Technology Transfer and Domestic Innovation: Evidence from the High-Speed Rail Sector in China

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Abstract

This paper investigates China's high-speed railway (HSR) technology introduction to show how it spurs innovation in local regions and in relevant industries. The large-scale technology introduction, covering specific technology categories and directly benefiting railway-related firms from various cities, enables us to specifically depict how foreign technology is digested and spurs follow-up innovation in and out of directly receiving firms. We find that technology transfer leads to a 42% significant increase in HSR-related patents granted in cities with direct technology receivers. In addition, we also find evidence on sizable spillovers to firms that are not directly related to the railway industry, whereas technology similarity and the existence of relevant research institutions play important roles.

Keywords: Innovation; Foreign Technology Transfer; Knowledge Spillover; China

JEL classification: O25; O33; O38

1 Introduction

Over the past decades, emerging economies, notably China, have experienced impressive growth in technological innovations. It is widely believed that direct technology transfers from OECD multinationals to their subsidiaries in developing countries help these countries gradually approach the technology frontier, but how large are these effects? How is advanced transferred technology digested, renovated and diffused in a developing country? Although many empirical studies support the presence of productivity spillovers of FDI (Javorcik, 2004 [24]; Liu et al., 2000 [30]), it is difficult to disentangle the contributions of direct technology transfer from the overall benefits of FDI, which include forming trade networks, innovation in advertising and management, introducing new products and generating new demands. A clean identification of the direct impacts of technology transfer is necessary for further examining the mechanisms of technology spillovers from multinational corporations (MNCs) to their host countries.

This paper attempts to identify the direct and spillover effects of foreign technology transfer by exploiting the introduction of the state-of-art high-speed railway (HSR, thereafter) in China during its unprecedented large-scale expansion of the HSR system. This is a classic example of the Chinese government's promotion of '*quid pro quo*', also known as market for technology, policies that aimed at helping Chinese companies acquire advanced technology from foreign multinationals by asking the latter to sign technology transfer contracts to enter Chinese markets (Holmes et al., 2015) [20]. There is an abundance of anecdotes about the existence and importance of these type of policies. However, rigorous empirical evidence on their effectiveness, as well as the impacts on innovation out of their direct focus through knowledge spillovers, is scarce if not nonexistent. A major empirical difficulty in examining the effects of direct international technology transfer is that the technology transfer contracts between firms are usually business secrets, and a large proportion of them happened without written contracts. Even if information on technology cooperation between firms is publicly available, the exact types of technology transferred are not usually observed by researchers.

In this project, we have data access to the recent massive wave of HSR technology introduction to China. This setting is ideal for studying the impacts of international technology

transfer on developing countries' domestic innovation for a number of reasons. One the one hand, the scale and coverage of this wave of technology transfer was unprecedented. The two major train manufacturers in China, China Southern Railway Corp. (CSR) and China Northern Railway Corp. (CNR) signed technology transfer contracts with all of the four major technology providers at the time and introduced a complete line of HSR technology ranging from engines, dynamos, and electricity transmissions to railway signal control systems.[1] Many of these technologies have applications separate from the HSR system and have great potential for technology spillovers.[2] On the other hand, we have clear information on the types of technology introduced and the identities of the firms that received them. These firms, owned by CSR or CNR, are located in 25 cities. Individual CSR- and CNR-affiliated firms usually only import particular subsets of technology, which provides us with helpful variation in the magnitude of technology transfer at the subsidiary-technology level. We also have a list of certificated suppliers for the HSR by the Ministry of Railway (MoR). This helps us separate the effects of demand-driven innovation from knowledge spillovers because we can focus on firms that are neither receivers of these technologies nor direct suppliers to the Chinese HSR projects.

We assemble a unique dataset that matches information on patents that were applied for at the State Intellectual Property Office of China (SIPO) to firm-level variables from the Annual Survey of Industrial Firms (ASI) of China from 1996 to 2009. Firms are geocoded according to their addresses to study the spillover effects within city. We begin by estimating a triple-difference model that relates technology transfer within a given technology class (defined by 4-digit International Patent Class (IPC)), city and year to total patents applied in the same technology class, city and subsequent years, conditioning on a full set of city, technology class, year fixed effects and flexible growth trends. Our preliminary analyses reveal a significant 42% increase in HSR-related patents granted in cities with direct technology receivers. The magnitude drops to 20% after we exclude patents that were applied for directly by CSR or CNR affiliates and HSR suppliers, but it remains significant. These findings

[1]The four major providers include Alstom, Siemens, Bombardier, and Kawasaki Heavy Industries. Apart from the four major technology providers, CSR and CNR also work with other foreign firms, such as Toshiba, General Electric and ABB, on technology solutions for specific parts.

[2]China Railway Yearbooks (2002-2005).

show that technology transfers from developed countries do significantly spur innovation in receiving developing countries, within and outside of the direct technology recipients.

We then further examine the mechanisms behind the knowledge spillovers from both cross-city and within-city perspectives. Our results from both dimensions suggest that technological similarity plays an important role: for cross-city analysis, we observe a significant increase in patent applications in technology classes that are closer to the transferred technology; for within-city firm level analysis, we find that firms within a few miles distance to the technology receiving firms apply (and are subsequently granted) for more patents. Moreover, the firms closer to direct technology receivers not only innovate more, but also experience *real economic gains* in terms of higher revenue and productivity after the technology transfer. Such effects are stronger for firms with similar technology to the technology-receiving firms but not for firms with stronger input-output linkages to the railway sector. Another piece of evidence on the heterogeneity of spillover effects is that cities with stronger university research background in related fields have much greater increases in patents from non-railway related firms in HSR technology classes, even if these cities do not have any CSR or CNR subsidiaries and do not receive technology transfer directly.

Our findings have a number of policy implications. First, our estimation shows the effectiveness and limitations of '*quid-pro-quo*' policies and the role of government-promoted technological pushes in domestic innovation activities. This could be a very important lesson to learn for other emerging markets that aspire to develop technological bases from scratch. Of course, some special institutional features in our example, such as the large Chinese market for railway and the monopoly power of CSR and CNR in this market might facilitate or hinder the implementation of this policy. Hence, we find it necessary to examine the actual mechanisms at work during and after the whole process of technology transfer, such as changes in patenting behavior of receiving firms in different areas, channels of knowledge spillovers, and changes in product market performance of relevant firms.

Second, our findings provide evidence on the importance of absorptive capacity, such as technology similarity and relevant university research capacity, on the magnitude of technology transfer spillovers. Our results indicate that firms located in technology-receiving cities specializing in similar technology experience the largest positive spillovers from the technol-

ogy transfer. This finding highlights the importance of within-city clustering of high-tech firms. Policy makers who want to maximize the impacts of introduced foreign technology may want to place them in cities with existing clusters of technologically related firms or implement other industrial policies to enhance the local spillovers of technology. Our findings also reveal the complementarity between basic research strength and specific technology, underlining the importance of universities and other basic research institutes as intermediaries of knowledge spillovers into firms and cities that do not have direct access to the transferred technology. From a policy perspective, encouraging industry-university cooperation in digesting transferred technology may prove to be highly important in making better and wider use of this technology.

The paper is structured as follows: section 2 discusses related literature; section 3 prepares the readers with the institutional knowledge of technology transfer in the HSR sector in China; section 4 introduces the data and identification strategies; section 5 presents the main findings; section 6 discusses the mechanisms; and section 7 concludes.

2 Related Literature

Our paper has its antecedents in the rich literature of FDI and other MNC activities in the developed and developing countries. Keller (2010) [26] systematically examines technology spillovers through international trade and MNC activities and finds imports to be a more significant channel of technology diffusion than exports. Blalock and Gertler (2005) [6] distinguish two types of externalities through FDI: horizontal flows to local competitors (or spillovers) and vertical flows to backward-linked suppliers. Hale and Long (2007) [17] finds mixed evidence on the effects of FDI spillovers on the productivity of Chinese domestic firms. Using a production function approach, Barrell and Pain (1997) [5] find that FDI has a significant effect on technical progress in the private sector in the United Kingdom. The closest paper on FDI-driven innovation is Lin and Cheung (2004) [12], which finds positive effects of FDI in domestic patent application at the provincial level. The spillover effect is the strongest for minor innovations such as external design patents. Our main contribution to this literature is to single out the pure impacts of technology transfer from the aggregate

effects of FDI and MNC activities in general, which allows us to clearly examines the channels of technology spillovers on domestic innovation. In additional, being able to merge firm characteristics with patents application data allows us to separate knowledge spillovers from product market impacts and delve deeper into mechanisms.

The recent paper by Giorcelli (2016) [18] is one of a few papers that directly look at technology transfer on firm performance, exploiting the transfer of the US expertise into Italy during the Marshall Plan. They find that management and technology transfer has persistent effect on firms' survivorship, sales, employment and productivity, with the transfer of management practices playing a more long-lasting role. Our paper deals with an episode of technology transfer that is of larger scale and covers more frontier technologies. As a result, we focus on the role of technology transfer in spurring innovation not only in direct receivers, but also in other related firms, and looks closer into the spillover mechanisms.

A number of papers emphasize the importance of absorptive capacity as a key mechanism of FDI's effect. For example, Borensztein et al. (1998) [10] find that FDI contributes to economic growth only when a sufficient absorptive capability (such as minimum stock of human capital) is available in the host country. Using the cases of Czech Republic and Russia, Sabirianova et al. (2005) [34] argue that firms need to be more technologically advanced and open to competition in order to be able to gain from foreign presence. In the context of China, the recent paper by Lu et al. (2017) [31] find that FDI has a negative and significant effect on the productivity of domestic firms in the same industry, which is not attenuated by absorptive capacity, measured by firms' R&D investment and ownership structure. Our paper adds to the discussion by quantifying absorptive capacity using technology similarity and the presence of university research strength, and showing the importance of absorptive capacity on positive FDI spillovers at both firm level and aggregate (city-year-technology class) level.

We also contribute to the rich literature on knowledge spillovers. The seminal paper by Jaffe, Trajtenberg, and Henderson (1993) [23] shows the importance of geographic proximity in explaining the transmission of knowledge using US patent citation data. Bloom, Schankerman and Van Reenen (2013) [9] investigate the externalities of R&D spending through knowledge spillovers and product market rivalry channels and find both channels important, al-

though significant heterogeneity exists across sectors. Our paper is particularly interested in how far a top-down massive technology import plan initiated by the government can go in private sector innovation. We are able to separate knowledge spillovers from product market effects quite cleanly and look more closely at the actual mechanisms at work with detailed information on HSR-driven demands.

On a related note, this paper looks at university-industry collaboration and spillovers from a novel perspective. Two aspects of our research stand out as interesting. First, different from the majority of literature on university-industry relationships in innovation — which study how university research is disseminated into related industries and how it leads to joint university-firm R&D activities (Abramovsky et. al. (2007) [2], Abramovsky and Simpson (2011) [1], Anselin et. al. (1997)[3], Audrestsch et al. (2004) [4], Kantor and Walley (2014) [25], Sharon and Schankerman (2013) [7]) — we focus on the other way around by studying how a sudden shock to the knowledge stock of a few firms exerts wider impacts on innovation in related sectors through industry-university knowledge flows. Only a small body of literature examines the industry-to-academia feedback loop empirically (Furman and MacGarvie (2007)[15] and Sohn (2014)[35]). To our best knowledge our paper is one of the few that looks at both sides of the feedback loop and focuses on causal identification. Second, contrary to the previous research that mostly focuses on localized knowledge spillovers and local agglomeration, we examine the roles of both geographic proximity and technological similarity in the transmission of knowledge out of direct transferred-technology-receiving firms. We find that in this special case of knowledge spillovers from firms to universities, technological similarity plays a much more important role, suggesting that industry-university knowledge transmission is usually intentional and targeted, which is likely to overcome most geographical barriers. This implication echoes and complements previous research on university-industry joint research projects (D'Este et. al. 2012[13]) that finds industrial firm clusters and previous collaboration experiences relax the effects of geographic proximity on determining university-industry collaboration.

An analogy can be drawn between this large-scale import of HSR technology and the defense-driven R&D spending in the US during cold war. They are both plausibly exogenous government-led pushes in a country's technology capital in particular sectors. A major

difference here is that China is a developing country that is attempting to catch up with the technology frontier whereas a 'big push' in the US is pushing the global technology frontier forward. There is also a small body of literature on the effects of US defense spending on innovation. For instance, Draca (2013) [14] shows that defense procurement accounted for 6-11% of the increases in patenting during the early Reagan build-up period in the US. The magnitude is noticeably smaller for that found in our Chinese HSR technology import study, which could potentially reflect the differences between the difficulties of developing new technology and adapting existing technology.

3 Background

3.1 China's technology transfer in the HSR sector

State planning for China's HSR began in the early 1990s, but the actual mass construction of the HSR was not on the agenda until the first decade of the 21st century, following the pressing need to increase railway capacity due to seriously overcrowded conventional lines. In 2003, Zhijun Liu, the then newly appointed Minister of Railway of China, proposed his 'Great Leap Forward' strategy, which focused on introducing HSR (Liu, 2003) [30]. From the very beginning, the state planners in China focused on achieving indigenous HSR technology. Developing indigenous capability based on acquired existing foreign technology appeared to be the fastest and surest way to reach this goal. The massive introduction of foreign technology began in 2004 and ended in 2006.

During this process, China introduced complete procedures for high-speed train manufacturing on four main modes (CSR-1, CRH-2, CRH-5 and CRH-3) from four companies (Alstom, Siemens, Bombardier, and Kawasaki Heavy Industries). Typically, the Ministry of Railway (MoR) signed train procurement and technology transfer contracts with the targeted foreign firms at the same time, a classic example of 'quid-pro-quo', also known as the market for technology policy. The tasks of developing indigenous technologies based on the acquired ones were then assigned to one of the subsidiaries of CSR or CNR. [3] According to

[3]Details on major technology transfer contracts are reported in Table A6.

official MoR reports as well as interviews with engineers from CSR and CNR, a technology transfer contract normally consists of four components:

1. "Joint design" of train modes based on foreign prototypes that incorporate adaptation to the Chinese environment
2. Access to train blueprints
3. Instructions on manufacturing procedures
4. Necessary training of engineers

It is worth noting that the principles of design, as well as the data that support them, were not transferred. Chinese engineers were taught the how but not the why of building trains, and they must reverse-engineer if they wish to develop new variations of the prototype.[4] To absorb and digest these technologies as quickly as possible, the responsible subsidiaries of CSR and CNR usually work with local universities or other research institutions, creating possible knowledge spillovers from corporations to schools. After three years of technology assimilation, China had 'mastered the core technologies in producing high-speed trains.', according to the ex-chief engineer of MoR in 2007.[5] Apart from acquiring manufacturing procedures for the whole train, the MoR also managed to introduce technologies for certain critical parts, such as the traction motor, braking system and series pantograph from Mitsubishi, Hitachi, ABB, etc., to other subsidiaries.

According to Chinese and international patent law, Chinese firms that receive transferred technology are not allowed to file these technologies in China or any other countries. Therefore, the effects on new patents are not the mechanic effects of receiving transferred foreign technology. However, the technology receivers can benefit from follow-up research that adapts these technologies to other uses and patents for subsequent innovations. CSR and CNR firms and other related firms can also draw inspiration from the design principles for these technologies to create new inventions. On rare occasions, technology transfers appear in the form of jointly owned patents by newly formed CSR/CNR and foreign partner

[4]Here are more details about how the learning process works documented in a published book on HSR development (Gaotiejianwen, 2015 [16]): the two contracted foreign producers received 60 orders each of high-speed trains. Among the 60 orders,three orders were imported which the Chinese engineers were allowed to observe the process; six orders were imported as parts and later assembled by the Chinese engineers under guidance from the foreign partners; the rest of the 51 orders were made by gradually replacing the foreign parts with domestically produced parts which facilitated the digestion of transferred technologies.

[5]`http://finance.qq.com/a/20120702/004961.htm`

joint ventures.

3.2 Technology-receiving firms

By 2004, 18 firms were affiliated with the CNR and 15 with the CSR, the two major Chinese locomotive and rolling stock manufacturers. All of the major HSR-related technology transfer contracts were awarded to their subsidiaries. As described in Figure 1, these 33 firms were located in 25 different cities ranging from Beijing to Meishan, Sichuan, granting us a nice layer of variation. Among them, four subsidiaries (CSR Sifang in Qingdao, CSR Zhuzhou, CNR Tangshan, CNR Changchun) received a complete set of high-speed train manufacturing technology. Due to the possibility that not all of the technology transfer details were reported in the China Railway Yearbooks, our main source of technology transfer information, we labeled all cities with CSR and CNR subsidiaries as technology-receiving cities in our main specification. In an alternate specification, we define a city to be a technology-receiving city only when a technology transfer contract was awarded to a firm in this city.

Several unique characteristics of China's HSR project make it an ideal setting for studying the impacts of massive international technology transfers on host developing countries.

First of all, the entire HSR project in China was a response to its pressing demand for extra railway capacity and ambition to revolutionize its transportation system. Moreover, the decision to transfer technology was made very abruptly, partially attributable to the determination and maneuvering of the then MoR minister, Zhijun Liu, who wanted to advance the Chinese HSR plan as quickly as possible. Therefore, it is quite unlikely that this wave of technology transfer followed a latent surge in knowledge stock within the railway sector that was expected to come into fruition around and after foreign technology transfer, a major challenge to difference-in-differences identification that plagued previous literature on FDI and domestic innovation.

Second, the technology transferred to China because of its HSR project covers a broad scope of technology classes ranging from high-voltage electrical transmission and preservation, signal control systems, and precision machinery and instruments to new materials. Thus, it is unlikely that we are only picking up a random surge in innovation in a narrowly defined technology class. In addition, the wide range of advanced technologies that have

been transferred has applications outside of railway-related sectors, which makes significant knowledge spillovers possible. For instance, the technology of highly stable and energy-efficient dynamos can be adapted and used in other vehicles such as submarines, and the signal control system can be easily adapted to metro systems. The technologies in kinetic energy conversion and preservation might inspire innovation in automobiles and renewable energy sectors.

4 Data and Identification Strategies

Our analysis draws on three main sources of data: patent applications and grant data in China covering 1996 to 2011 from the State Intellectual Property Office of China (SIPO); and firm-level data from 1998 to 2009 collected by the National Bureau of Statistics of China (NBS) and technology transfer data from the Chinese Railway Yearbooks. In our analysis, we match patents data to the firm level data by the names of applicants. We will describe them in turn.

4.1 Patent-firm matched dataset

The patent data we use include all published invention and utility model patents over the period 1996 to 2011 granted by the State Intellectual Property Office of China (SIPO). We focus on this period because the number of patents applied for before 1995 is very small and there exists downward bias for patents filed after 2011 because of the time lag between application and grant. Because only granted patents appear in the SIPO database, and the typical patent grant cycle in China is some years (1-2 years for utility model patents and 3-4 years for invention patents), it is likely that the processes of granting patents filed after 2011 had not been completed by 2015. There are three types of patents under the current Chinese patent law: inventions, utility models, and industrial designs. Invention means any new technical solution that relates to a product, a process or an improvement thereof. Utility model refers to any new technical solution that relates to a product's shape and/or structure that makes the product fit for practical use. Design refers to any new design of shape, color and/or pattern of a product that creates an aesthetic feeling and is fit for industrial

application.[6] Here, we only focus on invention and utility model patents because industrial design patents usually have little technology content and are not the major focus on CSR, CNR and other railway-related firms.

Our other data source is the annual industrial surveys conducted by the National Bureau of Statistics (NBS) in China. These firm-level surveys include balance-sheet data for all industrial state-owned and non-state-owned firms with sales above 5 million *yuan*. The industries here include mining, manufacturing and public utilities. A comparison with the 2004 full census of industrial firms reveals that these firms (accounting for 20% of all industrial firms) employ approximately 70% of the industrial workforce and generate 90% of output and 98% of exports (Brandt et al., 2012) [11].

The matching of patent and firm database is described in Xie and Zhang (2015) [36]. Patents can be applied for by individuals, firms, or other institutions. Those patents applied for by firm record only firm names rather than the unique firm identification code used in the industrial surveys. As such, Xie and Zhang (2015) [36] had to use firm names as a bridge to match the two databases. They showed that the matching rate was rather high and that the matching error was less than 10 percent.

In addition to the NBS annual industrial surveys, we also attempt to identify the list of firms that were missing from the NBS surveys from *Qichacha* (*http://www.qichacha.com/*), which is an online yellow page on registered firms. We were able to identify 109,078 out of 150,010 missing firms from the NBS surveys using Qichacha, which allowed us to collect the basic registration information of the firms, including the founding year, ownership status and registration address. It is also worth noting that we geocode the firm data from both sources based on the firm registration address, and use the geocoded information to study the localization effect of technology transfer.

4.2 HSR technology transfer data

The information on the types of technology transferred in China's HSR project is drawn from Chinese Railway Yearbooks from 2003 to 2006. The railway yearbook series contains detailed reports about the major events that happened in the CSR and CNR and their subsidiaries,

[6] Source:`http://www.cipahk.com/patfaqs.htm`

including detailed descriptions about their technology transfer contracts. An example of such a description is shown in Figure 2. It lists the name of the technology introduced, the foreign partner involved, the receiving CSR or CNR subsidiary and, sometimes, the value of the contracts.

To map information from the yearbooks to the SIPO patent categorizations and arrive at a definition of HSR technology, we extract keywords from the descriptions of technology and match them to patent descriptions in the SIPO database. After an initial coarse matching of keywords, we also test different ways to refine our definition of introduced HSR technology. In our main specification, we exclude technology class matches in SIPO with less than 1% of the patents in this class filed by CSR, CNR and their subsidiaries from 2004. We use the technology class definition with full matches in our robustness check.

4.3 Empirical strategy

The baseline estimation strategy is a triple-difference specification of the form:

$$\begin{aligned} LogPatent_{i,j,t} = & \beta_0 + \beta_1 HSRCity_i * HSRTech_j * After_t + \\ & \beta_2 HSRCity_i * HSRTech_j + \beta_3 HSRCity_i * After_t + \\ & \beta_4 HSRTech_j * After_t + \gamma Year_t + \theta City_i + \phi HSRTech_j \\ & + \epsilon_{i,j,t} \end{aligned} \tag{1}$$

where $LogPatent_{i,j,t}$ is the number of patents applied by city i in year t within technology class j, γ is a vector of year fixed effects, θ is a vector of city fixed effects, ϕ is a vector of the IPC 2-digit technology class fixed effects, and $HSRCity_i * HSRTech_k * After_t$ is the product of HSR technology-receiving city indicator, railway-related technology indicator and post-technology transfer indicator, our DDD term of interest. We also control for all three pairwise DD terms. In some regressions we also control for the time trends of cities, technology classes and their cross-terms. The error term $\epsilon_{i,j,t}$ is clustered at the city level. In our specification, we exploit three layers of variations: the difference between technology-

receiving cities and other cities, railway-related technology and others, and patents filed before and after technology transfer.

The identifying assumption of our triple-difference estimation is the parallel trends in railway-related patents between HSR-technology-receiving cities and other cities. However, the HSR-technology-receiving cities are not chosen randomly: they are the cities with CSR or CNR subsidiaries and tend to be larger and more innovative than other cities. Therefore, the main identification challenge for our specification is that the trajectory of increases in railway-related patents might differ between cities with CSR or CNR subsidiaries and those without. More specifically, if absent technology transfer, railway-related patent applications increase at a higher rate in CSR/CNR cities and the differences between cities diverge more than those for patents in other technology classes as time passes, we obtain a positive estimate for the DDD term. We plot the trends of patent growth from 1996 to 2012 in Figure 3 to check the parallel trends. Although from the graph, cities with CSR/CNR subsidiaries experienced slightly higher increases in HSR-related patent applications prior to 2004 (especially during 1998-2000), the trends in increasing numbers of patents are fairly parallel between different types of cities and technology classes. Additionally, there are clear trend breaks between different types of technology classes for both technology-receiving and non-receiving cities after 2005, which lends support to our identification strategy.

To sharpen our identification, we control for the linear year trends of individual cities and technology classes as well as that of the cross-terms of the HSR-technology-receiving city indicator and the 2-digit digit dummies. These time trends should be able to absorb most inherent differences in the trajectories of patent growth between technology-receiving cities and the others within any technology class. In addition, to avoid the concerns that our inference is affected by serial correlation due to the time-series nature of our data, we later adopt the method used in Bertrand et. al.(2004) [8] to collapse our full dataset into two pre/post periods. All of the main results are robust to this specification.

Another concern with our identification strategy is that the patenting office may be more willing to accept railway-related patents after the HSR technology transfer to encourage domestic innovation in the related industries. In this case, the positive impact of technology transfer, if there is any, is not due to changes in domestic innovation effort but is the

consequence of relaxed patent standards related to the transferred technologies. To rule out this possibility, we plot the invention grant rate of the transferred technology categories and the other categories in Figure 4.[7] Generally, the grant rate of the railway-related categories is higher than that for the rest of the inventions. However, the grant rates of the two groups are parallel over years, showing no trend break in 2004. Therefore, we are confident that the technology transfer in 2004 did not induce the patenting office to grant more local railway-related innovations.

5 Findings

5.1 Descriptive statistics

Table 1 shows the summary statistics for the key variables. In Panel A, we report the key economic indicators in technology-receiving and non-receiving cities in 1996, 2004 and 2010. Generally, the technology-receiving cities are significantly larger than the non-receiving cities in terms of population. The GDP per capita in technology-receiving cities is also higher than that in the non-receiving cities in 2004 and 2010. However, the GDP growth rates are very similar in these two types of cities in all three reported years.

Panel B reports the number of different types of patents by technology category (transferred and non-transferred technologies) and city type (technology-receiving and non-receiving cities). The total number of HSR-related patents increased by more than six times in technology-receiving cities from 2004 to 2010, on average. These patents also increase by slightly less than five times in non-receiving cities during the same period, and overall, the scale of HSR-related patents is much smaller in non-receiving cities compared with receiving cities. The general pattern shows that technology-receiving cities have significantly more patents in all three reported years and all technology categories, as shown in column 5.

[7] We only plot the grant rate of inventions because we have no information on the grant rate of utility model patents.

5.2 Main results

Table 2 represents the baseline triple-difference estimation results. Controlling for city, year and technology class fixed effects, as well as city and technology class specific linear time trends, we observe a 42% increase in HSR patent applications in cities with CSR or CNR affiliates after 2004, suggesting a large aggregate effect of HSR technology transfer on domestic innovation. We then check the differential impacts of technology transfer on different types of patents. The impact on utility model patents (less involved innovations) is 38.4% as indicated in column 2, and the impact on invention is relatively smaller, 26.7%, as reported in column 3. To ensure that the results are not driven by divergent patent growth patterns between different technology classes in technology-receiving and non-receiving cities, we further control for city type by technology type year trend in columns 4-6. The impact remains the same after the inclusion of the additional set of fixed effects.

To separate the effects of direct technology transfer within CSR/CNR affiliates and broader spillover effects, we exclude patents filed by these affiliates from our sample in Table 3. We find that the effects of HSR technology transfer decrease by half, indicating the importance of direct absorption by receiving firms of technology transfers. Among different patent categories, the reductions in utility model patents are more pronounced when CSR/CNR affiliates are excluded, consistent with circumstances under which a larger proportion of patents filed by direct receivers of foreign technology are smaller adaptations whereas the innovations stimulated by foreign technology transfers in other firms are more substantial. The finding is consistent with the "small incremental inventive steps" hypothesis raised by Puga and Trefler (2010) [32] to explain developing countries' progressions through the steps on the global technological ladder.

To further separate demand-driven innovation from knowledge spillovers, we then isolate firms that are listed as the certified suppliers to China's railway projects by the Ministry of Railway (MoR)[8]; the results are reported in Table 4. Again, we observe a small drop in the estimated technology transfer effects on utility model patents. Surprisingly, there are very few changes in invention patents. This finding suggests that within HSR technology

[8]Suppliers to China's railway projects must apply for certification from the MoR; public information is online. There are 1172 certified suppliers.

classes, the stimulation of innovation along the supply chain does not appear to be large in magnitude compared other possible channels of spillovers, such as knowledge spillovers across similar technology classes.

5.3 Heterogeneity

The above analysis suggests that technology transfer in the HSR sector generates sizable direct impact to the receiving firms and knowledge spillovers to non-related industries. However, an alternative explanation is that government might direct more resources to technology receiving cities or technology receiving categories, or both, as an attempt to facilitate the digestion of transferred technology. Therefore, it is challenging to conclude that the observed spillover effect is a response to the transferred technology instead of concerted government investments.

In this subsection, we try to mitigate the concern that the spillover effects are driven by directional government intervention instead of transferred technology. By saying that, we explore the heterogeneity in the spillovers of HSR technology transfer in firms with different characteristics. We are especially interested in the heterogeneous effects regarding to firms' ownership status and age. We have two hypotheses to be examined: if the spillover effect is mainly driven by government directed resources instead of transferred technology, 1) we are more likely to observe larger knowledge spillovers in state-owned enterprises (SOEs) than private-owned enterprises (POEs) since the former are better connected and hence more accessible to government resourced; and 2) we are more likely to observe larger spillover effects in newly founded firms if the government established new firms to house R&D activities or the availability of extra funds encouraged the spin-off companies from research institutions.

Broadly speaking, there are two types of applicants: firms and non-firms.[9] We further separate firms into SOEs and POEs and estimate the treatment effects for SOE, POE and non-firms. Figure 5 shows the magnitude and significance of the triple-difference coefficients.[10] It is apparent that the treatment effect is larger in POEs than in SOEs for both types of patents (Panel (a) of Figure 5).[11] When we further exclude the direct receivers of

[9]Non-firms include research institutions (such as universities) and individual applicants.

[10]The full estimation results are available in appendix Table A.1.

[11]For non-firms, the direct effect of technology transfer is not defined since none of them are direct receivers

technology transfer and the suppliers in the railway sector, the effect for POE still strongly dominates within the sample of firms. It is also worth noting that the effect for non-firms is even larger than the effect for POE, potentially driven by patent application from universities or other research institutions.

To test the second hypothesis, we exploit potential heterogeneous effect by firm's age. If the government set up new firms to host R&D in HSR and apply for patents, we will observe a larger spillover effect for younger firms than for older firms. We first calculate the median age of the firm at the time of the patent application, which is nine years' old. Then we separately estimate the effects for younger firms and older firms. However, the effect is similar for both types of firms which is shown in Figure 6.[12]

The above results on heterogeneity suggest that the spillover effect of technology transfer is mainly contributed by POEs and non-firm applicants, such as universities. In addition, the results are not driven by newly founded firms. Both findings indicate that although we cannot rule out the possibility of government interventions, they do not seem to drive the differential patterns of innovation behavior across different types of firms in response to external transferred technology. Therefore, we believe spontaneous responses to external surge of knowledge in relevant sectors are more likely to account for the observed spillover effects instead of targeted government investments. In section 6, we will examine further evidence on the channels of spillover, which is also consistent with a spontaneous knowledge spillover story.

5.4 Robustness checks

The above main results suggest a significant positive impact of HSR technology transfer on the domestic innovation of related technologies not only from direct receiving firms but also from firms in non-railway-related industries. Before we proceed with the discussions of the potential mechanisms of this impact, we provide a series of robustness checks in this section to ensure that our estimated results are robust to various specifications.

of technology transfer. Therefore we only report the effect on non-firms in Panel (b) which represents the spillover effect of technology transfer.

[12]The full estimation results are available in appendix Table A.2.

First, we tested different definitions of technology class as well as treatment year. Table 5 shows that our DDD estimates on total patents and those that excluded directly relevant firms are robust to an uncensored definition of technology class whereby we keep all of the technology classes with matches from China Railway Yearbooks keywords.

Additionally, we change the year of technology transfer from 2004 to 2005 for the CSR/CNR subsidiary cities whose technology transfer times are not precisely documented in the railway yearbooks to account for possible delays. Again, we find similar results, as shown in Table 6.

As mentioned earlier in Section 3.2, the information about technology transfer in some cities is quite brief. Therefore, it is a pity that we cannot code out city-specific technology transfers based on railway yearbooks. However, it is well documented that three cities received technology transfer for producing the whole train, including Qingdao, Changchun and Tangshan, while the rest of the CSR/CNR branches received technologies for producing certain parts. We take such variation as a proxy for differences in intensities of technology transfer and separately estimate the treatment effects for the three cities with intensive technology transfer and the rest of the cities with lower treatment intensity.

Table 7 reports the estimation results by different treatment intensity. The first row reports the triple-difference coefficient for cities in charge of producing parts, while the second role reports the main coefficient for cities in charge of producing the whole train. The effect of technology transfer on patent growth is much larger for the three cities with intensive transfers (60.2%) compared to the rest of the technology receiving cities (38.7%). However, such effect is mainly driven by the growth of utility models instead of invention. The effect after excluding CSR/CNR and certified suppliers also has similar pattern. One possible explanation for the insignificant spillover effect on inventions could be the lack of strong universities in railway-related research in the three cities, which will be discussed further in Section 6.2.

In Table 8, we follow Bertrand et al. (2004) [8] and collapse the time dimension of our sample into pre/post treatment groups to address serial correlation. Again, the point estimates and standard errors stay almost the same.

As an additional effort to strengthen our triple-differences specification, we further refine

the selection of control cities to make the treated and control groups more comparable. Thus, we adopt the nearest neighbor matching algorithm to find the nearest three neighbors for each treated city regarding the population and its growth rate, GDP and the number of patents, as well as government spending on scientific research. We arrive at 32 control cities for the 23 treated cities in our refined sample. The control and treated cities do not have significant differences in terms of all of the matching variables, as indicated in Table A.3. We use this refined sample to replicate the main regressions in Tables 2 and 4, and the results remain very similar to the main findings, as shown in Table 9.

Lastly, to confirm that the positive impact in our regressions is truly from the policy shock in the HSR technology sectors rather than other confounding factors, we further conduct a placebo test by randomly choosing 13 IPC4 categories to be the placebo-treated categories. We run 100 regressions using each set of the placebo treatment and find that only 3 of them produce significantly positive results. Thus, we are driven to believe that our estimated results capture the real impact of technology transfer in the HSR-related sector.

6 Mechanisms of Spillovers

Because we find a significant impact of HSR technology transfer in the non-rail related sectors, we are interested in the mechanisms that could explain these knowledge spillovers. In this section, we first present some cross-city evidence, where we further explore the roles of geographic distance and technological similarity, as well as the importance of university research in the diffusion of transferred technology to other cities and technology classes. We then present within-city evidence to understand the localized spillovers of CSR/CNR subsidiaries on nearby firms' innovation activities and other outcomes.

6.1 Cross-City Evidence: Geographic and Technological Proximity

To understand how a larger-scale technology transfer program changes the innovation landscape of a developing country as a whole, it would be interesting to see how the other sectors

and cities could benefit from sudden increases in knowledge stock in the railway sector. One possibility is that the knowledge spillovers spread to nearby cities, and thus, cities closer to the technology-receiving cities will have higher patent growth in the affected categories compared with cities that are farther away. The other possibility is that the knowledge spillovers spread to similar technology categories. After all, in Griliches (1992) [19], knowledge spillovers are defined as "working on similar things and hence benefiting much from each others research." Thus, technologies that are more similar to the transferred technologies may see higher patent growth.

Table 10 displays the results for geographic proximity. We interact the logged distance from the centroid of a city to the closest technology-receiving cities with the technology dummy and year dummy, and we include the pairwise difference-in-differences terms and the main effect of distance. In general, we do not find any large effects on patent growth in cities that are closer to HSR technology-receiving cities, both within and outside of HSR-related technology classes. This finding indicates that either closeness in technology diffusion only has weak impacts or this spillover effect is very local and only presents within cities. As suggested by Rosenthal and Strange (2003) [33], the localization effects of being near similar businesses decay rapidly with distance and may disappear after 10 miles. We will discuss about such localization effects in the next subsection.

However, in Table 11, we observe a significant impact of technology proximity on the spillovers of HSR technology. We measure technology proximity using Kay et al.'s (2014) technology similarity matrix, which assigns a measure from 0 to 1 as the similarity between two 4-digit technology classes based on co-citation. The first row in Table 11 indicates a significant increase in patents applications in technology classes that are close to HSR technology in HSR technology-receiving cities after the introduction of foreign technology: doubling the similarity measure increases the patents by more than 3%, compared with a direct impact of 40%. Excluding CSR and CNR firms as well as direct suppliers to China's HSR projects from the sample does not appear to greatly diminish the role of technology similarity, which indicates that the knowledge spillovers across similar technologies occur largely outside of the railway sector. It is worth noting that these effects are mainly restricted to utility model patents. A somewhat puzzling finding is a small but significant negative

effect of technology proximity in patent applications in non-technology-receiving cities after 2004. We think that this finding might be attributable to competition in both output and input markets, but it is open to other interpretations.

It is also worth noting that the significant impact of technology proximity on the spillovers of HSR technology provides a compelling evidence of technology-driven (instead of government-driven) spillovers: if the results are driven by government's investment in HSR technology in the technology receiving cities, we would not observe a significant correlation between technology similarity and knowledge spillovers.

6.2 Cross-City Evidence: University research

Universities play a central role in local technology spillovers, not only as producers of basic research but also by promoting the exchanges of ideas and mobility of highly skilled labor through firm-university cooperation. Understanding the role played by basic research institutions in transmitting a knowledge stock shock within a few firms in one particular sector to other firms and related sectors is crucial. This mechanism of firm-university knowledge transmission is especially relevant in our HSR technology example because the MoR explicitly mobilized universities, colleges and science research centers to work along with CSR and CNR in the digestion, absorption and re-innovation of imported foreign technology. Most notably, in 2008, the MoR signed an agreement[13] with the MoS (Ministry of Science) of China to help develop technologies to create a network that could support train speeds of 350 kph or more, a significant breakthrough relative to the foreign technology that was introduced, which only applied to a system of trains with speeds of 250 kph. According to the agreement, the MoS is responsible for providing funding opportunities to universities, national laboratories and engineering research centers for relevant research programs, which usually involves the cooperation of one of the CSR or CNR subsidiaries and the funded research institutes. We believe that during this process, these research institutions gain access to the transferred technology, study the fundamentals and benefit other firms with related technology problems through either public knowledge sharing or private cooperation.

In testing the role of universities in promoting technology spillovers, our hypothesis is

[13] `http://www.most.gov.cn/tpxw/200802/t20080227_59350.htm`

that we should observe more rapid patent growth in HSR or closely related sectors filed by non-CSR/non-CNR firms after the introduction of foreign technology into cities with more university research activities in relevant technology classes prior to the massive technology transfer project. We define "relevant technology" as the 2-digit technology classes that encompass our 4-digit HSR technology, which includes basic research in transportation and electricity conversion and distribution. Prior to 2004, only 63 cities had patents applied for by universities in relevant technology classes, and they were heavily skewed. Therefore, instead of using the actual previous university patent applications as the measure of university research strength, we define a dummy that switches on for the 63 cities with early relevant university patent applications.

Table 12 shows the estimation results in cities with and without relevant university patent applications prior to 2004. As seen, the spillover of imported technology to non-CSR/non-CNR firms as well as firms that are not certified MoR suppliers occurs almost exclusively in cities with previous university research experience in relevant fields (Panel A). In cities without patents applied for by universities before 2004 in broad HSR-relevant technology classes, the direct impact on total patents is similar to that estimated in the baseline but there is almost no impact of technology transfer on patent applications outside of the direct receivers of the imported technology (Panel B).[14] This finding is consistent with our previous evidence on the importance of technology similarity rather than geographic proximity in knowledge spillovers: technology transmission to related fields is likely to occur through firm-university or university-university cooperation in cities with strong academic research backgrounds in relevant fields, rendering geographic distance less of a barrier.

One limitation of the dummy measure mentioned above is that it might be capturing not only the university research strength but also the city's general research strength in the relevant areas. Thus, we alternatively use the ratio of university-applied patents to total patent applications in those areas as our second measure. The results are shown in Appendix Table A.5. The effects are largely consistent with those using the dummy of

[14]We also apply a DDDD design where we interact the dummy of university research with the triple-difference and pairwise difference-in-difference terms. The results are consistent with Table 11 which are available in Appendix Table A.4. Interestingly, we also observe higher patent growth in narrowly defined HSR technology classes in cities that are not directly receiving HSR technology but that have relevant university research experience.

previous university research activities. Cities with higher university patents/total patents ratios witness higher growth in patents in HSR technology classes filed by firms that do not directly receive transferred technology. This evidence shows the complementarity between basic research and specific technology. With regard to policy, governments should take into consideration the country's or region's basic research strength in decisions that involve foreign technology transfers and allocations of transferred technology to different regions.

6.3 Within-City Firm Level Analysis

In the above subsection, we show that cross-city geographic proximity has little effect on the magnitude of technology transfer spillovers. One possibility is that the localized knowledge spillovers of being near similar businesses decay rapidly with distance and are limited within cities. To further examine the within-city technology spillovers, we identify the geographic location of the technology receiving firms (i.e., CSR/CNR subsidiaries) and estimate such localization effect using geocoded firm-level data. More importantly, leveraging data on firm outcomes including revenue and TFP allows us to evaluate the real economic impacts of foreign technology transfer on domestic firms, in addition to innovation outcomes. Specifically, we estimate the following model,

$$\begin{aligned} Outcome_{i,j,t} =& \beta_0 + \sum_{d=1}^{10} \beta_d DistanceBand_{i,j,d} * After_t + \sum_{d=1}^{10} \gamma_d DistanceBand_{i,j,d} \\ &+ CountyFE * After_t + IndustryFE * After_t + YearFE + \epsilon_{i,j,t} \end{aligned} \tag{2}$$

where $Outcome_{i,j,t}$ represents the logs of firm level outcomes of firm j in city i in year t, including innovation output, such as the total number of patents, utility model and invention patents, and other performance outcomes including firm revenue, total factor productivity (TFP) and firm entry. $DistanceBand_d$ is a series of dummy variables for each distance band, which takes the value one if firm j lies within band d. We consider ten distance bands, each spanning two miles, until 20 miles from the technology receiving firms. $After_t$ is a dummy variable indicating if year t is after the technology transfer. Thus, the coefficients

β_d identify the localized spillovers of technology transfer on nearby firms. The specification also controls for distance band fixed effects, county-by-after fixed effects, 2-digit-industry-by-after fixed effects and year fixed effects. The robust standard errors are clustered at the city level. When using the number of patents filed by each firm as the outcome, we encounter a large number of observations of zero patent filing. We follow Liu and Qiu (2016) [29] to define $outcome_{i,j,t} = ln((Y^2_{i,j,t} + 1)^{1/2})$, where $Y_{i,j,t}$ is the total number of patent filings. We exclude firms who are certified suppliers of MoR since we are interested in the spillovers to non-supply chain firms.

The coefficients on the interaction terms of distance bands and after variable, as well as the 95% confidence intervals, are plotted in Figures 7 and 8, where the excluded group is the patenting outcomes of firms *within* the same city but at least 20 miles away from the technology receiving firms. In addition to the estimation on the full sample, we also partition the data by the medians of technology similarity and input-output links[15], respectively. The idea is to understand if the spillovers are larger for firms that are technologically similar, who can learn from transferred and upgraded technology more easily; or larger for firms that are more likely to benefit from the extra demand of HSR as suppliers[16], and as a result obtain more resources and face stronger need to innovate.

Figure 7 shows the localization effect on firm level patenting outcomes and conveys three main messages. First, firms closer to the technology receiving firms experienced significantly higher patent growth after the technology transfer. Such effect is the largest for firms within two miles to the CSR/CNR firms and decays to zero after approximately 16 miles. Second, the localized spillovers on patenting are mainly driven by the growth of utility model patents instead of the invention patents, which are small-step innovations that ask for protection over

[15]Technology similarity is generated at each four-digit industry, according to how similar are the patents applied by firms within each industry to those applied by CNR/CSR firms before 2004. Technology similarity across patent classes are defined in Kay et al. (2014). Technology similarity to the railway sector at industry level is then defined as a weighted average of technology similarity to the patent classes where CNR/CSR firms patented at before 2004, weighted by both the number of patents within each technology class by CNR/CSR firms and the number of patents within each technology class by patents applied by firms in the relevant industries before 2004. Input-output linkage, also defined at four-digit-industry level, is the share of input of the railway sector that comes from each industry, calculated according to the IO table of China in 2012.

[16]We have excluded the direct suppliers to the MoR but we cannot rule out positive spillovers due to extra demand to the suppliers of suppliers, etc.

a shorter period. Third, the effect is generally larger for technologically-similar firms but not for firms with closer input-output linkages with the technology receivers, suggesting that the localized spillover is likely to be driven by technology similarity instead of increased demand along the supply chain.

In addition to firms' patenting outcomes, Figure 8 reports the localization effects on other firm performance measurements, including firms' revenue, total factor productivity (TFP) and new entry.[17] We find that firms closer to the technology receiving firms experienced higher revenue growth and increased TFP and marginally more firm entry after the technology transfer. The evidence also suggests that the localization effect on revenue is mainly driven by firms with above-median technology similarity instead of closer input-output linkages.

We also conduct a series of robustness checks by further refining the technology receiving firms to only the ones with R&D centers of CSR/CNR subsidiaries[18] and find consistent evidence (see Appendix Figures B.1 and B.2). The localization effects on firms' patenting activities are positive and significant for firms within two miles of the R&D centers, and only driven by nearby firms with similar technologies (Figure B.1). The localization effect on nearby firms' revenue and TFP is also larger for firms with above-median technology similarity but not for firms with above-median input-output linkages. The positive effects are generally larger for the sample of cities that house R&D centers of CSR/CNR firms, which indicates that the spillovers to other firms are stronger where the transferred technology is more intensely studied and digested.

To summarize, the within-city firm level analysis suggests positive localization effect on nearby firms' patenting activities, revenue, and productivity. Such effect is generally stronger for firms with higher similarity to the transferred technologies, but not for firms with stronger input-output links with the technology receiving firms. The positive and large revenue and productivity effects suggest that firms closer to direct technology receivers not only innovate more, but also experience economic gains. In another word, the large surge in patent activities in our main findings are associated with significant real economic benefits

[17] We calculate firm-level TFP following Brandt et al. (2012). We define a firm to be a new entrant if it appears in the industrial firm survey for the first time in a particular year.

[18] There are 25 cities with CSR/CNR subsidiaries, but only 13 of them also have CSR/CNR R&D centers.

to the innovators and the whole economy, other than purely driven by extra incentives to patent.[19] The results are also consistent with the cross-city evidence that technology similarity serves as the major mechanism affecting the magnitude of knowledge spillovers.

7 Concluding Remarks

This paper aims to make two primary contributions. First, we evaluate the impacts of one of the largest technology transfer plans in the world, i.e., the introduction of HSR technology into China. This unprecedented natural experiment provides us with an excellent opportunity to evaluate the effectiveness and limitations of '*quid pro quo*' markets for technology strategy in catching up with global technology frontiers. Second, we further examine different mechanisms that might contribute to the absorption, digestion and diffusion of introduced foreign technology in developing countries. Although the direct impacts within receiving firms are the largest, firms outside of the railway sector also experience significantly large increases in related patents, and consequently, larger economic gains in terms of revenue and productivity. We find a significant role of technology proximity both across cities and within the technology receiving cities that could explain the technological spillovers. In addition, university research also help facilitate the digestion of foreign technology and stimulate domestic innovation.

Concerns regarding the external validity of this natural experiment may arise because some of the special institutional features in our example, such as the large Chinese market for railway and the monopoly power of CSR and CNR in this market, might have facilitated or hindered implementing the full market for technology policy. However, the fact that we still find large and significant treatment effects after excluding CSR/CNR affiliates as well as MoR certified supplies suggests that many of the activities are in sectors other than the directly-impacted sector. Our further investigation reveals sizable spillovers to technologically similar firms, suggesting that absorptive capacity of foreign technologies, other than government initiatives, might be the primary explanation of patent booms in the

[19] Hu et al. (2017) [21] finds that non-innovation related motives for acquiring patents may have played an important role in the patenting surge.

indirectly affected sectors.

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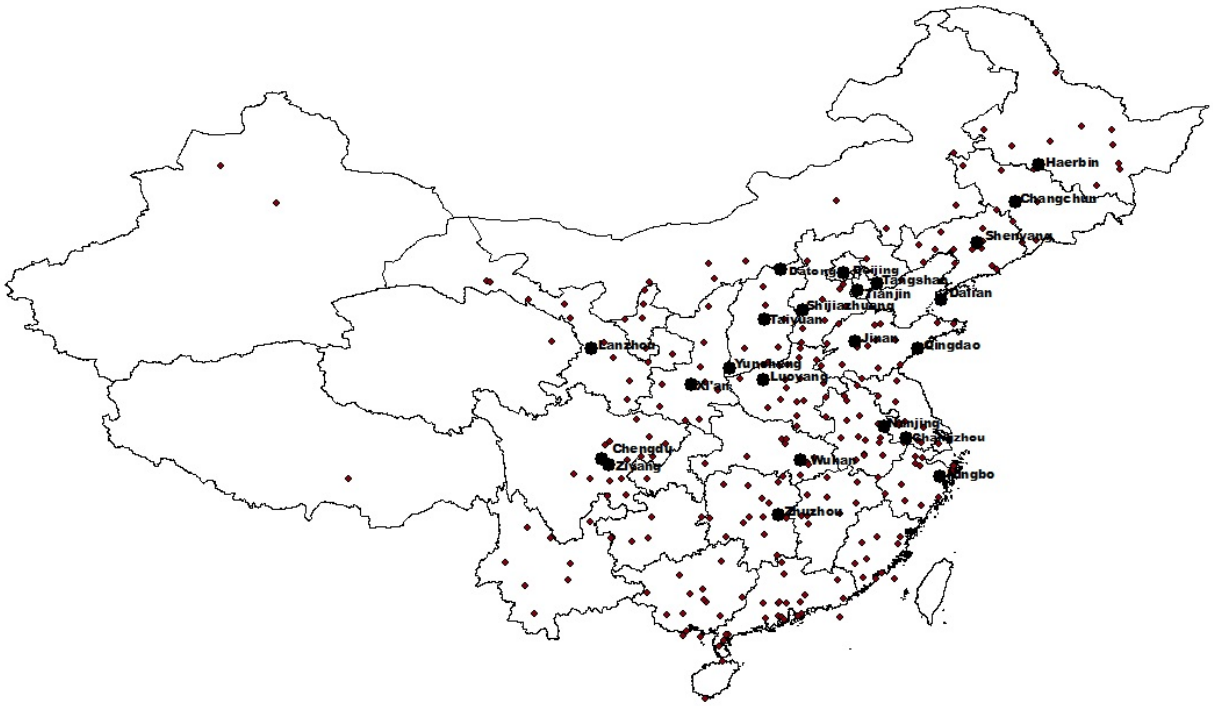
Figure 1: Technology-Receiving Cities



Note: Technology-receiving cities are labeled and marked with large black dots.

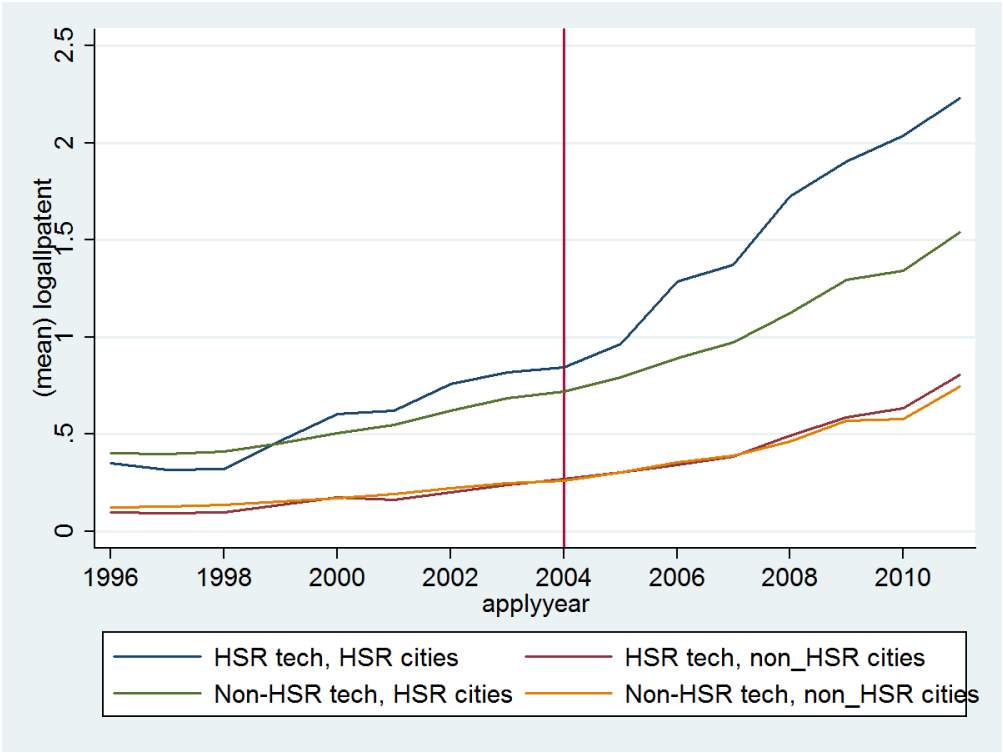
Source of the map: Michigan China Data Center.

Figure 2: An Example of a Technology Transfer Document

在该项目中，同时引进日本东芝公司的交流传动系统、交流传动控制和微机网络控制系统、主变流器、主变压器、牵引电机、辅助系统及辅助变流器、转向架、车体、整车等设计与制造技术；引进德国福伊特驱动技术股份有限公司的驱动装置（齿轮箱装配、抱轴箱等）设计和制造技术。（冯　琳）

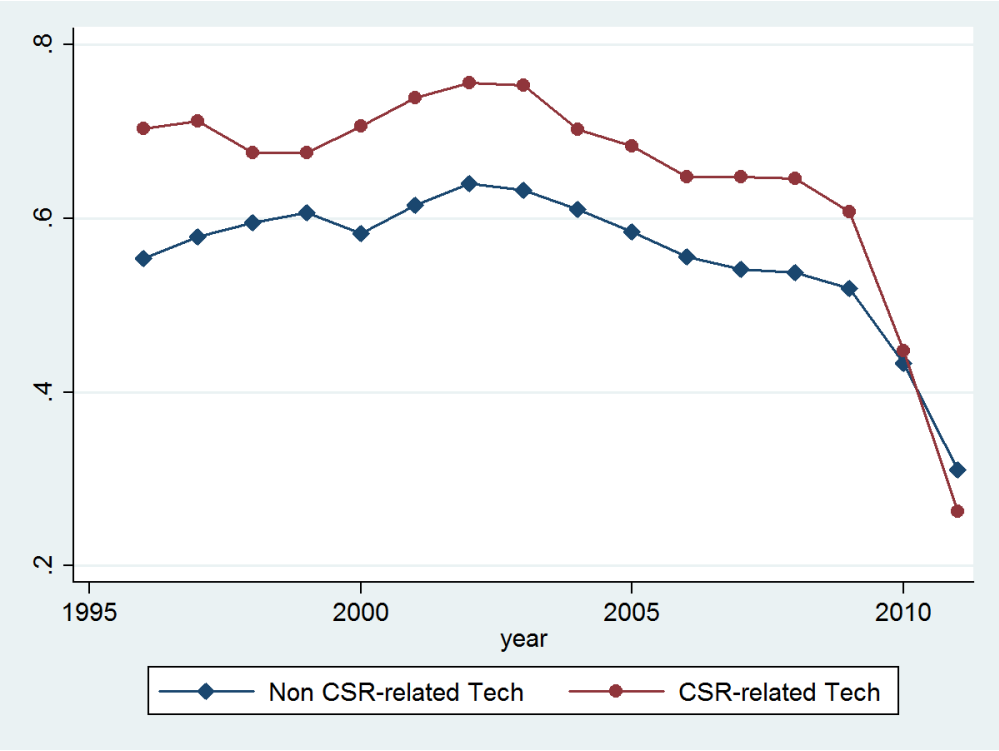
Data Source: China Railway Yearbook (2005). Translation: In this project, we (CNR Dalian Subsidiary) received technology transfer from Toshiba on AC drive system, AC drive control and computer network control systems, main converter, main transformer, traction motor, auxiliary system and auxiliary converter, bogie and the design of train body. We also received technology transfer from Voith, on the design and manufacturing of the actuating system (gearbox assembly and axle suspension, etc.).

Figure 3: Growth Trend of Patents



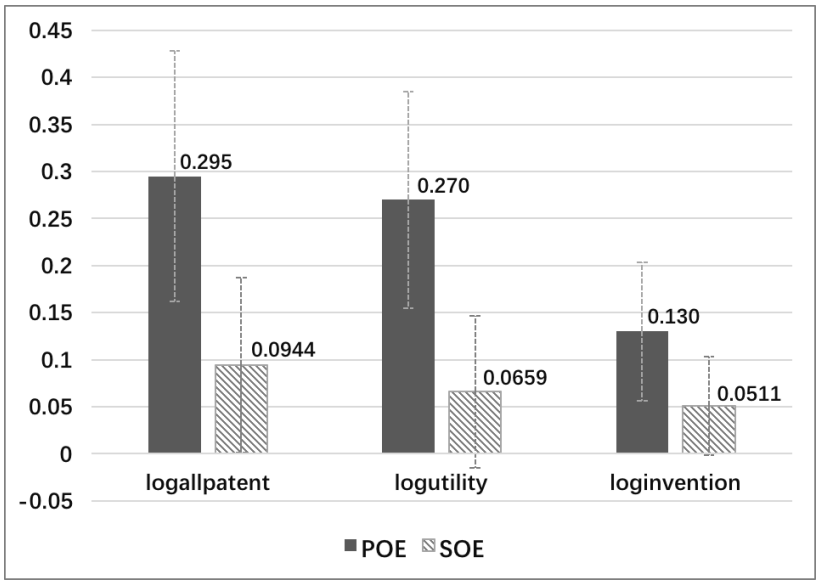
Data Source: Authors' calculations based on the SIPO database. This graph depicts the time trends of the averages of the (log) total patent number granted within each IPC 4 digit category-city combination of four groups: HSR-technology receiving cities and HSR-relevant technology classes (blue line), HSR-technology receiving cities and non-HSR technology classes (red line), non-HSR-technology-receiving cities and HSR-relevant technology classes (green line), and non-HSR-technology-receiving cities and non-HSR-relevant technology classes (yellow line).

Figure 4: Patent Grant Rates of HSR-related Inventions and Other Inventions

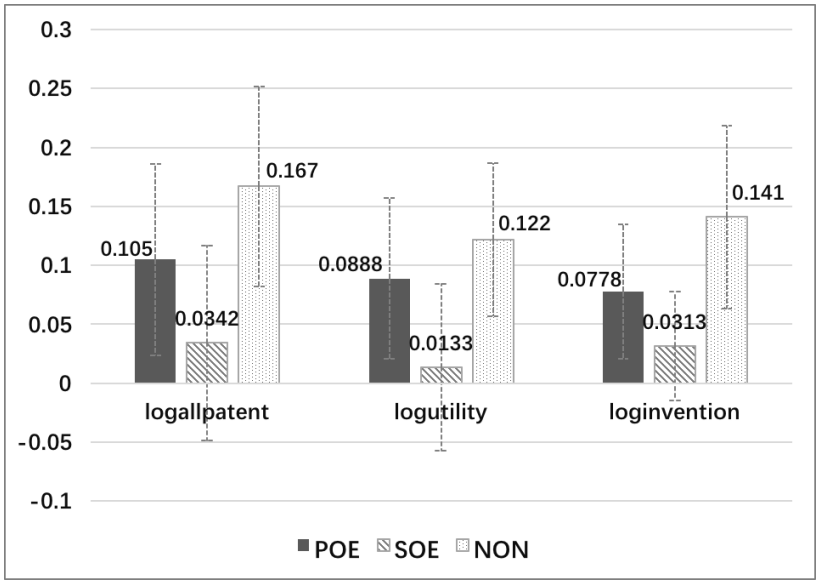


Data Source: Authors' calculations based on the SIPO database. This graph depicts the time trends of patent grant rate across HSR-related and non-HSR-related technology classes.

Figure 5: Coefficients comparison: Private/State/Non firms



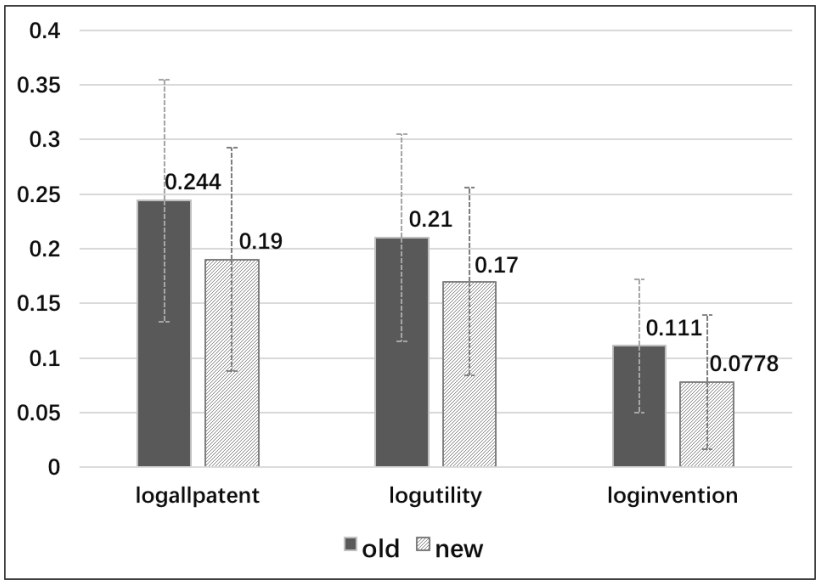
(a) Full sample



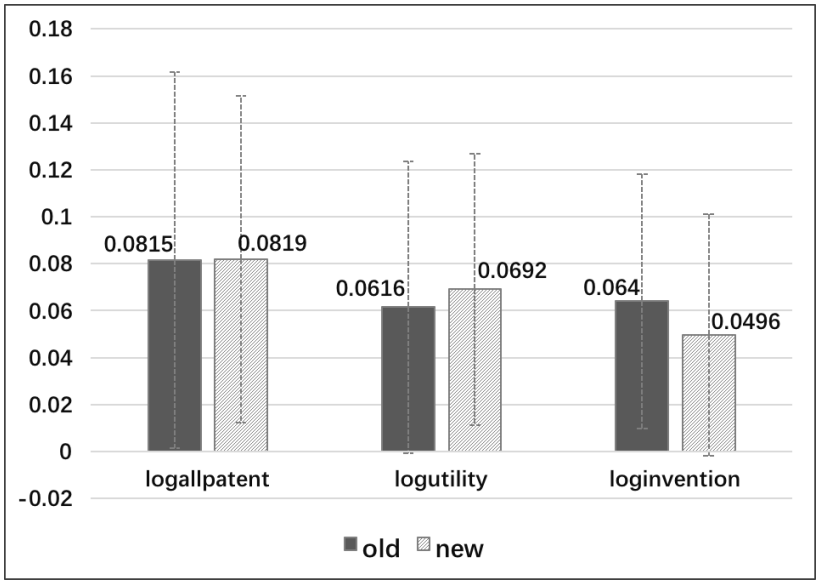
(b) Exclude CSR/CNR/Certified Suppliers

Notes: 1. This figure visualizes the triple difference coefficients in Table A.1. Panel (a) corresponds to columns 1-3 in Table A.1, while panel (b) corresponds to columns 4-6 in Table A.1; 2. The coefficients are presented in bar charts as well as shown in numbers, with their 95% confidence intervals.

Figure 6: Coefficients comparison: Old and New firms



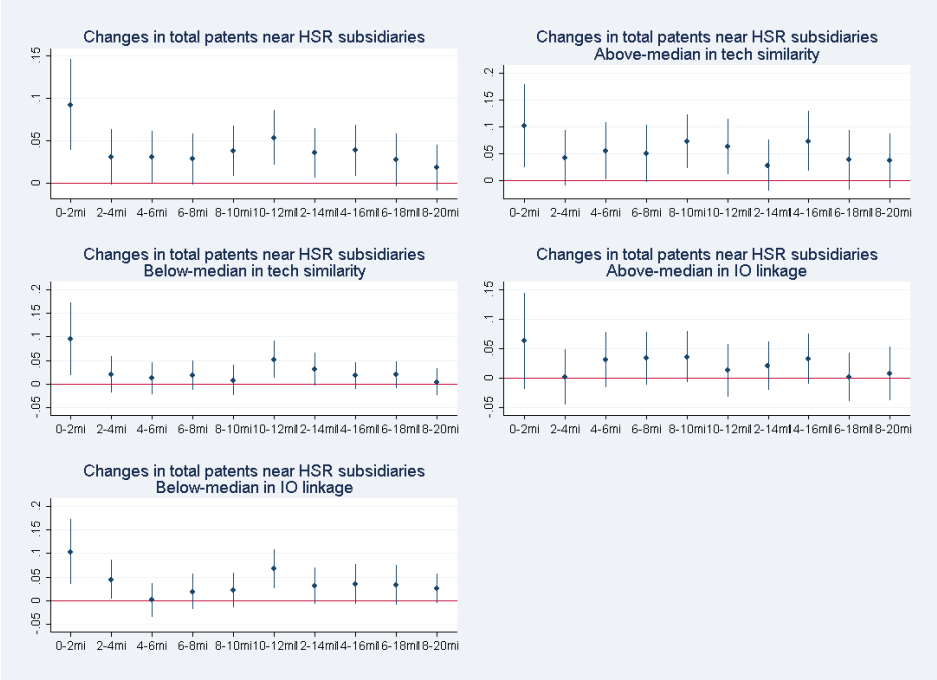
(a) Full sample



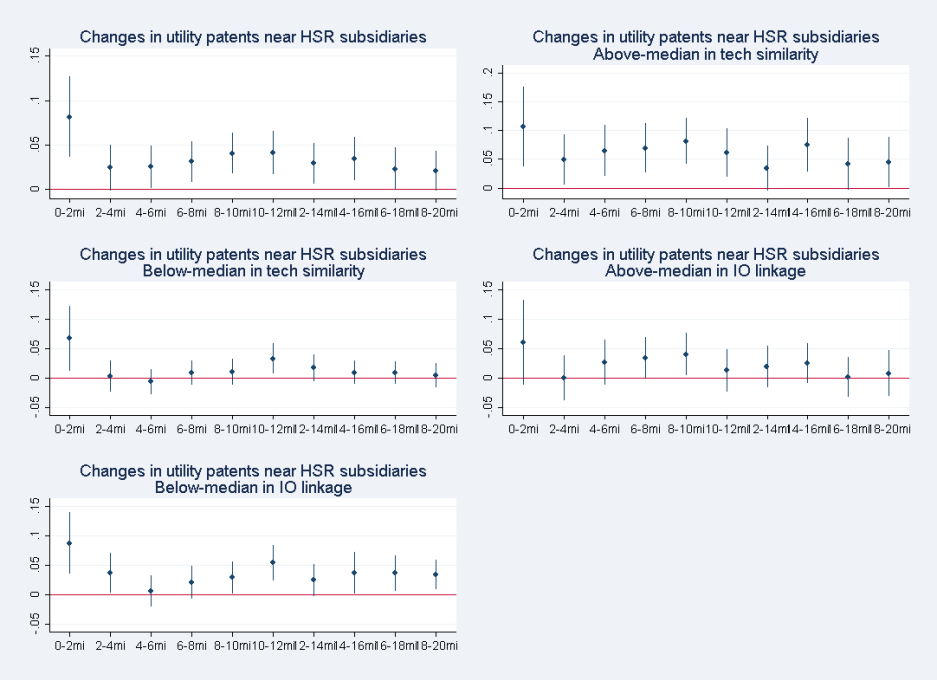
(b) Exclude CSR/CNR/Certified Suppliers

Notes: 1. This figure visualizes the triple difference coefficients in Table A.2. Panel (a) corresponds to columns 1-3 in Table A.1, while panel (b) corresponds to columns 4-6 in Table A.2; 2. The coefficients are presented in bar charts as well as shown in numbers, with their 95% confidence intervals.

Figure 7: Distance to CSR/CNR firms and Firm Patenting Outcomes

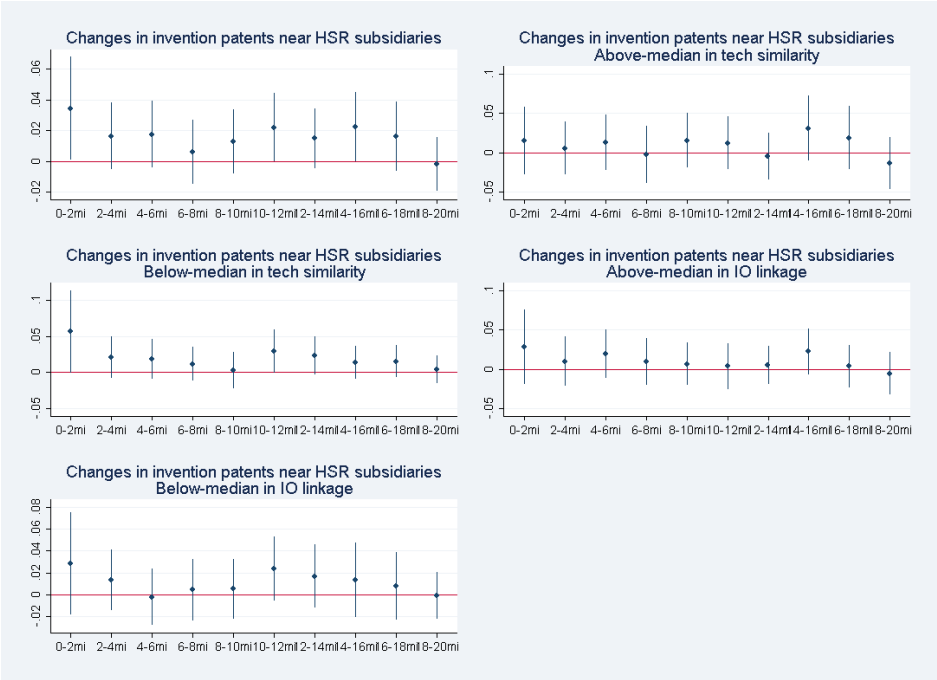


(a) Total Patents



(b) Utility Model Patents

Figure 7: Distance to CSR/CNR firms and Firm Patenting Outcomes



(c) Inventions

Notes: 1. This figure visualizes the β_d coefficients in Equation (2). The regression tables are available upon request. 2. The coefficients are presented in dots, with their 95% confidence intervals.

Figure 8: Distance to CSR/CNR firms and Firm Performance

(a) Revenue

(b) Total Factor Productivity

Figure 8: Distance to CSR/CNR firms and Firm Performance

(c) Firm Entry

Notes: 1. This figure visualizes the β_d coefficients in Equation (2). The regression tables are available upon request. 2. The coefficients are presented in dots, with their 95% confidence intervals.

Table 1: Summary Statistics

Panel A: City Level Economic Variables						
	HSR cities		Non-HSR cities		Difference between HSR and Non-HSR cities	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
GDP per capita 1996	9.681	(3.291)	7.351	(8.755)	2.331	(1.928)
GDP growth 1996	0.193	(0.053)	0.174	(0.075)	0.019	(0.017)
GDP per capita 2004	21.550	(10.128)	13.381	(23.110)	8.169	(3.518)**
GDP growth 2004	0.195	(0.036)	0.194	(0.058)	0.001	(0.012)
GDP per capita 2010	50.734	(23.111)	28.370	(22.289)	22.364	(4.751)***
GDP growth 2010	0.184	(0.029)	0.197	(0.039)	-0.013	(0.008)
population 1996	5766.776	(2557.171)	3019.944	(2498.963)	2746.832	(573.772)***
population 2004	6358.079	(2474.543)	4015.468	(2827.906)	2342.611	(599.160)***
population 2010	7271.600	(3727.994)	3987.834	(3137.841)	3283.766	(677.262)***

Panel B: Patents by City Type and Technology Type				
	HSR cities		Non-HSR cities	
	HSR tech	Non-HSR tech	HSR tech	Non-HSR tech
total patents 1996	12.64	601.96	1.59	71.68
	(3.49)	(179.03)	(0.23)	(7.55)
utility patents 1996	11.6	523.76	1.53	65.55
	(3.08)	(145.68)	(0.22)	(6.80)
invention patents 1996	1.04	78.2	0.06	6.13
	(0.45)	(34.64)	(0.02)	(0.82)
total patents 2004	62.64	1604.48	11.61	242.56
	(28.41)	(481.79)	(5.85)	(43.27)
utility patents 2004	29.08	1030.16	6.01	188.29
	(7.96)	(245.53)	(1.12)	(28.79)
invention patents 2004	33.56	574.32	5.6	54.27
	(20.51)	(241.75)	(3.59)	(14.48)
total patents 2010	383.76	5758.72	52.81	858.07
	(142.67)	(1649.93)	(14.46)	(147.76)
utility patents 2010	170.96	3718	30.96	652.24
	(42.87)	(862.51)	(6.05)	(104.24)
invention patents 2010	188.56	1979.84	19.77	198.09
	(101.47)	(933.55)	(7.46)	(42.27)

Notes:1. Data source is from China Statistical Yearbooks (1997,2005 and 2011) and SIPO database; 2. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 2: Impact of Technology Transfer on Domestic Innovation

	Full Sample					
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After	0.423***	0.384***	0.267***	0.423***	0.384***	0.267***
	(0.0587)	(0.0533)	(0.0451)	(0.0587)	(0.0533)	(0.0451)
HSRCity*After	-0.0171	-0.0337**	-0.00456	-0.0170	-0.0336**	-0.00453
	(0.0157)	(0.0150)	(0.00860)	(0.0157)	(0.0150)	(0.00860)
Tech*After	0.0199**	-0.00271	0.0355***	0.0200**	-0.00264	0.0356***
	(0.00913)	(0.00772)	(0.00776)	(0.00914)	(0.00772)	(0.00776)
HSRCity*Tech	0.0720**	0.0698***	0.0259	0.0595***	0.0194	0.0577***
	(0.0284)	(0.0239)	(0.0176)	(0.0229)	(0.0202)	(0.0170)
Tech	-0.0208***	-0.0290***	0.0106***	-0.0182***	-0.0225***	0.00897***
	(0.00539)	(0.00494)	(0.00296)	(0.00535)	(0.00506)	(0.00274)
Observations	1,677,088	1,677,088	1,677,088	1,677,088	1,677,088	1,677,088
R-squared	0.334	0.297	0.274	0.338	0.303	0.282
CITY, YEAR, IPC2 FE	YES	YES	YES	YES	YES	YES
IPC2*YEAR	YES	YES	YES	YES	YES	YES
CITY*YEAR	YES	YES	YES	YES	YES	YES
HSRCITY*IPC2*YEAR	NO	NO	NO	YES	YES	YES

Notes:1. The table reports triple difference estimation results from equation 1. logallpatent is the log sum of patents granted within each IPC 4 digit category-city group for each year. logutility is the log sum of utility-model patents. loginvention is the log sum of invention patents. HSRCity is an indicator on whether or not the city is a HSR-technology receiving city. Tech is an indicator on whether or not the patents belong to HSR-related IPC 4-digit technology classes. After is a dummy that switches on for all years after 2004. All the regressions include city, year and IPC2 fixed effects, as well as IPC2 and city specific year trends. The last three columns report results by controlling for HSR-city*IPC2 specific year trend as well. 2. Robust clustered standard error at the city level. 3. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 3: Impact of Technology Transfer on Domestic Innovation (Excluding CSR/CNR Subsidiaries)

	Exclude CSR/CNR Subsidiaries					
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After	0.207***	0.181***	0.191***	0.207***	0.181***	0.191***
	(0.0463)	(0.0416)	(0.0401)	(0.0463)	(0.0416)	(0.0401)
HSRCity*After	-0.0140	-0.0307**	-0.00284	-0.0140	-0.0306**	-0.00281
	(0.0161)	(0.0155)	(0.00859)	(0.0161)	(0.0155)	(0.00859)
Tech*After	0.0191**	-0.00350	0.0356***	0.0192**	-0.00343	0.0356***
	(0.00911)	(0.00769)	(0.00774)	(0.00912)	(0.00769)	(0.00774)
HSRCity*Tech	0.0689**	0.0676***	0.0243	0.0626***	0.0226	0.0581***
	(0.0281)	(0.0236)	(0.0176)	(0.0232)	(0.0206)	(0.0171)
Tech	-0.0211***	-0.0293***	0.0106***	-0.0190***	-0.0233***	0.00864***
	(0.00538)	(0.00493)	(0.00296)	(0.00533)	(0.00504)	(0.00273)
Observations	1,677,088	1,677,088	1,677,088	1,677,088	1,677,088	1,677,088
R-squared	0.333	0.296	0.273	0.337	0.302	0.282
CITY, YEAR, IPC2 FE	YES	YES	YES	YES	YES	YES
IPC2*YEAR	YES	YES	YES	YES	YES	YES
CITY*YEAR	YES	YES	YES	YES	YES	YES
HSRCITY*IPC2*YEAR	NO	NO	NO	YES	YES	YES

Notes:1. The table reports triple difference estimation results from equation 1, on a sample that excludes the patents applied by CSR/CNR subsidiaries. logallpatent is the log sum of patents granted within each IPC 4 digit category-city group for each year. logutility is the log sum of utility-model patents. loginvention is the log sum of invention patents. HSRCity is an indicator on whether or not the city is a HSR-technology receiving city. Tech is an indicator on whether or not the patents belong to HSR-related IPC 4-digit technology classes. After is a dummy that switches on for all years after 2004. All the regressions include city, year and IPC2 fixed effects, as well as IPC2 and city specific year trends. The last three columns report results by controlling for HSR-city*IPC2. 2. Robust clustered standard error at the city level. 3. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 4: Impact of Technology Transfer on Domestic Innovation in Non-Railway Related Firms

	Exclude CSR/CNR/Certified Suppliers					
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After	0.201***	0.174***	0.190***	0.201***	0.174***	0.190***
	(0.0456)	(0.0407)	(0.0400)	(0.0456)	(0.0407)	(0.0400)
HSRCity*After	-0.0136	-0.0303*	-0.00263	-0.0136	-0.0302*	-0.00260
	(0.0161)	(0.0155)	(0.00851)	(0.0161)	(0.0155)	(0.00851)
Tech*After	0.0192**	-0.00368	0.0362***	0.0193**	-0.00361	0.0363***
	(0.00909)	(0.00763)	(0.00792)	(0.00909)	(0.00763)	(0.00792)
HSRCity*Tech	0.0660**	0.0660***	0.0230	0.0602***	0.0218	0.0568***
	(0.0274)	(0.0230)	(0.0174)	(0.0228)	(0.0205)	(0.0169)
Tech	-0.0216***	-0.0294***	0.00977***	-0.0196***	-0.0235***	0.00788***
	(0.00525)	(0.00492)	(0.00249)	(0.00525)	(0.00504)	(0.00236)
Observations	1,677,088	1,677,088	1,677,088	1,677,088	1,677,088	1,677,088
R-squared	0.333	0.296	0.273	0.337	0.302	0.282
CITY, YEAR, IPC2 FE	YES	YES	YES	YES	YES	YES
IPC2*YEAR	YES	YES	YES	YES	YES	YES
CITY*YEAR	YES	YES	YES	YES	YES	YES
HSRCITY*IPC2*YEAR	NO	NO	NO	YES	YES	YES

Notes:1. The table reports triple difference estimation results from equation 1, on a sample that excludes the patents applied by CSR/CNR subsidiaries and the certified suppliers to CSR/CNR. logallpatent is the log sum of patents granted within each IPC 4 digit category-city group for each year. logutility is the log sum of utility-model patents. loginvention is the log sum of invention patents. HSRCity is an indicator on whether or not the city is a HSR-technology receiving city. Tech is an indicator on whether or not the patents belong to HSR-related IPC 4-digit technology classes. After is a dummy that switches on for all years after 2004. All the regressions include city, year and IPC2 fixed effects, as well as IPC2 and city specific year trends. The last three columns report results by controlling for HSR-city*IPC2 specific year trend as well. 2. Robust clustered standard error at the city level. 3. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 5: Robustness Check using Alternative Technology Definition

	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After	0.360***	0.331***	0.259***	0.213***	0.194***	0.206***
	(0.0499)	(0.0456)	(0.0454)	(0.0486)	(0.0448)	(0.0444)
HSRCity*After	-0.0193	-0.0358**	-0.00677	-0.0156	-0.0322**	-0.00471
	(0.0159)	(0.0152)	(0.00865)	(0.0163)	(0.0157)	(0.00856)
Tech*After	0.0746***	0.0543***	0.0438***	0.0750***	0.0543***	0.0448***
	(0.0101)	(0.00877)	(0.00772)	(0.0101)	(0.00879)	(0.00779)
HSRCity*Tech	0.112***	0.0756***	0.0471***	0.113***	0.0775***	0.0471***
	(0.0276)	(0.0247)	(0.0137)	(0.0274)	(0.0249)	(0.0135)
Tech	-0.00938**	-0.0127***	0.00867***	-0.0104**	-0.0134***	0.00780***
	(0.00475)	(0.00411)	(0.00218)	(0.00467)	(0.00408)	(0.00201)
Observations	1,677,088	1,677,088	1,677,088	1,677,088	1,677,088	1,677,088
R-squared	0.338	0.303	0.283	0.337	0.302	0.282
CITY, YEAR, IPC2 FE	YES	YES	YES	YES	YES	YES
IPC2*YEAR	YES	YES	YES	YES	YES	YES
CITY*YEAR	YES	YES	YES	YES	YES	YES
HSRCITY*IPC2*YEAR	YES	YES	YES	YES	YES	YES

Notes:1. The table reports triple difference estimation results from equation 1, using alternative definition of HSR-related technology. logallpatent is the log sum of patents granted within each IPC 4 digit category-city group for each year. logutility is the log sum of utility-model patents. loginvention is the log sum of invention patents. HSRCity is an indicator on whether or not the city is a HSR-technology receiving city. Tech is an indicator on whether or not the patents belong to HSR-related IPC 4-digit technology classes. After is a dummy that switches on for all years after 2004. All the regressions include city, year and IPC2 fixed effects, as well as IPC2, city and HSR-city*IPC2 specific year trends. The last three columns report results on a sample that excludes the patents applied by CSR/CNR subsidiaries and certified suppliers. 2. Robust clustered standard error at the city level. 3. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 6: Robustness Check using Alternative Year of Treatment

	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After2005	0.443***	0.402***	0.276***	0.204***	0.176***	0.193***
	(0.0561)	(0.0513)	(0.0446)	(0.0460)	(0.0411)	(0.0396)
HSRCity*After2005	0.00814	-0.00158	0.0149	0.00819	-0.00107	0.0153
	(0.0170)	(0.0161)	(0.0112)	(0.0174)	(0.0164)	(0.0113)
Tech*After2005	0.0207**	-0.00155	0.0361***	0.0199**	-0.00268	0.0367***
	(0.00908)	(0.00763)	(0.00773)	(0.00904)	(0.00753)	(0.00790)
HSRCity*Tech	0.0690***	0.0275	0.0664***	0.0680***	0.0281	0.0648***
	(0.0254)	(0.0216)	(0.0201)	(0.0250)	(0.0218)	(0.0199)
Tech	-0.0185***	-0.0231***	0.00873***	-0.0199***	-0.0240***	0.00768***
	(0.00534)	(0.00503)	(0.00273)	(0.00524)	(0.00501)	(0.00234)
Observations	1,677,088	1,677,088	1,677,088	1,677,088	1,677,088	1,677,088
R-squared	0.338	0.303	0.282	0.337	0.302	0.282
CITY, YEAR, IPC2 FE	YES	YES	YES	YES	YES	YES
IPC2*YEAR	YES	YES	YES	YES	YES	YES
CITY*YEAR	YES	YES	YES	YES	YES	YES
HSRCITY*IPC2*YEAR	YES	YES	YES	YES	YES	YES

Notes: 1. The table reports triple difference estimation results from equation 1. logallpatent is the log sum of patents granted within each IPC 4 digit category-city group for each year. logutility is the log sum of utility-model patents. loginvention is the log sum of invention patents. HSRCity is an indicator on whether or not the city is a HSR-technology receiving city. Tech is an indicator on whether or not the patents belong to HSR-related IPC 4-digit technology classes. After2005 is a dummy that switches on for all years after 2005. All the regressions include city, year and IPC2 fixed effects, as well as IPC2, city and HSR-city*IPC2 specific year trends. The last three columns report results on a sample that excludes the patents applied by CSR/CNR subsidiaries and certified suppliers. 2. Robust clustered standard error at the city level. 3. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 7: Heterogeneous Effects in Cities With Different Treatment Intensities

	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After	0.387***	0.348***	0.265***	0.185***	0.159***	0.193***
	(0.0569)	(0.0502)	(0.0492)	(0.0460)	(0.0409)	(0.0429)
HSRCity_Whole*Tech*After	0.602***	0.586***	0.177*	0.321***	0.304***	0.124
	(0.142)	(0.127)	(0.0942)	(0.113)	(0.0941)	(0.0789)
HSRCity*After	-0.0144	-0.0275	-0.0120	-0.0111	-0.0242	-0.0102
	(0.0178)	(0.0167)	(0.00866)	(0.0183)	(0.0173)	(0.00860)
HSRCity_Whole*After	-0.0223	-0.0362	0.0169	-0.0185	-0.0329	0.0187
	(0.0187)	(0.0369)	(0.0211)	(0.0201)	(0.0377)	(0.0203)
Tech*After	0.0212**	-0.00177	0.0370***	0.0191**	-0.00390	0.0369***
	(0.00912)	(0.00764)	(0.00781)	(0.00905)	(0.00755)	(0.00796)
HSRCity*Tech	0.0726***	0.0319	0.0613***	0.0733***	0.0344	0.0601***
	(0.0244)	(0.0213)	(0.0191)	(0.0242)	(0.0216)	(0.0190)
HSRCity_Whole*Tech	-0.0978**	-0.107***	-0.0128	-0.0972**	-0.104***	-0.0130
	(0.0458)	(0.0314)	(0.0306)	(0.0467)	(0.0295)	(0.0329)
Tech	-0.0172***	-0.0220***	0.00954***	-0.0187***	-0.0230***	0.00848***
	(0.00536)	(0.00504)	(0.00278)	(0.00525)	(0.00501)	(0.00240)
Observations	1,677,088	1,677,088	1,677,088	1,677,088	1,677,088	1,677,088
R-squared	0.337	0.302	0.281	0.336	0.301	0.281
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
IPC FE	YES	YES	YES	YES	YES	YES
IPC*YEAR	YES	YES	YES	YES	YES	YES
CITY*YEAR	YES	YES	YES	YES	YES	YES
CITY*TECH*YEAR	YES	YES	YES	YES	YES	YES

Notes:1. The table reports triple difference estimation results in cities with different treatment intensities. logallpatent is the log sum of patents granted within each IPC 4 digit category-city group for each year. logutility is the log sum of utility-model patents. loginvention is the log sum of invention patents. HSRCity is 1 if a city received HSR technology transfer in terms of parts, otherwise 0. HSRCity_Whole is 1 if a city received HSR technology transfer in terms of the whole train, otherwise 0; Tech is an indicator on whether or not the patents belong to HSR-related IPC 4-digit technology classes. After is a dummy that switches on for all years after 2004. All the regressions include city, year and IPC2 fixed effects, as well as IPC2 and city specific year trends. The last three columns report results by controlling for HSRcity*IPC2 and HSRCity_Whole*IPC2 specific year trend as well. 2. Robust clustered standard error at the city level. 3. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 8: Robustness Check using Collapsed Data

	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After	0.469***	0.476***	0.357***	0.192**	0.197**	0.207***
	(0.0854)	(0.0814)	(0.0810)	(0.0836)	(0.0801)	(0.0715)
HSRCity*After	0.288***	0.227***	0.358***	0.275***	0.216***	0.350***
	(0.0643)	(0.0585)	(0.0605)	(0.0660)	(0.0597)	(0.0617)
Tech*After	0.0484***	0.0565***	0.0450***	0.0440***	0.0524***	0.0431***
	(0.0130)	(0.0124)	(0.0121)	(0.0130)	(0.0125)	(0.0121)
HSRCity*Tech	0.146***	0.144***	0.103**	0.139***	0.141***	0.0942**
	(0.0467)	(0.0436)	(0.0433)	(0.0456)	(0.0428)	(0.0429)
Tech	-0.0518***	-0.0770***	0.0170***	-0.0518***	-0.0769***	0.0175***
	(0.0108)	(0.0106)	(0.00628)	(0.0108)	(0.0106)	(0.00617)
Observations	345,094	345,094	345,094	345,094	345,094	345,094
R-squared	0.171	0.165	0.211	0.170	0.165	0.211
CITY, YEAR, IPC2 FE	YES	YES	YES	YES	YES	YES

Notes:1. IPC2 specific year trend, City specific year trend, and HSRCity*IPC2 specific year trend are not included in the regressions since the collpased data only has two periods. 2. Robust clustered standard error at the city level. 3. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 9: Robustness Check using Nearest Neighbor Matching

	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After	0.366***	0.340***	0.224***	0.162***	0.146***	0.148***
	(0.0728)	(0.0659)	(0.0593)	(0.0586)	(0.0525)	(0.0547)
HSRCity*After	0.0160	0.00319	-0.00248	0.0189	0.00601	-0.000381
	(0.0203)	(0.0190)	(0.0116)	(0.0206)	(0.0194)	(0.0116)
Tech*After	0.0683*	0.0196	0.0909***	0.0701**	0.0213	0.0934***
	(0.0345)	(0.0298)	(0.0336)	(0.0346)	(0.0298)	(0.0336)
HSRCity*Tech	0.0623**	0.0288	0.0580***	0.0617**	0.0304	0.0559***
	(0.0296)	(0.0276)	(0.0201)	(0.0295)	(0.0278)	(0.0200)
Tech	-0.0106	-0.0193	0.0173*	-0.0141	-0.0225	0.0161*
	(0.0171)	(0.0173)	(0.00940)	(0.0171)	(0.0173)	(0.00938)
Observations	426,896	426,896	426,896	426,896	426,896	426,896
R-squared	0.342	0.313	0.306	0.341	0.312	0.306
CITY, YEAR, IPC2 FE	YES	YES	YES	YES	YES	YES
IPC2*YEAR	YES	YES	YES	YES	YES	YES
CITY*YEAR	YES	YES	YES	YES	YES	YES
HSRCITY*IPC2*YEAR	YES	YES	YES	YES	YES	YES

Notes:1. The table reports triple-difference -matching estimation results from equation 1, on a matched sample where we match the technology receiving cities to similar cities on 2003 pollution, GDP, patents application and the 1996-2003 growth trends of these variables. logallpatent is the log sum of patents granted within each IPC 4 digit category-city group for each year. logutility is the log sum of utility-model patents. loginvention is the log sum of invention patents. HSRCity is an indicator on whether or not the city is a HSR-technology receiving city. Tech is an indicator on whether or not the patents belong to HSR-related IPC 4-digit technology classes. After is a dummy that switches on for all years after 2004. All the regressions include city, year and IPC2 fixed effects, as well as IPC2, city and HSR-city*IPC2 specific year trends. The last three columns report results on a sample that excludes the patents applied by CSR/CNR subsidiaries and certified suppliers. 2. Robust clustered standard error at the city level. 3. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 10: Mechanisms: Geographic Proximity

	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
Ln(Distance)*Tech*After	-0.0115	-0.00700	-0.00767	-0.0114	-0.00741	-0.00676
	(0.0110)	(0.00962)	(0.0101)	(0.0111)	(0.00960)	(0.0106)
Tech*After	0.0867	0.0418	0.0805	0.0841	0.0415	0.0757
	(0.0592)	(0.0517)	(0.0548)	(0.0598)	(0.0515)	(0.0569)
Ln(Distance)*After	0.00833*	0.00936**	0.00235	0.00836*	0.00931**	0.00245
	(0.00474)	(0.00439)	(0.00292)	(0.00477)	(0.00440)	(0.00300)
Ln (Distance)*Tech	0.0108	0.00639	0.00623	0.00983	0.00611	0.00482
	(0.00683)	(0.00506)	(0.00503)	(0.00613)	(0.00493)	(0.00371)
Ln (Distance)	-10.31***	-7.657***	-4.821***	-10.33***	-7.673***	-4.818***
	(2.470)	(2.119)	(1.089)	(2.476)	(2.112)	(1.097)
Tech	-0.0782**	-0.0599**	-0.0258	-0.0735**	-0.0587**	-0.0191
	(0.0367)	(0.0280)	(0.0253)	(0.0335)	(0.0274)	(0.0191)
Observations	1,452,976	1,452,976	1,452,976	1,452,976	1,452,976	1,452,976
R-squared	0.299	0.270	0.238	0.299	0.270	0.238
CITY, YEAR, IPC2 FE	YES	YES	YES	YES	YES	YES
IPC2*YEAR	YES	YES	YES	YES	YES	YES
CITY*YEAR	YES	YES	YES	YES	YES	YES

Notes:1. This table reports the results on spillovers of transferred technology to other cities, on a sample that excludes the HSR-technology receiving cities. logallpatent is the log sum of patents granted within each IPC 4 digit category-city group for each year. logutility is the log sum of utility-model patents. loginvention is the log sum of invention patents. Ln(Distance) is the straight line distance from the city examined to the closest Technology receiving city. HSRCity is an indicator on whether or not the city is a HSR-technology receiving city. Tech is an indicator on whether or not the patents belong to HSR-related IPC 4-digit technology classes. After is a dummy that switches on for all years after 2004. All the regressions include city, year and IPC2 fixed effects, as well as IPC2, city and HSR-city*IPC2 specific year trends. The last three columns report results on a sample that excludes the patents applied by CSR/CNR subsidiaries and certified suppliers. 2. Robust clustered standard error at the city level. 3. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 11: Mechanisms: Technology Proximity

	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
Ln(Similarity)*HSRCity*After	0.0332***	0.0546***	0.0118	0.0261***	0.0481***	0.00934
	(0.00754)	(0.00863)	(0.00885)	(0.00769)	(0.00896)	(0.00883)
HSRCity*After	0.149***	0.232***	0.0595	0.114***	0.200***	0.0487
	(0.0393)	(0.0386)	(0.0444)	(0.0403)	(0.0406)	(0.0443)
Ln(Similarity)*After	-0.00665***	-0.000321	-0.00970***	-0.00665***	-0.000315	-0.00964***
	(0.00179)	(0.00196)	(0.00131)	(0.00178)	(0.00195)	(0.00130)
Ln (Similarity)*HSRCity	-0.00867*	0.0226***	-0.0316***	-0.00886*	0.0223***	-0.0316***
	(0.00452)	(0.00514)	(0.00660)	(0.00453)	(0.00515)	(0.00660)
Ln (Similarity)	-0.0230***	-0.00850***	-0.0162***	-0.0234***	-0.00878***	-0.0164***
	(0.00166)	(0.00138)	(0.00121)	(0.00165)	(0.00138)	(0.00120)
Observations	1,265,248	1,265,248	1,265,248	1,265,248	1,265,248	1,265,248
R-squared	0.365	0.321	0.315	0.364	0.320	0.315
CITY, YEAR, IPC2 FE	YES	YES	YES	YES	YES	YES
IPC2*YEAR	YES	YES	YES	YES	YES	YES
CITY*YEAR	YES	YES	YES	YES	YES	YES

Notes:1. This table reports the results on spillovers of transferred technology to other technology classes, on a sample that excludes the patents under HSR-related technology classes. logallpatent is the log sum of patents granted within each IPC 4 digit category-city group for each year. logutility is the log sum of utility-model patents. loginvention is the log sum of invention patents. Ln(Similarity) is the similarity measure (Kay et. al. 2014) between the technology class examined and the most similar HSR-related technology class. HSRCity is an indicator on whether or not the city is a HSR-technology receiving city. Tech is an indicator on whether or not the patents belong to HSR-related IPC 4-digit technology classes. After is a dummy that switches on for all years after 2004. All the regressions include city, year and IPC2 fixed effects, as well as IPC2, city and HSR-city*IPC2 specific year trends. The last three columns report results on a sample that excludes the patents applied by CSR/CNR subsidiaries and certified suppliers. 2. Robust clustered standard error at the city level. 3. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 12: Mechanisms: Spillover Effects in Cities With and Without Railway-related Research Universities

In cities with university patents in railway before 2004						
	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After	0.384***	0.359***	0.252***	0.175***	0.160***	0.168***
	(0.0783)	(0.0722)	(0.0559)	(0.0528)	(0.0493)	(0.0499)
HSRCity*After	-0.00574	-0.0167	-0.00727	-0.00304	-0.0135	-0.00601
	(0.0192)	(0.0164)	(0.0139)	(0.0194)	(0.0166)	(0.0140)
Tech*After	0.120***	0.0519**	0.143***	0.125***	0.0556**	0.148***
	(0.0264)	(0.0219)	(0.0287)	(0.0266)	(0.0218)	(0.0297)
HSRCity*Tech	0.0679*	0.0357	0.0588**	0.0688*	0.0379	0.0595**
	(0.0345)	(0.0305)	(0.0252)	(0.0344)	(0.0309)	(0.0247)
Tech	0.00732	-0.0129	0.0356***	0.00229	-0.0160	0.0312***
	(0.0156)	(0.0132)	(0.0115)	(0.0149)	(0.0132)	(0.00941)
Observations	508,272	508,272	508,272	508,272	508,272	508,272
R-squared	0.334	0.312	0.298	0.333	0.311	0.298
In cities without university patents in railway before 2004						
	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After	0.276***	0.262***	0.0916**	0.0189	0.0239	0.0235
	(0.0537)	(0.0506)	(0.0429)	(0.0451)	(0.0414)	(0.0363)
HSRCity*After	-0.0155	-0.0189	-0.0141	-0.0101	-0.0147	-0.0105
	(0.0410)	(0.0429)	(0.00947)	(0.0427)	(0.0447)	(0.00984)
Tech*After	-0.00163	-0.0112	0.0118***	-0.00437	-0.0138**	0.0109***
	(0.00754)	(0.00693)	(0.00387)	(0.00736)	(0.00678)	(0.00372)
HSRCity*Tech	0.0194	0.0123	0.0111	0.0238	0.0160	0.0116*
	(0.0152)	(0.0159)	(0.00706)	(0.0152)	(0.0167)	(0.00635)
Tech	-0.0268***	-0.0275***	0.000477	-0.0271***	-0.0278***	0.000381
	(0.00511)	(0.00501)	(0.00118)	(0.00509)	(0.00499)	(0.00117)
Observations	1,168,816	1,168,816	1,168,816	1,168,816	1,168,816	1,168,816
R-squared	0.221	0.208	0.139	0.220	0.207	0.138
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
IPC FE	YES	YES	YES	YES	YES	YES
IPC*YEAR	YES	YES	YES	YES	YES	YES
CITY*YEAR	YES	YES	YES	YES	YES	YES
CITY*TECH*YEAR	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors in parentheses. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

A Tables

Table A.1: Heterogeneous Effects: Private-owned, State-owned Firms and Non-firms

Private-owned enterprises						
	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After	0.295***	0.270***	0.130***	0.105**	0.0888**	0.0778***
	(0.0677)	(0.0586)	(0.0375)	(0.0414)	(0.0349)	(0.0290)
Observations	829,626	829,626	829,626	829,626	829,626	829,626
R-squared	0.329	0.307	0.220	0.327	0.305	0.219
State-owned enterprises						
	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After	0.0944**	0.0659	0.0511*	0.0342	0.0133	0.0313
	(0.0474)	(0.0413)	(0.0268)	(0.0421)	(0.0360)	(0.0235)
Observations	231,854	231,854	231,854	231,854	231,854	231,854
R-squared	0.158	0.134	0.117	0.156	0.132	0.116
Non-firms						
	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES				logallpatent	logutility	loginvention
HSRCity*Tech*After				0.167***	0.122***	0.141***
				(0.0433)	(0.0331)	(0.0395)
Observations				2,330,207	2,330,207	2,330,207
R-squared				0.197	0.169	0.180
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
IPC FE	YES	YES	YES	YES	YES	YES
IPC*YEAR	YES	YES	YES	YES	YES	YES
CITY*YEAR	YES	YES	YES	YES	YES	YES
CITY*TECH*YEAR	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors in parentheses. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table A.2: Heterogeneous Effects: Old Firms and New Firms

Old firms (established years¿9)						
	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After	0.244***	0.210***	0.111***	0.0815**	0.0616*	0.0640**
	(0.0566)	(0.0485)	(0.0310)	(0.0409)	(0.0317)	(0.0277)
Observations	659,848	659,848	659,848	659,848	659,848	659,848
R-squared	0.300	0.282	0.182	0.298	0.279	0.180
New firms (established years $\leq$ 9)						
	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After	0.190***	0.170***	0.0778**	0.0819**	0.0692**	0.0496*
	(0.0521)	(0.0440)	(0.0314)	(0.0355)	(0.0295)	(0.0262)
Observations	656,488	656,488	656,488	656,488	656,488	656,488
R-squared	0.277	0.253	0.185	0.276	0.252	0.185
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
IPC FE	YES	YES	YES	YES	YES	YES
IPC*YEAR	YES	YES	YES	YES	YES	YES
CITY*YEAR	YES	YES	YES	YES	YES	YES
CITY*TECH*YEAR	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors in parentheses. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table A.3: Balancing Test of the Matching Sample

Variables	Treated	Control	Difference
	(N=23)	(N=32)	
population at 2003	649.24	607.03	42.21
	(90.23)	(96.2)	(121.35)
GDP at 2003	12.91	9.86	3.05
	(1.64)	(2.17)	(2.92)
Gov spend in scientific research at 2003	8486.78	5887.31	2599.47
	(4594.37)	(3532.59)	(5702.11)
No. of patents at 2003	473.78	238.62	235.15
	(172.90)	(108.28)	(194.24)
GDP growth (96-03)	1.58	2.01	-0.42
	(0.46)	(0.67)	(0.88)
population growth (96-03)	0.407	0.84	-0.43
	(0.345)	(0.115)	(0.76)
patents growth (96-03)	5.14	4.07	1.07
	(0.66)	(0.73)	(1.03)

Notes:1. Standard errors are reported in parentheses. 2. T-test result is reported in the last column. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table A.4: Mechanisms: University Research (Dummy)

	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After*School_D	0.100	0.0953	0.147**	0.148**	0.134**	0.131**
	(0.0945)	(0.0877)	(0.0704)	(0.0690)	(0.0638)	(0.0614)
HSRCity*After*School_D	0.00983	0.00223	0.00699	0.00709	0.00127	0.00468
	(0.0452)	(0.0459)	(0.0168)	(0.0468)	(0.0477)	(0.0170)
Tech*After*School_D	0.165***	0.124***	0.152***	0.169***	0.127***	0.156***
	(0.0297)	(0.0258)	(0.0326)	(0.0303)	(0.0260)	(0.0338)
HSRCity*Tech*School_D	0.0202	0.0183	0.0201	0.0181	0.0170	0.0209
	(0.0485)	(0.0412)	(0.0298)	(0.0459)	(0.0395)	(0.0279)
Tech*School_D	0.0417**	0.0355**	0.0201	0.0380**	0.0339**	0.0158
	(0.0198)	(0.0145)	(0.0159)	(0.0178)	(0.0141)	(0.0122)
HSRCity*Tech*After	0.280***	0.263***	0.0985**	0.0233	0.0254	0.0304
	(0.0538)	(0.0507)	(0.0430)	(0.0449)	(0.0410)	(0.0362)
HSRCity*After	-0.0155	-0.0189	-0.0142	-0.0101	-0.0147	-0.0106
	(0.0410)	(0.0429)	(0.00947)	(0.0427)	(0.0447)	(0.00983)
Tech*After	-0.0182**	-0.0314***	0.000548	-0.0198**	-0.0329***	0.000278
	(0.00854)	(0.00790)	(0.00540)	(0.00832)	(0.00774)	(0.00521)
HSRCity*Tech	0.0269	-0.00885	0.0348***	0.0308	-0.00496	0.0352***
	(0.0252)	(0.0255)	(0.00965)	(0.0235)	(0.0244)	(0.00888)
Tech	-0.0277***	-0.0306***	0.00435*	-0.0283***	-0.0312***	0.00425*
	(0.00563)	(0.00544)	(0.00244)	(0.00552)	(0.00537)	(0.00228)
After*School_D	-0.0177	-0.0327***	0.00868	-0.0176	-0.0328***	0.00887
	(0.0130)	(0.0112)	(0.00922)	(0.0130)	(0.0112)	(0.00946)
Observations	1,677,088	1,677,088	1,677,088	1,677,088	1,677,088	1,677,088
R-squared	0.338	0.303	0.282	0.337	0.302	0.282
CITY, YEAR, IPC2 FE	YES	YES	YES	YES	YES	YES
IPC2*YEAR	YES	YES	YES	YES	YES	YES
CITY*YEAR	YES	YES	YES	YES	YES	YES
HSRCITY*IPC2*YEAR	YES	YES	YES	YES	YES	YES

Notes:1. This table reports the results on the relevance of university research activities on spillovers of transferred technology. $School_D$ is an indicator of whether or not there are any university patents within HSR-related technology classes in the city. HSRCity is an indicator on whether or not the city is a HSR-technology receiving city. Tech is an indicator on whether or not the patents belong to HSR-related IPC 4-digit technology classes. After is a dummy that switches on for all years after 2004. The last three columns report results on a sample that excludes the patents applied by CSR/CNR subsidiaries and certified suppliers. Robust clustered standard error at the city level.

Table A.5: Mechanisms: University Research (Ratio)

	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
HSRCity*Tech*After*Ratio	0.125	0.191	0.153	0.283*	0.287*	0.281*
	(0.272)	(0.266)	(0.197)	(0.167)	(0.170)	(0.157)
HSRCity*After*Ratio	0.137*	0.135*	0.0183	0.136	0.135*	0.0145
	(0.0808)	(0.0794)	(0.0423)	(0.0823)	(0.0813)	(0.0418)
Tech*After*Ratio	0.409***	0.245**	0.405***	0.416***	0.251***	0.408***
	(0.0897)	(0.0963)	(0.0928)	(0.0899)	(0.0964)	(0.0934)
HSRCity*Tech*Ratio	-0.0774	-0.0578	0.0145	-0.0916	-0.0653	0.00974
	(0.155)	(0.129)	(0.0884)	(0.150)	(0.124)	(0.0891)
Tech*Ratio	0.108**	0.106**	0.0293	0.109**	0.106**	0.0318
	(0.0495)	(0.0439)	(0.0277)	(0.0489)	(0.0437)	(0.0265)
HSRCity*Tech*After	0.328***	0.302***	0.167***	0.0715	0.0708	0.0621**
	(0.0855)	(0.0760)	(0.0553)	(0.0461)	(0.0433)	(0.0299)
HSRCity*After	-0.0325	-0.0428	-0.00809	-0.0288	-0.0394	-0.00520
	(0.0275)	(0.0280)	(0.0118)	(0.0283)	(0.0289)	(0.0116)
Tech*After	-0.000437	-0.0162*	0.0173***	-0.00160	-0.0177**	0.0179***
	(0.00925)	(0.00867)	(0.00652)	(0.00919)	(0.00856)	(0.00690)
HSRCity*Tech	0.0610*	0.0188	0.0489***	0.0646**	0.0227	0.0487***
	(0.0326)	(0.0300)	(0.0150)	(0.0326)	(0.0301)	(0.0145)
Tech	-0.0252***	-0.0302***	0.00845***	-0.0269***	-0.0313***	0.00705***
	(0.00615)	(0.00591)	(0.00319)	(0.00594)	(0.00588)	(0.00242)
After*Ratio	-0.0824*	-0.114***	-0.00251	-0.0827*	-0.114***	-0.00295
	(0.0436)	(0.0429)	(0.0214)	(0.0438)	(0.0429)	(0.0216)
Observations	1,497,472	1,497,472	1,497,472	1,497,472	1,497,472	1,497,472
R-squared	0.335	0.301	0.282	0.334	0.300	0.282
CITY, YEAR, IPC2 FE	YES	YES	YES	YES	YES	YES
IPC2*YEAR	YES	YES	YES	YES	YES	YES
CITY*YEAR	YES	YES	YES	YES	YES	YES
HSRCITY*IPC2*YEAR	YES	YES	YES	YES	YES	YES

Notes:1. This table reports the results on the relevance of university research activities on spillovers of transferred technology. Ratio is the ratio between university patents and total patents within HSR-related technology classes in the city prior to 2004, which takes zero if there are no university patents in related fields by 2004. HSRCity is an indicator on whether or not the city is a HSR-technology receiving city. Tech is an indicator on whether or not the patents belong to HSR-related IPC 4-digit technology classes. After is a dummy that switches on for all years after 2004. The last three columns report results on a sample that excludes the patents applied by CSR/CNR subsidiaries and certified suppliers. Robust clustered standard error at the city level.

Table A.6: Major technology transfer contract details

Mode	Technology provider	CSR/CNR receiver	Type	Technology transfer fee (billion RMB)	No. of trains	Total contract value (billion RMB)	Source
CRH1	Bombadier	Qingdao Sifang	Joint venture	0	40	5.2	Bombadier website 1
CRH2	Kawasaki	Qingdao Sifang	Technology transfer	0.6	60	9.3	Kawasaki website 2
CHR3	Siemens	Tangshan	Technology transfer	0.8	60	13	Railway yearbook
CHR5	Alstom	Changchun	Technology transfer	0.9	60	4.7	Alstom website 3

Notes:1. "High speed Train CRH1 – China", 10/2004, `http://www.bombardier.com/en/transportation/projects/project.emu-china.html?f-region=all&f-country=all&f-segment=all&f-name=SPACIUM`

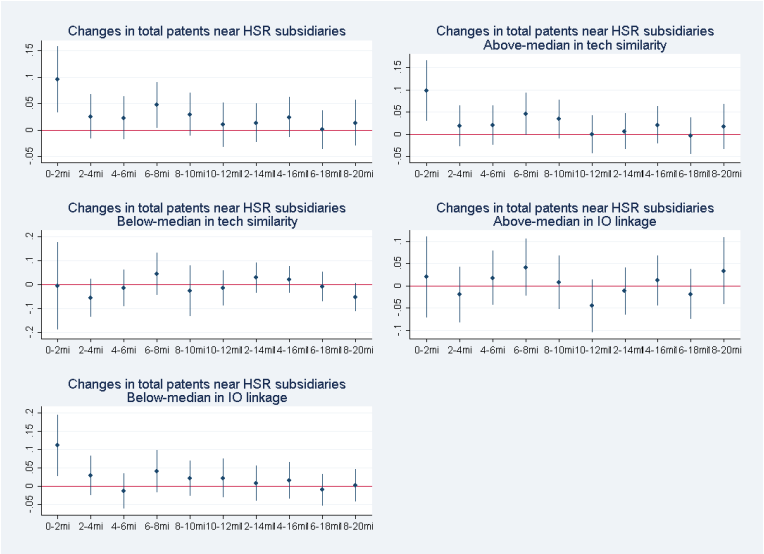
2. "Kawasaki Wins High-Speed Train Order for China", 20/10/2004, `http://www.khi.co.jp/en/corp/newsroom/news/detail/ba041020.html`

3. "From Savigliano to Changchun: The First EMU Train to China is on its way", 14/12/2006, `http://www.alstom.com/press-centre/2006/12/From-Savigliano-to-Changchun-The-First-EMU-Train-to-China-is-on-its-way-20061214/`

4. Information on technology transfer fee is collected by Caixin reporters featured in Caixin cover story in July 12, 2012 (Volume 26).

B Figures

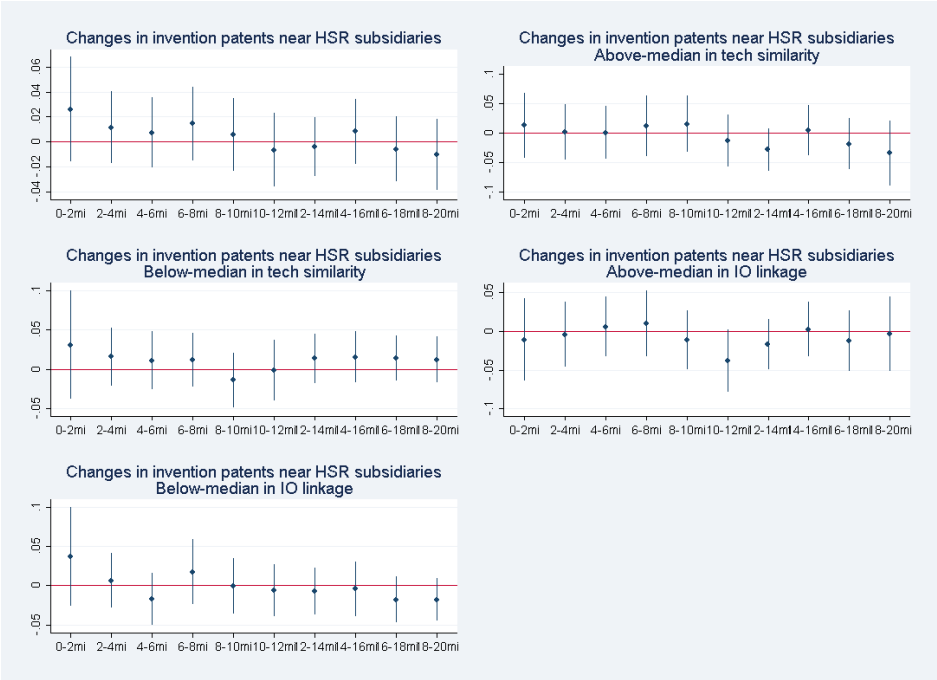
Figure B.1: Distance to CSR/CNR R&D centers and Firm Patenting Outcomes



(a) Total Patents

(b) Utility Model Patents

Figure B.1: Distance to CSR/CNR R&D centers and Firm Patenting Outcomes



(c) Inventions

Notes: 1. This figure visualizes the β_d coefficients in Equation (2). The regression tables are available upon request. 2. The coefficients are presented in dots, with their 95% confidence intervals.

Figure B.2: Distance to CSR/CNR R&D centers and Firm Performance

(a) Revenue

(b) Total Factor Productivity

Figure B.2: Distance to CSR/CNR R&D centers and Firm Performance

(c) Firm Entry

Notes: 1. This figure visualizes the β_d coefficients in Equation (2). The regression tables are available upon request. 2. The coefficients are presented in dots, with their 95% confidence intervals.