Does Foreign Technology Transfer Spur Domestic Innovation? Evidence from the High-Speed Rail Sector in China

Yatang Lin [†]

Yu Qin[‡]

Zhuan Xie[¶]

This version: January 1, 2019

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

Abstract

This paper investigates the introduction of high-speed railway (HSR) technology into China to study the local impacts of foreign technology transfer. The large-scale technology transfer project, covering specific technological categories and directly benefiting railway-related firms in various cities, enables us to describe how foreign technology is digested and spurs follow-up innovation in firms apart from directly receiving ones. We find that technology transfer generates significant localized spillovers to nearby firms not only in terms of more patents, but also as higher productivity and revenue growth. Moreover, technological similarity, rather than input-output linkages, plays a dominant role in explaining the knowledge spillover both at the firm level and the aggregate level, which indicates the importance of absorptive capacity in digesting foreign technologies. We also find that cities with stronger university research background in related fields have much greater increases in patents from non-railway related firms. Overall, our paper sheds new light on the innovation policy of developing countries as well as the global business strategy of multinational corporations (MNCs).

[†]Department of Economics, Division of Environment and Division of Social Science, HKUST, Hong Kong (email:linyt@ust.hk).

[‡]Department of Real Estate, 4 Architecture Drive, National University of Singapore, 117566, Singapore. (email: rstqyu@nus.edu.sg).

[§]State Administration of Foreign Exchange, 100032, Beijing, China. (email:liuhuosishui@163.com).

[¶]We are grateful to Xiaobo Zhang for sharing with us the Chinese patent data, and to Luciano Kay and Ismael Rafols for sharing with us their technological similarity calculations. We thank Duyi Chen for her excellent research assistance. All errors are ours.

1 Introduction

Over the past few decades, emerging economies, notably China, have experienced impressive growth in technological innovations. It is widely believed that direct technology transfers from the OECD's multinationals help these countries to gradually approach the technology frontier, but how pervasive are such effects? How is advanced transferred technology digested, renovated and diffused in a developing country? Although many empirical studies support the presence of productivity spillovers from FDI (Javorcik, 2004 [26]; Liu et al., 2000 [34]), it is difficult to disentangle the contributions of direct technology transfer from the overall benefits of such investments, which include the formation of trade networks, innovation in advertising and management, the introduction of new products and competition. A clean identification of the direct impacts of technology transfer is necessary before researchers and further examine the mechanisms of technology spillovers from multinational corporations (MNCs) to their host countries.

This paper contributes to the literature by revisiting the empirical evidence on the localized impacts of technology transfer in three areas. First, to isolate the role of technology transfer from other impacts of FDI, we exploit a major technology transfer event: the introduction of state-of-art high speed railway (HSR, thereafter) technology into China. Two features of this event make it an ideal setting to study the local spillovers of foreign technology. On 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 beyond the HSR system and have great potential for technology spillovers.[2] On the other, the whole HSR technology transfer program was introduced and implemented rather abruptly following the appointment of a new Minister of Railway of China, Zhijun Liu, in 2003. Direct receivers of this wave of technology transfer are pre-existing CSR/CNR subsidiaries with R&D centers located in 14 cities. We documented detailed information on the types of technology introduced and the location of the firms that received them. This created plausibly exogenous changes in technology

[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).

stock at a very local level.

Second, a major empirical challenge in the literature of FDI spillovers is the endogenous allocation of FDI technology transfer projects over space and time. The nature of this technology transfer event allows us to improve on the identification strategy used in the literature by restricting our attention to cities with foreign technology receivers. In practice, using a difference-in-differences design, we identify the localized spillovers of this plausibly exogenous technology transfer event by comparing the innovation and economic performance outcomes of firms within 10 miles from the nearest technology receiver to those within 10-20 miles. We also propose an event study design that allows us to transparently and non-parametrically test whether or not firms that are closer to the direct technology receivers display differential pre-trends in technological development.

Finally, compared with the studies in the literature, each of which focuses on a subset of indicators for firm performance, we assemble a comprehensive dataset that matches the information on patents that were applied for at the State Intellectual Property Office of China (SIPO) to firm-level variables from China's Annual Survey of Industrial Firms (ASI) from 1998 to 2009. This let us explore a long list of indicators that trace firms' innovation activities to their indicators of performance, such as productivity and revenue. One criticism of the use of patents as a measure of innovation in China is the influence of government policies in pushing for additional patent applications over time (Hu (2010)[22]. Hu et al. (2017) [21]). We complement firms' patent data with their performance measures to uncover the real economic impacts of innovation associated with technology spillovers.

The rich panel data on firms also allows us to explore mechanisms at work. To distinguish the effects of demand-driven innovation from those of knowledge spillovers, we obtain a list of certificated suppliers by the Ministry of Railway (MoR). We focus our attention on firms that are neither receivers of transferred technologies nor direct suppliers to China's railway sector. Additionally, the local spillovers of FDI technology transfer hinge on the absorptive capacity of domestic firms. To weigh the relative importance of different dimensions of firm absorptive capacity, we construct measures of technological similarity and the input-output linkages of firms from the direct technology receivers. These enable us to examine whether or not the spillover effects on domestic firms are stronger for firms sharing similar technology to the directly affected firms or those with stronger backward input-output linkages. Contrary to the literature that usually identifies the greatest spillovers in backward-linked suppliers, we find that firms which share similar technology to the HSR sector benefit most from the introduction of foreign technology.

We find that the introduction of HSR technology into China's railway sector leads to a significant 3.2-5.8% growth in patenting activities among firms close to the direct receivers of foreign technologies. Moreover, these localized spillovers are associated with *real economic gains*, such as significant growth in total factor productivity and revenue. Our event study supports the parallel trend assumption of the difference-in-differences design. It also suggests that it takes a few years for domestic firms to digest transferred technology and produce indigenous innovation, especially when the inventions are significant.

With respect to the heterogeneity in firm-level absorptive capacity, we find that the role of technological similarity dominates the role of input-output linkage in promoting invention and productivity growth; at aggregate level analysis (city-technology class-year level), we observe a significant increase in patent applications in technology classes that are closer to the transferred technology. Another piece of evidence on the heterogeneity of spillover effects is that cities with a 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 have no CSR or CNR subsidiaries and receive no direct transfers of technology.

Our findings have a number of policy implications. First, our study evaluates 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 specifying technology transfer as a pre-condition for the entry into Chinese markets.(Holmes et al., 2015) [19]. This could be a very important lesson to learn for other emerging markets that aspire to develop technological bases from scratch. Second, our findings provide evidence of the importance of absorptive capacity, most importantly, technological similarity, on the magnitude of technology transfer spillovers. Our results indicate that the greatest positive spillovers from the technology transfer are gained by firms close to technology-receiving firms and specializing in similar technology as them. This finding identifies the importance of clustering high-tech firms within the same city. Policymakers who want to maximize the impacts of introduced foreign technology may want to place it in cities where clusters of technologically related firms already exist or to implement other industrial policies that enhance the local spillovers of technology.

The paper is structured as follows: section 2 discusses the related literature; section 3 prepares 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 using firm-level analysis; and section 6 concludes.

2 Related Literature

Our paper has its antecedents in the rich literature of FDI and foreign technology transfer in developing countries. The evidence is mixed across contexts, largely because FDI spillovers operate through varied channels (Hale and Long (2007) [17], Keller (2010) [29]). The literature identifies a 'competition effect' that affects firms negatively, and a positive 'agglomeration effect' through channels such as knowledge spillovers, input sharing, and labor pooling. Previous empirical research documents larger positive impacts on backward-linked suppliers (Blalock and Gertler (2008) [6], Javorcik, 2004 [26]), but little or even negative intra-industry spillovers, possibly due to intensified competition (Lu et al. (2017) [35]). Lin and Cheung (2004) [12] is among the few papers with innovation as the main outcome and finds positive effects of FDI in domestic patent application at the provincial level.

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 examine the channels of technology spillovers on domestic innovation. The merging of firm-level data with patent data also allows us to trace spillover effects along the dimensions of technological similarity and input-output linkages. Our paper also finds stronger spillover effects for technologically similar firms, controlling for supplier linkages.

A number of papers focus on the importance of absorptive capacity as a key mechanism in the effect of FDI. 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. Blalock and Gertler (2008) [6] looks at the role of firm capabilities in the effects of foreign technology spillovers.

Using cases from the Czech Republic and Russia, Sabirianova et al. (2005) [41] argue that firms need to be technologically advanced and open to competition if they want to gain from foreign presence. In the context of China, Lu et al. (2017) [35] find that FDI has a negative 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 technological similarity. Contrary to the literature that identifies the backward input-output relationship as the most important dimension of absorptive capacity, our paper finds that firms which share similar technology to the HSR sector benefit most from the introduction of foreign technology.

We also contribute to the rich literature on local knowledge spillovers. The seminal paper by Jaffe, Trajtenberg, and Henderson (1993) [25] 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 the channels of knowledge spillover and product market rivalry and find both channels important. Other papers look at spillovers from university to private industry (Jaffe, 1989 [24]; Kantor and Walley, 2014 [27]). Our paper is particularly interested in how far a top-down government-initiated massive technology import plan spurs private sector innovation.

On a related note, this paper also looks at university-industry collaboration and spillovers, (Perkman et al. 2013 [38]). 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) [27], 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)[42]). 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 role of 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 importing of HSR technology and the defense-driven R&D spending in the US during the Cold War. They are both plausibly exogenous government-led pushes in particular sectors of a country's technological capital. A major difference here is that China is a developing country that is attempting to catch up with the technological frontier whereas the 'big push' in the US is to push forward the world's technology frontier. 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 in the US accounted for 6-11% of the increases in patenting during the early Reagan build-up period. The size is noticeably smaller for that found in our paper, which may reflect the differences between the difficulties of developing new technology and of 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, then newly appointed Minister of Railway of China, proposed his "Great Leap Forward" strategy, which focused on introducing HSR (Liu, 2003) [34]. From the very beginning, the state planners in China focused on securing indigenous HSR technology. Developing indigenous capability based on acquired existing foreign technology appeared to be the fastest and surest way to attain 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-3 and CRH-5) from four companies (Alstom, Siemens, Bombardier, and Kawasaki Heavy Industries). Typically, the Ministry of Railway (MoR) signed train procurement and technology transfer contracts with all four 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 official MoR reports, as well as interviews with engineers from CSR and CNR, a technology transfer contract normally consists of four components:

1. The "Joint design" of train modes based on foreign prototypes, which incorporate adaptations to the Chinese environment
2. Access to train blueprints
3. Instructions on manufacturing procedures

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

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 are taught the hows but not the whys 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 worked 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 to other subsidiaries the technology for certain critical parts, such as the traction motor, braking system and series pantograph from Mitsubishi, Hitachi, ABB, etc.

According to Chinese and international patent law, Chinese firms that receive transferred technology are not allowed to file this technology in China or any other country. Therefore, the effects on new patents are not the mechanical effects of receiving the transferred foreign technology. However, the technology receivers can benefit from follow-up research that adapts these technologies to other uses and patents in the interests of 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 joint ventures by CSR/CNR and a foreign partner.

Another important feature of the transferred technologies is that many of them have broad applications outside the railway industry. For example, traction motors can be applied to the subway system and air conditioning system;[6] the bearings for the bullet trains is of a similar type to the ones used in wind power plants;[7] air suspension, part of the bogie, is needed in bridges and elsewhere in the construction industry.[8] Given the applicability of the transferred technology in

[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 for high-speed trains. Among the 60 orders, three were imported whose design and manufacture Chinese engineers were allowed to observe; six orders were imported as parts and later assembled by 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 the transferred technologies.

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

[6] This is the link to a news article (in Chinese) introducing the applications of traction motors.

[7] This is quoted from the documentary introducing the indigenous innovation in China's high-speed rail sector (approximately at 12'10" of the following video: http://tv.cctv.com/2017/01/24/VIDEZWuDfjN3DlJDN0CBHdI8170124.shtml).

[8] This is quoted from the documentary introducing the indigenous innovation in China's high-speed rail sector (approximately at 2'30" of the following video: http://tv.cctv.com/2017/01/24/VIDEZWuDfjN3DlJDN0CBHdI8170124.shtml).

non-railway related industries, it is therefore worth examining whether these foreign technologies spurred domestic innovation outside the railway sector.

3.2 Technology-receiving firms

In this paper, we label the "treated firms" of the high-speed rail technology transfer as the CSR/CNR subsidiaries which have an R&D center. These R&D centers host the core competence of the R&D capacity of CSR/CNR which are spread over 14 cities in China.[9] As described in Figure 1, these R&D centers are located in 14 different cities ranging from provincial capitals such as Nanjing and Wuhan, to small cities such as Meishan and Ziyang, granting us a useful source of variation. Since not all of the technology transfer details may have been reported in our main source of technology transfer information, the China Railway Yearbooks, we labeled all the CSR and CNR R&D centers "technology-receiving firms" in our within-city specification, and labeled all cities with such R&D centers "technology-receiving cities" in our cross-city specification.

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 its ambition to revolutionize its transportation system. Moreover, the decision to transfer technology was made very suddenly, and may in part have been 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 to fruition around or after a foreign technology transfer, a major challenge to difference-in-differences identification that has plagued previous literature on FDI and domestic innovation.

Second, the HSR technology transferred to China covers a broad scope of technological 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 no more than 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 (as discussed in Section 3.1), which makes significant knowledge spillovers

[9] These cities include Tangshan, Datong, Yongji, Dalian, Changchun, Zhuzhou, Qingdao, Jinan, Nanjing, Changzhou, Qiqihaer, Meishan, Wuhan, and Ziyang. The data source is from http://www.chinatax.gov.cn/n810341/n810755/c2431231/content.html.

possible.

4 Data and Identification Strategies

Our analysis draws on three main sources of data: patent applications and grant data in China covering 1998 to 2011 from the State Intellectual Property Office of China (SIPO); 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 firm-level data by the names of the patent applicants. Below we describe these sources in turn.

4.1 Patent-firm matched dataset

The patent data that we use include all published invention and utility model patents over the period 1998 to 2011 granted by the State Intellectual Property Office of China (SIPO). We focus on this period because we cannot match patents with information about firms before 1998. In addition, the number of patents applied for before 1998 is very small, while after 2011 there is a downward bias for patents filed 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 few 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 patent under 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.[10] Here, we focus only on invention and utility model patents because industrial design patents usually have little technological content and are not the major focus in CSR, CNR and other railway-related firms.

Our other data source is the annual industrial surveys conducted by the country's National Bureau of Statistics (NBS). 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

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

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 patents and firm database is described in Xie and Zhang (2015) [43]. Patents can be applied for by individuals, firms, or other institutions. Those patents applied for by firms record only the name of the firm, not the unique firm identification code used industrial surveys. Hence, matching the two databases obliged Xie and Zhang (2015) [43] to use firm names as a bridge. They show that the matching rate was rather high and that the matching error was less than 10 percent.

4.2 HSR technology transfer data

The information on the types of technology transferred in China's HSR project is drawn from the Chinese Railway Yearbooks from 2003 to 2006. The railway yearbook series contains detailed reports about the year's major events for the CSR and CNR and their subsidiaries, including detailed descriptions of their technology transfer contracts. It lists the name of the technology introduced, the foreign partner involved, the receiving CSR or CNR subsidiary and, sometimes, the value of the contract.

To map information from the yearbooks to the SIPO patent categorizations and arrive at a definition of HSR technology, we extracted keywords from the descriptions of technology and match them to patent descriptions in the SIPO database. After an initial rough matching of keywords, we also tested different ways to refine our definition of the introduced HSR technology. In our main specification, we exclude technology class matches in the SIPO if they contain 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 some robustness checks.

4.3 Empirical strategy

To examine the localized technology spillovers, we identify the geographic location of the technology-receiving firms (i.e., CSR/CNR R&D centers) 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 first estimate the following model,

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

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 and total factor productivity (TFP)[11]. $DistanceBand_d$ 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, up to 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 firm 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) [33] to define $outcome_{i,j,t} = ln((Y_{i,j,t}^2 + 1)^{1/2})$, where $Y_{i,j,t}$ is the total number of patent filings. In our main analysis, we exclude firms who are certified suppliers of MoR since we are interested in the spillovers to non-supply chain firms.

We then categorize the distance bands into a binary variable. Specifically, we define a dummy variable for being close to one or more CSR/CNR R&D centers, which equals one if a firm is within 10 miles of a CSR/CNR R&D center, otherwise zero. The specification is very similar to Equation (1), which is as follows,

$$
\begin{aligned}
Outcome_{i,j,t} = & \beta_0 + \beta Near_{i,j} * After_t + \gamma Near_{i,j} + CountyFE * After_t + IndustryFE * After_t \\
& + YearFE + \epsilon_{i,j,t} \qquad (2)
\end{aligned}
$$

where $Near_{i,j}$ is the dummy variable indicating whether firm j in city i is within 10 miles to a CSR/CNR R&D center, otherwise zero. The rest of the definitions are the same as in Equation (1). We limit the sample to firms that are within 20 miles to a CNR/CSR R&D center, so effectively

[11] We calculate firm-level TFP following Brandt et al. (2012).

we are comparing firms within 10 miles to those within 10-20 miles in a difference-in-differences setting. In some specifications, we replace the $Near_{i,j}$ variable with the direct distance measure as a robustness check.

The identification of this model hinges on the parallel trends in innovation and performance outcomes between firms close to HSR R&D centers (within 10 miles) and those at some little (10 miles to 20 miles). Although there is the possibility that the government might strategically send resources to firms in cities and sectors with closer connections to the HSR industry, so as to maximize the benefits of HSR technology transfer, it is quite unlikely that the additional government help is targeted at firms according to their distance from HSR R&D centers. We control for the interaction terms between the "after" dummy and the 4-digit industry code as well as the distance from CBD, in order to alleviate this concern as much as possible. The inclusion of these controls does not change the main effects much. In addition, to test the parallel trend assumptions, we examine the dynamic impact of the HSR technology transfer over time using an event study design. The specification is as below,

$$\begin{aligned} Outcome_{i,j,\tau} =& \beta_0 + \sum_{\tau=-6}^{5} \beta_\tau Near_{i,j} * Year_\tau + \gamma Near_{i,j} + + CountyFE * After_t \\ & + IndustryFE * After_t + YearFE + \epsilon_{i,j,\tau} \end{aligned} \tag{3}$$

where τ stands for the event year of technology transfer, i.e., $\tau = 0$ for year 2004. $Year_\tau$ is a dummy variable that equals to one if a certain year belongs to event year τ, otherwise zero. We use one year before the technology transfer, i.e., $\tau = -1$ as the benchmark year. Therefore, the coefficient β_τ estimates the impact of technology transfer in event year τ, relative to year $\tau = -1$. If the parallel trend hypothesis holds for the difference-in-differences specification, β_τ should be indifferent from zero for years prior to the event. The rest of the specification is the same as Equation (1).

Another concern is that the patenting office may have been more willing to accept railway-related patents after the HSR technology transfer to encourage domestic innovation in the related industries strategically. In this case, the positive impact of technology transfer, if there had been any, would not have been due to changes in the effort to boost domestic innovation but is the consequence of relaxed patent standards related to the transferred technologies. Although it is unlikely that this channel affects our main results, as our identification relies on the differential response to the technology transfer event of firms at different distance bands from HSR R&D centers, it is still more than possible that the selective granting behavior affects our interpretation of the heterogeneous effects across industries and technological classes.

To rule out this possibility, we plot the invention grant rate of the transferred technology categories and the other categories in Figure 2.[12] 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 ran 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 four groups of observations by treatment status and by comparing before and after. On average, firms with close proximity to the CSR/CNR R&D centers (treatment group) were slightly less innovative (measured by the number of utility patents, invention patents and total number of patents), less productive (measured by total factor productivity) and with greater revenue than firms slightly further away (the control group) before the technology transfer (upper and lower left panels). However, after the technology transfer the firms close to the CSR/CNR R&D centers had slightly more utility patents, greater revenue, and were catching up on productivity better than firms slightly further away. Thus, the comparison of raw averages seems to suggest positive spillovers of technology transfer to nearby firms. We next present the regression results, controlling for other confounding factors.

5.2 Main results

Figure 3 shows the localization effect on firm-level patenting outcomes. The coefficients on the interaction terms of distance bands and after variables, as well as the 95% confidence intervals, are plotted in Figure 3, 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. The figure shows that firms closer to the technology-receiving firms experienced significantly higher patent growth after the

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

technology transfer. Such an effect is the greatest for firms within two miles from the CSR/CNR firms and decays to zero as distance increases.

We also present the estimation results of the localization effect in Table 2. In Panel A, we categorize the distance of a firm to the nearest CSR/CNR R&D center using 10 miles as a cutoff (the counterfactual group includes the firms that are slightly further away, i.e., at least 10 miles away but within 20 miles from the nearest CSR/CNR R&D centers), and regress firm-year level patenting outcomes on the interaction of this binary measure and the "after" dummy. In Panel B, we directly interact the distance measure with the 'after' dummy. Both panels suggest the positive and significant impact of transferred technology on firm patenting outcomes in columns 1-3, where we control for the fixed effects at the level of county and 4-digit industry. When we further control for firm fixed effects (in columns 4-6), the coefficients in some specifications decline, especially in Panel A, but the signs and significant levels are largely consistent.

In addition to the estimation on the full sample, we also partition the data by the medians of technological similarity[13]. 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,[14] and as a result, obtain more resources and have a stronger need to innovate.

Table 3 reports the results on partitioned samples by technological similarity. We control for firm fixed effects across all the specifications. The results suggest significantly differential treatment effects for firms with and without similar technologies to CSR/CNR firms. Specifically, nearby firms with similar (above-median) technologies to CSR/CNR firms experienced significantly higher patent growth in all the specifications. Firms within 10 miles from the CSR/CNR firms experienced 3.0% growth in inventions and 5.6% growth in utility model patents after the technology transfer, compared to firms that were slightly further away (10-20 miles). However, the treatment effect is zero for firms with dissimilar technologies to CSR/CNR firms. This contrast indicates the importance of technological similarity in facilitating localized spillovers: firms that share similar technologies with the CSR/CNR firms may have a greater capacity to learn from the new tech-

[13] The technology similarity measure is generated at each four-digit industry, according to the similarity of the patents applied by firms within each industry before 2004 to those applied for by CSR/CNR firms. technological similarity across patent classes is defined in Kay et al. (2014), which assigns a measure from 0 to 1 as the similarity between two 4-digit technology classes based on co-citation. technological similarity to the railway sector at industry level is then defined as a weighted average of technological similarity to the patent classes where CSR/CNR firms patented at before 2004, weighted by both the number of patents within each technology class by CSR/CNR firms and the number of patents within each technology class by patents applied for by firms in the relevant industries before 2004.

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

nologies and innovate more. To summarize, the within-city firm-level analysis suggests a positive localized effect on nearby firms' patenting activities. Such an effect is generally stronger for firms that are more similar in the transferred technologies.

5.3 Robustness checks and event study

The above main results suggest a significant positive impact of HSR technology transfer on the domestic innovation of related technologies from nearby firms in non-railway-related industries. In this section, before we proceed with the discussions of the potential mechanisms of this impact, we provide a series of robustness checks to ensure that our estimated results are robust to various specifications.

First, in the main results, we exclude the direct suppliers of CSR/CNR in the sample. In Tables B.1 and B.2, we include these firms again and replicate the results in Table 2, using the complete specification (with firm fixed effect). The estimated coefficients in all three panels look very similar, suggesting that the role of demand-driven innovation and productivity growth has quite limited power to explain our findings.

Second, we study the dynamic effect of technology transfer using event study as shown in Equation (4). We plot the coefficients for each β_τ as well as the 95% confidence interval. Figure 4 conveys the message that most of the specifications support the parallel trend hypothesis of difference-in-differences, because almost all the coefficients before the event year (2004) are not different from zero. In addition, the event study suggests that it takes time to innovate: the coefficients on patenting outcomes are small and insignificant in the first few years after the technology transfer, especially for substantial innovations such as invention patents. The spillovers arrive earlier and are greater in magnitude for small-step innovations such as utility model patents.

5.4 The role of technological similarity and input-output linkage

Apart from technology spillovers, an alternative explanation of the sizable spillovers may be the increasing demand for high-speed trains and parts. The extra demand induces firms to innovate and the effects are more pronounced for firms closer to CSR/CNR R&D centers because these firms are also more likely, due to the closeness, to develop the input-output relationship with CSR/CNR subsidiaries.

We have partially ruled out this mechanism by excluding the direct suppliers of the Ministry of Railway in the main specification. As shown in Table B.1 and Table B.2, the main effects are quite similar whether with or without these suppliers. However, we cannot wholly eliminate the firms in the complete network of high-speed rail supply chain, such as the suppliers' suppliers. To address this issue, we calculate the input-output linkage of each firm in our sample to the railway sector. Input-output linkage, defined at four-digit-industry level, is the share of input of the railway sector that comes from each industry, calculated according to the Input-Output table for China in 2012. We then run a horse-race model using the main specification by interacting the $Near*After$ dummy with the firm's input-output linkage to the railway sector, and the firm's technological similarity to the transferred technology, respectively and both. We can then understand the importance of each channel and the dominant channel between these two if any.

Table 4 shows the findings of the horse-race model. For each outcome, we run three specifications. The first two specifications control separately for the triple interactions of $Near * After$ with IO linkage and with technological similarity. The third specification includes both interaction terms. For the utility model and total patents, we find positive and significant coefficients when separately interacting IO linkage and technological similarity with the $Near * After$ dummy.[15] This indicates that firms with closer input-output linkages, or similar technologies to the transferred ones are more likely to innovate more. However, when we control for both interactions in one specification, the significance on input-output linkage disappears for the utility model and total patents, whereas the significance on technological similarity remains. The overall message conveyed by this horse-race model is that technological similarity is the dominant mechanism explaining the localized spillover in patenting outcomes.

In Appendix A, we also provide further evidence of the importance of technological similarity using aggregate level analysis (city-technology class-year level). Again, we observe a significant increase in patent applications in technology classes that are closer to the transferred technology. 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 the technology transfer directly.

[15] The estimates for invention patents are positive and marginally significant in column 2, suggesting that technological similarity plays a positive role in promoting inventions.

5.5 Economic outcomes

In addition to firms' patenting outcomes, we take the discussion one step further to examine the impact of technology transfer on firms' economic outcomes, measured by firms' total factor productivity and revenue. The first column in Table 5 adopts the same specification as is shown in the first three columns in Table 3, while columns 2-4 follow the three specifications in the horse-race model in Table 4.

As shown in the first column in Table 5, firms near to the CSR/CNR R&D centers experienced a productivity growth of approximately 5.1% to 6.0% after the technology transfer, and a revenue growth of, albeit marginally significant, approximately 4%. The positive large revenue and productivity effects suggest that firms closer to the direct receivers of technology not only innovate more but also experience economic gains. In other words, the great surge in patent activities in our main findings is associated with significant real economic benefits to the innovators and the whole economy, and not purely driven by extra incentives to patent.[16] The event study on the economic outcomes is presented in Figure 5.[17] The dynamic effect suggests significantly positive and increasing effect of technology transfer especially on firm's productivity growth after 2004, and shows no effect before the policy (compared to 2003 as the baseline year), consistent with the findings in Table 5.

Columns 2-4 of Table 5 show the results of the horse-race model on the economic outcomes. We find that firms that are technologically more similar to the CSR/CNR firms experienced significantly higher productivity growth, even after controlling for the firms' input-output linkages to the affected firms, while input-output linkage is the dominant mechanism explaining the revenue growth of nearby firms after the shock. Such findings again substantiate the importance of technological similarity in boosting technology upgrades and productivity growth.

6 Concluding Remarks

This paper aims to make two primary contributions. First, we evaluate the impacts of one of the greatest technology transfer plans in the world, namely, the introduction of HSR technology into China. This unprecedented natural experiment provides us with an excellent opportunity to

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

[17] Due to data availability, we cannot calculate the total factor productivity for firms in 2004. Therefore the coefficients for the year 2014 are missing for the event study on TFP.

study the local spillovers of foreign technology. By linking several datasets together, we assemble a comprehensive data set that allows us to trace firms' innovation activities and economic performance over time. We found that technology transfer generates significant localized spillovers to nearby firms not only in terms of more patents, but also in the forms of higher productivity and revenue growth. Second, we further examine different mechanisms that might contribute to the absorption, digestion, and diffusion of introduced foreign technology in developing countries. We find a significant role of technology proximity both at the firm level and the city-patent technology class-year level that could explain the technological spillovers, which dominates the role of input-output linkages. This finding suggests the importance of absorptive capacity on digesting transferred technologies.

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 and MoR certified supplies suggest 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 the absorptive capacity of foreign technologies, other than government initiatives, is the primary explanation of patent booms in the indirectly affected sectors.

Our paper provides important implications not only for MNCs global strategy in technology transfer but also for public policies aimed at fostering innovation in developing countries. Our results suggest that foreign technology transfer has the largest spillover impacts in technologically similar firms, but not much in firms with backward linkages. So an MNC that is making decisions on the sites of technology transfer should consider industrial clusters consisting of backward suppliers other than firms that work on similar technological fields to avoid spillovers to competitors. This finding is particularly timely with increasing FDI activities of MNCs in developing countries.

References

[1] Abramovsky, Laura, and Helen Simpson. "Geographic proximity and firm: university innovation linkages: evidence from Great Britain." Journal of Economic Geography (2011)

[2] Abramovsky, Laura, Rupert Harrison, and Helen Simpson. "University research and the location of business R&D." The Economic Journal 117.519 (2007): C114-C141.

[3] Anselin, Luc, Attila Varga, and Zoltan Acs. "Local geographic spillovers between university research and high technology innovations." Journal of Urban Economics 42.3 (1997): 422-448.

[4] Audretsch, David B., and Maryann P. Feldman. "Knowledge spillovers and the geography of innovation." Handbook of Regional and Urban Economics 4 (2004): 2713-2739.

[5] Barrell, Ray, and Nigel Pain. "Foreign Direct investment, technological change, and economic growth within Europe." The Economic Journal 107.445 (1997): 1770-1786.

[6] Blalock, Garrick, and Paul J. Gertler. "Welfare gains from foreign direct investment through technology transfer to local suppliers." Journal of International Economics 74.2 (2008): 402-421.

[7] Belenzon, Sharon, and Mark Schankerman. "Spreading the word: Geography, policy, and knowledge spillovers." Review of Economics and Statistics 95.3 (2013): 884-903.

[8] Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. How much should we trust differences-in-differences estimates?. No. w8841. National Bureau of Economic Research, 2002.

[9] Bloom, Nicholas, Mark Schankerman, and John Van Reenen. "Identifying technology spillovers and product market rivalry." Econometrica 81.4 (2013): 1347-1393.

[10] Borensztein, Eduardo, Jose De Gregorio, and Jong-Wha Lee. "How does foreign direct investment affect economic growth?." Journal of International Economics 45.1 (1998): 115-135.

[11] Brandt, Loren, Johannes Van Biesebroeck, and Yifan Zhang. "Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing." Journal of Development Economics 97.2 (2012): 339-351.

[12] Cheung, Kui-yin, and Lin Ping. "Spillover effects of FDI on innovation in China: Evidence from the provincial data." China Economic Review 15.1 (2004): 25-44.

[13] D'Este, Pablo, Frederick Guy, and Simona Iammarino. "Shaping the formation of university: industry research collaborations: what type of proximity does really matter?." Journal of Economic Geography (2012)

[14] Draca, Mirko. "Reagan's innovation dividend? Technological impacts of the 1980s US defense build-up." (2013).

[15] Furman, Jeffrey L., and Megan J. MacGarvie. "Academic science and the birth of industrial research laboratories in the US pharmaceutical industry." Journal of Economic Behavior & Organization 63.4 (2007): 756-776.

[16] Gaotiejianwen. "High-speed rail in colour." (2015) Hunan Literature and Art Publishing House, Changsha, China.

[17] Hale, Galina, and Cheryl Long. "Are there productivity spillovers from foreign direct investment in China?." Pacific Economic Review 16.2 (2011): 135-153.

[18] Griliches, Zvi. "The Search for R&D Spillovers." The Scandinavian Journal of Economics (1992): S29-S47.

[19] Holmes, Thomas J., Ellen R. McGrattan, and Edward C. Prescott. "Quid pro quo: technology capital transfers for market access in China." (2015) Review of Economic Studies, forthcoming

[20] Holmstrom B (1989) Agency costs and innovation. J. Econom. Behav. Organ.12(3):305–327.

[21] Hu, Albert GZ, Peng Zhang, and Lijing Zhao. "China as number one? Evidence from China's most recent patenting surge." Journal of Development Economics 124 (2017): 107-119.

[22] Hu, Albert Guangzhou. "Propensity to patent, competition and China's foreign patenting surge." Research Policy 39.7 (2010): 985-993.

[23] Hu, Albert GZ, Gary H. Jefferson, and Qian Jinchang. "R&D and technology transfer: firm-level evidence from Chinese industry." Review of Economics and Statistics 87.4 (2005): 780-786.

[24] Jaffe, Adam B. "Real effects of academic research." The American Economic Review (1989): 957-970.

[25] Jaffe, Adam B., Manuel Trajtenberg, and Rebecca Henderson. "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations." The Quarterly Journal of Economics 108.3 (1993): 577-598.

[26] Javorcik, Beata Smarzynska. "Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages." American Economic Review (2004): 605-627.

[27] Kantor, Shawn, and Alexander Whalley. "Knowledge spillovers from research universities: evidence from endowment value shocks." Review of Economics and Statistics 96.1 (2014): 171-188.

[28] Kay, Luciano, et al. "Patent overlay mapping: Visualizing technological distance." Journal of the Association for Information Science and Technology 65.12 (2014): 2432-2443.

[29] Keller, Wolfgang. "International trade, foreign direct investment, and technology spillovers." Handbook of the Economics of Innovation 2 (2010): 793-829.

[30] Liu, Shimeng. "Spillovers from universities: Evidence from the land-grant program." Journal of Urban Economics 87 (2015): 25-41.

[31] Liu, Z.(2003): tie lu shi shi kua yue shi fa zhan zhan lue.

[32] Liu, Zhiqiang. "Foreign direct investment and technology spillovers: Theory and evidence." Journal of Development Economics 85.1-2 (2008): 176-193.

[33] Liu, Qing, and Larry D. Qiu. "Intermediate input imports and innovations: Evidence from Chinese firms' patent filings." Journal of International Economics 103 (2016): 166-183.

[34] Liu, Xiaming, Chengang Wang, and Yingqi Wei. "Causal links between foreign direct investment and trade in China." China Economic Review 12.2 (2001): 190-202.

[35] Lu, Yi, Zhigang Tao, and Lianming Zhu. "Identifying FDI Spillovers." Journal of International Economics (2017).

[36] Manso G (2011) Motivating innovation. J.Finance 66(5):1823–1860.

[37] Nie, Huihua, Jiang, Ting, Yang, Rudai, 2012. "A Review and Reflection on the Use and Abuse of Chinese Industrial Enterprises Database," MPRA Paper 50945, University Library of Munich, Germany.

[38] Perkmann, Markus, et al. "Academic engagement and commercialisation: A review of the literature on university–industry relations." Research policy 42.2 (2013): 423-442.

[39] Puga, Diego and Trefler, Daniel (2010), "Wake up and smell the ginseng: International trade and the rise of incremental innovation in low-wage countries", Journal of Development Economics, 91(1):64-76.

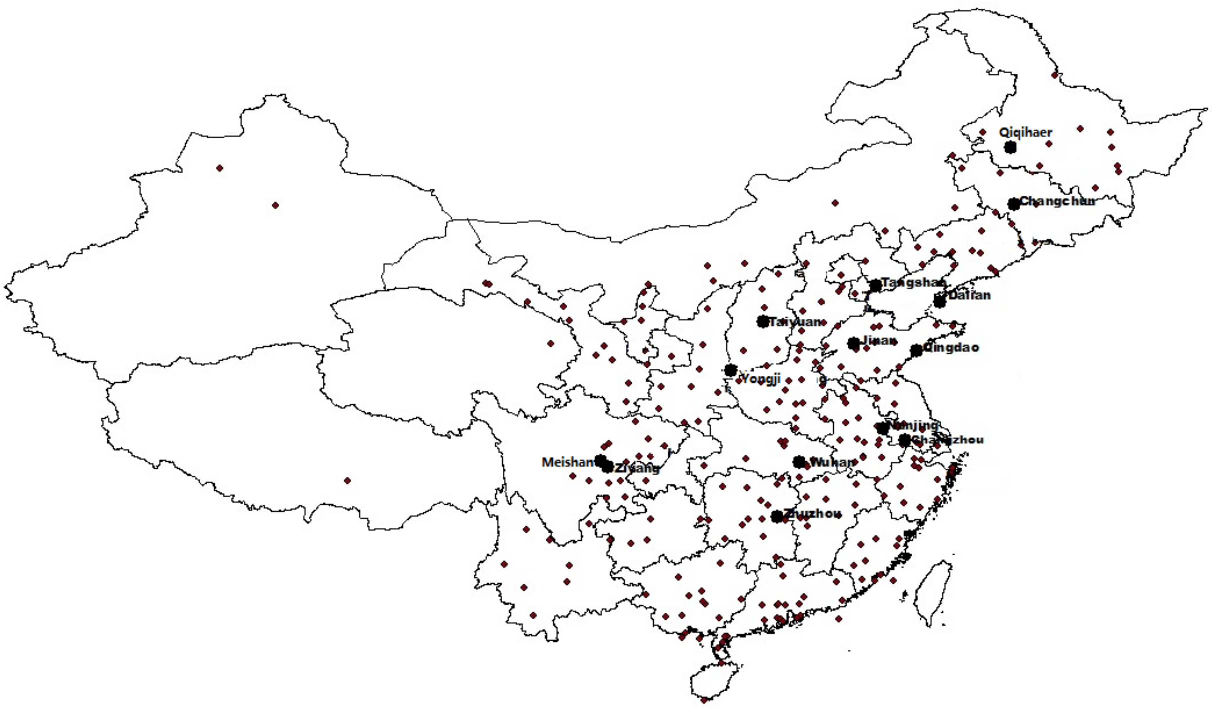
[40] Rosenthal, Stuart S. and Strange, W. ”Geography, industrial organization, and agglomeration”, Review of Economics and Statistics, 85.2 (2003):377-393.

[41] Sabirianova, Klara, Jan Svejnar, and Katherine Terrell. ”Distance to the efficiency frontier and foreign direct investment spillovers.” Journal of the European Economic Association 3.2-3 (2005): 576-586.

[42] Sohn, Eunhee (2014). ”The Impact of Local Industrial R&D on Academic Science: Evidence From the Agricultural Biotechnology Industry.” Academy of Management Annual Meetings Best Paper Proceedings.

[43] Xie, Zhuan and Zhang, X. ”The Patterns of Patents in China”, China Economic Journal 8.2 (2015): 122-142.

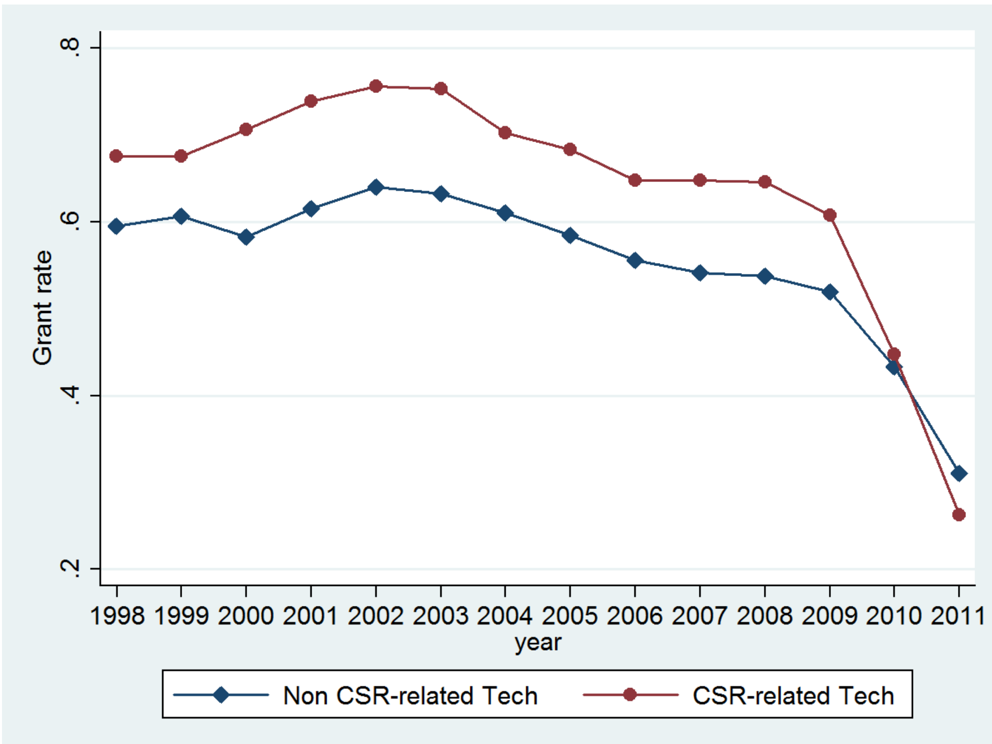
Figure 1: Technology-Receiving Cities



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

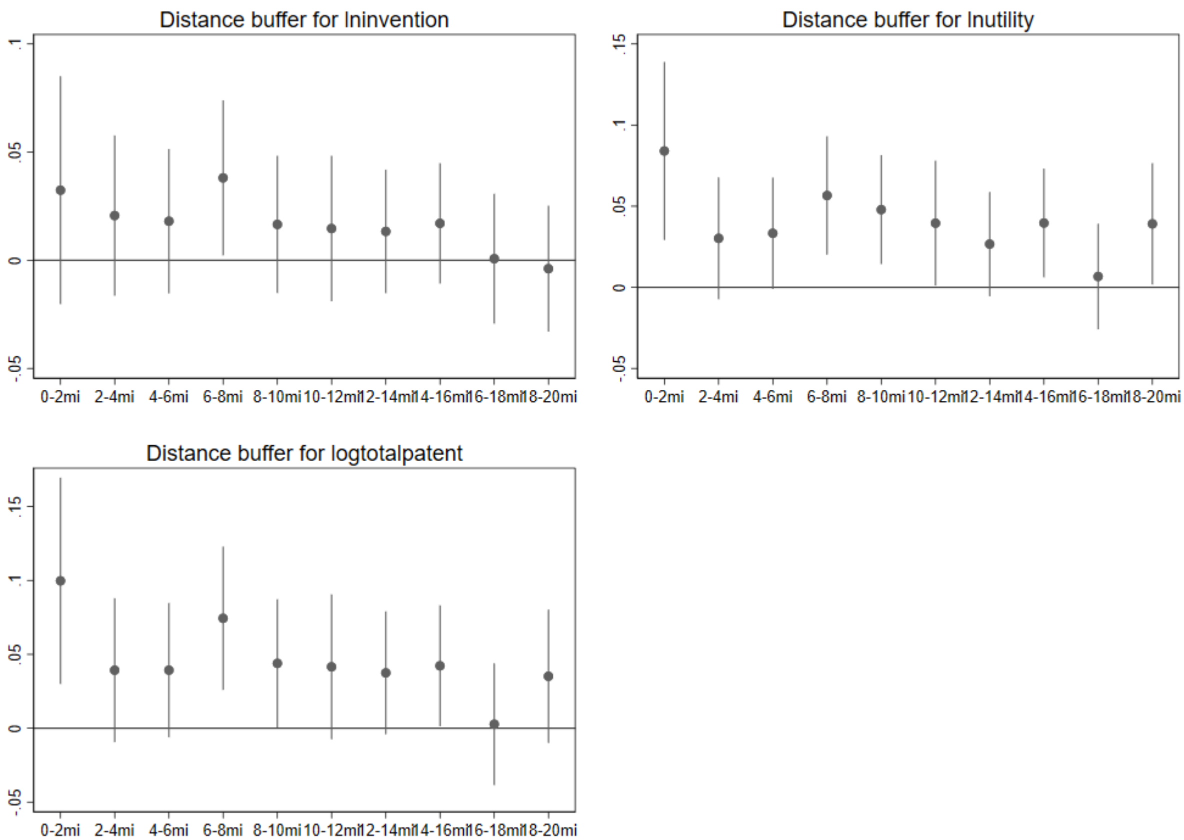
Source of the map: Michigan China Data Center.

Figure 2: Patent Grant Rates of HSR-related Inventions and Other Inventions



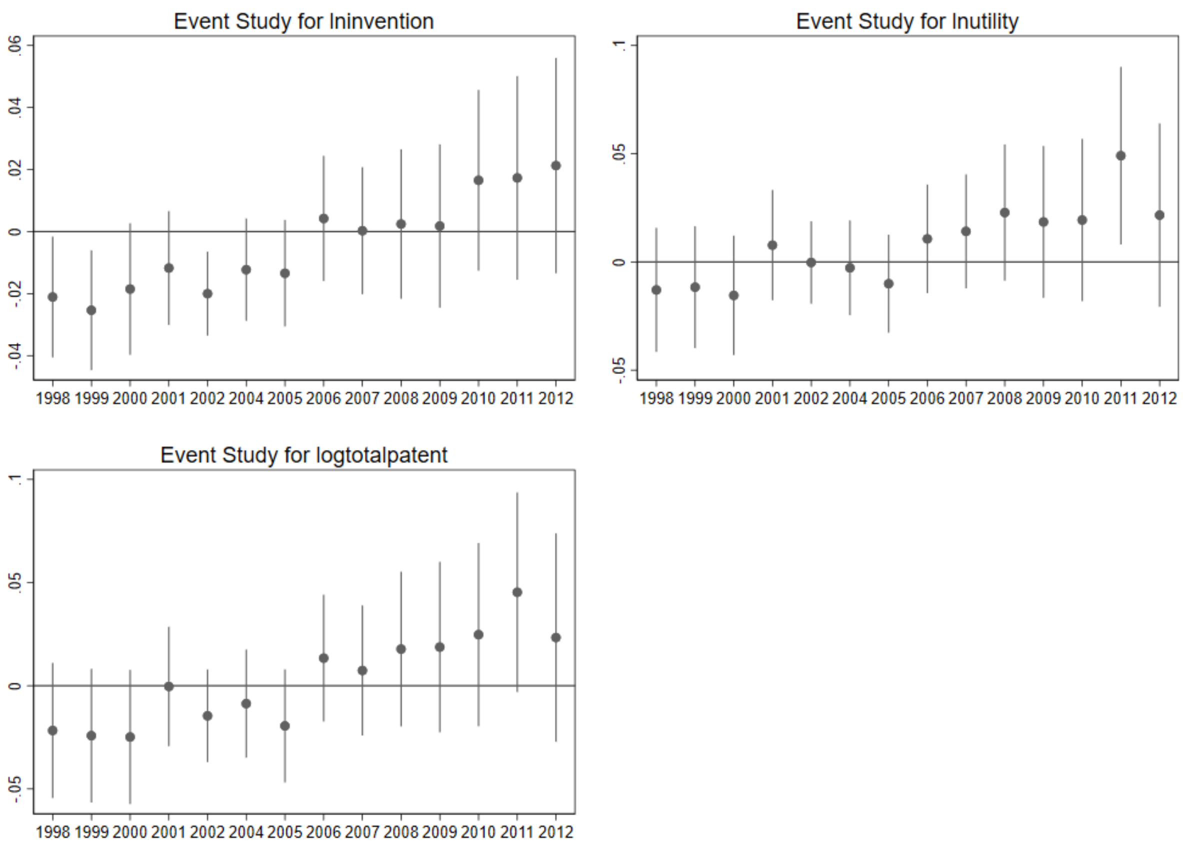
Data Source: Authors' calculations based on the SIPO database. This graph depicts the time trends of patent grant rate across HSR-related and non-HSR-related technology classes.

Figure 3: Distance to CSR/CNR firms and Firm Patenting Outcomes



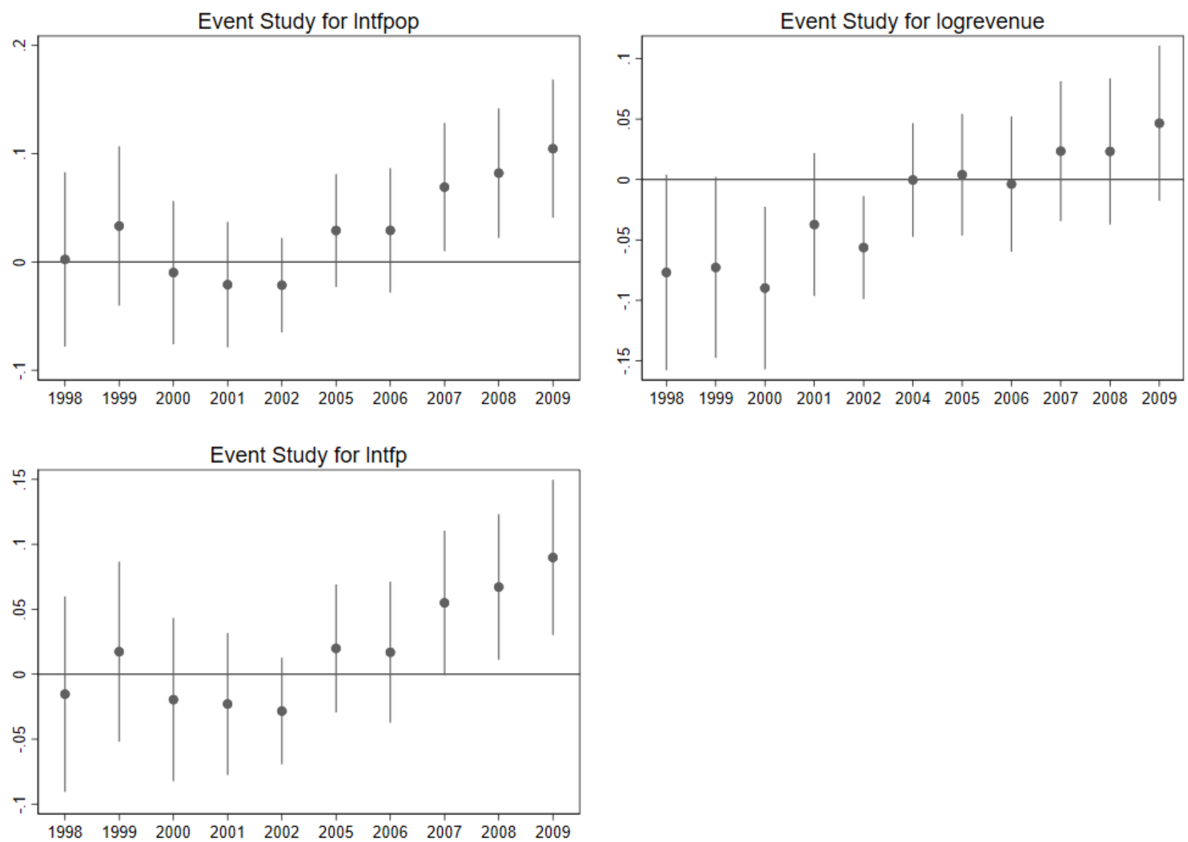
Notes: 1. This figure visualizes the β_d coefficients in Equation (1). The regression tables are available upon request. 2. The coefficients are presented in dots, with their 95% confidence intervals.

Figure 4: Dynamic Effect of Localized Spillovers (Patenting Outcomes)



Notes: 1. This figure visualizes the β_τ coefficients in Equation (3). The regression tables are available upon request. 2. The coefficients are presented in dots, with their 95% confidence intervals. 2003 is the base year. Observations in 2004 are dropped for some specifications because of the inconsistency in variable definitions in the 2004 economic census. (Nie et al. (2012) [37])

Figure 5: Dynamic Effect of Localized Spillovers (Economic Outcomes)



Notes: 1. This figure visualizes the β_τ coefficients in Equation (3). The regression tables are available upon request. 2. The coefficients are presented in dots, with their 95% confidence intervals. 2003 is the base year. Observations in 2004 are dropped for some specifications because of the inconsistency in variable definitions in the 2004 economic census. (Nie et al. (2012) [37])

Table 1: Summary Statistics

Firms within 0-10 miles range from the closest CSR/CNR plant						Firms within 0-10 miles range from the closest CSR/CNR plant				
Before HSR technology transfer						After HSR technology transfer				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Utility Patents	34,285	0.101	0.857	0	75	90,813	0.488	4.329	0	371
Invention Patents	34,285	0.049	0.602	0	46	90,813	0.343	4.224	0	378
Total Patents	34,285	0.151	1.187	0	76	90,813	0.832	7.489	0	521
TFP(OP)	31,895	18.948	38.029	0.0003	1514.827	46,950	41.370	80.624	0.0004	4716.986
Revenue	33,467	106819.6	837472.9	1	5.33E+07	58,364	212707	1880206	1	9.32E+07
Firms within 10-20 miles range from the closest CSR/CNR plant						Firms within 10-20 miles range from the closest CSR/CNR plant				
Before HSR technology transfer						After HSR technology transfer				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Utility Patents	30,673	0.121	1.786	0	153	90,714	0.468	6.193	0	717
Invention Patents	30,673	0.070	2.237	0	261	90,714	0.448	9.676	0	1846
Total Patents	30,673	0.192	3.708	0	388	90,714	0.916	13.919	0	1946
TFP(OP)	28,630	22.850	66.892	0.0002	6230.663	47,830	43.048	92.367	0.0002	10406.64
Revenue	29,939	101018.7	765306.8	2	3.18E+07	58,313	166023	1751181	1	1.40E+08

Notes: The table is based on authors' calculation. Information on patents is collected from SIPO patent database; information on total factor productivity and revenue is from the annual industrial surveys conducted by the National Bureau of Statistics in China.

Table 2: Impact of Technology Transfer on Firms' Innovation Outcomes

	Panel A					
VARIABLES	lninvention	lnutility	lntotalpatent	lninvention	lnutility	lntotalpatent
Near*After	0.0182***	0.0262***	0.0346***	0.00994	0.0190*	0.0180
	(0.0055)	(0.0071)	(0.0087)	(0.0082)	(0.0105)	(0.0127)
County FE	Y	Y	Y	N	N	N
4 Digit Industry FE	Y	Y	Y	N	N	N
Firm FE	N	N	N	Y	Y	Y
Observations	129,202	129,202	129,202	126,618	126,618	126,618
R-squared	0.108	0.141	0.155	0.463	0.470	0.499
	Panel B					
	lninvention	lnutility	lntotalpatent	lninvention	lnutility	lntotalpatent
Distance*After	-0.0028***	-0.0037***	-0.0053***	-0.0018**	-0.0023**	-0.0031**
	(0.0006)	(0.0007)	(0.0009)	(0.0008)	(0.0011)	(0.0013)
County FE	Y	Y	Y	N	N	N
4 Digit Industry FE	Y	Y	Y	N	N	N
Firm FE	N	N	N	Y	Y	Y
Observations	129,202	129,202	129,202	126,618	126,618	126,618
R-squared	0.108	0.141	0.155	0.463	0.470	0.499

Notes:1. The table reports difference-in-differences estimation results from Equation 2. lntotalpatent is the log sum of patents granted in a firm for each year. lnutility is the log sum of utility-model patents. lninvention is the log sum of invention patents. Near is a dummy variable indicating whether a firm is within 10 miles from the closest CSR/CNR R&D centers. Distance is the geographic distance from a firm to the closest CSR/CNR R&D centers. After is a dummy indicating whether the year is after 2004 or not. 2. Robust standard errors clustered at firm level. 2. * 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 Firms' Innovation Outcomes by technological similarity

	Panel A: Firms with Similar (above-median) technological similarity to CSR/CNR firms						
VARIABLES	lninvention	lnutility	lntotalpatent		lninvention	lnutility	lntotalpatent
Near*After	0.0298**	0.0559***	0.0598***	Distance*After	-0.0028***	-0.0052***	-0.0062***
	(0.0121)	(0.0163)	(0.0192)		(0.0011)	(0.0017)	(0.0019)
Firm FE	Y	Y	Y		Y	Y	Y
Observations	66,187	66,187	66,187		66,187	66,187	66,187
R-squared	0.504	0.495	0.528		0.504	0.494	0.528
	Panel B: Firms with Dissimilar (below-median) technological similarity to CSR/CNR firms						
VARIABLES	lninvention	lnutility	lntotalpatent		lninvention	lnutility	lntotalpatent
Near*After	-0.0133	-0.0177	-0.0242	Distance*After	-0.0005	0.0007	0.000
	(0.0109)	(0.0116)	(0.0152)		(0.0011)	(0.0011)	(0.0015)
Firm FE	Y	Y	Y		Y	Y	Y
Observations	59,624	59,624	59,624		59,624	59,624	59,624
R-squared	0.437	0.460	0.483		0.437	0.460	0.483

Notes:1. The table reports difference-in-differences estimation results from Equation 2. lntotalpatent is the log sum of patents granted in a firm for each year. lnutility is the log sum of utility-model patents. lninvention is the log sum of invention patents. Near is a dummy variable indicating whether a firm is within 10 miles from the closest CSR/CNR R&D centers. After is a dummy indicating whether the year is after 2004 or not. 2. Robust standard errors clustered at firm level. 2. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 4: Technological similarity, Input-Output Linkage, and Firms' Innovation Outcomes

VARIABLES	lninvention			lnutility			lntotalpatent		
Near*After	0.0102	0.0099	0.0098	0.0144	0.0103	0.0105	0.0152	0.0112	0.0114
	(0.0085)	(0.0085)	(0.0085)	(0.0110)	(0.0109)	(0.0109)	(0.0131)	(0.0131)	(0.0131)
Near*After*IO linkage	0.0038		0.0017	0.0190***		-0.0042	0.0169***		-0.0053
	(0.0033)		(0.0042)	(0.0051)		(0.0061)	(0.0058)		(0.0069)
Near*After*Tech Similarity		0.0035	0.0025		0.0257***	0.0282***		0.0239***	0.0270***
		(0.0028)	(0.0035)		(0.0047)	(0.0058)		(0.0053)	(0.0065)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	130,831	130,914	130,823	130,831	130,914	130,823	130,831	130,914	130,823
R-squared	0.461	0.461	0.461	0.466	0.466	0.466	0.496	0.496	0.497

Notes:1. The table reports difference-in-differences estimation results from Equation 2 but controls for the triple interactions of the DID term with input output linkage and technological similarity. lntotalpatent is the log sum of patents granted in a firm for each year. lnutility is the log sum of utility-model patents. lninvention is the log sum of invention patents. Near is a dummy variable indicating whether a firm is within 10 miles from the closest CSR/CNR R&D centers. After is a dummy indicating whether the year is after 2004 or not. 2. Robust standard errors clustered at firm level. 2. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 5: Impact of Technology Transfer on Firms' Economic Outcomes

VARIABLES	lntfpop			
Near*After	0.0596**	0.0529*	0.0477*	0.0481*
	(0.0270)	(0.0278)	(0.0278)	(0.0278)
Near*After*IO linkage		0.0168*		-0.0117
		(0.0091)		(0.0143)
Near*After*Tech Similarity			0.0258***	0.0328***
			(0.0075)	(0.0118)
Firm FE	Y	Y	Y	Y
Observations	82,451	82,373	82,451	82,373
R-squared	0.975	0.975	0.975	0.975
VARIABLES	lntfp			
Near*After	0.0511**	0.0440*	0.0391	0.0393
	(0.0252)	(0.0260)	(0.0260)	(0.0260)
Near*After*IO linkage		0.0265***		-0.0018
		(0.0085)		(0.0136)
Near*After*Tech Similarity			0.0315***	0.0326***
			(0.0070)	(0.0111)
Firm FE	Y	Y	Y	Y
Observations	83,496	82,373	82,451	82,373
R-squared	0.993	0.993	0.993	0.993
VARIABLES	logrevenue			
Near*After	0.0399*	0.0259	0.0279	0.0263
	(0.0215)	(0.0219)	(0.0219)	(0.0219)
Near*After*IO linkage		0.0397***		0.0420***
		(0.0080)		(0.0121)
Near*After*Tech Similarity			0.0220***	-0.0028
			(0.0068)	(0.0103)
Firm FE	Y	Y	Y	Y
Observations	96,027	95,938	96,019	95,930
R-squared	0.998	0.998	0.998	0.998

Notes:1. The table reports the double difference results from Equation 2 (column 1) and controls for the triple interactions of the DID term with input output linkage and technological similarity (columns 2-4). lntfpop and lntfp are the two measures of TFP in log form calculated from ASIF database. logrevenue is the revenue of the firm in log form in each year calculated from ASIF database. Near is a dummy variable indicating whether a firm is within 10 miles from the closest CSR/CNR R&D centers. After is a dummy indicating whether the year is after 2004 or not. 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.

Appendices

A Aggregate Level Analysis using Patent Data

A.1 Identification strategy and main results

The main finding discussed in Section 5 suggests positive localized spillover of technology transfer, especially on firms whose technology is similar to the transferred technologies. In this section, we would like to further confirm the role of technological similarity using the whole universe of patents applied by not only firms, but also institutions (such as universities and research institutions) and individuals, instead of only focusing on firms. The baseline estimation strategy is a triple-difference specification of the form,

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

where we interact the technological similarity measure with the $HSRCity * After$ dummy (and exclude the patent classes directly affected by the technology transfer from the sample). Therefore β_1 is the main coefficient of interest. $LogPatent_{i,j,t}$ 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 3-digit technology class fixed effects. We also control for all three pairwise DD 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 results in Table B.3 indicate 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 approximately 2.9%. 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 technological 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.2 The Role of 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[18] 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 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 B.4 shows the estimation results in cities with and without relevant university patent

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

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).This finding is consistent with our previous evidence on the importance of technological 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. 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.

B Tables

Table B.1: Impact of Technology Transfer on Firms' Innovation Outcomes (Include CSR/CNR suppliers)

	Panel A: Full Sample		
VARIABLES	lninvention	lnutility	lntotalpatent
Near*After	0.0112	0.0184*	0.0190
	(0.00820)	(0.0105)	(0.0126)
Observations	128,123	128,123	128,123
R-squared	0.465	0.473	0.503
	Panel B: Firms with Similar Technology		
VARIABLES	lninvention	lnutility	lntotalpatent
Near*After	0.0306**	0.0558***	0.0602***
	(0.0120)	(0.0161)	(0.0190)
Observations	67,084	67,084	67,084
R-squared	0.503	0.498	0.531
	Panel C: Firms with Dissimilar Technology		
VARIABLES	lninvention	lnutility	lntotalpatent
Near*After	-0.0100	-0.0182	-0.0212
	(0.0115)	(0.0115)	(0.0155)
Observations	60,240	60,240	60,240
R-squared	0.443	0.459	0.485

Notes: 1. The table reports difference-in-differences estimation results from Equation 2. lntotalpatent is the log sum of patents granted in a firm for each year. lnutility is the log sum of utility-model patents. lninvention is the log sum of invention patents. Near is a dummy variable indicating whether a firm is within 10 miles from the closest CSR/CNR R&D centers. After is a dummy indicating whether the year is after 2004 or not. 2. Robust standard errors clustered at firm level. 2. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table B.2: Impact of Technology Transfer on Firms' Innovation Outcomes (Include CSR/CNR suppliers)

	Panel A: Full Sample		
VARIABLES	lninvention	lnutility	lntotalpatent
Distance*After	-0.0022***	-0.0027**	-0.0036***
	(0.0008)	(0.0011)	(0.0013)
Observations	128,123	128,123	128,123
R-squared	0.465	0.473	0.503
	Panel B: Firms with Similar Technology		
VARIABLES	lninvention	lnutility	lntotalpatent
Distance*After	-0.0036***	-0.0060***	-0.0072***
	(0.0012)	(0.0017)	(0.0020)
Observations	67,084	67,084	67,084
R-squared	0.504	0.498	0.531
	Panel C: Firms with Dissimilar Technology		
VARIABLES	lninvention	lnutility	lntotalpatent
Distance*After	-0.0005	0.0009	0.0000
	(0.0011)	(0.0011)	(0.0015)
Observations	60,240	60,240	60,240
R-squared	0.443	0.459	0.485

Notes:1. The table reports difference-in-differences estimation results from Equation 2. lntotalpatent is the log sum of patents granted in a firm for each year. lnutility is the log sum of utility-model patents. lninvention is the log sum of invention patents. Distance is a continuous variable measuring the straight-line distance from a firm to the closest CSR/CNR R&D centers. After is a dummy indicating whether the year is after 2004 or not. 2. Robust standard errors clustered at firm level. 2. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table B.3: technological similarity and Firms' Innovation Outcomes: Aggregate Level Analysis

	Full Sample			Exclude CSR/CNR/Certified Suppliers		
VARIABLES	lntotalpatent	lninvention	lnutility	lntotalpatent	lninvention	lnutility
ln(Similarity)*HSRcity*After	0.0291***	0.0069	0.0457***	0.0168*	0.0025	0.0347***
	(0.0083)	(0.0084)	(0.0113)	(0.0087)	(0.0084)	(0.0122)
Observations	1,265,248	1,265,248	1,265,248	1,265,248	1,265,248	1,265,248
R-squared	0.365	0.314	0.320	0.364	0.314	0.319
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. lntotalpatent is the log sum of patents granted within each IPC 4 digit category-city group for each year. lnutility is the log sum of utility-model patents. lninvention 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. 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 B.4: Spillover Effects in Cities With and Without Railway-related Research Universities

	Cities with university patents in railway before 2004					
VARIABLES	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
	Full Sample			Exclude CSR/CNR/Certified Suppliers		
HSR City*Tech*After	0.527***	0.492***	0.327***	0.171**	0.158**	0.160***
	(0.109)	(0.098)	(0.062)	(0.068)	(0.067)	(0.059)
Observations	508,272	508,272	508,272	508,272	508,272	508,272
R-squared	0.333	0.309	0.294	0.331	0.308	0.294
	Cities without university patents in railway before 2004					
	logallpatent	logutility	loginvention	logallpatent	logutility	loginvention
	Full Sample			Exclude CSR/CNR/Certified Suppliers		
HSR City*Tech*After	0.318***	0.303***	0.104**	0.007	0.008	0.038
	(0.052)	(0.053)	(0.047)	(0.067)	(0.065)	(0.046)
Observations	1,168,816	1,168,816	1,168,816	1,168,816	1,168,816	1,168,816
R-squared	0.220	0.208	0.138	0.220	0.208	0.138
City FE*YEAR FE	YES	YES	YES	YES	YES	YES
IPC4*YEAR FE	YES	YES	YES	YES	YES	YES
IPC3*HSR City*TREND	YES	YES	YES	YES	YES	YES
IPC3*HSR City*TREND$\hat{2}$	YES	YES	YES	YES	YES	YES

Notes:1. This table reports the results on spillovers of transferred technology in cities with and without universities specializing in HSR related technologies. The full sample (columns 1-3) includes all the patent applications while the restricted sample (columns 4-6) exclude patents applied by CSR/CNR firms and the direct suppliers of MoR. lntotalpatent is the log sum of patents granted within each IPC 4 digit category-city group for each year. lnutility is the log sum of utility-model patents. lninvention 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. 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.