non-connected city-years. Treated observations have, on average, nine times as many patent applications (4,566 vs. 506), nine times as many lapses (743 vs. 84).

The main regression models include the following control variables: log-transformed real GDP adjusted for 1978 CPI, log-transformed population, S&T expenditure as a share of GDP to proxy research intensity, higher-education institution count for university presence, secondary and tertiary industry shares (industrial structure), log-transformed broadband subscribers to take into account intangible information flow and connection, log-transformed road passenger volume and civil aviation passengers to control for alternative transportation connection, and a dummy for the presence of a specialised intellectual property court or tribunal to control for local IP enforcement environment. Additionally, I also control for the number of valid patent stocks allowed to lapse at the beginning of the year. For the DRDID estimator, I use the similar set of covariates to estimate the propensity score for being treated at each time period, including real GDP, population, GDP per capita, second and third industry share, road passenger volume, and provincial capital indicator, with all continuous variables log-transformed.

4.3 Patent Lapse and Survival Analysis: Patent Level

To analyze the lapse behavior at the patent level, this study also implements survival analysis. The survival analysis focuses on the time duration until one or more events happen, such as death in biological organisms and failure in mechanical systems. In this study, the event of interest is the patent lapse, which occurs when a patent is not renewed and hence loses its legal protection. The survival time is defined as the time duration from the patent application date to the patent lapse date. For patents that are still active at the end of the observation period, their survival times are right-censored.

Let T denote a non-negative random variable representing the survival time of a patient, with probability density function $f(t)$ and cumulative distribution function $F(t) = Pr(T \leq t)$. The survival function $S(t)$ is defined as the probability that a patent survives beyond time t:

$$S(t) = 1 - F(t) = Pr(T > t)$$

The hazard function $h(t)$ represents the instantaneous rate of patent lapse at time t, given that the patent has survived up to time t:

$$h(t) = \lim_{\Delta t \to 0} \frac{Pr(t + \Delta t > T > t | T > t)}{\Delta t} = \frac{f(t)}{S(t)}$$

Hence, the cumulative hazard function $H(t)$ is:

$$H(t) = \int_0^t h(u)du = \int_0^t \frac{f(u)}{S(u)}du = -\ln(S(t))$$

There are various models to study the survival time of a patient, including non-parametric approaches, semi-parametric models, and parametric ones. Non-parametric approaches include the Kaplan-Meier estimator and the Nelson-Aalen estimator, which do not impose specific assumptions on the survival function form. The Kaplan-Meier estimate is defined as:

$$\hat{S}(t) = \prod_{j | t_j \leq t} (\frac{n_j - d_j}{n_j})$$

where n_j is the number of patents at risk at time t_j and d_j is the number of patents lapsing at time t_j.

Semi-parametric model features the Cox Proportional Hazards model, which assumes the hazard rate of patent to lapse j to be:

$$h(t|\mathbf{x}_j) = h_0(t) \exp(\mathbf{x}_j \beta_x) \tag{59}$$

where the $h_0(t)$ is a baseline hazard function, which the Cox model does not make an assumption about and therefore leaves unestimated. The exponential part includes explanatory variables $\mathbf{x}$ and their corresponding coefficients β_x. The proportional hazard assumption implies that the hazard ratios between different patents are constant over time. The hazard ratio between patent j and patent m is given by:

$$\frac{h(t|\mathbf{x}_j)}{h(t|\mathbf{x}_m)} = \frac{\exp(\mathbf{x}_j\beta_x)}{\exp(\mathbf{x}_m\beta_x)} = \exp((\mathbf{x}_j - \mathbf{x}_m)\beta_x)$$

where the explanatory variables include only time-invariant covariates. Therefore, the hazard ratio is independent of time t. However, the model as specified in equation 59 could be extended to include time-varying covariates $\mathbf{x}_j(t)$, which allows the hazard function to vary over time:

$$h(t|\mathbf{x}_j, \mathbf{x}_j(t)) = h_0(t)\exp(\mathbf{x}_j\beta_x + \mathbf{x}_j(t)\beta_{x(t)}) \tag{60}$$

where the $\mathbf{x}_j(t)$ are time-varying covariates and $\beta_{x(t)}$ are their corresponding coefficients. The $x_j(t)$ could be varying by the time of data collection, such as the forward citation received every year; it could be also be a time-invariant variable, yet multiplied with a function of time t, such as t, $\mathbb{1}[t > 5]$ or $\exp(-0.35t)$. The hazard ratios therefore could vary over time, either due to time-changing covariates or time-changing coefficients.

There are several covariates other than the HSR-related variables included in the Cox model, including collaboration status, patent family size, number of new applications within the same IPC subclass, number of applicants, number of inventors, number of backward citations, number of claims, number of forward citations received, application cohort and IPC classification. Among them, the number of new applications within the same IPC subclass and forward citations received are time-varying covariates, which are updated every year. These covariates are included to control for other factors that may influence the hazard of patent lapse, and to better isolate the effect of HSR connection on patent survival.

5 Renewal Behavior and Technology Obsolescence

This section explores the patent activities in China and the spatial-temporal distribution of technology obsolescence, and inspects the renewal behavior of different types of patents by different applicant types.

Similar to other jurisdictions, the patent office in China requires patent holders to pay an annual fee in order to keep the patent in force. The annual fee payment scheme is specified in the "Detailed Rules for the Implementation of the Patent Law of the People's Republic of China," and CNIPA's announcements pertaining to annual fee standards, which complement the patent law in terms of execution guidance. The annuity fee varies depending on patent types and patent age. Tables 6 and 7 show invention patents and utility model patents have different annual fee standards, with the former patent holders paying for a higher level of annual fees compared to the latter ones; moreover, the annual fee increases as the patent ages, starting from 900 (600) RMB for the first year and ending with 8000 (2000) RMB for the final year for the invention (utility model) patents. Patent applicants might apply for an annual fee reduction for the first 3 years from the year of issue of a patent due to financial difficulty: individual patent applicants could apply for up to 85% reduction, while organization patent applicants can apply for up to 70% reduction. In 2016, the reduced payment was extended to the first 6 years from the year of issue of a patent. Qualified entities for the reduction application include (1) individuals with annual incomes less than sixty thousand RMB; (2) enterprises with taxable income in the previous year less than 1 million; (3) all public institutions, social groups, and non-profit research institutes. There are also penalties for late payment: the patent holders must pay a surcharge of 5% of the total annuity fee for each month exceeding the designated payment date, and the surcharge will go up to 25% of the annuity fee; if the patent holders fail to pay the annuity fee and the surcharge within 6 months from the due date, the patent right will be ceased.

Patent holders start paying for the annuity fee once the patent right is granted; the first payment should be settled within 2 months of the patent grant notification. Until the patents

reach their protection term, patent holders must settle the annuity fee for the subsequent year before the application date in each year. The following Table 8 uses two patents by the BYD company to illustrate the patent renewal scheme. The first patent is CN2004101040055, filed on 30 December 2004. Upon grant of the patent, BYD must pay the annuity fee by 30 December each year to maintain the patent's validity. In this particular case, the notification of patent grant was issued to BYD on 27 June 2008. Following BYD's acceptance of the patent right, the company paid the fourth-year annual fee (covering the protection from 31 December 2007 to 30 December 2008) on 24 July 2008. Subsequently, BYD paid the fifth-year annual fee (covering the period from 31 December 2008 to 30 December 2009) on 19 November 2008. The final annual payment for this patent occurred on 21 November 2023, corresponding to the twentieth year of protection (covering 31 December 2023 to 30 December 2024), which represents the statutory maximum duration of invention patent protection in China. Another example of the BYD patent is CN2004101040074, also filed on 30 December 2004. The notification of patent grant was sent to the BYD company on 9 November 2007, and the company paid for the 4th annuity fee on 12 December 2007, which extends the patent right to the period between 31 December 2007 and 30 December 2008. The 5th year annuity fee was settled on the same date as the CN2004101040055. However, the last recorded payment was made for the 18th year on 15 November 2021. This patent was prematurely terminated on 30 December 2022, at the age of eighteen years.

Renewal behavior of granted patents in general reflects how much confidence patent holders have in their current patents. If they believe that the current and future values of their patent exceed the renewal fees, they would be more likely to renew their patents; otherwise, the patent holders would lose their patent rights. Moreover, the value of the renewed patents includes more than commercialization potential, but also includes the ability of the patent holders to deter competitors from using or benefiting from the patented technology.

Figure 4 shows the distribution of the final legal status of patents by different application cohorts and applicant types, capturing the full lifecycle from application to grant, and

ultimately to lapse.

The plots reveal a fundamental structural difference between the two primary patent types: utility patents (left column) and invention patents (right column). Because utility patents in China do not undergo substantive examination, their status transitions almost exclusively between "Granted" (yellow/light green) and various forms of "Lapse" (blue shades). In contrast, invention Patents are subject to rigorous substantive examination. Consequently, the right-hand column displays a significant proportion of applications in the "Rejection," "Withdrawal," or "Examination" phases (orange/red shades), representing a major regulatory filter between application and grant that does not exist for utility patents.

Firm applicants (Figures 4c and 4d), which constitute the majority of the dataset, largely drive the aggregate trends seen in Figures 1.4a and 1.4b. Their behavior regarding patent lapse reflects a commercial cost-benefit analysis. For firms, the "Termination due to non-payment of annual fees" (dark blue) generally signifies a strategic decision: the commercial value of the technology no longer justifies the escalating annual maintenance fees. In recent cohorts, the expanding "Granted" area for firms indicates a maturing industrial R&D landscape where companies are maintaining valid patents for longer periods to protect market share, rather than abandoning them quickly. Firms show a disciplined lifecycle: they survive the application phase, maintain the grant during the product's commercial peak, and allow the patent to lapse once the technology becomes obsolete or the product is discontinued.

Research Institutes (Figures 4e and 4f) exhibit distinct lifecycle behaviors. They demonstrate the highest success rates during the application phase; particularly for invention patents (Figure 4f), the "Granted" area is notably larger and the "Rejection" area smaller compared to other groups, suggesting high technical merit. However, their lapse behavior differs from that of firms. While firms allow patents to lapse in response to market signals, research institutes often exhibit higher lapse rates after the initial grant period (the transition from yellow to blue). This is frequently because their incentives are front-loaded: the primary goal is often scientific recognition, project completion, or meeting academic perfor-

mance metrics (KPIs) upon the grant of the patent. Unless the technology is successfully licensed or transferred to the private sector, institutes often lack the commercial revenue streams to support long-term maintenance fees, leading to abandonment despite the high technical quality of the invention.

Individual applicants (Figures 4g and 4h) display the most volatile behavior. For invention patents (Figure 4h), individuals face the highest rates of rejection and withdrawal, indicating a failure to pass substantive examination. Crucially, for Utility Models (Figure 4g), the rate of "Termination due to non-payment" is disproportionately high and occurs very early in the lifecycle. This pattern suggests that patents held by individuals are often abandoned almost immediately after the initial grant benefits are realized. Based on these disparities, the analysis excludes patents applied for by individuals from this analysis. The high rejection rates and rapid lapse suggest that individual patenting is driven by non-market incentives, such as seeking residency benefits (hukou), fulfilling personal performance metrics, or claiming short-term subsidies, etc., rather than genuine commercial innovation. Unlike firms (who maintain patents for market protection) and institutes (who maintain patents for technology transfer potential), individual applications might introduce significant noise.

Figure 5 shows the spatial distribution of average ages of patents across different regions in China, disaggregated by patent type and International Patent Classification (IPC) section. The color gradient serves as a proxy for patent value and maintenance strategy, where blue color indicates longer survival times and red colors indicate shorter lifespans. A comparative analysis of invention patents (Figure 5a) and utility patents (Figure 5b) reveals quite a different intellectual property landscape in China.

The most pronounced finding is the structural divergence in longevity between invention patents and utility patents. As shown in 5a, invention patents exhibit a predominantly lighter and bluer complexion across most provinces, indicating a significantly higher average age, often exceeding 60 months. This persistence suggests that invention patents, which undergo substantive examination, are generally treated as long-term assets worth the cost of

renewal fees. Conversely, Figure 5b is dominated by deep red tones across almost all sectors and regions, reflecting a systemic tendency for utility patents to lapse shortly after issuance (typically within 35–45 months). First, the difference could be driven by different allowed maximum protection terms: invention patents can be protected for up to 20 years, while utility patents only last for 10 years. Yet, this pattern might also corroborate the "low-quality" hypothesis regarding Chinese utility patents, implying that a substantial portion are filed to satisfy short-term administrative incentives, such as government subsidies, tax breaks for "High-Tech Enterprise" status, or tenure requirements, rather than to protect genuine technological innovation. Once these immediate benefits are realized, the patents are frequently abandoned to avoid maintenance costs.

Geographically, the data reveals a significant "coastal-inland" divide that underscores the uneven distribution of innovation quality. In Figure 5b, the coastal provinces—specifically the Pearl River Delta (Guangdong), the Yangtze River Delta (Shanghai, Jiangsu, Zhejiang), and the Bohai Rim (Beijing, Tianjin), consistently display higher patent longevity (blue/light blue). This is particularly evident in high-technology sectors such as section H for Electricity and G for Physics. The longevity in these regions correlates with the concentration of China's leading technology firms and advanced manufacturing bases, where IP rights are critical for market competition. In contrast, inland and western provinces show a prevalence of orange and red hues even within invention patents. This suggests that while policy-driven incentives have successfully encouraged patenting activity among the central and western regions of China, the commercial opportunity and subsequent maintenance of these patents lag behind the coastal innovation hubs.

Sector-specific analysis highlights notable regional specializations. In Figure 5a, while the Tibet Autonomous Region exhibits a deep blue coloration in Section D (Textiles & Papers), indicating high patent longevity, this result should be interpreted with caution. This outlier is likely an artifact of small sample size variance. Given Tibet's significantly lower volume of patent filings compared to coastal provinces (by 2024, the valid invention patent stock of

Tibet is 1392, about 0.03% of the national stock, according to the China Intellectual Property Statistical Yearbook 2024), the 'average' lifespan is highly sensitive to a handful of long-lived patents. Therefore, the deep blue color likely represents a statistical outlier, rather than a systemic regional advantage in textile innovation or commercialization. However, Section H (Electricity) shows the highest concentration of long-lived patents in Guangdong, aligning with the province's status as a global hub for electronics and telecommunications hardware.

6 Impact of HSR on Technology Obsolescence

6.1 City level results

Tables 9 and 10 present estimation results for invention and utility patents, respectively. Each table reports three estimators, namely, TWFE, DRDID, and SA, separately for all applicant patents and firm applicant patents across three outcome panels: (A) log number of lapsed patents, (B) log lapse-to-stock ratio, and (C) log patent applications. Full TWFE results with all controls are reported in Appendix Tables 17 and 18.

A crucial feature of both tables is the divergence between the TWFE estimator and the robust alternatives, especially for the invention patents. For invention patents (Panel A of Table 9), TWFE yields small positive and entirely insignificant coefficients (0.007 for all applicants; 0.052 for firms), while DRDID and SA consistently deliver negative and significant effects. Relying solely on TWFE would lead to the misleading conclusion that HSR has no impact on invention patent lapse, or even increases it. This divergence arises from the well-documented failure of TWFE in staggered adoption designs with heterogeneous treatment effects (A. C. Baker et al., 2022; De Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021). When cities are connected to HSR at different times, TWFE implicitly uses already-connected cities as the control group for later-connected ones. Since the event-study results in Section 6.1.1 confirm that the lapse-reduction effect deepens considerably over time, hence early adopters have much lower lapse counts later in the panel and using them as a control

group makes late adopters appear to have a relative increase in lapsing patents, which inflates the TWFE estimate upward and can reverse its sign. Appendix Figure 14 formalizes this via the Goodman-Bacon (2021) decomposition: for invention patent lapse, the cohort-versus-cohort comparisons, where already-treated cities serve as controls, carry 57.7% of the total TWFE weight and yield average local ATETs of 0.47 for full sample and 0.44 fpr firm subsample, mechanically pulling the aggregate TWFE estimate above zero. For utility patents, TWFE remains in the negative direction (Panel A of Table 10: -0.085 for all; -0.045 for firms) but systematically underestimates the magnitude relative to DRDID and SA. Given these identification concerns, the discussion below focuses on DRDID as the preferred estimator, with SA providing corroborating evidence.

Panel A of Table 9 shows that an HSR connection leads to a substantial and significant reduction in the log number of lapsed invention patents. Under DRDID, the impact of HSR on all-applicant patents is statistically significant with a magnitude of -0.189, implying approximately a 17% decline in lapsed invention patents. The SA estimator yields a comparable estimate of -0.217, which suggests about 19.5% of HSR-induced lapse reduction. The firm-applicant sample delivers similar point estimates: DRDID estimator reports a coefficient of -0.268, suggesting that HSR connection reduces firm patent lapse by roughly 24%; the SA estimate is -0.147, which translates into about 14% of reduction in lapsed patents. The analysis pays special attention to firm patents based on the following argument. Firms are profit-maximising entities with the resources and strategic incentives to actively reassess their IP portfolios in response to new economic opportunities. HSR broadens market reach, raising the expected commercial value of holding an active invention patent, and firms respond by paying renewal fees on patents they might otherwise have abandoned. Non-firm applicants, primarily individuals and universities or research institutes, hold fewer resources and are less sensitive to the market-access channel, so their renewal behavior could be less responsive. Panel B examines the lapse-to-stock ratio to isolate whether the absolute reduction in lapse reflects a deeper structural shift in renewal propensity relative to the patent stock.

The effects here are more muted: all coefficients are negative but statistically insignificant across estimators and samples, with the weakest signal being a marginally significant SA estimate for firms (-0.124). This suggests that while HSR reduces the absolute flow of lapsing invention patents, the lapse rate conditional on stock size is not dramatically altered. Panel C shows that HSR also generates a significant decline in invention patent applications for the all-applicant sample (-0.131 for DRDID, and -0.093 for SA), but the firm-only coefficient is smaller and statistically insignificant across all estimators. This divergence between the all-sample and firm-sample application effects suggests the aggregate decline in new filings is partly driven by non-firm applicants reducing opportunistic or low-quality filings in the more competitive post-HSR environment, while firms themselves maintain or only marginally reduce their filing rates.

Table 10 reports results for utility patents, which represent incremental innovations with shorter lifecycles and lower commercial value than invention patents. Notably, unlike for invention patents, even the TWFE estimator captures a negative effect of -0.085 on utility lapse for the all-applicant sample, indicating that the TWFE bias is less severe, presumably because treatment effect heterogeneity across cohorts is smaller for this patent type. Under DRDID, the all-applicant effect is -0.145 and the firm effect is -0.190, corresponding to 13% and 17% reductions, respectively; under SA, both are larger in magnitude, yielding estimates of -0.270 and -0.287, corresponding to 24% and 25% reductions for all-applicant and firm patents, respectively. Panel B reveals a distinctive pattern for utility patents: while the all-applicant lapse-to-stock ratio coefficients remain insignificant under DRDID, the firm-only coefficients are strongly negative and significant. Both estimators report about a 16% reduction in lapsed patents due to HSR. This indicates that firms actively reduce their lapse rate relative to their patent stock, not merely in absolute terms, which suggests a deliberate strategic retention of utility patents. Firms appear to be holding on to a larger share of their existing utility patent stock, consistent with the hypothesis that HSR raises the market value of even incremental innovations by expanding the geographic scope of their commercial

application. Panel C shows that utility patent applications decline modestly under SA (-0.090 for all; -0.112 for firms), but DRDID estimates are small and insignificant, echoing the weak and delayed application response seen in the event study.

Comparing Tables 9 and 10 reveals several systematic differences. First, the TWFE bias is qualitatively more severe for invention patents, while for utility patents, TWFE still aligns with the robust estimators in terms of coefficient signs. This reflects that invention patent renewal behavior is more strategically dynamic and cohort-heterogeneous, amplifying the staggered-DiD contamination in TWFE. Second, for lapse levels (Panel A), the SA point estimates are actually larger for utility patents (-0.270 for all; -0.287 for firms) than for invention patents (-0.217 for all; -0.147 for firms), though the DRDID preferred estimates show the firm effect being larger for invention (-0.268) than utility (-0.190). The SA–DRDID discrepancy is consistent with the later event study finding that SA pre-trends are problematic for invention patents but less so for utility, potentially inflating SA estimates for utility relative to DRDID. Third, the lapse-to-stock ratio (Panel B) shows stronger and more significant effects for utility firm patents than for invention firm patents, suggesting that even conditional on stock size, firms retain a greater fraction of their utility patent portfolio post-HSR. Fourth, new applications (Panel C) show a more notable all-applicant decline for invention than utility patents under DRDID, consistent with the interpretation that the competitive pressure induced by HSR connectivity particularly deters low-quality invention patent filings.

6.1.1 Event Study Results

To validate the parallel trends assumption and trace the dynamics of the treatment effect over time, I estimate event-study specifications using both the DRDID estimator and the SA interaction-weighted estimator. A necessary condition for causal identification is that treated and control cities would have trended in parallel absent the HSR connection. The key diagnostic is whether the pre-treatment coefficients (periods $t \leq -2$) cluster around zero. Results are presented in six figures, one for each combination of patent type (invention,

utility) and outcome (log lapsed count, log lapse-to-stock ratio, log applications). This section will lead with a detailed discussion of the pre-trend patterns, then interpret the post-treatment dynamics in light of the pre-trend validation.

Figure 6 reports the estimation with the invention lapse count as the outcome variable. Under the SA estimator (top row), pre-period point estimates are systematically negative for both all applicants and firms, already around -0.1 to -0.2 at t = -4 to t = -6 or earlier, indicating that treated cities were experiencing declining lapse counts before HSR arrived. This pre-existing downward drift raises serious concerns about identification under the SA design, which is restricted to never-treat cities as the control group. Under the DRDID estimator (bottom row), pre-period estimates cluster tightly around zero for both samples, providing strong support for parallel trends. This contrast arises because DRDID constructs its comparison group through doubly-robust reweighting of "not-yet-treated" units, purging systematic compositional differences between early and late adopters that the SA design cannot fully absorb. Figure 7 summarizes results for the invention lapse ratio. The SA pre-trends still show a similar downward drift for both applicant groups, with estimates around -0.1 to -0.2 in the earliest pre-periods. The DRDID pre-period estimates are more mixed, but lack the systematic negative drift of the SA design, providing reasonable support for parallel trends on this outcome.

Figure 8 presents results for utility lapse count. The SA pre-trends are milder than for invention patents, staying in the range of -0.05 to 0.05 for both applicant groups. The DRDID pre-periods show a modest positive offset at $t = -5$ and $t = -6$ (approximately 0.10 to 0.13) before converging toward zero at $t = -3$ and $t = -2$ for the full sample, yet shows no sign of violation for the firm patents. Figure 9 reports the utility lapse ratio. DRDID pre-period estimates show a mild positive offset at very early periods ($t = -5, -6$) but converge cleanly to zero by $t = -2$ for the full sample, while showing the parallel trend for the firm sample is more or less satisfied for firm patents. The SA design shows more irregular pre-period behaviour, particularly for firm applicants. Again, the DRDID evidence provides stronger

support for parallel trends, while the SA design's reliance on never-treated controls appears to be more vulnerable to pre-existing differences in lapse behavior.

Finally, Figures 10 and 11 reports for patent applications for both types of patents. Both invention and utility application outcomes exhibit the cleanest pre-trends across all outcomes examined. SA and DRDID pre-period estimates for both applicant groups hover near zero with no systematic drift, providing the strongest parallel-trend validation in the analysis. This is consistent with the interpretation that new filing decisions are unlikely to be anticipated or altered in advance of HSR connection.

The event study plots also provide evidence on the dynamic effect of HSR connection. The following discussion will prioritize the DRDID results given that they are potentially more robust and reliable. The post-treatment trajectory for invention patent lapse (bottom row of Figure 6) follows a clear pattern: the ATET is near zero at the year of HSR opening ($t = 0$), then turns negative and progressively deepens, reaching approximately -0.15 by year one, maximum at -0.25 by year three and then bouncing back to around -0.20 by year four. The firm panel (bottom right) shows a sharper trajectory, with ATETs reaching -0.25 to -0.35 by years three to five, reinforcing that the aggregate effect is concentrated among firm applicants. For utility patent lapse (Figure 8), the DRDID post-treatment path also turns negative from $t = 1$ onward, reaching approximately -0.12 to -0.15 by years two to four and -0.15 to -0.25 in years five for all applicants. The firm panel shows slightly deeper estimates in later periods. The SA utility estimates are broadly consistent in direction, and the milder pre-trend contamination makes the SA post-treatment magnitudes more trustworthy for utility than for invention patents.

Figure 7 shows that the DRDID post-treatment coefficients for the invention lapse-to-stock ratio are generally negative but substantially noisier than the lapse count estimates, with mostly insignificant results. Some negative point estimates emerge at $t = 3$, but the pattern is irregular. This is consistent with the aggregate Panel B result in Table 9: while absolute lapse falls, the lapse rate conditional on the patent stock is not substantially reduced

in a cleanly identified dynamic pattern. For utility patents (Figure 9), the DRDID post-treatment path for firms is more distinctly negative in later periods ($t = 5$ and $t = 6$: approximately -0.25 to -0.30), consistent with the significant aggregate DRDID Panel B estimate for utility firm patents in Table 10.

For invention patent applications (Figure 10), the DRDID post-treatment coefficients (bottom row) remain very close to zero for the first four years and then decline more sharply at $t = 5$ and $t = 6$ (approximately -0.2 and -0.4 for all applicants; -0.2 and -0.25 for firms). The SA estimates (top row) show a gradual and modest negative path from $t = 1$ onward, reaching around -0.13 to -0.17 by years two to three for all applicants, with a broadly similar pattern for firms. Both estimators show that the decline of new invention patent filings is a long-run phenomenon and usually happen in the later periods. For utility patent applications (Figure 11), the DRDID post-treatment coefficients are more modest throughout: small negative values from $t = 0$ onward (around -0.05 to -0.10) for both applicant groups, with no sharp late-period drop.

6.1.2 Heterogeneity by Patent Age

The aggregate estimates in Section 6.1 average the HSR effect across all patents in a city-year, irrespective of how old those patents are. Yet renewal decisions are inherently age-dependent: fees escalate with each successive renewal, the remaining commercial life shortens, and the economic rationale for retention therefore varies substantially across a patent's lifecycle. To assess whether HSR's lapse-suppression effect operates uniformly or is concentrated at particular lifecycle stages, I estimate the baseline model separately for each patent age cohort (ages 1–20 for invention patents; ages 1–10 for utility patents). Figure 12 plots the three estimators' coefficients and 90% confidence intervals for log lapsed patent counts, combining all four samples (invention and utility, all and firm applicants) in a single four-panel display; Figure 13 repeats the exercise for the log lapse-to-stock ratio. The figures reproduce the TWFE–DRDID–SA divergence documented in Section 6.1 and illuminate the precise lifecycle

stages driving the aggregate results.

The top row of Figure 12 displays treatment effects on log lapsed invention patents by age, for all applicants (left panel) and firm applicants (right panel). The TWFE estimator (blue circles) is positive at young to mid ages (ages 1–12) for both samples before drifting toward zero for older patents, a pattern consistent with the upward sign bias documented in Table 9. The DRDID estimator (red squares) reveals a more nuanced lifecycle pattern: effects are small at age 1, turn sharply negative from ages 3 to 9, with the deepest points around ages 3 and 6 for full sample, and around age 6 for firms, recover toward zero at ages 10–11, then turn positive at ages 12–13 and again at ages 15–18, before returning close to zero at ages 19–20. The SA estimator (green triangles) partially agrees with the mid-life negative segment, with negative estimates at ages 4–6 and positive estimates between ages 11 and 18 for full sample, and positive estimates between ages 11 and 17 for firm patents.

All three estimators in general reveal a trend of HSR-induced drop at the early age and then increasing lapse behavior at the later age, despite different magnitudes. This lifecycle pattern has a natural economic interpretation. At ages 1–2, renewal fees are still low and patents are typically in their peak-productivity phase, and most patentees renew regardless of HSR connectivity. It is at the intermediate ages of about 3 to 9, when fees have escalated to the point where the renewal decision becomes marginal, but a sufficiently productive life is able to justify payment. The transition from age 3 to 4 corresponds to the first increase in the renewal thresholds after three years of fixed annual fee from 900 RMB to 1200 RMB, and the age of 6 to 7 is another increasing stage from 1200 RMB to 2000 RMB (See 6). During this period, HSR's market-access gains most directly the cost-benefit calculation in favour of retention. At ages 12–13 and 15–18, the positive DRDID coefficients suggest that HSR may modestly increase lapse for older invention patents. During this late lifecycle stage, the renewal fees are double and even triple the fee at age 7, and the remaining commercial life becomes shorter, so the option value of continued maintenance is already low. HSR's connectivity benefits may be less relevant for these older patents: improved

market access raises the opportunity cost of maintaining older and less commercially relevant patents by exposing firms to new markets and technologies, hence encouraging concentration of maintenance resources on newer and potentially higher-value assets. The approaching statutory expiry at age 20 further reduces the option value of continued maintenance at the tail of the lifecycle.

The bottom row of Figure 12 reveals a significantly different age profile for utility patents. Under the DRDID estimator, the protection effect of HSR is consistently negative across almost the entire utility patent lifecycle, except for the final two years of statutory protection. The firm-applicant panel (right panel) shows an even stronger effect at age 1 (DRDID $\approx$ -0.36), bounces back to close to zero between ages 2 and 4, and grows again between ages 5 and 7. Two features distinguish this pattern from invention patents. First, the absence of a mid-life concentration reflects the compressed lifecycle of utility patents: with a maximum of ten years, every age represents a meaningful share of the total productive life, so the marginal decision to renew is consequential at every stage. Second, the particularly strong firm effect at age 1 suggests that HSR causes firms to retain newly-registered utility patents they would have immediately abandoned in the absence of improved market access. The SA estimator broadly corroborates these DRDID findings, with negative estimates across ages 1–8 for both samples. As before, TWFE fails to detect these effects, remaining near zero or slightly positive for all ages.

Figure 13 shows that neither patent type exhibits a robust age-specific pattern in the lapse-to-stock ratio. For invention patents (top row), all three estimators cluster near zero across ages 1–20, with no age window generating a statistically meaningful decline in the lapse rate conditional on stock size. An exception might be the early stage of patent life at age 3, where both robust DID estimators give negative coefficients for HSR impacts, which suggests that HSR connection might increase the stock of mid-life patents by protecting more early-stage patents from lapsing. The utility lapse ratio (bottom row) is similarly noisy, with point estimates scattered around zero and wide confidence intervals throughout. This is consistent

with the aggregate Panel B results in Tables 9 and 10, which show that the lapse ratio is not significantly reduced even though absolute lapse counts fall: the stock denominator adjusts broadly in line with the numerator, leaving the ratio largely unchanged at each specific age.

The age-heterogeneity analysis enriches the aggregate results in three ways. First, it explains why TWFE is biased upward for invention patents but less so for utility patents. If the true effect is concentrated at mid-life ages (3–9) for invention patents, and treated cities might be systematically different from control cities in the age distribution of their patent stocks, TWFE's failure to account for this compositional difference is especially consequential for invention, producing a sign reversal. Utility patents' broad-based age profile makes such compositional bias less severe. Second, the results give a clue to the potential mechanism behind the aggregate lapse reduction. For invention patents, it is primarily the early stage patents aging 3–9 and exploring potential application and markets that respond to HSR. This is a precise, economically coherent channel: improved market access raises the continuation value at exactly the moment when patent-holders are most likely to abandon otherwise valuable assets for cost reasons. For utility patents, the uniform age profile suggests the value-enhancement mechanism is more broadly applicable, consistent with the finding in Section 6.1 that even the full sample utility effect is statistically significant. Third, the absence of lapse-ratio heterogeneity across ages reassures that the aggregate null for Panel B is not a false alarm of averaging offsetting positive and negative ratio effects across age bins; the lapse ratio genuinely does not change sharply at any lifecycle stage.

6.2 Patent-Level Analysis

To complement the aggregate city-level estimates with individual patent-level evidence, I conduct a Cox proportional hazards regression analysis, which models the hazard rate of patent lapse as a function of HSR connectivity and other covariates at the patent level. This approach allows for a more granular examination of how HSR affects the timing of lapse decisions at the individual patent level, while controlling for patent-specific characteristics

such as age, technology class, and inventor number etc. The patent-level framework also enables direct empirical tests of the four theoretical channels identified in Section 3.3, by using variables that correspond to each channel's structural parameter. In this section, I specifically focus on firm patents, as they are the primary drivers of the aggregate effects observed in the previous section and have clear financial motivations and constraints. The analysis is structured around three sets of samples: all firm patents; firm patents from cities eventually connected to the HSR network by the end of the study period; and firm patents filed before HSR connection, referred to as legacy patents. This division allows the analysis to assess whether the protection or destruction effects of HSR are more pronounced for which types of patents.

6.2.1 Full Sample Results

Tables 11 and 12 present the baseline Cox regression results for all firm patents, for invention patents and utility models respectively. Columns (1) and (2) in each table use the HSR indicator to capture the treatment effect of being connected to the HSR network, while columns (4) to (6) use GDP-based and population-based market access and access to knowledge resources via the HSR network as the key independent variables to proxy accessibility to market and resources increased by HSR connectivity.

As Column (1) in Table 11 shows, the influence of HSR connection on the lapse of invention patents is statistically significant and the hazard ratio is 1.051 holding other factors constant, which is equivalent to a 5.1% increase in the hazard of patent lapse for HSR-connected patents compared to non-HSR-connected patents. This result is the opposite of the city-level results and suggests that, on average, HSR connectivity is associated with a higher likelihood of patent lapse for invention patents. The analysis interact the HSR connection indicator with the collaboration status of patents, and the results in Column (2) show that the destruction effect of HSR connectivity is primarily driven by non-collaborative patents, while collaborative patents experience a reduced hazard of lapse after HSR connection. Having

an HSR station increases the hazard rate of non-collaborative invention patents by about 7.2% (derived from a coefficient of 1.072), but for collaborative patents, having an HSR station actually decreases the hazard rate by about 6.7% (1 - 1.072 $\times$ 0.870). This suggests that the increased market access provided by HSR may lead to more intense competition for non-collaborative patents, which are typically more vulnerable to obsolescence, while collaborative patents may benefit from shared resources and networks that mitigate the competitive pressures. Columns (3) to (5) estimate the influence of HSR-induced accessibility on the external market and research on patent survival. All three HSR network measurements have a statistically significant effect on the patent lifespan, and all reduce the hazard of patent lapse, with the population and market access measures (GDP and population-based) showing a stronger effect than the access to knowledge resources. Specifically, a one percent increase in the GDP-based market access via HSR network is associated with a 4.6% decrease in the hazard of patent lapse, and a one percent increase in the population-based market access via HSR network is associated with a 5.8% decrease in the hazard of patent lapse. Meanwhile, a one percent increase in access to knowledge resources via the HSR network is associated with about a 4.9% decrease in the hazard of patent lapse. The relatively smaller effect size for access to knowledge resources compared to market access suggests that while improved connectivity may facilitate knowledge diffusion and collaboration opportunities, it is the enhanced market access that plays a more important role in sustaining the commercial viability of invention patents and thus reducing obsolescence. This suggests that the improved market access provided by HSR may be a more important channel for reducing patent obsolescence than access to knowledge resources, at least in the context of firm invention patents in China.

Table 12 presents the corresponding results for utility models, revealing a strikingly different pattern. Column (1) shows that HSR connectivity significantly reduces the hazard of utility model lapse, with a hazard ratio of 0.874 or a 12.6% reduction relative to non-HSR-connected patents. This stands in contrast to the positive hazard effect observed for invention patents and aligns more closely with the aggregate city-level findings. Column (2)

shows that both non-collaborative and collaborative utility models benefit from HSR connectivity, with the advantage stronger for collaborative patents: the combined hazard ratio for collaborative patents is approximately 0.793 (0.879×0.902), implying a 20.7% reduction in lapse risk. Unlike the case of invention patents, there is no destruction effect for non-collaborative utility models. The HSR connectivity uniformly lowers the hazard of lapse regardless of collaboration status. Columns (3) to (5) confirm that all three channels of HSR-induced accessibility reduce the hazard of utility model lapse. A 1% increase in GDP-based market access is associated with an 8.6% decrease in the lapse hazard, somewhat larger than the 4.6% decrease found for invention patents. Population-based market access and access to knowledge resources yield reductions of 7.5% and 6%, respectively. These results suggest that utility models, which tend to represent more incremental and commercially oriented innovations with closer ties to local manufacturing relationships, are particularly responsive to the market expansion opportunities provided by HSR connectivity.

6.2.2 Eventually Treated Cities Results

Tables 13 and 14 report the Cox regression results for the subsample of patents from cities that eventually receive HSR connection by the end of the study period. This subsample allows investigation to focus on the patents that are most likely to be directly affected by HSR connectivity, and to assess whether the effect of HSR is more pronounced for these patents applied after HSR connection. Specifically, Columns (1) and (2) shows if patents applied after HSR connection in the eventually treated cities experience a different hazard of lapse compared to patents applied before HSR connection. Columns (3) to (5) estimate the influence of HSR-induced accessibility to external market and rivals on patent survival for patents in eventually treated cities.

Table 13 summarizes the results for invention patents. Column (1) shows that, among patents from eventually treated cities, those applied after HSR connection have a hazard ratio of 0.780 compared to those applied before HSR connection, which means that the hazard of

patent lapse is reduced by about 22% for patents applied after HSR connection. This result is consistent with the city-level findings and suggests that HSR connectivity is associated with a lower likelihood of patent lapse for invention patents in eventually treated cities. Column (2) shows that the interaction between HSR connection and collaboration status is consistent with the full sample results in Column (2) from Table 11, with collaborative patents experiencing a much lower hazard of lapse after HSR connection. The reduction in hazard rate for being filed after HSR connection is 34.4% (1 - 0.812 $\times$ 0.808). Besides, for non-collaborative patents from HSR cities experience an increased hazard of lapse, those applied after the HSR connection also experience a lower hazard rate compared to those applied before the HSR connection, with the hazard rate reduced by 18.8%. Columns (3) and (4) show that both measures of HSR-induced accessibility have a statistically significant effect on patent survival, with increased market access and access to knowledge resources via the HSR network being associated with a reduced hazard of patent lapse. Specifically, a one percent increase in the GDP-based market access via HSR network is associated with a 6% decrease in the hazard of patent lapse, and a one percent increase in the population-based market access via HSR network is associated with an 8.4% decrease in the hazard of patent lapse. Columns (5) to (6) switch to another dimension of HSR-induced accessibility, which is the potential influence of competition from other cities via the HSR network. There are two measurements for this dimension: one is the number of valid patents within the same IPC subclass from other cities connected by HSR, and the other is the number of firms with valid patents within the same IPC subclass from other cities connected by HSR. Both are weighted by HSR network travel time. It's found that both patent-based and firm-based competition from other cities via HSR network has a statistically significant effect on patent survival: a one percent increase in the rival level due to HSR network, either measured by valid patent stock or active firm number, increases the hazard of patent lapse by between 1.1% and 1.3%.

Table 14 reports the corresponding results for utility models in eventually treated cities. Column (1) shows that utility models filed after HSR connection have a hazard ratio of

0.816 relative to those filed before, translating into an 18.4% reduction in the lapse hazard. Column (2) reveals that the collaboration premium also exists: while non-collaborative utility models applied after HSR connection already experience a 17.5% lower lapse hazard, the combined hazard ratio for collaborative patents applied after HSR is approximately 0.662 (0.825×0.802), a 33.8% reduction. Columns (3) and (4) confirm that HSR-induced market access reduces the hazard of utility model lapse at magnitudes consistent with the full-sample results, with the GDP-based measure associated with an 8.6% decrease and the population-based measure with a 7.5% decrease. Columns (5) and (6) present a notable contrast to the invention patent findings: for utility models in eventually treated cities, a one percent increase in HSR-connected external competitors, measured either by valid patent stock or by active firm count within the same IPC subclass, is associated with a statistically significant 1.1% decrease in the hazard of lapse. This is the opposite of the result for invention patents. The finding suggests that, for utility models, a denser competitive environment reachable via HSR signals a vibrant product market that reinforces the commercial returns to maintaining patents, rather than accelerating obsolescence through technological substitution.

6.2.3 Legacy Patents

Tables 15 and 16 present the Cox regression results for the subsample of patents filed before HSR connection, referred to as legacy patents. This subsample allows examination of whether HSR connectivity has a significant impact on the survival of older patents that were not directly influenced by improved market access at the time of their application, but may still benefit from enhanced diffusion and complementary innovation opportunities after HSR connection. This is arguably the cleanest test for the obsolescence effect of HSR, as legacy patents are not subject to the influence of HSR on the application process, and any change in their hazard of lapse can be more confidently attributed to the HSR connectivity.

Specifically, Columns (1) and (2) of Table 15 show the impact of HSR connection on invention patents and the heterogeneity due to collaboration status. First, connecting the

HSR network increases the hazard rate of legacy by 10.6% according to Column (1), and there is no statistically significant heterogeneity in terms of collaboration status based on Column (2). The coefficient for the HSR station (1.109) after controlling for the interaction between it and collaboration status is comparable to the one without the interaction (1.106), suggesting that for legacy invention patents, HSR connectivity is associated with a higher likelihood of patent lapse, and this effect does not differ significantly between collaborative and non-collaborative patents. Columns (3) examine whether the age at which the HSR connection happens has an influence on the hazard of patent lapse, and test for a non-linear impact of HSR connection. The results show that the age of legacy invention patents at the time of HSR connection, both linear and quadratic terms, has a statistically significant effect on the hazard of patent lapse. The baseline effect of age is positive. For every additional year a legacy patent has aged prior to the HSR station opening, its hazard rate initially increases by 5.0%. Yet as the quadratic term is slightly less than 1, it acts as a dampening factor on the linear increase. Therefore, they suggest that the hazard rate for legacy patents rises as their "age at treatment" increases, but it does so at a diminishing rate. For relatively young legacy patents at the time of HSR arrival, getting slightly older significantly increases their hazard rate; however, as legacy patents get much older, the quadratic term starts to pull that growth slightly downward. The additional risk associated with each extra year of age becomes smaller and smaller.

Columns (4) to (7) look at the competition channel for legacy invention patents. Columns (4) and (5) still use the HSR-induced change in external competitors, and the patterns are consistent with the ones from 11: a one percent increase in the competition level due to HSR connection will increase the hazard rate by about 1.5%. Columns (6) and (7) examine how the HSR connection interacts with the concentration level to influence patent survival. The HHI gap measures the disparity between IPC-subclass-level Herfindahl–Hirschman index at the local patent market and the national market. The HHI index is computed from the share of valid patents within each IPC subclass held by each firm. A positive difference between

the local and national HHI indices indicates that the local market facing each patent is less competitive than the national market, whereas a negative difference indicates a more competitive local market. Column (6) reports the result for the current year's competition level difference. The current year's disparity between local and national market concentration has no baseline effect on the hazard rate of legacy patents. Furthermore, the current local competitive environment does not alter how the HSR station impacts legacy patents. Short-term, contemporaneous differences in local versus national competitiveness do not explain legacy patent survival, nor do they interact meaningfully with the HSR shock. Column (7) employs a different approach with a three-year rolling window: for any given year t, the firm count is defined as the number of firms with valid patents over the period $[t-2, t]$. Therefore, it reflects the general market structure from the past. Column (7) first shows that the coefficient for rolling HHI gap is statistically significant: historical lack of local competition strongly increases the baseline hazard rate by 29%. In other words, legacy patents from cities with uncompetitive local markets are inherently much more likely to lapse. A higher HHI index suggests that a few firms dominate the local market, legacy patents in such cities may be less likely to be maintained due to the lack of motivation to rely on the intellectual property right for exclusive protection, and the lack of competitive pressure to innovate and maintain patents. The interaction between HSR indicator and HHI gap is also statistically significant yet less than 1, suggesting arrival of an HSR station dampens or mitigates the effect of the rolling HHI gap: when the local market is connected to the external via HSR, one unit increase in the rolling HHI gap will only increase the hazard rate by 16% ($0.906 \times 1.29 - 1$). This suggests that HSR connectivity can partially offset the negative consequences of being in a historically uncompetitive local market, likely by facilitating access to external markets and resources that raise the awareness and value of maintaining patents even for firms in less competitive environments.

Table 16 reports the results for legacy utility models, which differ substantially from those for legacy invention patents. Column (1) shows that HSR connection is associated with a

statistically significant reduction in the lapse hazard of legacy utility models, with a hazard ratio of 0.982, equivalent to a 1.8% decrease. This contrasts with the 10.6% increase in lapse hazard found for legacy invention patents, indicating that HSR tends to protect rather than destroy legacy utility models. Column (2) reveals an important heterogeneity: while non-collaborative legacy utility models experience a modest 2.4% reduction in lapse hazard after HSR connection, collaborative legacy utility models face a reversal of this effect, with the combined hazard ratio of approximately 1.093 (0.976×1.120) implying a 9.3% increase in lapse risk. This contrasts with the statistically insignificant collaboration interaction found for legacy invention patents, and may reflect the dissolution of collaborative arrangements as HSR broadens the set of potential partners and raises the outside option for joint incremental innovation. Column (3) shows that the age of legacy utility models at the time of HSR connection has a positive and statistically significant linear effect on the lapse hazard (hazard ratio 1.015 per additional year of age at treatment), while the quadratic term is statistically insignificant. In contrast to the concave age-at-treatment profile found for legacy invention patents, where the marginal risk of ageing diminishes at higher ages, the relationship for utility models is approximately linear, suggesting a simpler proportional accumulation of lapse risk with age at HSR arrival. Columns (4) and (5) show that external competition via HSR decreases the lapse hazard for legacy utility models, which is consistent with the results of HSR city patents (Table 14).

Columns (6) and (7) examine the interaction between market concentration and HSR connectivity for legacy utility models, and reveal a pattern that contrasts sharply with that of invention patents. Column (6) shows that the baseline HHI gap has a strong negative effect on the lapse hazard (hazard ratio 0.817), meaning that legacy utility models in locally concentrated markets, where local competition is less intense than the national average, are substantially less likely to lapse. One unit increase in the disparity between local and national HHI level brings about 3.3% decrease in the lapse hazard rate. This is the opposite of the finding for legacy invention patents, where local market shelter is associated with higher

lapse rates. The interaction between HSR and the HHI gap (hazard ratio 0.967) suggests that HSR connectivity further reinforces the negative impact of HHI gaps: among HSR cities, one unit increase in the HHI gap will reduce the hazard rate by 21% (1 - 0.967 $\times$ 0.817). Column (7) reveal similar pattern with the rolling HHI gap: the baseline effect remains negative (hazard ratio 0.955), and the interaction with HSR further reduces the lapse hazard (hazard ratio 0.899). Notably, the direct HSR station coefficient is statistically insignificant in Columns (6) and (7) once market structure terms are included, suggesting that the market concentration channel mediates the HSR effect for legacy utility models. Together, these results indicate that utility models depend more heavily on local commercial relationships for their maintenance value: locally dominant firms with utility model portfolios are well-positioned to leverage HSR connectivity to extend their market reach, partially preserving the advantages that underpin their patent maintenance decisions.

6.2.4 Comparing Invention Patents and Utility Models

In general, the Cox regression results reveal systematic differences between invention patents and utility models in how HSR connectivity affects patent maintenance decisions. For invention patents, the dominant protection channels are enhanced market access and knowledge network effects for patents filed after the HSR connection, especially for the collaborative patents. On the other hand, the destructive effect manifests as heightened competitive pressure on legacy and non-collaborative patents, which face an elevated risk of obsolescence as HSR-enabled market integration intensifies technological rivalry. At the aggregate level, the net effect is a reduction in lapse, driven by the composition of the patent portfolio shifting toward more survivable patents that disproportionately benefit from improved connectivity. For utility models, by contrast, the market access channel operates uniformly across all subsamples and reduces lapse hazards in the full sample, in eventually treated cities, and among legacy patents alike. Importantly, the competition channel is muted or even inverted: external competitors accessible via HSR are associated with lower lapse hazards for utility models

in eventually treated cities, and the competitive pressure effect is substantially smaller for legacy utility models than for their invention patent counterparts.

These differences are consistent with the underlying nature of the two patent types. First, invention patents typically protect more radical, knowledge-intensive innovations with potentially broader technological scope and longer commercial horizons. Their survival is therefore more sensitive to creative destruction: the arrival of new HSR-enabled competitors from distant cities can render the underlying technology obsolete and make continued maintenance economically non-optimal. Utility models, by contrast, are designed to protect incremental, product-specific innovations whose commercial value is more closely tied to local manufacturing and distribution relationships. HSR connectivity tends to reinforce these relationships by expanding accessible market reach rather than disrupting them through technological substitution. Second, the divergence in market structure effects further supports this interpretation. For legacy utility models, a concentrated local market is a reliable predictor of lower lapse risk, implying that local incumbents derive real maintenance value from their market position. However, for legacy invention patents, local shelter is actually associated with higher lapse rates, consistent with the idea that sheltered firms face weaker incentives to sustain frontier technologies. Finally, the contrasting collaboration dynamics underscore the asymmetry: collaborative legacy utility models are more likely to lapse after HSR connection, as broadened connectivity raises the outside option for joint incremental partnerships, whereas collaboration status is essentially irrelevant for the legacy invention patent lapse response. Together, these patterns suggest that transportation infrastructure interacts differently with radical versus incremental innovation, with market access gains primarily benefiting the former through knowledge networks and the latter through commercial channel expansion.

6.3 Reconciling City-Level and Patent-Level Evidence

Before moving on to the discussion section, I here discuss the potential reasons behind the disparity between city-level results and patent-level results for the invention patents.

The city-level DRDID estimates establish that HSR connectivity reduces the log number of lapsed invention patents by 18.9% (all applicants) and 26.8% (firm applicants). Yet the patent-level Cox regression for the full sample of firm invention patents returns a hazard ratio of 1.051, implying that the presence of an HSR station is associated with a 5.1% increase in the per-patent lapse hazard. No such tension exists for utility models. Both the aggregate city-level estimates and the patent-level hazard ratios point in the same renewal-promoting direction, with a full-sample hazard ratio of 0.874 consistent with the DRDID coefficient of -14.5%.

The resolution lies in recognising that the two estimands measure fundamentally different objects. The patent-level Cox hazard ratio is a within-patent-type estimate of how much faster a given invention patent lapses once its city is connected to HSR, averaged across all patents and cohorts. The city-level DRDID, by contrast, measures the net change in the total flow of lapsed patents or the ratio of lapsed patents over valid stock at the city level, capturing the full portfolio-wide response, including changes in the cohort composition of the active patent stock. Three forces explain why the city-level aggregate can be negative even when the average per-patent hazard is positive.

First, and most important, is a cohort-heterogeneity and stock-composition effect. The Cox subsample results reveal a fundamental asymmetry between legacy and post-connection patents: firm invention patents filed after HSR arrival in eventually-treated cities carry a lapse hazard 22% below the pre-HSR baseline (HR = 0.780), while legacy patents filed before HSR arrival have a hazard rate higher by 10.6% (HR = 1.106) after the connection to the HSR network. The full-sample hazard ratio of 1.051 is a weighted average over both cohorts, dominated by the legacy incumbents that constitute the majority of the active stock in the years immediately following connection. The city-level DRDID, by contrast, measures

the evolution of the aggregate lapse flow as post-HSR cohorts progressively displace legacy patents through natural attrition. When post-HSR patents arrive with their substantially lower lapse hazard, the valid stock of patents in the city becomes increasingly composed of these more survivable cohorts. Hence, the portfolio-average hazard rate falls and aggregate lapse counts decline even if any given legacy patent continues to face elevated lapse risk. The city-level age-heterogeneity results provide direct evidence: the DRDID coefficient is significantly negative at patent ages 3–9 (approximately -0.10 to -0.27), reflecting protection concentrated among younger cohorts, and turns positive at ages 12–13 and 15–18, reflecting mild lapse acceleration for the older legacy patent segment. The event study pattern reinforces this mechanism: the magnitude of the DRDID treatment effect grows monotonically in post-event years, as successive waves of post-HSR patents augment the low-hazard cohort share of the city portfolio.

Second, there is a selective portfolio-cleansing mechanism. The elevated legacy hazard (HR = 1.106) is not uniform across the legacy stock but is concentrated among patents that were commercially marginal even before HSR arrival, that is, those in relatively monopolistic local markets and those at intermediate lifecycle stages when connection occurs (Table 15). Their accelerated exit, driven by inward diffusion of competing technologies and expanded competitive exposure via Channels 2 and 4, removes low-value assets from the active portfolio. The remaining stock in subsequent periods, therefore, carries a lower average lapse propensity than the pre-connection portfolio would have, and the city-level DRDID captures the steady-state lapse flow from this leaner, higher-quality portfolio rather than the transitional acceleration that elevates the Cox full-sample estimate. The contrast with utility models sharpens this interpretation: legacy utility models show virtually no lapse acceleration (HR = 0.982), no portfolio cleansing occurs, and no disparity between city-level and patent-level estimates arises.

Third, there is a unit-of-analysis and general equilibrium discrepancy. The Cox model conditions on observable patent-level characteristics, such as technology class, claim count,

family scope, inventor count, etc., and estimates the marginal effect of HSR for a patent with given attributes. Therefore, it cannot capture firm-level portfolio reallocation toward higher-quality technologies or the entry of innovative firms drawn to HSR-connected cities. All of these general equilibrium responses alter the aggregate lapse count at the city level without affecting the per-patent hazard conditional on observed characteristics. The city-level DRDID, which compares the total lapse flow across cities, captures all such responses by construction. The absence of a significant city-level effect on invention patent applications (Table 9) rules out a simple volume-expansion explanation and points instead to quality upgrading within a broadly constant application rate, a channel identified only by the aggregate estimator.

For utility models, the absence of any such disparity is itself informative. The full-sample Cox hazard ratio (HR = 0.874) and the city-level DRDID coefficient (−14.5%) are directionally consistent and broadly comparable in magnitude after accounting for the log-level versus hazard-rate translation. This consistency reflects the fact that renewal-promoting channels dominate uniformly across all utility model cohorts: the full-sample hazard is below unity, the eventually-treated subsample hazard is also below unity (HR = 0.816), and the legacy subsample hazard (HR = 0.982) is only marginally below unity with a small magnitude. There is no large within-type cohort heterogeneity to average over, and accordingly no compositional distortion between the patent-level and city-level estimates.

Together, these reconciliation findings underscore that the net city-level effect of HSR on invention patent lapse is the composition-weighted outcome of two opposing forces operating over distinct patent cohorts: Schumpeterian pressure accelerating the exit of pre-existing marginal legacy patents, and market-access and discovery gains producing a wave of post-connection patents with substantially lower lapse propensity whose growing portfolio share suppresses the aggregate lapse count.

7 Discussion

7.1 Mechanism: Evidence on the Four Theoretical Channels

The city-level and patent-level results, taken together, provide systematic empirical traction on each of the four channels through which HSR connectivity affects patent maintenance decisions in Section 3.3. This section discusses what the evidence says about each channel and how the interplay among them explains the observed patterns.

Channel 1: Market Access. The theory predicts that a transportation-induced expansion of market access $\mathcal{A}_n$ raises the patentee's initial rent level and, through it, the present value of renewal (Section 3.3.1). The patent-level results provide direct support. GDP-based and population-based market access via the HSR network are consistently and significantly associated with lower lapse hazards across all subsamples and both patent types: for invention patents, a one percent increase in GDP-based market access reduces the lapse hazard by 4.6%, and for utility models the corresponding reduction is 6.9%. The larger Channel 1 response for utility models is theoretically coherent: incremental, commercially oriented innovations with close ties to local manufacturing depend more directly on accessible market size, so the initial-rent-scaling mechanism of Channel 1 is more binding for them. At the aggregate city level, the DRDID estimates (-18.9% for invention, -14.5% for utility) confirm that the market access channel is sufficiently strong to generate a net reduction in lapse counts despite the simultaneous operation of renewal-opposing forces.

Channel 3: Multi-Market Discovery. Channel 3 predicts that broader geographic connectivity expands the search space for new profit applications, raising the continuation value through an order-statistics effect and lowering the renewal threshold (Section 3.3.3). Collaborative patents, which by construction could represent inventive activity spanning multiple locations, provide the most natural empirical proxy. Across all specifications, collaborative patents exhibit substantially lower lapse hazards after HSR connection than non-collaborative

ones: in the eventually-treated sample, the combined post-HSR hazard ratio for collaborative invention patents is $0.812 \times 0.808 \approx 0.66$ (a 34% reduction), versus 18.8% for non-collaborative patents. The same pattern holds for utility models ($0.825 \times 0.802 \approx 0.66$). This collaboration premium is consistent with the discovery mechanism of Proposition 1: firms that have already extended their innovative search across locations arrive at higher-quality best applications, and HSR further amplifies this advantage by expanding the reachable search space M_n.

Channel 2: Knowledge Spillovers and Schumpeterian Depreciation. Channel 2 predicts that better connectivity accelerates the diffusion of competing innovations, shrinking the carry-forward factor ρ_{in} and raising the lapse hazard (Section 3.3.2). The variable measuring access to external knowledge resources in the full-sample Cox regression has a negative hazard ratio for both invention (HR 0.951) and utility models (HR 0.945), hence suggesting a sheltering phenomenon. However, this apparent contradiction can be reconciled: the measurement of access to external knowledge resources captures outward access to the knowledge frontier, which also identifies complementary applications and reduces the uncertainty in the continuation value, effectively reinforcing Channel 3. The clearest signature of Channel 2 as a destructive force is instead found in the legacy patent results. For legacy invention patents, HSR connection raises the lapse hazard by 10.6%, precisely as Channel 2 predicts for pre-existing technologies that now face faster inward diffusion of superior innovations from a newly connected external environment. The age-at-treatment profile results in a concave, diminishing-rate increase in lapse hazard with the patent's age at HSR arrival, which further reflects the technology life-cycle dimension of Channel 2: older patents are more likely to have been partly superseded by subsequent innovations that travel along the HSR network, so the marginal obsolescence pressure is highest for moderately aged legacy patents and gets tuned down as the remaining unexpired term shrinks. The much weaker legacy-patent effect for utility models (HR 0.982 versus 1.106 for invention) is consistent with a lower knowledge-diffusion sensitivity γ_d for incremental technologies, which are less

exposed to Schumpeterian displacement.

Channel 4: Competitive Crowding. Channel 4 predicts that market integration raises the effective number of Cournot competitors and lowers per-patent flow rents (Section 3.3.4). The external-competitor variables in the Cox regressions provide the most direct test. For invention patents in eventually treated cities, a one percent increase in HSR-connected competitors, measured by valid patent stock or active firm count, raises the lapse hazard by approximately 1%. For legacy invention patents the effect is even larger (1.4–1.6%). Nonetheless, for utility models in eventually treated cities, the same competitive-exposure measures are associated with a slight decrease in lapse hazard (HR 0.992), and the effect for legacy utility models is negligible (HR 1.001). This patent-type asymmetry is consistent with the theory: Channel 4 is proportional to the entry elasticity α_m (Assumption 4), which is plausibly lower for utility-model technologies whose markets are more locally segmented and whose incremental improvements are less directly challenged by distant competitors. In the utility model context, the arrival of connected competitors may signal an expanding product-market opportunity, therefore reinforcing Channel 1 and not a substitutive threat.

7.2 Balancing Renewal-Promoting and Renewal-Opposing Forces

Proposition 2 implies that the net effect of transportation on renewal depends on whether the current patent value lies above or below a threshold $\bar{R}^*(\Gamma_n, M_n)$. Patents above the threshold are in the protection regime dominated by Channels 1 and 3; those below it are in the destruction regime dominated by Channels 2 and 4. The subsample structure of the Cox analysis provides a natural way to probe this prediction.

For patents filed after HSR connection (i.e., the eventually-treated specification), lapse hazards are uniformly lower for both invention patents (HR 0.780) and utility models (HR 0.816), and the market access and discovery channels dominate. This is consistent with newer patents entering the renewal problem at higher initial rents $R^{\mathrm{M}}_{in0} = \kappa q_i \mathcal{A}^{\mathrm{post}}_n$, placing

them above $\bar{R}^*$ and in the protection regime. For legacy patents, i.e., pre-existing assets that continue to require maintenance decisions after HSR arrives, the balance reverses for invention patents (HR 1.106 for destruction effect) but remains mildly sheltering for utility models (HR 0.982). This asymmetry maps directly to the cross-type difference in Γ_n: invention patents face higher depreciation sensitivity γ_d and entry elasticity α_m, yielding a larger Γ_n and a higher threshold $\bar{R}^*$ that more legacy invention patents fall below. On the other hand, utility models, with lower Γ_n, exhibit a lower threshold and remain in the renewal-promoting regime even when they predate HSR connection.

7.3 Relationship to Existing Literature

This study sits at the intersection of three bodies of work: the literature on transportation infrastructure and innovation, the literature on patent renewal and technology obsolescence, and the broader quantitative spatial economics literature. Therefore, it attempts to extend each in distinct ways by combining the three streams of literature together.

The dominant theme in the existing transportation-innovation literature is the creation of new innovations: city-level patent counts, R&D investment, collaborative patent counts, and knowledge spillovers (Fan & Xu, 2022; Hanley et al., 2022; Inoue et al., 2017; Lu et al., 2022; Wang et al., 2022). These studies establish that HSR generally promotes innovation quantity and quality, primarily through factor mobility, face-to-face interaction, and access to external knowledge resources. The present study is among the first to examine the sustainability side of the innovation: rather than asking whether HSR creates new technologies, it asks whether HSR allows existing technologies to remain commercially viable, or accelerates their retirement. The finding that HSR reduces lapse at the city-aggregate level, while simultaneously raising the individual lapse hazard for non-collaborative and legacy invention patents, reveals a tension that aggregate innovation measures would miss. The same infrastructure that stimulates the creation of high-quality, multi-city collaborative innovations also intensifies the Schumpeterian pressure on the incumbents they partly displace. This connects

directly to D. Sun et al. (2021), who showed that radical innovations benefit more from HSR than incremental ones. This study completes the other side of the story and documents the complementary result that radical innovations are also more exposed to the competitive obsolescence that HSR enables. The research gap explicitly identified in Section 2 is directly addressed here, extending the findings of Yu et al. (2019) to a longer time horizon (2002–2019), a broader set of patent types, and a richer set of mechanisms identified through the Cox regression framework. Besides, while the focus of this study is not about the creation of new innovations, the analysis part still includes an examination of the effect of HSR on patent applications, and finds no significant effect and even a slightly negative influence of HSR on the birth of new patents. This is contraditory to the current existing literature on the positive effect of HSR on innovation creation, and suggests that the innovation-creation effect of HSR may be more nuanced than previously thought. A further study using more detailed data and more refined methods is needed to reconcile this tension.

The foundational framework of Pakes (1986) treats the renewal decision as a pure financial option exercise by a representative patentee in an aspatial market. Subsequent contributions introduced litigation risk (Lanjouw et al., 1998), international portfolio decisions (Deng, 2011), heterogeneous patent-specific depreciation (Bessen, 2008; Hughes, 2024), and oligopolistic market structure (G. Zhang et al., 2014). A dimension kept being ignored in this literature is space. The present study introduces location as a systematic determinant of both the depreciation rate and the continuation value. Hence, this study views the renewal decision as reliant not only on the private quality of the innovation but on the patentee's position in a transportation network that governs market access, competitive exposure, and the breadth of discoverable profit applications. The Cox results confirm that location-specific variables, including market access, knowledge access, and competitor exposure via HSR, have statistically and economically significant effects on the lapse hazard, even after controlling for standard patent-quality proxies. This constitutes direct, patent-level evidence that the spatial dimension of the patent value problem is empirically first-order, complementing the

purely patent-characteristic approach of Kabore and Park (2019) and Maurseth and Svensson (2020). The collaboration findings extend Liu (2014), who showed that geographically dispersed inventor teams produce more durable patents, by showing that this premium is explicitly amplified by HSR connectivity, consistent with the multi-market discovery mechanism of Channel 3. Finally, the competitive crowding results provide patent-level confirmation of the market competition channel documented for UK patents by Bosworth and Jobome (2003), while the market access results complement the renewal-fee elasticity evidence of Thompson (2017) by showing that external market conditions matter at least as much as fee structures for the maintenance decision.

Finally, the theoretical framework borrows from the quantitative spatial economics literature, including the market access formulation of Allen and Arkolakis (2025) for Channel 1, the Schumpeterian depreciation structure of Aghion and Howitt (1992) for Channel 2, and the Cournot market integration structure of G. Zhang et al. (2014) for Channel 4. It then situates the patent renewal problem within this framework. The empirical results provide micro-level patent-survival evidence consistent with three predictions of this literature. First, the market access channel of Allen and Arkolakis (2025) and Akcigit and Melitz (2022) extends to technology *maintenance* decisions: better market access raises the present value of the patent-protected rent stream, not only the incentive to create new innovations. Second, the propagation of technological waves along transportation links documented by Berkes et al. (2025) has an observable counterpart in individual patent survival: legacy patents in HSR-connected cities, particularly those in formerly more monopolistic local markets, show accelerated lapse consistent with inward diffusion of superior competing technologies. Third, the concentration of the legacy lapse response in uncompetitive local markets, and its mitigation through HSR-enabled market access, echoes the general equilibrium reallocation effects modelled by Allen and Arkolakis (2025), although the present study's reduced-form estimates abstract from the full general equilibrium feedback and therefore represent a lower bound on the spatial reallocation implied by the theory.

7.4 Policy Implications

The channel decomposition carries implications that go beyond the reduced-form HSR effect. If the aggregate protection impact of HSR operates primarily through market access (Channel 1) and multi-market discovery (Channel 3), then policies that reinforce these channels, such as cross-regional collaborative R&D programmes, joint technology transfer initiatives between HSR-connected cities, and incentives for firm-level geographic knowledge search, should amplify and sustain the same protection effect. Conversely, the Schumpeterian depreciation channel (Channel 2) implies that rapid diffusion of frontier technologies from innovation hubs will accelerate the obsolescence of legacy invention patents in peripheral regions. Firms in concentrated local markets are especially exposed: the Cox results show that their legacy invention patents have the highest baseline lapse rates, and HSR only partially offsets this disadvantage. Targeted transition support for these firms, technology adoption subsidies, IP portfolio management assistance, and retraining for workers in technology-intensive sectors, could complement infrastructure investment. The finding that the same market structure is associated with lower legacy utility model lapse rates, however, suggests that such support should be calibrated to innovation type: the firms most in need of transition assistance are those holding invention patent portfolios in relatively monopolistic markets, not those relying on utility models for incremental product improvements.

8 Conclusion

This study examines how China's rapid expansion of high-speed rail has reshaped the technology obsolescence landscape, using patent lapse data as the primary outcome and a combination of city-level difference-in-differences estimation and patent-level Cox proportional hazards regression. The city-level results establish that HSR connectivity leads to a statistically and economically significant reduction in the aggregate number of lapsed patents. Using the DRDID estimator, which is robust to heterogeneous treatment timing, HSR con-

nection is associated with an 18.9% reduction in the log number of lapsed invention patents and a 14.5% reduction for utility models among all applicants; the effects are larger for firm applicants (26.8% and 19.0%, respectively). These reductions are confirmed across multiple estimators and the event study results show that post-HSR treatment effects grow monotonically in post-connection years, consistent with the progressive accumulation of a post-HSR patent cohort with higher survival value. Heterogeneity analysis by patent age shows that the lapse-reducing effect of HSR is concentrated among younger patents, with the effect diminishing steadily at older ages for both patent types.

At the patent level, the Cox regression analysis reveals two distinct regimes separated by patent vintage and type. Patents filed after HSR connection in eventually-treated cities exhibit substantially lower lapse hazards than those filed before (hazard ratio 0.780 for invention patents and 0.816 for utility models), confirming that improved market access and expanded discovery opportunities raise the commercial value of newly filed innovations. Within this post-HSR cohort, collaborative patents benefit most: the combined post-HSR hazard ratio for collaborative patents is approximately 0.66 for both patent types, consistent with the multi-market discovery mechanism through which HSR amplifies the value of geographically distributed knowledge search. Legacy patents face a reversed pattern for invention patents (hazard ratio 1.106), as increased competitive exposure from newly connected external markets accelerates the obsolescence of pre-existing radical technologies. The effect is much weaker for legacy utility models (hazard ratio 0.982), reflecting their lower sensitivity to Schumpeterian competition and stronger dependence on local commercial relationships. Together, these findings indicate that HSR reshapes the composition of the active patent portfolio toward newer, higher-value innovations while simultaneously accelerating the displacement of the technological incumbents they partly supplant.

Several contributions follow from these findings. First, this study provides the first comprehensive patent-level evidence that transportation infrastructure systematically alters technology obsolescence dynamics in China, using a dataset that spans the full buildout of the

HSR network from 2002 to 2019 and covers both invention patents and utility models. Second, it extends the spatial patent renewal model to a setting with formal empirical tests of four distinct channels providing direct evidence on the sign and magnitude of each. Third, it documents a systematic asymmetry between radical and incremental innovations in their response to transportation connectivity: invention patents are more exposed to the Schumpeterian creative destruction enabled by HSR market integration, while utility models are more uniformly protected by the market access and discovery channels. This asymmetry has implications both for how the patent renewal literature models technology-specific depreciation and for how the transportation-innovation literature interprets aggregate patent-count statistics that pool both types.

Notwithstanding these contributions, three limitations point toward directions for future research. First, the theoretical framework introduces spatial elements into the patent renewal problem but abstracts from the full general-equilibrium feedback that a transportation improvement triggers. In practice, an HSR connection sets off a cascade of adjustments to wages, prices, trade flows, and migration that ultimately feed back into the patentee's rent stream in ways the partial-equilibrium framework does not capture. A complete treatment would require embedding the patent renewal problem inside a simultaneous wage-and-migration equilibrium of the type developed by Allen and Arkolakis (2025) and Redding and Rossi-Hansberg (2017), with firm-level and worker-level decision problems that lie beyond the scope of the present framework. The reduced-form estimates, therefore, reflect the net composite effect of all these adjustments and should be interpreted as policy-relevant parameters rather than structural primitives.

Second, the study remains empirically agnostic about the product- and supply-chain-level processes through which competition and technological replacement actually occur. Linking the aggregate lapse patterns documented here to specific product market dynamics, such as which incumbent products are displaced, by which entrants, and through which supply chains, would require firm-level production and transaction data at a finer resolution

than is currently available. This limitation also means that the study does not trace the direction of technological change induced by HSR connectivity. A rich body of research has shown that technological progress can be steered toward specific factor inputs (Acemoglu, 1998, 2002; Acemoglu et al., 2012); examining whether HSR-induced market integration directs innovation toward high-skill versus low-skill, clean versus conventional energy, or efficiency-enhancing versus scale-augmenting technologies would substantially deepen the welfare analysis of transportation infrastructure investment.

Third, this study does not examine the litigation channel through which transportation connectivity may independently influence patent maintenance decisions. The arrival of HSR could raise the risk of patent infringement by facilitating market entry from distant innovation hubs, leading to more aggressive enforcement, elevated litigation costs, and altered portfolio strategies. While this channel interacts with the competitive crowding mechanism identified in the theoretical framework, its empirical identification requires linking patent data with litigation records at a scale and coverage not currently available. Future research that integrates comprehensive Chinese patent data with court records on patent disputes could assess whether HSR-connected cities experience elevated litigation rates and whether this enforcement channel complements or offsets the market-access and discovery effects identified here.

Despite these limitations, the present study provides systematic evidence that major transportation infrastructure shapes not only the creation of new technologies but also the lifecycle and sustainability of existing ones. As China's HSR network continues to expand and other economies invest heavily in high-speed connectivity, understanding the full innovation dynamics of such investments is essential for designing complementary policies that maximise the welfare returns from infrastructure spending.

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Tables

Table 1: Transportation Channels in the Spatial Patent Renewal Model

Channel	Structural parameter	Mechanism	$\partial V/\partial$(ch.)	$d\bar{R}/d\mathcal{T}_n$
1. Market access	$R^{\mathrm{M}}_{in0} = \kappa q_i \mathcal{A}_n$	Larger market $\Rightarrow$ higher initial rent	$+$	$-$
2. Knowledge spillovers	$\rho_{in} = e^{-(d_i^0 + \gamma_d K_n)}$	Faster diffusion $\Rightarrow$ smaller carry-forward	$-$ (in ρ_{in})	$+$
3. Multi-market discovery	$z^{(M_n)} = \max_{m \in \mathcal{M}_n} z^m,\ z^m \sim G$	More search $\Rightarrow$ higher expected best application	$+$ (in M_n)	$-$
4. Competition	$m_n = m_0 + \alpha_m \mathcal{A}_n$	More rivals $\Rightarrow$ lower per-firm Cournot profit	$-$ (in m_n)	$+$

Note: Column "$d\bar{R}/d\mathcal{T}_n$" gives the sign of the channel's contribution to the renewal threshold: a negative sign means transportation lowers the threshold and promotes renewal; a positive sign means transportation raises the threshold and promotes lapsing. Independent policy levers: Ch. 2 responds to R&D subsidies (ϕ_m) independently of transportation; Ch. 4 responds to entry and competition policy (α_m).

Feature	Invention Patent	Utility Model Patent
Term of Protection	20 years, counted from the date of filing. [42]	10 years, counted from the date of filing. [42]
Patentability Requirements	Must possess novelty, inventiveness, and practical applicability. [22]	Must possess novelty, inventiveness, and practical applicability. [22]
Standard for Inventiveness	The invention has **prominent substantive features** and represents a **notable progress** compared with existing technology. [22]	The utility model has **substantive features** and represents **progress** compared with existing technology. [22]
Examination Procedure	The application undergoes a preliminary examination and, upon request, a **substantive examination**. [34, 35] The patent right is granted only after passing the substantive examination. [39]	The application undergoes only a **preliminary examination**. If no reason for rejection is found, the patent right is granted. [40]
Application Documents	Requires a request, a description and its abstract, and claims. [26]	Requires a request, a description and its abstract, and claims. [26]
Foreign Priority Period	12 months from the first foreign filing date. [29]	12 months from the first foreign filing date. [29]
Scope of Protection	The extent of protection is determined by the terms of the claims. The description and drawings can be used to interpret the claims. [56]	The extent of protection is determined by the terms of the claims. The description and drawings can be used to interpret the claims. [56]

Feature	Invention Patent	Utility Model Patent
Infringement Dispute	In a dispute involving a new product manufacturing process, the defendant must prove their process is different. [57]	In an infringement dispute, the people's court or the patent administrative department may require the patentee to provide a **retrieval report** issued by the patent administrative department of the State Council. [57]
Compulsory License	The provisions for granting a compulsory license apply to invention patents. [48, 49, 50]	The provisions for granting a compulsory license apply to utility model patents. [48, 49, 50]

Table 2: Comparison between invention and utility model patents as outlined in the Patent Law of the People's Republic of China (2000 Amendment). The numbers in brackets [ ] refer to the relevant articles in the provided document.

Table 3: Summary statistics of City-level Panel Data (2002-2019)

	N	Mean	SD	Min	Max
Patent applications	9900	1632.81	5966.53	0.00	125465.00
Patent grants	9900	928.70	3702.29	0.00	83219.00
Patent lapses	9900	267.25	1080.60	0.00	18926.00
Patent lapse ratio	9900	7.90	12.31	0.00	366.67
HSR open	9900	0.28	0.45	0.00	1.00
GDP (current prices, 100m CNY)	9900	1052.25	2545.34	10.55	38156.00
Registered population at year-end (10k persons)	9900	145.68	186.15	14.08	2479.00
Secondary industry share of GDP	9900	49.02	12.28	8.05	90.97
Tertiary industry share of GDP	9900	43.68	11.37	5.08	83.52
Science & technology expenditure as perc of GDP	9900	0.21	0.27	0.00	5.03
Highway passengers (10k persons)	9900	7641.71	12887.17	9.00	286557.00
Civil aviation passengers (10k persons)	9900	44965.61	1919972.37	0.00	133071893.75
Higher-education institutions (count)	9900	7.92	13.69	0.00	93.00
Science & technology expenditure (10k CNY)	9900	50338.45	265201.31	0.00	5549817.00
Patent beginning stock	9900	2429.32	10496.34	0.00	237496.00
Broadband subscribers (10k households)	9900	68.18	131.85	0.00	5174.00
Specialized IP court/tribunal	9900	0.01	0.11	0.00	1.00
Real GDP per capita (CNY/person)	9900	40811.34	36352.74	1225.38	354955.29
Provincial capital (dummy)	9900	0.14	0.35	0.00	1.00

Table 4: Summary statistics (HSR open)

	N	Mean	SD	Min	Max
Patent applications	2748	4565.77	10440.67	0.00	125465.00
Patent grants	2748	2603.65	6527.28	0.00	83219.00
Patent lapses	2748	743.38	1867.60	0.00	18926.00
Patent lapse ratio	2748	11.88	10.37	0.00	115.22
HSR open	2748	1.00	0.00	1.00	1.00
GDP (current prices, 100m CNY)	2748	2285.17	4293.46	30.17	38156.00
Registered population at year-end (10k persons)	2748	200.11	254.21	15.10	2479.00
Secondary industry share of GDP	2748	45.20	10.91	12.97	75.97
Tertiary industry share of GDP	2748	49.19	11.00	21.91	83.52
Science & technology expenditure as perc of GDP	2748	0.37	0.38	0.00	5.03
Highway passengers (10k persons)	2748	9096.74	16253.38	9.00	195597.00
Civil aviation passengers (10k persons)	2748	125887.99	3605411.11	0.00	133071893.75
Higher-education institutions (count)	2748	12.65	19.38	1.00	93.00
Science & technology expenditure (10k CNY)	2748	143623.23	481145.54	86.00	5549817.00
Patent beginning stock	2748	6869.70	18827.98	0.00	237496.00
Broadband subscribers (10k households)	2748	135.01	200.24	5.99	5174.00
Specialized IP court/tribunal	2748	0.05	0.21	0.00	1.00
Real GDP per capita (CNY/person)	2748	60142.41	43590.33	5445.13	354955.29
Provincial capital (dummy)	2748	0.21	0.41	0.00	1.00

Table 5: Summary statistics (HSR not open)

	N	Mean	SD	Min	Max
Patent applications	7152	505.88	1682.10	0.00	29150.00
Patent grants	7152	285.13	1056.16	0.00	20971.00
Patent lapses	7152	84.31	394.94	0.00	12012.00
Patent lapse ratio	7152	6.37	12.64	0.00	366.67
HSR open	7152	0.00	0.00	0.00	0.00
GDP (current prices, 100m CNY)	7152	578.53	1038.56	10.55	14875.80
Registered population at year-end (10k persons)	7152	124.76	146.86	14.08	2129.09
Secondary industry share of GDP	7152	50.48	12.47	8.05	90.97
Tertiary industry share of GDP	7152	41.56	10.78	5.08	80.89
Science & technology expenditure as perc of GDP	7152	0.15	0.17	0.00	2.33
Highway passengers (10k persons)	7152	7082.65	11282.48	77.00	286557.00
Civil aviation passengers (10k persons)	7152	13872.95	325465.64	0.00	17851480.93
Higher-education institutions (count)	7152	6.10	10.17	0.00	83.00
Science & technology expenditure (10k CNY)	7152	14495.81	61650.21	0.00	2150816.00
Patent beginning stock	7152	723.20	2418.03	0.00	55633.00
Broadband subscribers (10k households)	7152	42.49	79.29	0.00	1535.17
Specialized IP court/tribunal	7152	0.00	0.00	0.00	0.00
Real GDP per capita (CNY/person)	7152	33383.79	30011.08	1225.38	329894.59
Provincial capital (dummy)	7152	0.12	0.33	0.00	1.00

Table 6: Reference Table for Invention Patent Annual Fee Calculation (Unit: RMB Yuan)

Category	**Years 1–3**	**Years 4–6**	**Years 7–9**	**Years 10–12**	**Years 13–15**	**Years 16–20**
Annual Fee Standard	900	1200	2000	4000	6000	8000
70% Reduction Standard	270	360	600	1200	1800	2400
85% Reduction Standard	135	180	300	600	900	1200
5% Late Payment Surcharge	45	60	100	200	300	400
10% Late Payment Surcharge	90	120	200	400	600	800
15% Late Payment Surcharge	135	180	300	600	900	1200
20% Late Payment Surcharge	180	240	400	800	1200	1600
25% Late Payment Surcharge	225	300	500	1000	1500	2000

Note: All amounts are in RMB (Yuan).

Table 7: Reference Table for Utility Model Patent Annual Fee Calculation (Unit: RMB Yuan)

Category	**Years 1–3**	**Years 4–5**	**Years 6–8**	**Years 9–10**
Annual Fee Standard	600	900	1200	2000
70% Reduction Standard	180	270	360	600
85% Reduction Standard	90	135	180	300
5% Late Payment Surcharge	30	45	60	100
10% Late Payment Surcharge	60	90	120	200
15% Late Payment Surcharge	90	135	180	300
20% Late Payment Surcharge	120	180	240	400
25% Late Payment Surcharge	150	225	300	500

Note: All amounts are in RMB (Yuan).

Table 8: Comparison of Annual Fee Payment Timelines for Two BYD Invention Patents

Event Date	**CN2004101040055**	**CN2004101040074**
Application Date	30 Dec 2004	30 Dec 2004
Grant Notification	27 Jun 2008	09 Nov 2007
First Post-Grant Payment	24 Jul 2008 (4th year)	12 Dec 2007 (4th year)
Subsequent Payment Example	19 Nov 2008 (5th year)	19 Nov 2008 (5th year)
Last Recorded Payment	21 Nov 2023 (20th year)	15 Nov 2021 (18th year)
Expiry/Termination	30 Dec 2024 (age 20)	30 Dec 2022 (age 18)

Table 9: Estimation Results (Invention Patents)

	All			Firm		
	TWFE	DRDID	SA	TWFE	DRDID	SA
Panel A: Number of Lapsed Patents						
hsr_open	0.007	-0.189**	-0.217***	0.052	-0.268***	-0.147***
	(0.052)	(0.086)	(0.069)	(0.043)	(0.103)	(0.056)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,860	4,950	4,950	4,860	4,950	4,950
Panel B: Lapse-to-Stock Ratio						
hsr_open	-0.044	-0.058	-0.110	-0.034	-0.099	-0.124*
	(0.046)	(0.096)	(0.079)	(0.043)	(0.101)	(0.074)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,860	4,950	4,950	4,860	4,950	4,950
Panel C: Patent Application						
hsr_open	-0.021	-0.131**	-0.093*	0.051	-0.078	-0.093*
	(0.049)	(0.064)	(0.053)	(0.050)	(0.069)	(0.054)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,860	4,950	4,950	4,860	4,950	4,950

Standard errors in parentheses

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

Table 10: Estimation Results (Utility Patents)

	All			Firm		
	TWFE	DRDID	SA	TWFE	DRDID	SA
Panel A: Number of Lapsed Patents						
hsr_open	-0.085*	-0.145*	-0.270***	-0.045	-0.190*	-0.287***
	(0.050)	(0.082)	(0.071)	(0.046)	(0.098)	(0.069)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,860	4,950	4,950	4,860	4,950	4,950
Panel B: Lapse-to-Stock Ratio						
hsr_open	-0.074*	-0.096	-0.143**	-0.048	-0.177**	-0.178***
	(0.042)	(0.070)	(0.056)	(0.040)	(0.072)	(0.058)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,860	4,950	4,950	4,860	4,950	4,950
Panel C: Patent Application						
hsr_open	-0.062	-0.063	-0.090*	-0.043	-0.075	-0.112**
	(0.041)	(0.071)	(0.049)	(0.044)	(0.077)	(0.050)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,860	4,950	4,950	4,860	4,950	4,950

Standard errors in parentheses

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

Table 11: Cox Proportional Hazards Results for Invention Patents: Full Sample

	(1)	(2)	(3)	(4)	(5)
HSR Station	1.051***	1.072***			
	(0.008)	(0.009)			
HSR Station × Collaborative		0.870***			
		(0.017)			
Market access (GDP)			0.954***		
			(0.001)		
Market access (POP)				0.942***	
				(0.002)	
Access to research sources					0.951***
					(0.001)
Collaborative	1.502***	1.702***	1.533***	1.532***	1.569***
	(0.032)	(0.046)	(0.033)	(0.032)	(0.033)
Family country count	0.764***	0.764***	0.777***	0.763***	0.778***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Applications within IPC	0.992***	0.992***	0.993***	0.993***	0.994***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of applicants	0.919†	0.924†	0.926†	0.932	0.933
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
Number of inventors	0.664***	0.663***	0.662***	0.668***	0.665***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Number of backward citations	0.957***	0.957***	0.956***	0.957***	0.956***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of claims	0.752***	0.752***	0.766***	0.762***	0.777***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Number of forward citations	0.887***	0.887***	0.888***	0.888***	0.888***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Application Cohort:					
Applications cohort=2003	1.095***	1.095***	1.093***	1.092***	1.088***

	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Applications cohort=2004	1.157***	1.157***	1.152***	1.147***	1.143***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Applications cohort=2005	1.077***	1.076***	1.077***	1.074***	1.069**
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Applications cohort=2006	1.075***	1.075***	1.075***	1.070***	1.064**
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Applications cohort=2007	1.145***	1.146***	1.147***	1.143***	1.135***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Applications cohort=2008	1.070***	1.071***	1.070***	1.070***	1.058**
	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)
Applications cohort=2009	1.034†	1.035†	1.031	1.031	1.014
	(0.020)	(0.020)	(0.020)	(0.020)	(0.019)
Applications cohort=2010	0.963†	0.964†	0.955*	0.956*	0.937***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.018)
Applications cohort=2011	0.839***	0.839***	0.832***	0.833***	0.814***
	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)
Applications cohort=2012	0.806***	0.807***	0.794***	0.796***	0.777***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)
Applications cohort=2013	0.805***	0.806***	0.792***	0.795***	0.774***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)
Applications cohort=2014	0.755***	0.756***	0.741***	0.744***	0.724***
	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)
Applications cohort=2015	0.627***	0.627***	0.618***	0.620***	0.603***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)
Applications cohort=2016	0.592***	0.593***	0.584***	0.586***	0.570***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)
Applications cohort=2017	0.480***	0.481***	0.473***	0.475***	0.461***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)
Applications cohort=2018	0.036***	0.036***	0.036***	0.036***	0.035***

	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Applications cohort=2019	0.016***	0.016***	0.016***	0.016***	0.015***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
IPC Technology Class:					
B	0.977*	0.977*	1.004	1.002	1.014
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
C	0.873***	0.874***	0.891***	0.890***	0.903***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
D	1.110***	1.109***	1.119***	1.112***	1.123***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
E	0.989	0.989	1.027†	1.027†	1.038**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
F	0.991	0.990	1.016	1.011	1.020†
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
G	0.794***	0.794***	0.843***	0.836***	0.866***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
H	0.861***	0.861***	0.914***	0.897***	0.935***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Observations	5519011	5519011	5498026	5498026	5498026

Hazard ratios reported; robust standard errors in parentheses.

Sample restricted to firm patents only.

Base IPC section: A.

Significance levels: †p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table 12: Cox Proportional Hazards Results for Utility Models: Full Sample

	(1)	(2)	(3)	(4)	(5)
HSR Station	0.874***	0.879***			
	(0.002)	(0.002)			
HSR Station × Collaborative		0.902***			
		(0.008)			
Market access (GDP)			0.914***		
			(0.000)		
Market access (POP)				0.925***	
				(0.001)	
Access to research sources					0.940***
					(0.000)
Collaborative	0.909***	0.983	0.915***	0.914***	0.917***
	(0.010)	(0.012)	(0.010)	(0.010)	(0.010)
Family country count	0.420***	0.420***	0.432***	0.414***	0.427***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Applications within IPC	1.000	1.000	0.999*	0.999	0.999
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of applicants	1.067**	1.086***	1.121***	1.101***	1.146***
	(0.024)	(0.024)	(0.025)	(0.024)	(0.025)
Number of inventors	0.592***	0.592***	0.584***	0.593***	0.586***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of backward citations	0.928***	0.928***	0.929***	0.928***	0.928***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of claims	0.689***	0.689***	0.712***	0.695***	0.711***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of forward citations	1.021***	1.021***	1.021***	1.020***	1.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Application Cohort:					
Applications cohort=2003	1.015	1.015	1.007	1.009	1.008

	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Applications cohort=2004	0.994	0.995	0.981	0.980	0.982
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Applications cohort=2005	1.014	1.016	0.987	0.987	0.988
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Applications cohort=2006	1.014	1.016	0.968**	0.970**	0.969**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Applications cohort=2007	1.013	1.015	0.954***	0.957***	0.954***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
Applications cohort=2008	1.042***	1.044***	0.966***	0.970**	0.967**
	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
Applications cohort=2009	1.122***	1.124***	1.027**	1.032**	1.029**
	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
Applications cohort=2010	1.148***	1.150***	1.037***	1.045***	1.040***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
Applications cohort=2011	1.166***	1.169***	1.044***	1.054***	1.046***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
Applications cohort=2012	1.243***	1.247***	1.099***	1.112***	1.103***
	(0.012)	(0.012)	(0.010)	(0.011)	(0.010)
Applications cohort=2013	1.220***	1.224***	1.068***	1.085***	1.074***
	(0.012)	(0.012)	(0.010)	(0.010)	(0.010)
Applications cohort=2014	1.259***	1.263***	1.092***	1.112***	1.099***
	(0.012)	(0.012)	(0.010)	(0.011)	(0.010)
Applications cohort=2015	1.320***	1.323***	1.134***	1.157***	1.141***
	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)
Applications cohort=2016	1.268***	1.272***	1.082***	1.104***	1.090***
	(0.012)	(0.012)	(0.010)	(0.010)	(0.010)
Applications cohort=2017	1.135***	1.138***	0.958***	0.980*	0.964***
	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)
Applications cohort=2018	1.057***	1.060***	0.884***	0.907***	0.891***

	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)
Applications cohort=2019	0.325***	0.326***	0.271***	0.278***	0.272***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
IPC Technology Class:					
B	0.974***	0.973***	0.988***	0.989***	0.983***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
C	0.838***	0.838***	0.846***	0.851***	0.842***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
D	1.006	1.005	1.002	1.004	1.006
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
E	0.870***	0.870***	0.896***	0.892***	0.890***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
F	0.864***	0.863***	0.878***	0.876***	0.873***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
G	0.807***	0.807***	0.849***	0.833***	0.840***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
H	0.828***	0.828***	0.861***	0.845***	0.851***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	13858084	13858084	13786947	13786947	13786947

Hazard ratios reported; robust standard errors in parentheses.

Sample restricted to firm patents only.

Base IPC section: A.

Significance levels: †p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table 13: Cox Proportional Hazards Results for Invention Patents: Eventually Treated Cities

	(1)	(2)	(3)	(4)	(5)	(6)
After HSR	0.780***	0.812***				
	(0.005)	(0.005)				
After HSR × Collaborative		0.808***				
		(0.010)				
Market access (GDP)			0.940***			
			(0.002)			
Market access (POP)				0.916***		
				(0.002)		
Patent Rivals via HSR					1.011***	
					(0.000)	
Firm Rivals via HSR						1.013***
						(0.001)
Collaborative	1.520***	1.607***	1.542***	1.544***	1.524***	1.525***
	(0.032)	(0.034)	(0.033)	(0.033)	(0.033)	(0.033)
Family country count	0.756***	0.754***	0.780***	0.762***	0.756***	0.756***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Applications within IPC	0.992***	0.992***	0.993***	0.993***	0.993***	0.993***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of applicants	0.941	1.018	0.928†	0.938	0.924†	0.924†
	(0.043)	(0.046)	(0.042)	(0.042)	(0.042)	(0.042)
Number of inventors	0.664***	0.666***	0.661***	0.670***	0.672***	0.674***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Number of backward citations	0.957***	0.957***	0.956***	0.957***	0.958***	0.958***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of claims	0.761***	0.760***	0.770***	0.765***	0.754***	0.754***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Number of forward citations	0.889***	0.889***	0.888***	0.888***	0.888***	0.888***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

Applications cohort=2003	1.097***	1.098***	1.092***	1.089***	1.088***	1.087***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Applications cohort=2004	1.160***	1.162***	1.150***	1.143***	1.146***	1.145***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Applications cohort=2005	1.083***	1.086***	1.074***	1.068**	1.060**	1.058**
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Applications cohort=2006	1.083***	1.087***	1.072***	1.065**	1.050*	1.048*
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Applications cohort=2007	1.158***	1.164***	1.143***	1.137***	1.115***	1.113***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Applications cohort=2008	1.151***	1.162***	1.065***	1.063**	1.044*	1.043*
	(0.022)	(0.022)	(0.020)	(0.020)	(0.020)	(0.020)
Applications cohort=2009	1.113***	1.123***	1.025	1.024	1.000	1.000
	(0.021)	(0.022)	(0.020)	(0.020)	(0.019)	(0.019)
Applications cohort=2010	1.099***	1.111***	0.949**	0.948**	0.926***	0.925***
	(0.021)	(0.022)	(0.019)	(0.018)	(0.018)	(0.018)
Applications cohort=2011	0.979	0.988	0.825***	0.825***	0.803***	0.803***
	(0.019)	(0.020)	(0.016)	(0.016)	(0.016)	(0.016)
Applications cohort=2012	0.972	0.982	0.787***	0.787***	0.770***	0.769***
	(0.020)	(0.020)	(0.016)	(0.016)	(0.015)	(0.015)
Applications cohort=2013	0.984	0.995	0.784***	0.784***	0.768***	0.767***
	(0.020)	(0.020)	(0.016)	(0.016)	(0.015)	(0.015)
Applications cohort=2014	0.935**	0.944**	0.733***	0.734***	0.718***	0.718***
	(0.019)	(0.020)	(0.015)	(0.015)	(0.015)	(0.015)
Applications cohort=2015	0.789***	0.796***	0.611***	0.612***	0.599***	0.598***
	(0.017)	(0.018)	(0.013)	(0.013)	(0.013)	(0.013)
Applications cohort=2016	0.753***	0.756***	0.578***	0.578***	0.569***	0.568***
	(0.018)	(0.018)	(0.013)	(0.013)	(0.013)	(0.013)
Applications cohort=2017	0.616***	0.619***	0.468***	0.469***	0.467***	0.466***
	(0.019)	(0.019)	(0.014)	(0.014)	(0.014)	(0.014)

Applications cohort=2018	0.046***	0.047***	0.035***	0.036***	0.036***	0.036***
	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
Applications cohort=2019	0.021***	0.021***	0.016***	0.016***	0.017***	0.017***
	(0.021)	(0.021)	(0.016)	(0.016)	(0.017)	(0.017)
IPC Technology Class:						
B	0.983†	0.980*	1.006	1.001	0.982*	0.977*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
C	0.877***	0.875***	0.893***	0.892***	0.874***	0.872***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
D	1.106***	1.099***	1.115***	1.103***	1.099***	1.097***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
E	1.005	1.004	1.032*	1.032*	1.012	1.011
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
F	0.994	0.990	1.017	1.008	0.994	0.992
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
G	0.816***	0.816***	0.852***	0.845***	0.796***	0.794***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
H	0.876***	0.879***	0.925***	0.902***	0.858***	0.858***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	5514872	5514872	5498026	5498026	5510736	5510736

Hazard ratios reported; robust standard errors in parentheses.

Sample restricted to firm patents only.

Base IPC section: A.

Significance levels: †p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table 14: Cox Proportional Hazards Results for Utility Models: Eventually Treated Cities

	(1)	(2)	(3)	(4)	(5)	(6)
After HSR	0.816***	0.825***				
	(0.002)	(0.002)				
After HSR × Collaborative		0.802***				
		(0.006)				
Market access (GDP)			0.914***			
			(0.000)			
Market access (POP)				0.925***		
				(0.001)		
Patent Rivals via HSR					0.989***	
					(0.000)	
Firm Rivals via HSR						0.989***
						(0.000)
Collaborative	0.912***	1.017	0.915***	0.914***	0.911***	0.910***
	(0.010)	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)
Family country count	0.419***	0.414***	0.432***	0.414***	0.438***	0.437***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Applications within IPC	0.999	0.999†	0.999*	0.999	1.001†	1.001†
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of applicants	1.087***	1.164***	1.121***	1.101***	1.055*	1.056*
	(0.024)	(0.026)	(0.025)	(0.024)	(0.024)	(0.024)
Number of inventors	0.591***	0.592***	0.584***	0.593***	0.579***	0.579***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of backward citations	0.928***	0.928***	0.929***	0.928***	0.928***	0.928***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of claims	0.694***	0.694***	0.712***	0.695***	0.699***	0.698***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of forward citations	1.019***	1.019***	1.021***	1.020***	1.021***	1.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Application Cohort:						
Applications cohort=2003	1.006	1.007	1.007	1.009	1.012	1.011
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Applications cohort=2004	0.974*	0.974*	0.981	0.980	0.988	0.987
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Applications cohort=2005	0.982	0.983	0.987	0.987	1.004	1.002
	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
Applications cohort=2006	0.969**	0.973*	0.968**	0.970**	0.994	0.992
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Applications cohort=2007	0.958***	0.961***	0.954***	0.957***	0.988	0.985
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)
Applications cohort=2008	1.007	1.011	0.966***	0.970**	1.012	1.009
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Applications cohort=2009	1.077***	1.082***	1.027**	1.032**	1.081***	1.077***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
Applications cohort=2010	1.148***	1.154***	1.037***	1.045***	1.101***	1.097***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
Applications cohort=2011	1.186***	1.193***	1.044***	1.054***	1.117***	1.113***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
Applications cohort=2012	1.277***	1.284***	1.099***	1.112***	1.188***	1.183***
	(0.012)	(0.012)	(0.010)	(0.011)	(0.011)	(0.011)
Applications cohort=2013	1.268***	1.276***	1.068***	1.085***	1.162***	1.157***
	(0.012)	(0.012)	(0.010)	(0.010)	(0.011)	(0.011)
Applications cohort=2014	1.313***	1.322***	1.092***	1.112***	1.195***	1.190***
	(0.013)	(0.013)	(0.010)	(0.011)	(0.011)	(0.011)
Applications cohort=2015	1.386***	1.395***	1.134***	1.157***	1.256***	1.250***
	(0.013)	(0.013)	(0.011)	(0.011)	(0.012)	(0.012)
Applications cohort=2016	1.339***	1.346***	1.082***	1.104***	1.209***	1.203***
	(0.013)	(0.013)	(0.010)	(0.010)	(0.012)	(0.012)
Applications cohort=2017	1.202***	1.207***	0.958***	0.980*	1.088***	1.083***

	(0.012)	(0.012)	(0.009)	(0.009)	(0.010)	(0.010)
Applications cohort=2018	1.115***	1.120***	0.884***	0.907***	1.017†	1.012
	(0.011)	(0.011)	(0.009)	(0.009)	(0.010)	(0.010)
Applications cohort=2019	0.341***	0.343***	0.271***	0.278***	0.313***	0.312***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
IPC Technology Class:						
B	0.976***	0.975***	0.988***	0.989***	1.006*	1.007*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
C	0.839***	0.838***	0.846***	0.851***	0.818***	0.819***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
D	1.008	1.006	1.002	1.004	0.991	0.991
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
E	0.875***	0.874***	0.896***	0.892***	0.881***	0.880***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
F	0.865***	0.865***	0.878***	0.876***	0.881***	0.881***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
G	0.814***	0.814***	0.849***	0.833***	0.827***	0.828***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
H	0.833***	0.832***	0.861***	0.845***	0.863***	0.862***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	13838659	13838659	13786947	13786947	13815759	13815759

Hazard ratios reported; robust standard errors in parentheses.

Sample restricted to firm patents only.

Base IPC section: A.

Significance levels: †p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table 15: Cox Proportional Hazards Results for Invention Patents: Legacy Patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HSR Station	1.106***	1.109***				1.192***	1.209***
	(0.009)	(0.010)				(0.016)	(0.017)
HSR Station × Collaborative		0.982					
		(0.020)					
Age at treatment^2			0.997***				
			(0.000)				
Age at treatment			1.050***				
			(0.003)				
Patent Rivals via HSR				1.014***			
				(0.001)			
Firm Rivals via HSR					1.016***		
					(0.001)		
HSR Station × HHI gap						1.031	
						(0.031)	
HSR Station × HHI gap (rolling)							0.906***
							(0.025)
HHI gap						1.000	
						(0.026)	
HHI gap (rolling)							1.290***
							(0.031)
Collaborative	1.529***	1.553***	1.538***	1.555***	1.554***	1.620***	1.555***
	(0.047)	(0.054)	(0.047)	(0.048)	(0.048)	(0.052)	(0.049)
Family country count	0.807***	0.807***	0.810***	0.795***	0.796***	0.815***	0.808***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Applications within IPC	0.995***	0.995***	0.995***	0.996***	0.996***	1.000	0.999
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of applicants	1.080	1.078	1.090	1.075	1.075	1.010	1.074
	(0.073)	(0.073)	(0.074)	(0.074)	(0.074)	(0.072)	(0.075)

Number of inventors	0.686***	0.686***	0.684***	0.696***	0.697***	0.680***	0.682***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Number of backward citations	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***	0.952***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of claims	0.807***	0.807***	0.809***	0.806***	0.806***	0.822***	0.815***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Number of forward citations	0.882***	0.882***	0.883***	0.882***	0.882***	0.881***	0.881***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Applications cohort=2003	1.081***	1.081***	1.084***	1.075***	1.074***	1.098***	1.078***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)	(0.023)
Applications cohort=2004	1.121***	1.121***	1.129***	1.114***	1.113***	1.136***	1.114***
	(0.023)	(0.023)	(0.024)	(0.023)	(0.023)	(0.025)	(0.023)
Applications cohort=2005	1.035†	1.035†	1.054**	1.021	1.021	1.055*	1.025
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)	(0.021)
Applications cohort=2006	1.025	1.025	1.062**	1.005	1.005	1.046*	1.011
	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)	(0.021)	(0.020)
Applications cohort=2007	1.090***	1.090***	1.157***	1.064**	1.066**	1.113***	1.072***
	(0.021)	(0.021)	(0.023)	(0.021)	(0.021)	(0.022)	(0.021)
Applications cohort=2008	1.112***	1.112***	1.177***	1.071***	1.073***	1.139***	1.094***
	(0.022)	(0.022)	(0.023)	(0.021)	(0.021)	(0.023)	(0.022)
Applications cohort=2009	1.045*	1.045*	1.136***	1.000	1.002	1.064**	1.023
	(0.021)	(0.021)	(0.023)	(0.020)	(0.020)	(0.022)	(0.020)
Applications cohort=2010	1.068**	1.068**	1.148***	1.014	1.019	1.069**	1.028
	(0.022)	(0.022)	(0.024)	(0.021)	(0.021)	(0.023)	(0.021)
Applications cohort=2011	0.939**	0.938**	1.017	0.882***	0.886***	0.936**	0.899***
	(0.020)	(0.020)	(0.022)	(0.019)	(0.019)	(0.021)	(0.019)
Applications cohort=2012	0.969	0.969	1.033	0.930**	0.936**	0.973	0.919***
	(0.022)	(0.022)	(0.024)	(0.021)	(0.021)	(0.023)	(0.021)
Applications cohort=2013	0.962†	0.962†	1.020	0.907***	0.912***	0.961	0.903***
	(0.022)	(0.022)	(0.024)	(0.021)	(0.021)	(0.023)	(0.021)

Applications cohort=2014	0.925**	0.925**	0.991	0.866***	0.871***	0.934*	0.869***
	(0.023)	(0.023)	(0.025)	(0.022)	(0.022)	(0.025)	(0.022)
Applications cohort=2015	0.824***	0.824***	0.867***	0.782***	0.787***	0.854***	0.797***
	(0.026)	(0.026)	(0.027)	(0.025)	(0.025)	(0.028)	(0.026)
Applications cohort=2016	0.837***	0.837***	0.880***	0.804***	0.809***	0.893**	0.833***
	(0.031)	(0.031)	(0.033)	(0.031)	(0.031)	(0.035)	(0.032)
Applications cohort=2017	0.542***	0.542***	0.559***	0.526***	0.529***	0.586***	0.555***
	(0.041)	(0.041)	(0.043)	(0.041)	(0.042)	(0.047)	(0.044)
Applications cohort=2018	0.069***	0.070***	0.077***	0.066***	0.066***	0.070***	0.067***
	(0.026)	(0.026)	(0.029)	(0.027)	(0.027)	(0.028)	(0.028)
Applications cohort=2019	0.000	0.000	0.000***	0.000	0.000	0.000***	0.000
	(.)	(.)	(0.000)	(.)	(.)	(0.000)	(.)
IPC Technology Class:							
B	1.030*	1.030*	1.033**	1.040**	1.035**	1.025†	1.024†
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
C	0.949***	0.949***	0.953***	0.949***	0.947***	0.959***	0.952***
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
D	1.121***	1.121***	1.111***	1.107***	1.104***	1.076**	1.071**
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)	(0.024)
E	1.096***	1.096***	1.105***	1.125***	1.122***	1.062**	1.087***
	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.021)
F	1.159***	1.159***	1.165***	1.172***	1.167***	1.148***	1.126***
	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)
G	0.994	0.994	1.010	0.992	0.991	1.030*	1.016
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)
H	1.023*	1.023*	1.032**	1.015	1.016	1.067***	1.039***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Observations	2468842	2468842	2464703	2465510	2465510	2462033	2465566

Hazard ratios reported; robust standard errors in parentheses.

Sample restricted to firm patents only.

Base IPC section: A.

Significance levels: †p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table 16: Cox Proportional Hazards Results for Utility Models: Legacy Patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HSR Station	0.982***	0.976***				1.003	1.006
	(0.003)	(0.003)				(0.004)	(0.004)
HSR Station × Collaborative		1.120***					
		(0.012)					
Age at treatment^2			1.000				
			(0.000)				
Age at treatment			1.015***				
			(0.001)				
Patent Rivals via HSR				0.998***			
				(0.000)			
Firm Rivals via HSR					0.998***		
					(0.000)		
HSR Station × HHI gap						0.967**	
						(0.011)	
HSR Station × HHI gap (rolling)							0.899***
							(0.009)
HHI gap						0.817***	
						(0.006)	
HHI gap (rolling)							0.955***
							(0.006)
Collaborative	0.943**	0.890***	0.936***	0.943**	0.942**	0.968†	0.943**
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)
Family country count	0.568***	0.566***	0.582***	0.575***	0.574***	0.598***	0.578***
	(0.015)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Applications within IPC	0.995***	0.995***	0.994***	0.995***	0.995***	0.995***	0.995***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of applicants	1.190***	1.181***	1.215***	1.188***	1.188***	1.140**	1.185***
	(0.049)	(0.049)	(0.050)	(0.049)	(0.049)	(0.048)	(0.050)

Number of inventors	0.680***	0.680***	0.679***	0.675***	0.675***	0.677***	0.680***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of backward citations	0.904***	0.904***	0.904***	0.906***	0.906***	0.907***	0.905***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of claims	0.768***	0.768***	0.772***	0.774***	0.774***	0.776***	0.771***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of forward citations	1.075***	1.075***	1.076***	1.077***	1.077***	1.075***	1.077***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Application Cohort:							
Applications cohort=2003	1.001	1.000	1.013	0.999	0.999	1.023†	0.997
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)
Applications cohort=2004	0.966**	0.965**	0.992	0.964**	0.964**	1.004	0.960***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)
Applications cohort=2005	0.971**	0.970**	1.008	0.970**	0.969**	1.020	0.964**
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)
Applications cohort=2006	0.964***	0.962***	1.012	0.960***	0.959***	1.009	0.954***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.012)	(0.010)
Applications cohort=2007	0.955***	0.953***	1.015	0.952***	0.951***	1.004	0.945***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)
Applications cohort=2008	0.997	0.996	1.063***	0.994	0.993	1.048***	0.985
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)
Applications cohort=2009	1.067***	1.066***	1.148***	1.060***	1.058***	1.120***	1.048***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.012)	(0.010)
Applications cohort=2010	1.123***	1.122***	1.202***	1.109***	1.107***	1.175***	1.099***
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.013)	(0.011)
Applications cohort=2011	1.157***	1.155***	1.237***	1.143***	1.141***	1.209***	1.131***
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.013)	(0.011)
Applications cohort=2012	1.253***	1.252***	1.344***	1.229***	1.228***	1.313***	1.223***
	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.014)	(0.012)
Applications cohort=2013	1.182***	1.181***	1.265***	1.153***	1.151***	1.233***	1.146***

	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.014)	(0.012)
Applications cohort=2014	1.344***	1.342***	1.441***	1.310***	1.309***	1.408***	1.301***
	(0.014)	(0.014)	(0.015)	(0.013)	(0.013)	(0.015)	(0.013)
Applications cohort=2015	1.470***	1.468***	1.577***	1.452***	1.451***	1.565***	1.434***
	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.017)	(0.015)
Applications cohort=2016	1.385***	1.382***	1.485***	1.364***	1.362***	1.470***	1.343***
	(0.015)	(0.014)	(0.016)	(0.014)	(0.014)	(0.017)	(0.014)
Applications cohort=2017	1.268***	1.265***	1.370***	1.263***	1.261***	1.364***	1.242***
	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.016)	(0.014)
Applications cohort=2018	1.392***	1.389***	1.526***	1.403***	1.400***	1.505***	1.380***
	(0.016)	(0.016)	(0.018)	(0.017)	(0.017)	(0.019)	(0.017)
Applications cohort=2019	0.418***	0.417***	0.460***	0.423***	0.422***	0.447***	0.417***
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)	(0.009)
IPC Technology Class:							
B	0.945***	0.945***	0.948***	0.965***	0.964***	0.970***	0.956***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
C	0.816***	0.816***	0.821***	0.789***	0.789***	0.785***	0.795***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)
D	0.920***	0.920***	0.917***	0.905***	0.905***	0.914***	0.912***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
E	0.894***	0.894***	0.899***	0.906***	0.906***	0.917***	0.903***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
F	0.870***	0.870***	0.872***	0.881***	0.881***	0.891***	0.876***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
G	0.846***	0.846***	0.855***	0.858***	0.858***	0.859***	0.848***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
H	0.838***	0.837***	0.842***	0.856***	0.855***	0.867***	0.846***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	4613096	4613096	4593671	4599020	4599020	4580674	4598610

Hazard ratios reported; robust standard errors in parentheses.

Sample restricted to firm patents only.

Base IPC section: A.

Significance levels: †p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Figures

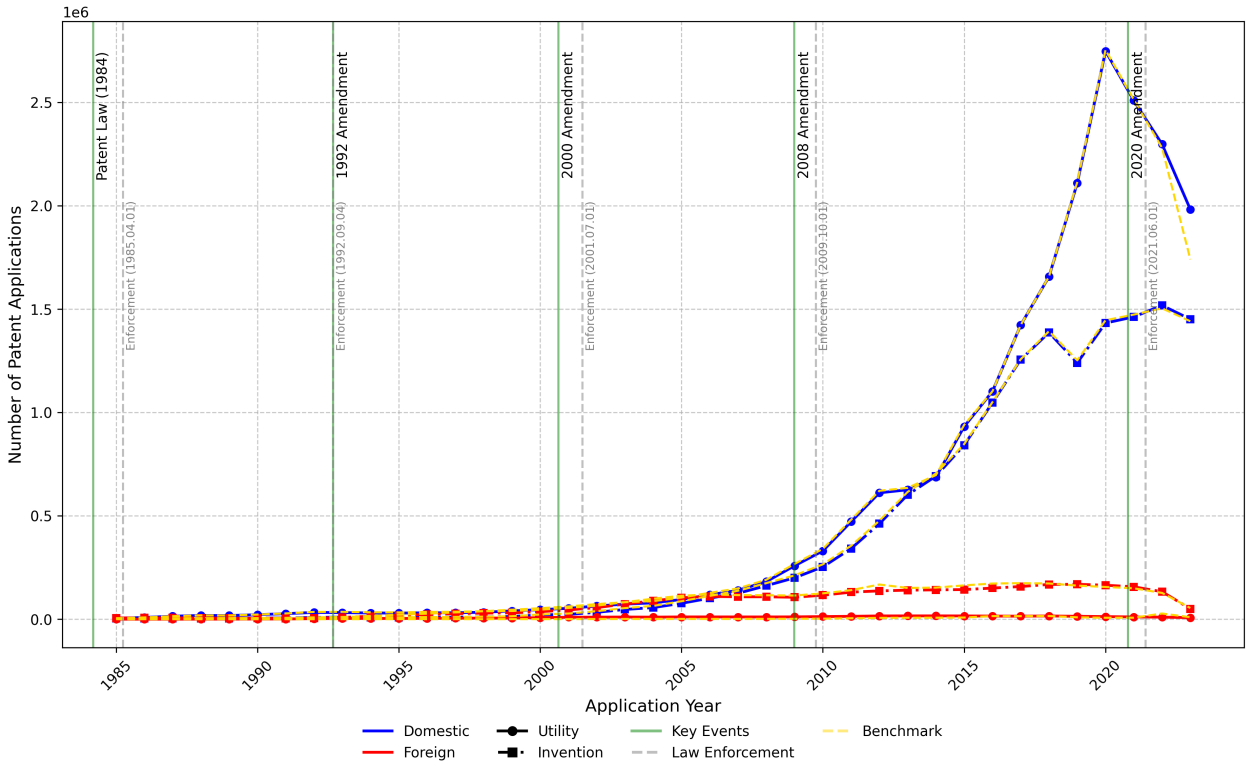
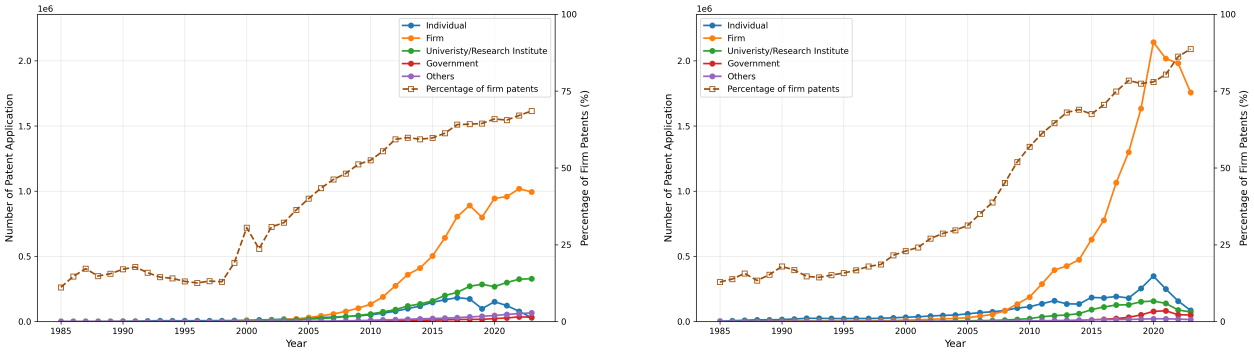


Figure 1: Patent Applications by Type and Applicant Origin Over Time



(a) Invention Patent

(b) Utility Patent

Figure 2: Patent Applications by Domestic Applicant: Applicant Type

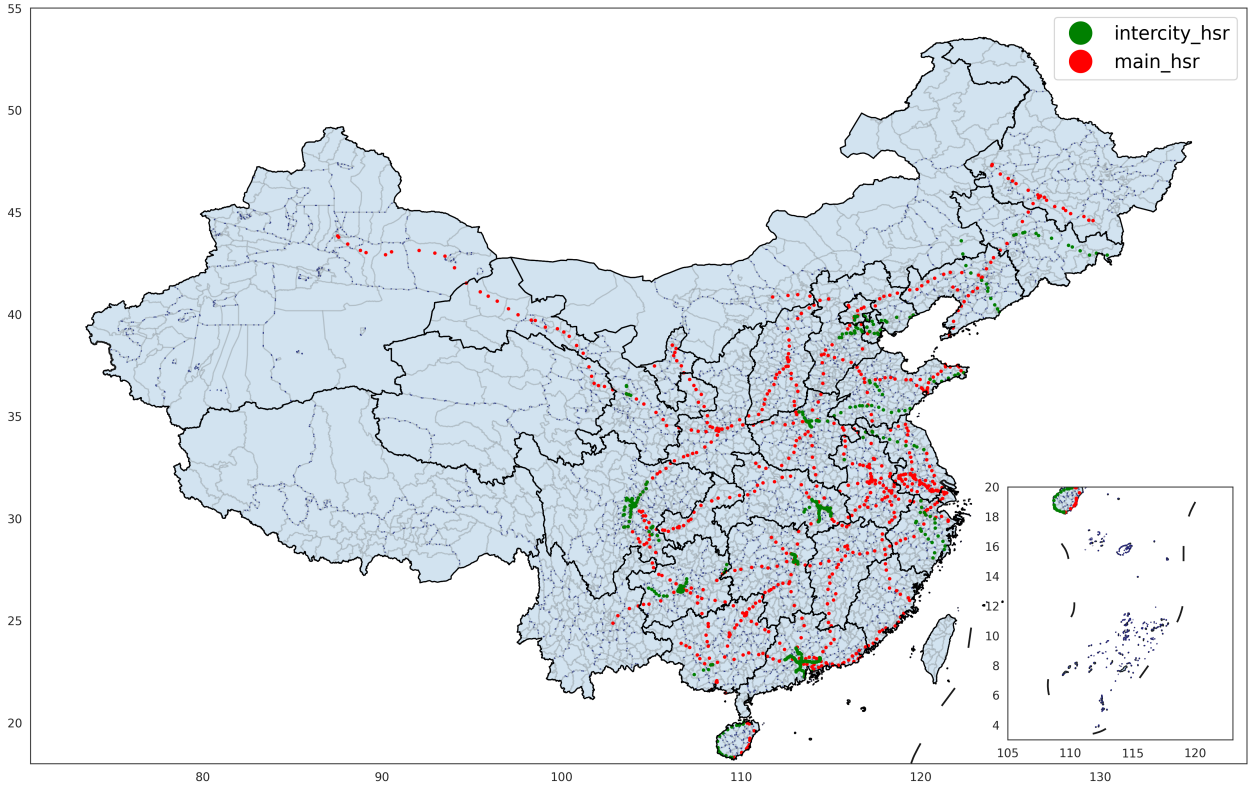
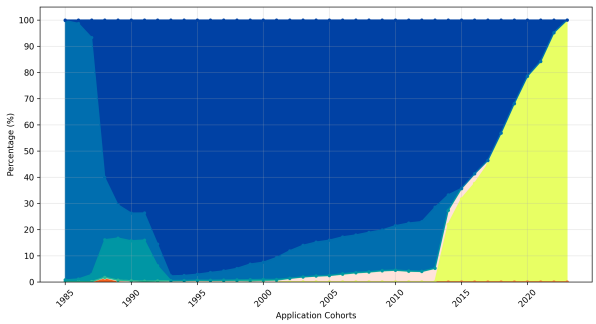
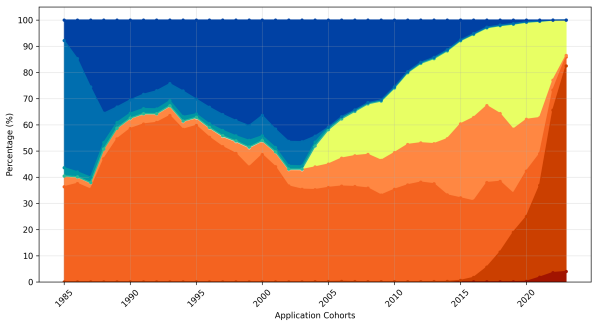


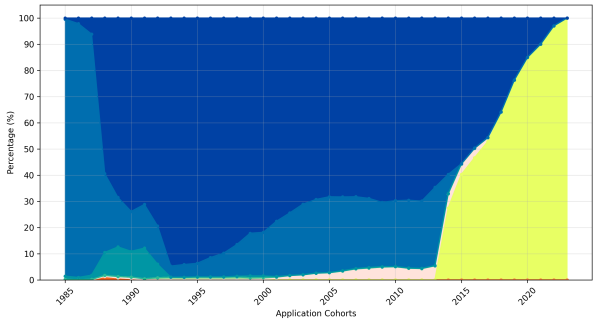
Figure 3: High Speed Railway Stations



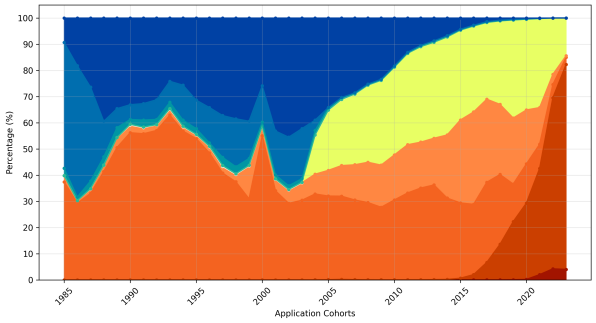
(a) All Patents: Utility



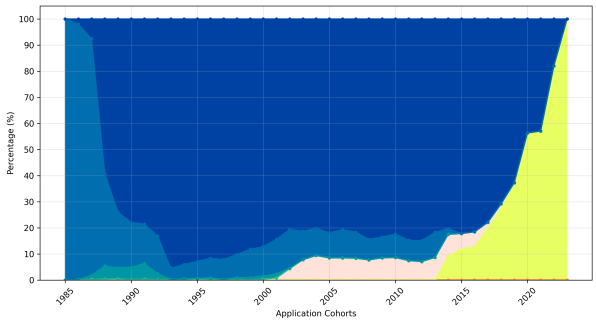
(b) All Patents: Invention



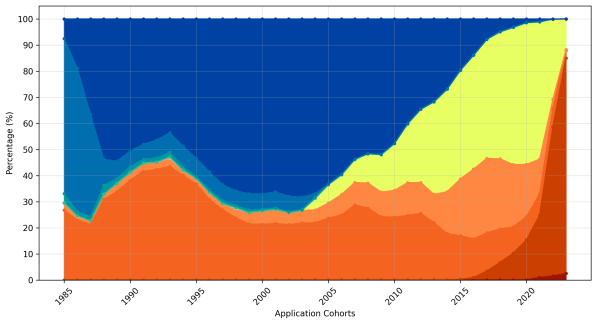
(c) Patents by firms: Utility



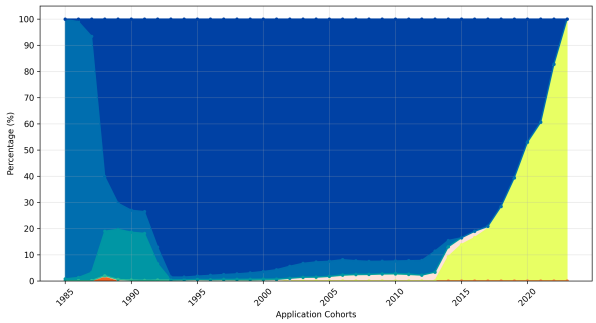
(d) Patents by firms: Invention



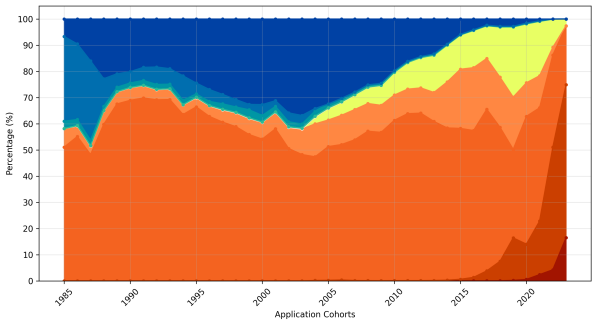
(e) Patents by research institutes: Utility



(f) Patents by research institutes: Invention



(g) Patents by individuals: Utility



(h) Patents by individuals: Invention

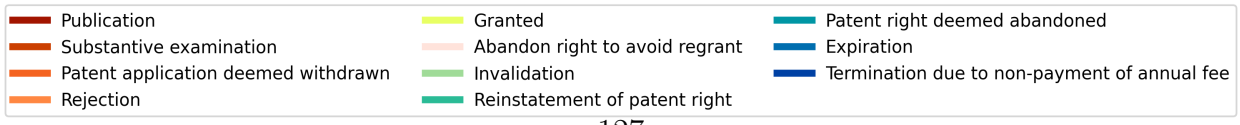
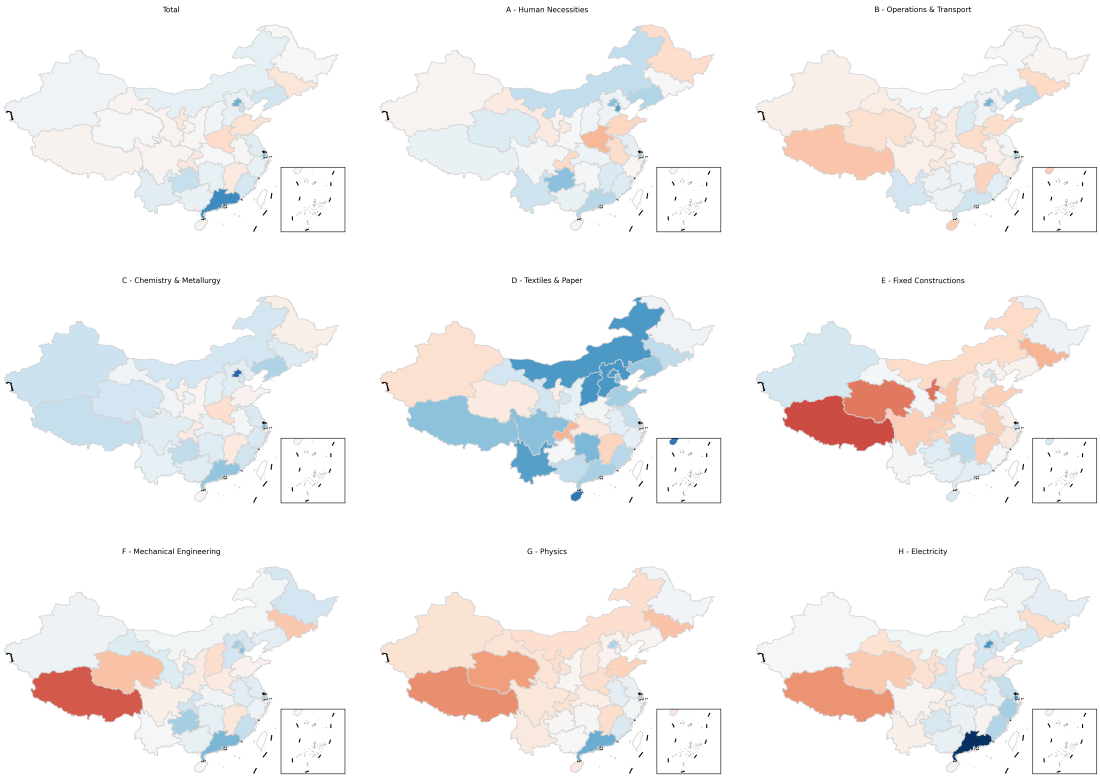
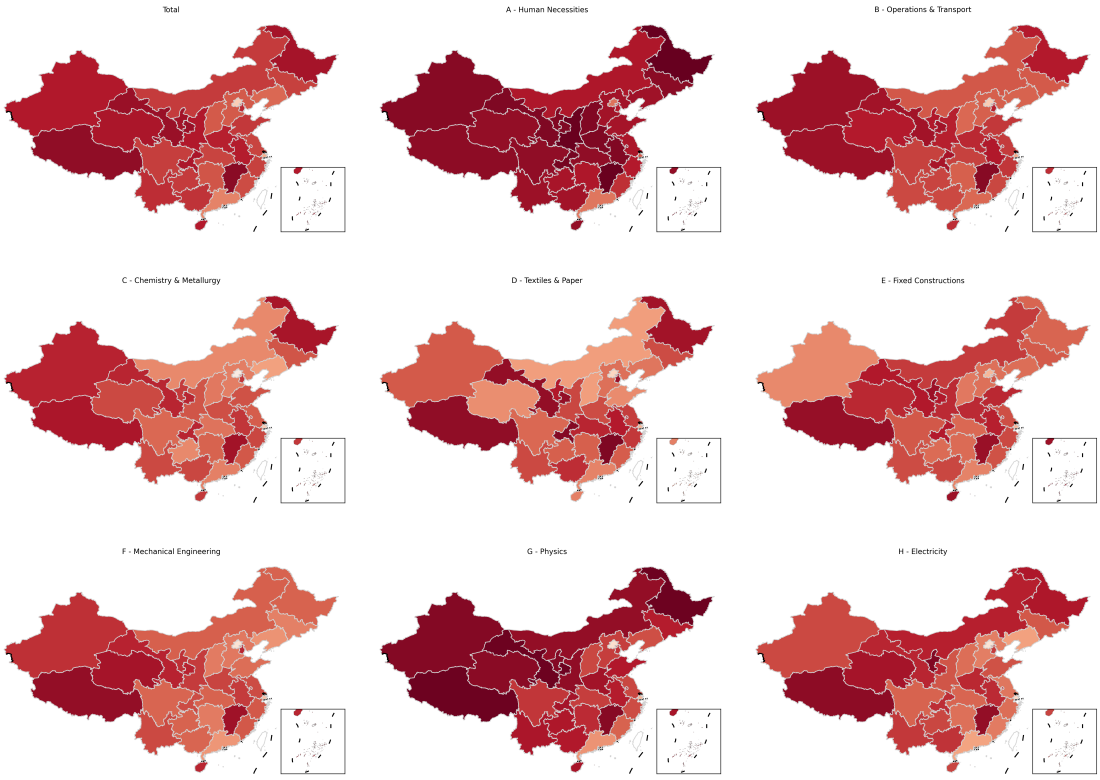


Figure 4: Final Observed Status of Patent: by Application Cohorts



(a) Invention



(b) Utility

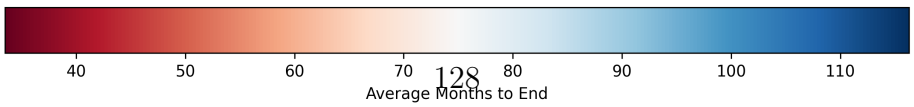
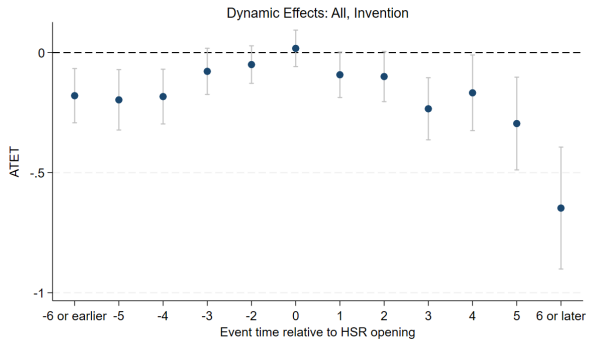
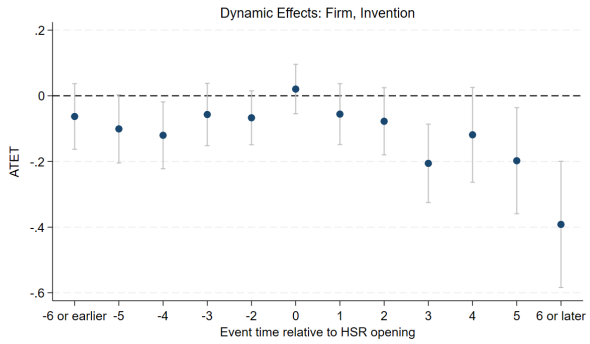


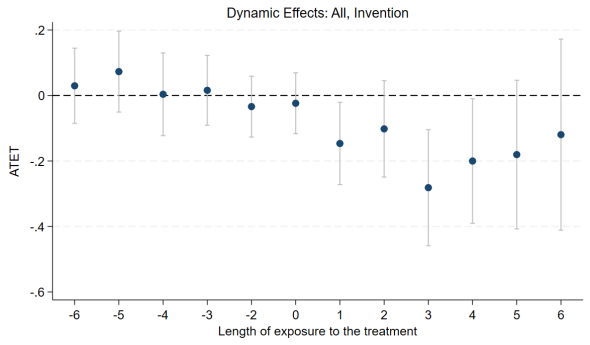
Figure 5: Spatial Distribution of Average Patent Age In China: By Different IPC Sections



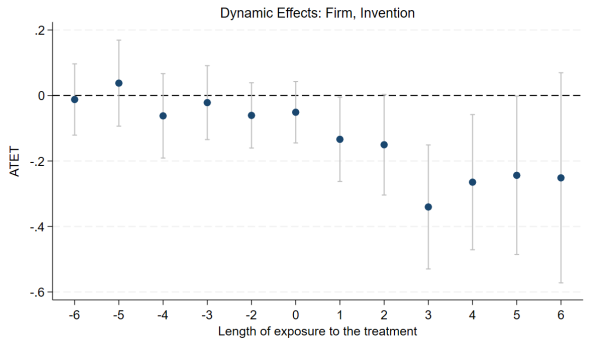
(a) SA, All Applicants



(b) SA, Firm Applicants



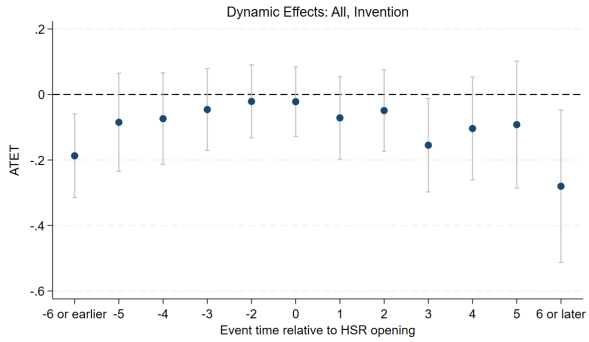
(c) DRDID, All Applicants



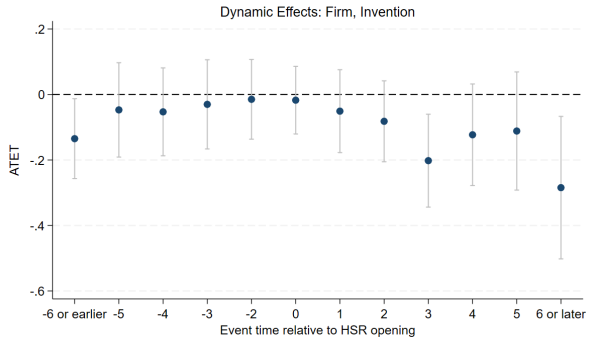
(d) DRDID, Firm Applicants

Figure 6: Event Study: Log Lapsed Invention Patents

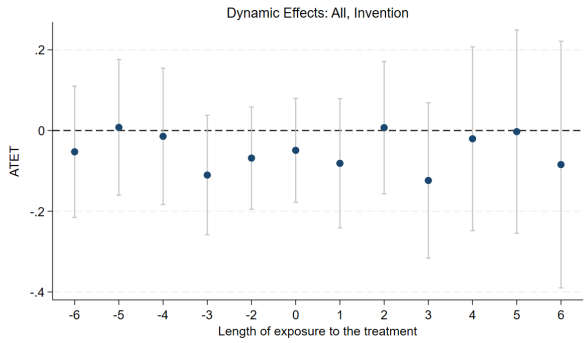
Notes: Top row: SA interaction-weighted estimator; bottom row: DRDID estimator. Left column: all applicants; right column: firm applicants. Bars are 90% confidence intervals. Outcome is the log number of lapsed invention patents.



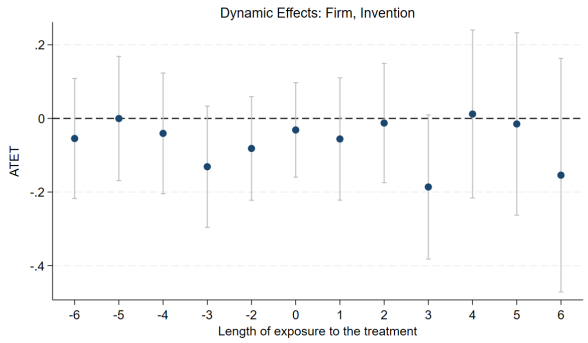
(a) SA, All Applicants



(b) SA, Firm Applicants



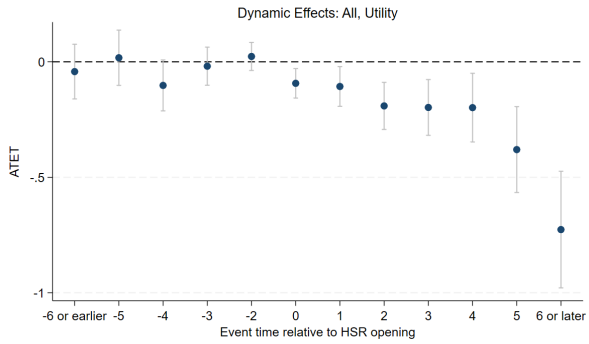
(c) DRDID, All Applicants



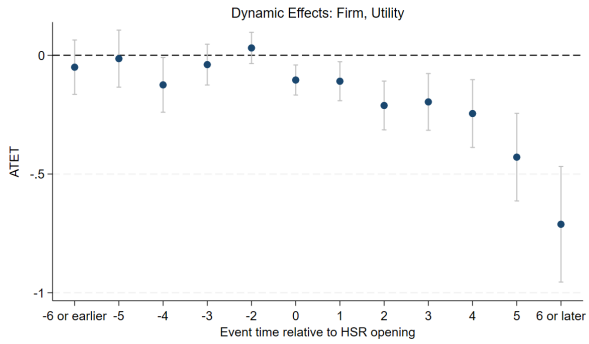
(d) DRDID, Firm Applicants

Figure 7: Event Study: Log Lapse-to-Stock Ratio, Invention Patents

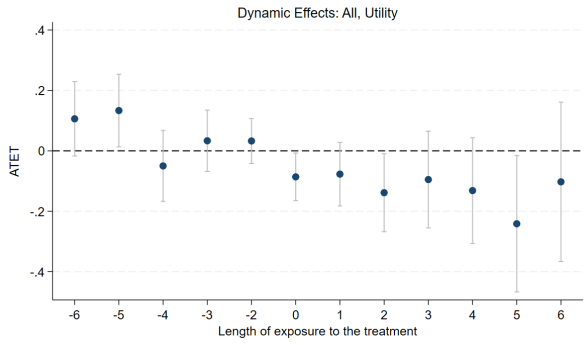
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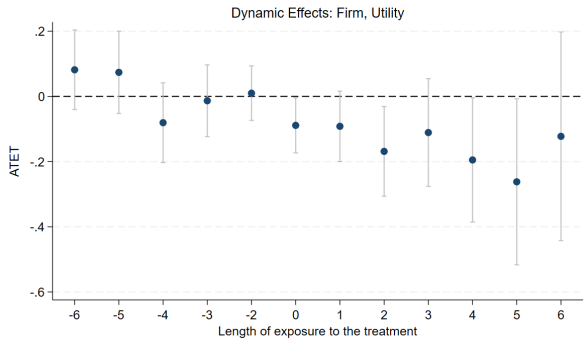
(a) SA, All Applicants



(b) SA, Firm Applicants



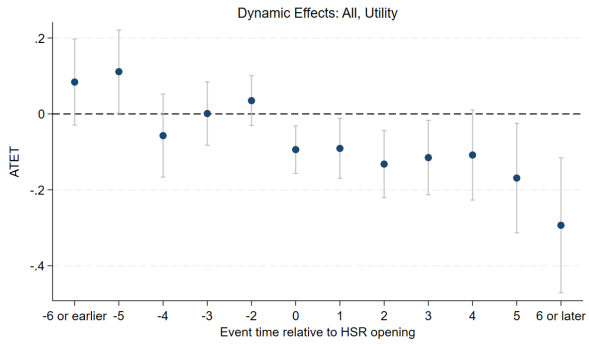
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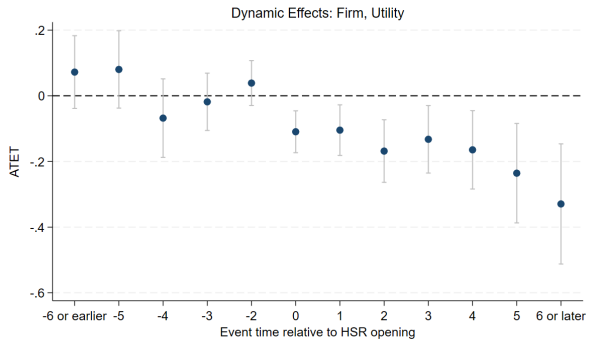
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Figure 8: Event Study: Log Lapsed Utility Patents

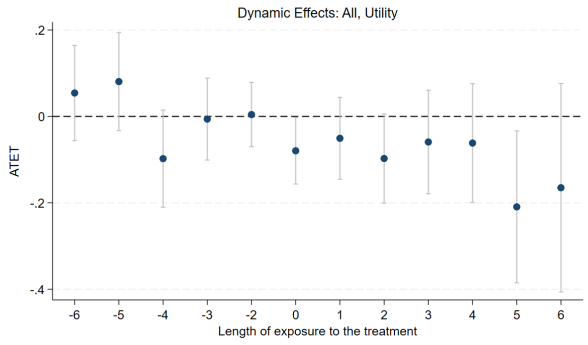
Notes: Top row: SA interaction-weighted estimator; bottom row: DRDID estimator. Left column: all applicants; right column: firm applicants. Bars are 90% confidence intervals. Outcome is the log number of lapsed utility patents.



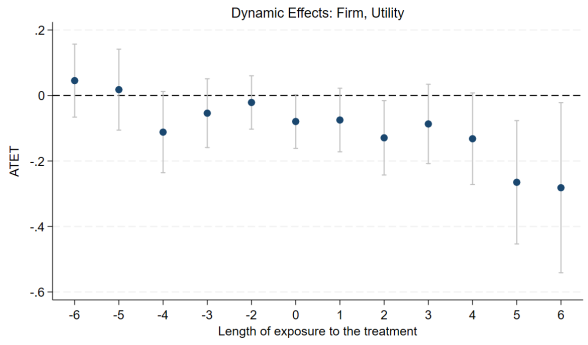
(a) SA, All Applicants



(b) SA, Firm Applicants



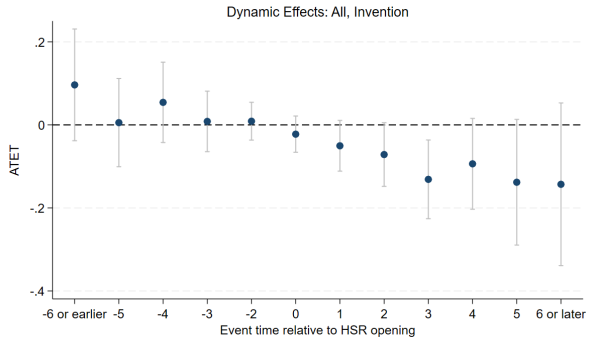
(c) DRDID, All Applicants



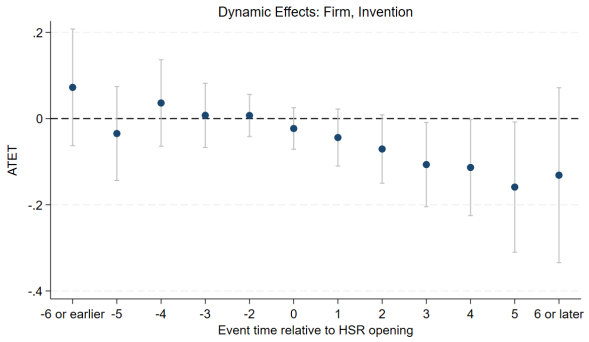
(d) DRDID, Firm Applicants

Figure 9: Event Study: Log Lapse-to-Stock Ratio, Utility Patents

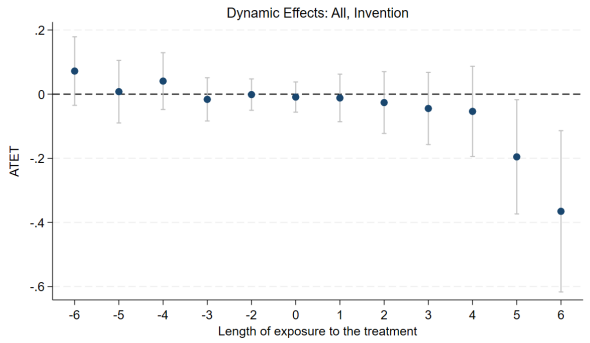
Notes: Top row: SA interaction-weighted estimator; bottom row: DRDID estimator. Left column: all applicants; right column: firm applicants. Bars are 90% confidence intervals. Outcome is the log lapse-to-stock ratio for utility patents.



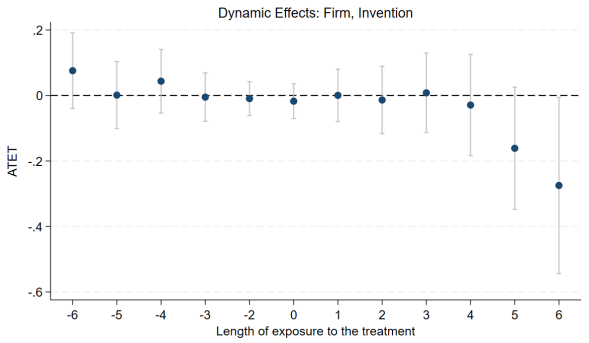
(a) SA, All Applicants



(b) SA, Firm Applicants



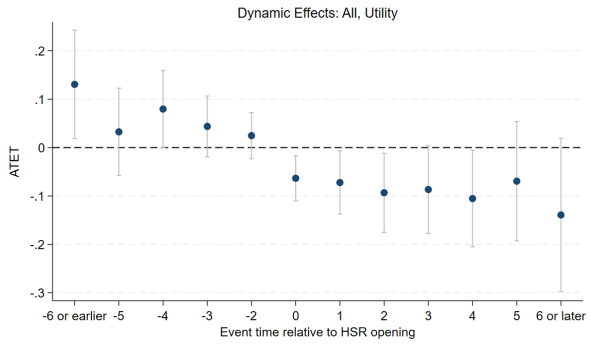
(c) DRDID, All Applicants



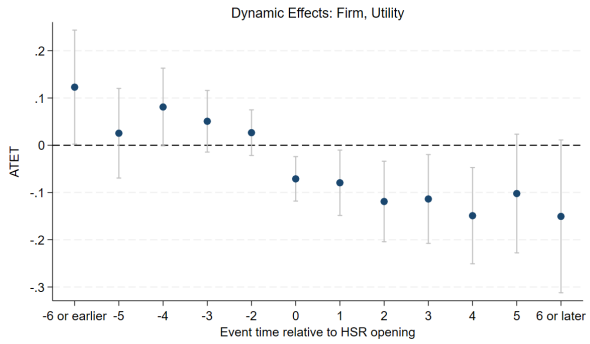
(d) DRDID, Firm Applicants

Figure 10: Event Study: Log Invention Patent Applications

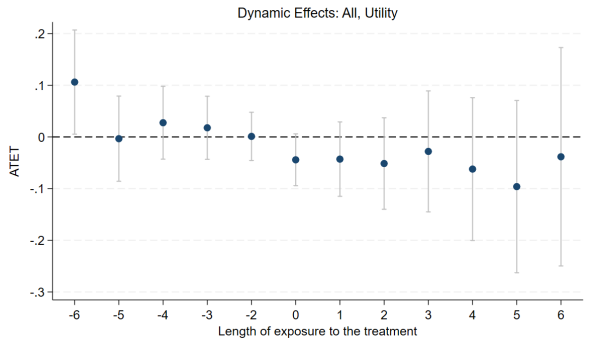
Notes: Top row: SA interaction-weighted estimator: DRDID estimator. Left column: all applicants; right column: firm applicants. Bars are 90% confidence intervals. Outcome is the log number of invention patent applications filed.



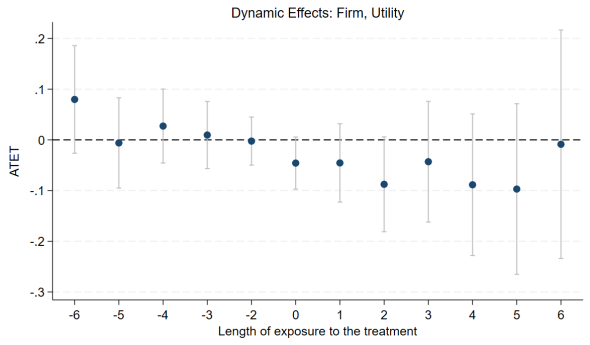
(a) SA, All Applicants



(b) SA, Firm Applicants



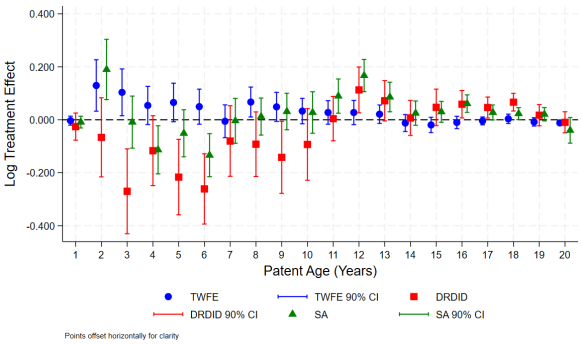
(c) DRDID, All Applicants



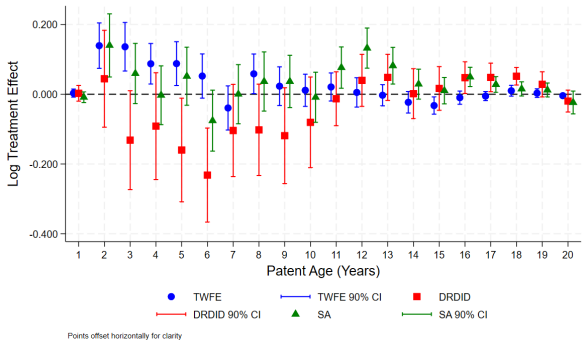
(d) DRDID, Firm Applicants

Figure 11: Event Study: Log Utility Patent Applications

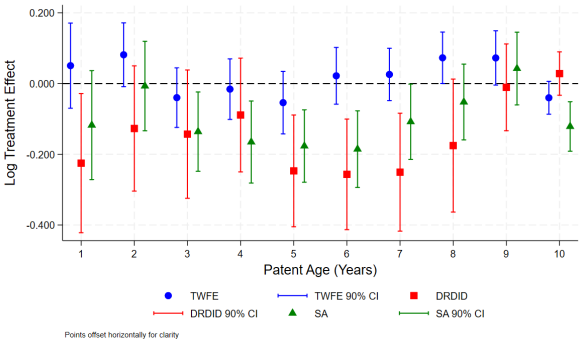
Notes: Top row: SA interaction-weighted estimator; bottom row: DRDID estimator. Left column: all applicants; right column: firm applicants. Bars are 90% confidence intervals. Outcome is the log number of utility patent applications filed.



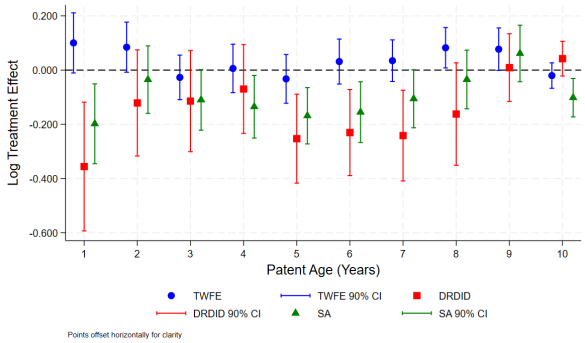
(a) Invention, All Applicants



(b) Invention, Firm Applicants



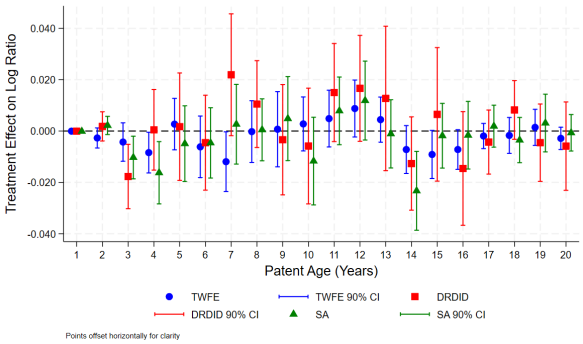
(c) Utility, All Applicants



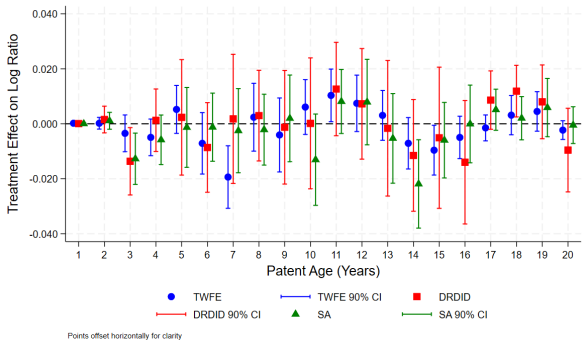
(d) Utility, Firm Applicants

Figure 12: Treatment Effects by Patent Age: Log Lapsed Patent Counts

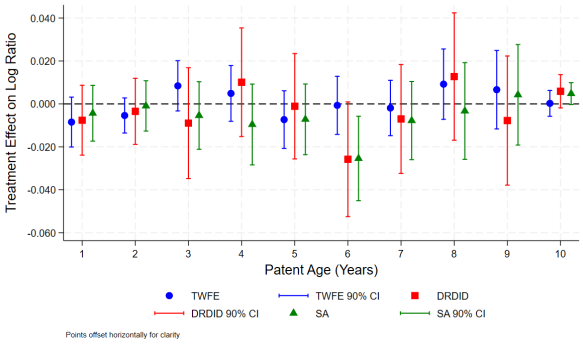
Notes: Each point plots the estimated ATET estimated separately at each patent age. Invention patents (top row) span ages 1–20; utility patents (bottom row) span ages 1–10, reflecting China's 10-year utility patent maximum. Blue circles: TWFE; red squares: DRDID (Callaway & Sant'Anna, 2021); green triangles: SA (L. Sun & Abraham, 2021). Bars denote 90% confidence intervals. Points are offset horizontally for clarity.



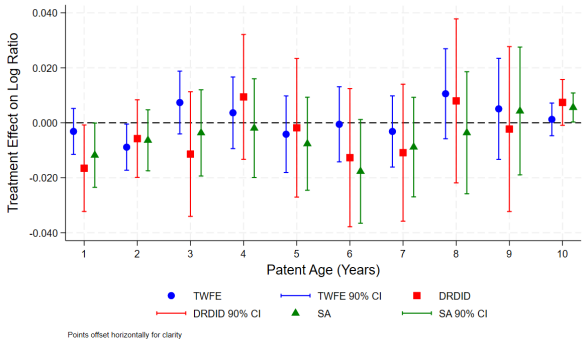
(a) Invention, All Applicants



(b) Invention, Firm Applicants



(c) Utility, All Applicants



(d) Utility, Firm Applicants

Figure 13: Treatment Effects by Patent Age: Log Lapse-to-Stock Ratio

Notes: Each point plots the estimated ATET on the log lapse-to-stock ratio at each patent age, for invention patents (top row, ages 1–20) and utility patents (bottom row, ages 1–10). Estimator colour codes and confidence interval notation as in Figure 12.

Appendix A. Bacon Decomposition of TWFE Estimates

The two-way fixed effects (TWFE) estimator in a staggered adoption design is a weighted average of all possible 2×2 difference-in-differences comparisons, but the weights can be negative when treatment effects are heterogeneous across cohorts (De Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021). Goodman-Bacon (2021) provides a complete algebraic decomposition attributing the TWFE coefficient to two distinct types of comparison: (i) clean comparisons between each treated cohort and the never-treated (or not-yet-treated) units, and (ii) contaminated comparisons between treated cohorts that use an already-treated cohort as the implicit control group. In the latter case, the already-treated cohort absorbs its own accumulated treatment effects into what should be a clean counterfactual trend, introducing bias whose sign and magnitude depend on the timing and persistence of those treatment effects across cohorts.

Figure 14 presents the decomposition for log lapsed patent count for invention patents (top row) and utility models (bottom row), each split by applicant sample. Each panel is a scatter plot in which the x-axis records the weight a given 2×2 comparison receives in the TWFE aggregation, and the y-axis records the corresponding local average treatment effect on the treated (ATET). Blue circles represent clean comparisons (treated cohort vs. never-treated or clean comparison units); pink diamonds represent cohort-vs-cohort comparisons in which one treated cohort's post-treatment period serves as the control window for another cohort.

Invention patents. The decomposition reveals severe contamination for invention patents. Cohort-vs-cohort comparisons (pink diamonds) account for 57.7% of the total TWFE weight and are concentrated in the positive quadrant, yielding average local ATETs of 0.47 (all applicants) and 0.44 (firm applicants). This sign reversal has a clear economic interpretation. Invention patent renewal behaviour is highly dynamic: early HSR adopters experience a sustained, deepening reduction in lapse counts over their post-treatment years (as confirmed by the DRDID event study in Figure 6). By the time later cohorts are treated, these early adopters have accumulated substantially lower lapse counts than in their initial post-treatment periods. When used as controls for later cohorts, they appear to have "unusually low" lapse rates, making the later-adopting cities look comparatively lapse-heavy and pushing the cohort-vs-cohort ATET above zero. Clean comparisons (blue circles) are, by contrast, concentrated in the negative quadrant and yield local ATETs consistent in direction and magnitude with the DRDID and SA estimates. Because the two groups of comparisons are weighted roughly equally but carry opposite signs, the aggregate TWFE collapses toward zero, which explains the observed TWFE coefficients of 0.007 (all applicants) and 0.052

(firms) in Table 9, which are small, positive, and statistically insignificant despite the true underlying treatment effect being negative and economically substantial.

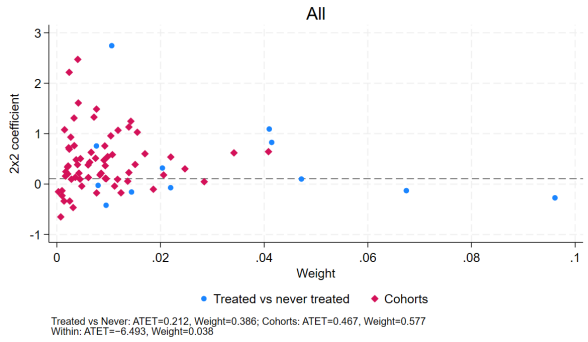
Utility models. The contamination is less severe for utility models. Cohort-vs-cohort comparisons are still present and carry a sizeable share of the TWFE weight, but their average local ATETs are smaller in absolute value and less uniformly positive. As a result, TWFE retains the correct negative sign (-0.085 for all applicants; -0.045 for firms) but systematically underestimates the magnitude relative to DRDID (-0.145 and -0.190). The milder contamination reflects the less pronounced dynamic heterogeneity in utility model renewal across cohorts: utility models have a maximum lifespan of 10 years in China, compressing the range over which treatment effects can compound and thereby limiting the scope for the time-path of early adopters to diverge from that of later cohorts.

Implications for estimator choice. The Bacon decomposition provides formal justification for the estimator preference throughout the main analysis. The TWFE estimate for invention patent lapse is not merely attenuated but sign-reversed, making it qualitatively misleading as a summary of the average treatment effect. The doubly-robust DiD (DRDID) estimator (Callaway & Sant'Anna, 2021) avoids this problem by constructing the comparison group for each cohort exclusively from not-yet-treated and never-treated units, and aggregating cohort-time ATETs with non-negative, cohort-size-proportional weights that eliminate the contamination from already-treated controls. The Sun–Abraham (SA) estimator (L. Sun & Abraham, 2021) applies the same logic through interaction-weighted estimation. Both approaches consistently deliver negative and significant estimates for invention patent lapse across all four applicant-sample combinations and are accordingly the preferred basis for inference. TWFE estimates are retained in the main tables for transparency and comparability with the broader DiD literature.

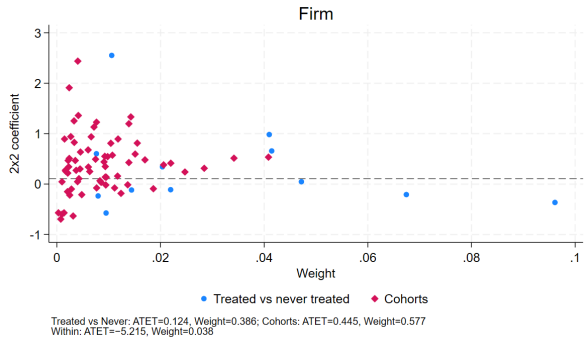
Appendix B. Full TWFE Regression Results

Tables 17 and 18 report complete TWFE regression results for invention patents and utility models, respectively, including all control variables. The main results tables (Tables 9 and 10) in the body of the chapter present only the key treatment effect coefficients alongside the preferred DRDID and SA estimates; the full specifications here confirm that those coefficients are stable to the inclusion of a comprehensive set of city-level controls.

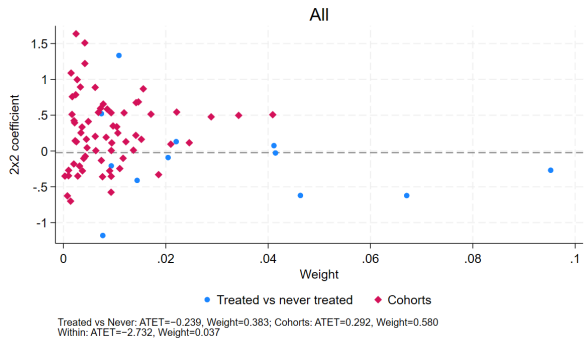
Both tables cover three outcomes, including log lapsed patent count, log lapse-to-stock ratio, and log patent applications, and two applicant samples (all applicants and firm appli-



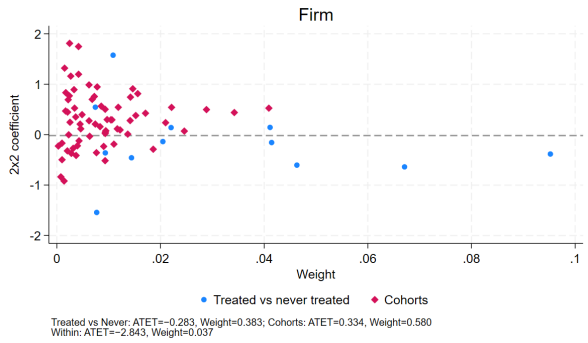
(a) Invention, All Applicants



(b) Invention, Firm Applicants



(c) Utility, All Applicants



(d) Utility, Firm Applicants

Figure 14: Bacon decomposition of TWFE estimates for log lapsed patent count.
Notes: Each panel plots the 2×2 DiD coefficient (y-axis) against its weight in the TWFE aggregation (x-axis) for every timing-group pair. Blue circles are clean "treated vs. never-treated" comparisons; pink diamonds are cohort-vs-cohort comparisons in which one cohort's post-treatment period is used as the control window for another. Summary statistics for each comparison type are reported below each panel. The decomposition follows Goodman-Bacon (2021).

cants), yielding six columns each. Controls include log real GDP, log population, secondary and tertiary industry shares, log road passenger volume, log air passenger volume, university count, state enterprise expenditure share, log beginning-year patent stock, a quadratic in patent stock, log internet users, and an IPC specialisation indicator. The inclusion of road and air passenger volumes is particularly important: it guards against the possibility that the HSR coefficient captures a general improvement in transport connectivity rather than the specific contribution of high-speed rail. The insignificance of both alternative transport controls in the utility model specification, alongside a significant HSR indicator in Lapse and Ratio columns, supports the interpretation that the effects documented in the main analysis are attributable to HSR connectivity specifically. For invention patents, the TWFE treatment effect is, as expected from the Bacon decomposition (Appendix Section 8), small and statistically insignificant in the Lapse columns despite the significant negative effects recovered by DRDID and SA in the main tables, while the Ratio and Application columns show negative point estimates that are closer to the robust estimators in direction if not in significance.

Table 17: TWFE Full Results - Invention

	ln_patent_lapse	ln_firm_inv_lapse	ln_patent_lapse_ratio	ln_firm_inv_lapse_ratio	ln_patent_application	ln_firm_inv_application
HSR Station	0.007	0.052	-0.044	-0.034	-0.021	0.051
	(0.052)	(0.043)	(0.046)	(0.043)	(0.049)	(0.050)
GDP (real prices, 100m CNY)	-0.086	-0.035	-0.062	-0.039	0.219***	0.226**
	(0.082)	(0.065)	(0.077)	(0.076)	(0.080)	(0.087)
Registered population at year-end (10k persons)	0.078	0.100	0.037	0.098	-0.113	-0.088
	(0.086)	(0.064)	(0.079)	(0.071)	(0.102)	(0.104)
Secondary industry share of GDP	-0.008*	0.000	-0.008	0.002	0.005	0.003
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Tertiary industry share of GDP	-0.007	0.003	-0.007	0.003	0.003	0.000
	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Highway passengers (10k persons)	0.035	0.029	0.015	0.011	0.036	0.027
	(0.036)	(0.025)	(0.035)	(0.030)	(0.036)	(0.032)
Civil aviation passengers (10k persons)	0.003	0.001	-0.005	-0.012*	-0.008	-0.008
	(0.009)	(0.007)	(0.008)	(0.007)	(0.006)	(0.006)
Higher-education institutions (count)	0.051***	0.023***	0.021***	0.009***	-0.001	0.006
	(0.006)	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)
Science & technology expenditure as perc of GDP	-0.129	-0.071	-0.185**	-0.133**	0.146**	0.133*
	(0.082)	(0.065)	(0.076)	(0.057)	(0.069)	(0.072)
Patent beginning stock	-0.178***	-0.171***	0.318***	0.308***	0.210***	0.154***
	(0.053)	(0.039)	(0.052)	(0.042)	(0.050)	(0.049)
Patent Stock × Patent Stock	0.103***	0.092***	-0.013***	-0.014***	-0.019***	-0.012**
	(0.005)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)
Broadband subscribers (10k households)	-0.023	-0.045	-0.022	-0.042	0.015	-0.007
	(0.049)	(0.032)	(0.039)	(0.033)	(0.036)	(0.038)
Specialized IP court/tribunal=0	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Specialized IP court/tribunal=1	-0.921***	-0.516***	-0.112	0.031	-0.204**	-0.059
	(0.142)	(0.096)	(0.094)	(0.077)	(0.081)	(0.094)
_cons	0.153	-0.859	0.678	-0.539	2.965***	2.947***
	(0.735)	(0.524)	(0.674)	(0.634)	(0.747)	(0.798)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,860	4,860	4,860	4,860	4,860	4,860

Table 18: TWFE Full Results - Utility

	ln_patent_lapse	ln_firm_inv_lapse	ln_patent_lapse_ratio	ln_firm_inv_lapse_ratio	ln_patent_application	ln_firm_inv_application
HSR Station	-0.085*	-0.045	-0.074*	-0.048	-0.062	-0.043
	(0.050)	(0.046)	(0.042)	(0.040)	(0.041)	(0.044)
GDP (real prices, 100m CNY)	-0.220***	-0.189**	-0.039	-0.034	0.242***	0.229***
	(0.085)	(0.092)	(0.061)	(0.067)	(0.086)	(0.084)
Registered population at year-end (10k persons)	0.060	0.088	0.027	0.054	-0.019	-0.012
	(0.098)	(0.098)	(0.074)	(0.079)	(0.083)	(0.086)
Secondary industry share of GDP	-0.014**	-0.015***	-0.000	-0.001	0.015***	0.012**
	(0.006)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Tertiary industry share of GDP	-0.013**	-0.012**	0.002	0.001	0.013***	0.010**
	(0.006)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Highway passengers (10k persons)	0.090**	0.103***	0.057*	0.058*	0.006	-0.001
	(0.035)	(0.034)	(0.029)	(0.030)	(0.026)	(0.027)
Civil aviation passengers (10k persons)	-0.010	-0.014**	-0.002	-0.006	0.006	0.001
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Higher-education institutions (count)	0.042***	0.033***	0.011**	0.006	0.009**	0.011***
	(0.008)	(0.007)	(0.005)	(0.004)	(0.004)	(0.004)
Science & technology expenditure as perc of GDP	-0.097	-0.111	-0.031	-0.041	0.021	0.010
	(0.066)	(0.072)	(0.060)	(0.065)	(0.054)	(0.056)
Patent beginning stock	0.185*	0.046	0.436***	0.407***	0.925***	0.889***
	(0.105)	(0.095)	(0.089)	(0.088)	(0.069)	(0.072)
Patent Stock × Patent Stock	0.076***	0.086***	-0.028***	-0.026***	-0.049***	-0.048***
	(0.008)	(0.007)	(0.007)	(0.006)	(0.005)	(0.006)
Broadband subscribers (10k households)	0.035	0.037	0.007	0.028	0.023	0.015
	(0.049)	(0.046)	(0.030)	(0.030)	(0.035)	(0.035)
Specialized IP court/tribunal=0	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Specialized IP court/tribunal=1	-0.670***	-0.657***	-0.017	-0.029	0.152**	0.208***
	(0.122)	(0.113)	(0.071)	(0.069)	(0.073)	(0.076)
_cons	-0.085	-0.190	-0.211	-0.372	-1.037	-0.608
	(0.857)	(0.761)	(0.575)	(0.577)	(0.756)	(0.787)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,860	4,860	4,860	4,860	4,860	4,860