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

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Abstract
How does the transfer of advanced technology spur innovation in developing countries? This paper exploits the large-scale introduction of high-speed railway (HSR) technology into China in 2004 as a natural experiment to address this question. The experiment is unique in the sense that this wave of technology transfer is large, abrupt and arguably exogenous in timing, covering a variety of technology classes and a large number of geographically-dispersed railway-related firms. With detailed information on the types of technology transferred and the identities of the receiving firms, as well as their product market specializations, we are able to depict a clear picture of how foreign technology is digested and spurs follow-up innovation in and out of directly receiving firms. Our findings suggest that technology transfer leads to significant growth in HSR-related patents in cities with direct receivers of imported technology after 2004 in a triple-difference estimation. We also observe sizable spillovers to firms that are not directly related to the railway industry. Technology similarity plays an important role in technology diffusion, but we do not observe any significant impacts of geographic proximity. Previous university research strength in relevant fields is also conducive to stronger technology spillovers.

Keywords: Innovation, Foreign Technology Transfer, Knowledge Spillover, China
JEL codes: O25; O33; O38

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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 foreign FDI (Javorcik, 2004 [19]; Liu et al, 2000 [22]), 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 examination of the mechanisms of technology spillovers from MNCs to their host countries.

This paper attempts to identify the direct effects of foreign technology transfer, as well as the mechanisms of transferred technology spillover by exploiting the introduction of the state-of-art high-speed railway (HSR) in China during its unprecedented large-scale expansion of the HSR system as a natural experiment. 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, McGrattan, and Prescott, 2015) [14]. 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. Most importantly, technology transfers are almost always endogenous: in most cases, firms that receive technology transfers have accumulated sufficient technology capital, and the sectors that foreign multinationals would like to invest in by injecting advanced technology are likely to be the ones with reasonable competitive advantages and would experience large subsequent growth anyway.

The nature of the recent massive wave of high-speed railway technology transfer in China helps us to overcome these obstacles. This setting is ideal for studying the impacts of international technology transfer on developing countries' domestic innovation for a number of reasons. First, the expansion of China's HSR system is very radical. It is a result of the pressing need for railway capacity due to seriously overcrowded conventional lines as opposed to developments in railway technology. The decision of technology transfer was also made rather abruptly in 2004 by the then Minister of Railways, Liu Zhijun, immediately after he took office in 2003, as an attempt to push his 'Great Leap forward' plan as rapidly as possible.[1] Second, 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[2] (Alstom, Siemens, Bombardier, and Kawasaki Heavy Industries) at the time and introduced a complete line of HSR technology ranging from engines, dynamos, and electricity transmissions to railway signal control systems. Many of these technologies have applications separate from the high-speed railway system and have great potential for technology spillovers.[3] Last but not least, 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 high-speed railway 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 project.

We assemble a unique dataset that matches information on patents that were applied for at the SIPO (State Intellectual Property Office of China) to firm-level variables from the Annual Survey of Industrial Firms (ASI) of China from 1996 to 2009. 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, conditioned on a full set of city, technology class and year fixed effects; technology class and city-specific year trends as well as different technology-specific year trends for technology-receiving cities and those that do not receive technology. The identifying assumption of our triple-difference estimation relies on parallel trends in patenting growth within each city and tech class. To substantiate this

[1] `http://www.theatlantic.com/international/archive/2011/03/china‘s-long-bumpy-road-to-high-speed-rail` `73192/` This article briefly described the history of Chinese high-speed railway development.

[2] 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.

[3] China Railway Yearbooks (2002-2005)

assumption, we present a graph (figure 3) that plots the increase in patents across different cities and different technology classes. It is clear that there exists a trend break in the patent application in railway-related sectors in CSR and CNR cities in 2004 that is not present in the patent applications in other cities or other technology classes.

Our preliminary analyses reveal a significant 42% increase in patents applied for in the city and tech class with HSR technology transfer. The number 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 show that technology transfers from developed countries do significantly spur innovation in receiving developing countries, within and outside of direct-recipient partners.

To strengthen our understanding of the mechanisms at work, we look at different types of patents applied for. In general, the impacts of foreign technology transfer are larger for utility model patents, granted in China for technical solutions that relate to shapes or structures. The effects on traditional invention patents are smaller in aggregate but larger (19%) than those on utility model patents after we exclude CSR and CNR affiliates and MoR direct suppliers. This finding suggests that within high-speed railway technology classes, the stimulation of innovation along the supply chain does not seem to be large in magnitude compared with other possible channels of spillovers, such as knowledge spillovers across similar technology classes. The finding also suggests that foreign imported technology has large impacts on the innovation activities of the firms that directly receive these technologies but that the impact is stronger in generating modest innovation than substantial inventions out of the receiving firms, a finding consistent with the "small incremental inventive steps" hypothesis raised by Puga and Trefler (2010) [23] to explain developing countries' progressions through the steps on the global technological ladder.

We then further examine the roles, geographic distance, technological similarity and university research strength in the diffusion of transferred technology to other cities and technology classes. Our results suggest that technological similarity plays an important role: we observe a significant increase in patent applications in technology classes that are closer to transferred technology. However, being closer to technology-receiving cities does not lead to increased patent applications after technology transfer, either within or outside of the transferred technology classes, which indicates that either geographic proximity does not matter or the effects are too local. Another piece of evidence on the heterogeneity of spillover effects is that cities with stronger university research backgrounds in related fields have much greater increases in patents from non-CSR and non-CNR firms in HSR technology classes, even if these cities do not have any CSR or CNR subsidiaries and do not receive technology transfer directly. A story that is consistent with both pieces of evidence is that the spread of transferred HSR technology to non-CSR and non-CNR firms and cities occurs mainly through the cooperation between CSR and CNR and other research institutes, most notably universities. Given the facts that the knowledge spillover from industry to university in this case is highly intentional and directional and that only a limited number of cities have strong basic research backgrounds in relevant fields, geographic barriers are largely overcome.

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 geographic and technological proximity on the magnitude of technology transfer spillovers. Our preliminary results indicate that firms that experience the largest positive spillovers from technology transfer are the firms located in technology-receiving cities that specialize in similar technology. We do not observe any spillovers out of the receiving cities. This finding highlights the important 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 high-speed rail 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 developing countries. Keller (2010) [17] 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) [4] 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) [13] finds mixed evidence on the effects of FDI spillovers on the productivity of Chinese domestic firms. The closest paper on FDI-driven innovation is Lin and Cheung (2004) [9], 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. 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.

We also contribute to the rich literature on knowledge spillovers. The seminal paper by Jaffe, Trajtenberg, and Henderson (1993) [18] shows the importance of geographic proximity in explaining the transmission of knowledge using US patent citation data. Bloom, Schankerman and Van Reenen (2013) [7] investigate the externalities of R&D spending through knowledge spillovers and product market rivalry channels and find both channels important, although 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 (Anselin et. al. (1997)[2], Audrestsch and Feldman (2004) [3], Kantor and Walley (2014) [16], Sharon and Schankerman (2013) [5]) — 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)[12] and Sohn (2014)[24]). 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[10]) 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) [11] 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 high-speed railway sector

State planning for China's high-speed railway began in the early 1990s, but 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 high-speed railways (Liu, 2003) [22]. From the very beginning, the state planners in China focused on achieving indigenous high-speed railway technology. Developing indigenous capability based on acquired existing foreign technology appeared to be the fastest and surest way to achieve 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. [4] According to 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. 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, but they still 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 appears in the form of jointly owned patents by newly formed CSR/CNR and foreign partner joint ventures.

[4] For example, the MoR signed contracts with Kawasaki Heavy Industries that involved procuring 60 CSR-2 (based on Shinkansen E2-1000) high-speed trains as well as transferring technology worth 0.6b RMB, approximately 0.1b dollars, to CSR Sifang in Qingdao.

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

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, whereas other firms are recorded by China Railway Yearbooks as having received a variety of other technologies. We use different definitions of HSR technology-receiving cities. Because of 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.

The special characteristics of China's high-speed railway project make it an ideal setting for studying the impacts of massive international technology transfers on host developing countries.

First of all, the entire high-speed railway project in China was a response to its pressing demand for extra railway capacity and ambition to revolutionize its transformation 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 high-speed railway project covers a wide 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 have 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 two main sources of data: patent applications and grant data in China covering 1996 to 2011 from the State Intellectual Property Office of China (SIPO) matched with 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. We will describe these 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 a number of 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 was 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

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

output and 98% of exports (Brandt et al., 2012) [8].

The matching of patent and firm database is described in Xie and Zhang (2015) [25]. 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) [25] 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.

4.2 High-speed railway technology transfer data

The information on the types of technology transferred in China's high-speed railway 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, 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 high-speed railway 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 high-speed railway 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:

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

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 high-speed railway 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 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 trend. 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) [6] 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 before 1996, during 2004 and after 2010 the technology transfer. 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 significantly 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 increased 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.

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 high-speed railway patent applications in cities

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

with CSR or CNR affiliates after 2004, suggesting a large aggregate effect of high-speed railway 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 specific 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 high-speed railway technology transfer decrease by half, indicating the importance of direct absorption by receiving firms of technology transfers. Among different patent categories, the decreases 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.

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 high-speed railway technology 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 Robustness Checks

The above main results suggest a significant positive impact of high-speed rail 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.

First, we tested different definitions of technology class as well as treatment year. Table

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

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.

In Table 7, we follow Bertrand et al. (2004) [6] 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 in terms of the population and its growth rate, GDP and the number of patents, as well as government spending in 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 11. 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 8.

Lastly, to confirm that the positive impact in our regressions is truly from the policy shock in the high-speed rail 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 significant impact of high-speed rail technology transfer in the non-rail related sectors, we are interested in the mechanisms that could explain these knowledge spillovers. In this section, we then further examine 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.

6.1 Geographic proximity and technological similarity

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, and thus, technologies that are more similar to the transferred technologies see higher patent growth.

Table 9 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 with closer location 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.

However, in Table 10, we observe significant impact of technology proximity in 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 13 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.

6.2 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[9] 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 kmh. 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 arrive at spin-offs that might be beneficial to other firms with related technology problems.

In testing the role of universities in promoting technology spillovers, our hypothesis is 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. We then interact the dummy of university research with the triple-difference and pairwise difference-in-difference terms. Table 11 shows the results. 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. In cities without patents applied for by universities before 2003 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. Interestingly, we also observe higher patent growth in narrowly defined HSR

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

technology classes in cities that are not directly receiving HSR technology but that have relevant university research experience. 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 Table 12. The effects are largely consistent with those using the dummy of 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.

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, the introduction of high-speed railway 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 significant large increases in related patents. We find a significant role of technology proximity but only a weak effect of geographic closeness in the spillover of technology across different technology classes and cities.

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 railway sector. Our further investigation reveals sizable spillovers to technologically similar sectors, but not to geographically closer cities. We also find that university research activities in related fields play an important role in the diffusion of knowledge.

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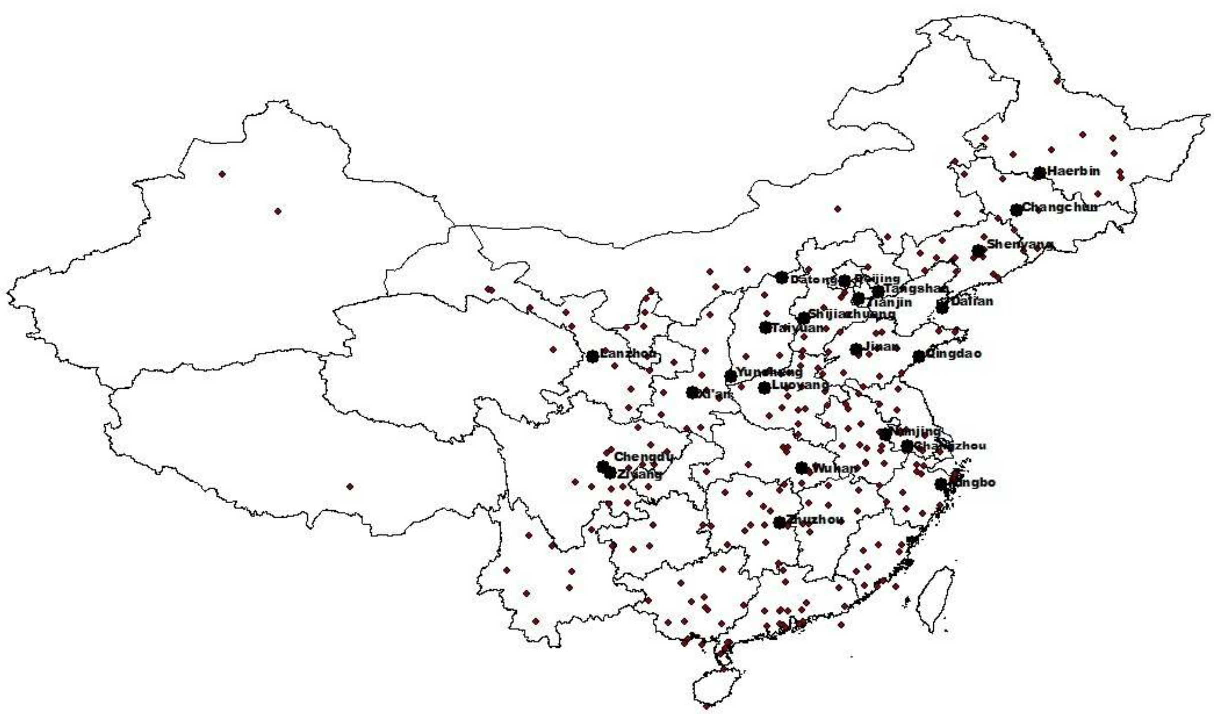
Figure 1: Technology-Receiving Cities



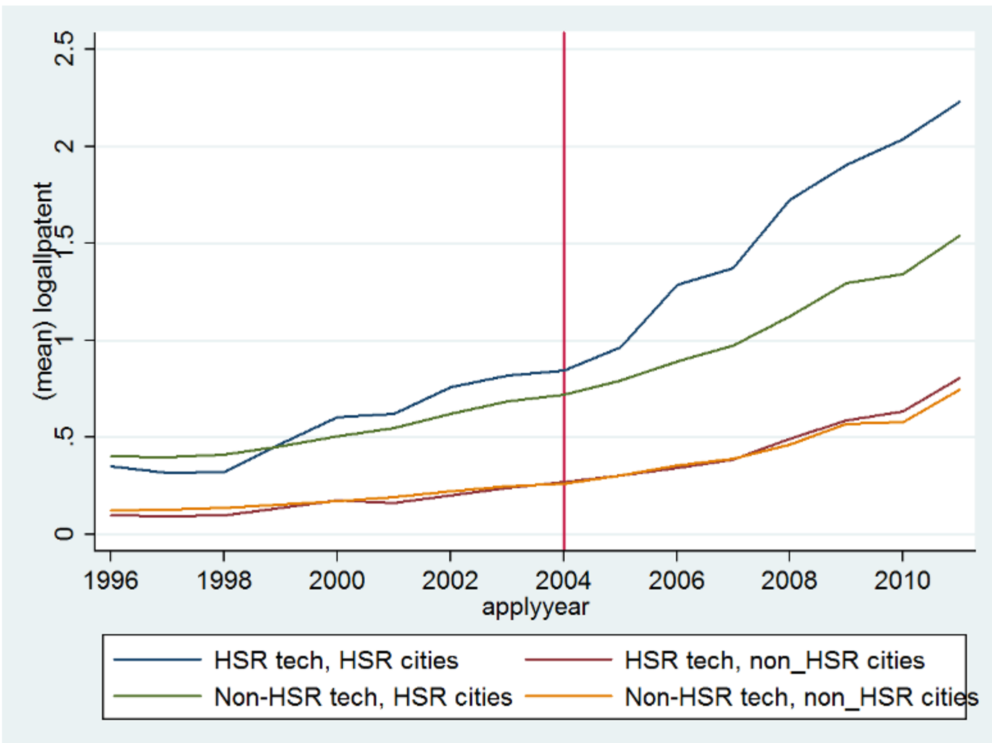
Technology-receiving cities are labeled and marked with large black dots.

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）

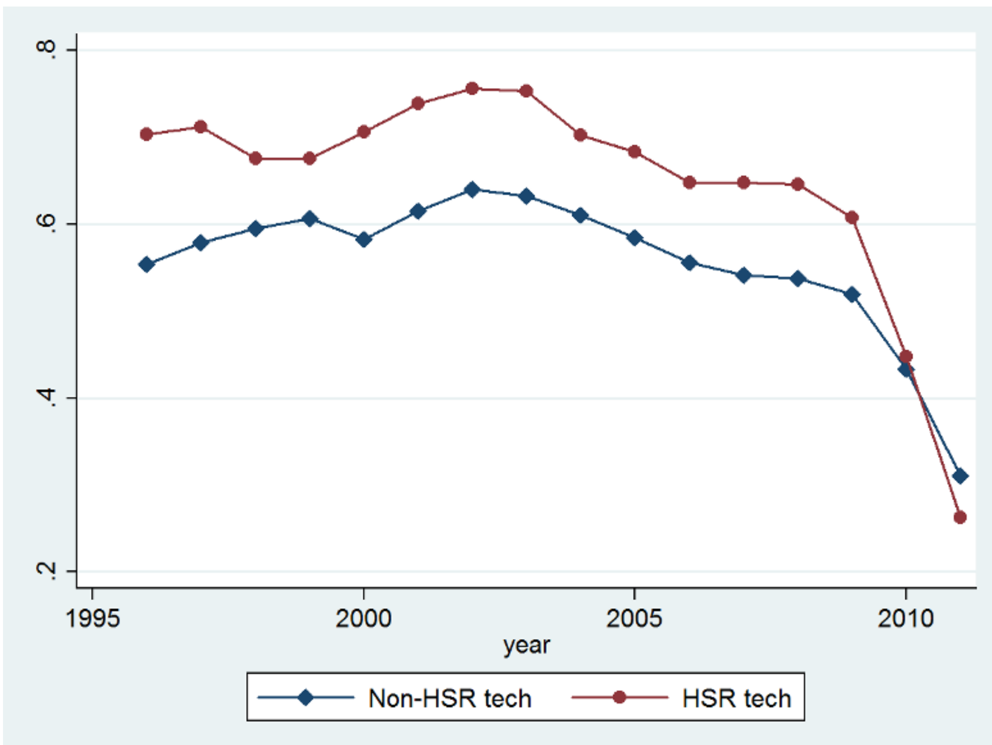
Data Source: China Railway Yearbook (2005). Translation: In this project, we (CNR Dalian Subsidiary) received technology transfer from Toshiba on AC drive system, AC drive control and computer network control systems, main converter, main transformer, traction motor, auxiliary system and auxiliary converter, 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.

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		Difference between HSR and Non-HSR cities
	HSR tech	Non-HSR tech	HSR tech	Non-HSR tech	
total patents 1996	12.64	601.96	1.59	71.68	541.33
	(3.49)	(179.03)	(0.23)	(7.55)	(57.58)***
utility patents 1996	11.6	523.76	1.53	65.55	468.28
	(3.08)	(145.68)	(0.22)	(6.80)	(48.13)***
invention patents 1996	1.04	78.2	0.06	6.13	73.05
	(0.45)	(34.64)	(0.02)	(0.82)	(10.15)***
total patents 2004	62.64	1604.48	11.61	242.56	1412.95
	(28.41)	(481.79)	(5.85)	(43.27)	(219.94)***
utility patents 2004	29.08	1030.16	6.01	188.29	864.94
	(7.96)	(245.53)	(1.12)	(28.79)	(127.22)***
invention patents 2004	33.56	574.32	5.6	54.27	548.01
	(20.51)	(241.75)	(3.59)	(14.48)	(95.37)***
total patents 2010	383.76	5758.72	52.81	858.07	5231.6
	(142.67)	(1649.93)	(14.46)	(147.76)	(756.13)***
utility patents 2010	170.96	3718	30.96	652.24	3205.76
	(42.87)	(862.51)	(6.05)	(104.24)	(563.15)***
invention patents 2010	188.56	1979.84	19.77	198.09	1950.54
	(101.47)	(933.55)	(7.46)	(42.27)	(312.18)***

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: 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 8: Impact of Technology Transfer on Domestic Innovation: 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 9: 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 10: 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 11: 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 12: 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.

A Table

Table A.1: 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.

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