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Diversification or specialization: Measuring the impact of high-speed rail connection on technological diversity in China

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ABSTRACT

Technological diversification and specialization have important roles in explaining volatility, innovation, income inequality, exports, and related concerns; however, the relationships between transportation improvement and technological diversification and specialization remains unexplored. Using Chinese city-level panel data, we investigate the impact of China's high-speed rail (HSR) connection on technological diversity using the difference-in-differences method and instrumental variable regressions. The results demonstrate that HSR connection leads to reductions in technological diversity, particularly in core cities, cities along the four longest HSR lines, and cities that were initially diversified. The findings indicate that HSR connection is conducive to technological specialization rather than diversification, offering new insights for understanding the relationship between transportation improvement and innovation and determining that HSR connection spurs intra-industry knowledge spillovers more than inter-industry knowledge spillovers.

Introduction

Diversification in a natural ecosystem refers to an increase in biodiversity. Similarly, diversification in an innovation ecosystem implies an increase in technological diversity, whereas specialization implies a decrease in technological diversity. A large body of literature has demonstrated that technological diversification is associated with a wide range of outcomes, including macroeconomic volatility (Koren & Tenreyro, 2013), firm financial and innovation performance (Choi & Lee, 2021; Kim et al., 2016; Pan et al., 2018; Wen & Zheng, 2020), innovation capability (Corradini & De Propris, 2015; Moaniba et al., 2019; Wang et al., 2016), regional resilience (Fusillo et al., 2022), and related positive outcomes. Conversely, other studies have shown that technological specialization has negative impacts on income inequality (Permana et al., 2018) and exports (Panda & Sharma, 2020; Vlčková & Stuchlíková, 2021). Despite the antecedents and moderating effects of technological diversification having also been widely investigated (Ceipek et al., 2019), the relationship between transportation improvement and technological diversification and specialization remains unexplored.

The aim of this study is to bridge the gap in knowledge regarding the effect of transportation improvement on technological diversification or specialization. To achieve this goal, the research determines Chinese city-level technological diversity using the Shannon–Wiener diversity index with a large-scale invention patent applications dataset. The difference-in-differences (DID) method and instrumental variable (IV) regressions are employed to estimate the impact of high-speed rail (HSR) connection on technological diversity. The IV for actual HSR connection is constructed using the 2004 planned HSR blueprint. We determine that HSR connection leads to a reduction in technological diversity, indicating a technological specialization effect rather than a diversification effect.

We also find that the technological specialization effect of HSR connection in core cities is greater than in peripheral cities. Core cities refer to large cities, provincial cities, subprovincial cities, provincial capitals, and cities located in eastern China. Our results also indicate that HSR connection leads to competing clusters in the cities along the four longest HSR lines, including the Beijing–Hong Kong line, the Shanghai–Kunming line, the Beijing–Shanghai line, and the Harbin–Dalian line. For cities with initially high technological diversity, HSR connection leads to a larger reduction in technological diversity.

The concept of knowledge spillovers is one of the main theoretical foundations referenced in existing literature for understanding how transportation improvement can affect innovation. As demonstrated by various works (Agrawal et al., 2017; Bottasso et al., 2022; Wang et al., 2018), road infrastructure spurs innovation by facilitating knowledge spillovers. Similar mechanisms regarding the impact of HSRs on

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innovation have also been confirmed in China (Dong et al., 2020; Hanley et al., 2022; Sun et al., 2021; Wang & Cai, 2020) and Japan (Hiroyasu et al., 2017; Komikado et al., 2021). In the context of this study, a reduction in technological diversity indicates that the innovation activities tend to be concentrated in some specific four-digit industries. The reduction in technological diversity resulting from HSR connection implies the acceleration of intra-industry knowledge spillovers more than inter-industry knowledge spillovers.

The contributions of this study are twofold. First, the results produce rigorous evidence that HSR connection reduces technological diversity. This finding implies that transportation improvement in China is conducive to technological specialization as opposed to technological diversification. To the best of our knowledge, no previous study has confirmed this conclusion. Second, the technological specialization effect of HSR connection implies that intra-industry knowledge spillovers are the reason behind HSR connection reducing technological diversity. As we mentioned above, the innovation literature has confirmed that HSR and road infrastructure have knowledge spillover effects on innovation. However, whether it is intra- or inter-industry spillovers remains unknown. This study reveals the new insight that intra-industry knowledge spillovers may dominate, as HSR connection leads to a reduction in technological diversity.

The remainder of this paper is organized as follows. Section 2 reviews the literature regarding the causes of technological diversification or specialization and the influence of HSR connection on innovation. Section 3 theoretically analyzes the relationship between HSR connection and technological diversification or specialization. Section 4 introduces the data, variables, and identification strategy. Section 5 reports the empirical results, and Section 6 concludes the findings.

Literature review

A substantial body of literature has investigated the causes of technological diversification. Ceipek et al. (2019) presented a detailed review, finding that researchers primarily focused on organization-level factors, whereas the role of regional context was rarely examined. Some new works have recently been introduced in this field. Santoalha (2019) investigated the impacts of cooperation within and between regions on technological diversification using OECD data. Chen (2019) found that environmental dynamism and environmental munificence had opposite effects on the technological diversification of Chinese listed firms. Castellacci et al. (2020) found that e-skill endowment fostered technological diversification in European regions, particularly for less developed regions and low levels of relatedness. Examining data from 182 countries, Catalán et al. (2020) found that scientific and technological cross-density has an important influence on technological diversification. Mewes and Broekel (2020) investigated the influence of research and development (R&D) subsidies on regional technological diversification, finding larger positive effects from joint R&D subsidized projects than noncollaborative projects.

In terms of the causes of technological specialization, some classic literature has discussed the impacts of innovation activities on international technological specialization (e.g. Alcorta & Peres, 1998; Malerba et al., 1997; Paci et al., 1997). In addition, a small amount of research has studied the influence of technological uncertainty and highly skilled migrants. Toh and Kim (2013) found that firms became more technologically specialized when confronting greater technological uncertainty in the US communications equipment industry. Caviggioli et al. (2020) demonstrated that highly skilled migrants are negatively correlated with the number of fields of technological specialization in European and US subregional geographical areas.

The relationship between HSR connection and technological innovation is a topic of increasing academic interest in China. Many studies have investigated the impact of HSR connection on innovation activities. For example, Gao and Zheng (2020) estimated the impacts of HSR connection on firm innovation in the Yangtze River Delta and the Pearl River Delta. Wang and Cai (2020) measured the impacts of HSR connection on the number of patents and collaborative innovation across cities. Dong et al. (2020) found that HSR connection promoted highly skilled teamwork by reducing cross-city commute times. Sun et al. (2021) examined the knowledge spillover effects of HSR connection. Hanley et al. (2022) investigated the impact of HSR connection on innovation collaboration at the city-pair level.

Overall, the influence of transportation improvement on technological diversification or specialization has been neglected in the existing literature; however, the relationship between HSR connection and innovation has aroused widespread research. Previous literature has provided generally consistent evidence that HSR connection has a positive effect on innovation, the primary theoretical foundation of which is knowledge spillover effects, including in forms of collaborative innovation, highly skilled teamwork, talent migration, and industrial agglomeration. It is essential to bridge the gap regarding the effect of HSR connection and technological diversification or specialization, in which determining the roles of knowledge spillovers is the key to investigating this problem.

Theoretical analyses

As a form of modern transport, one of the main advantages of HSR is speed, which reduces the travel time across cities. Thus, the construction of HSRs has an important role in resource reallocation, including the movement of human capital, goods, knowledge, and information between cities (Cheng et al., 2018; Dong et al., 2020; Zheng & Kahn, 2013). It has been proven that HSR connection is conducive to accelerating knowledge spillovers through highly skilled teamwork, industrial agglomeration, and collaborative innovation (Dong et al., 2020; Gao & Zheng, 2020; Hanley et al., 2022; Wang & Cai, 2020).

Knowledge spillovers may occur at intra- and inter-industry levels (Bernstein, 1988; Bernstein & Nadiri, 1988, 1989). These two forms of spillovers directly affect innovation activities, as knowledge spillovers are a prominent factor in promoting innovation (Dong et al., 2020; Gao & Zheng, 2020; Hiroyasu et al., 2017; Komikado et al., 2021; Sun et al., 2021; Wang & Cai, 2020). It is elementary that technologies will be concentrated in specific industries when intra-industry knowledge spillovers dominate. In contrast, technologies will be decentralized between industries when inter-industry knowledge spillovers dominate.

As illustrated by Fig. 1, the roadmap from HSR connection to technological diversification or specialization is clear. A technological diversification effect is evident when HSR connection promotes knowledge spillovers between industries, whereas a technological specialization effect is evident when HSR connection promotes knowledge spillovers within industries. Accordingly, a decrease in technological diversity should be apparent if HSR connection spurs intra-industry knowledge spillovers. Conversely, an increase in technological diversity should be apparent if HSR connection accelerates inter-industry knowledge spillovers.

Empirical design

Data

To investigate the impact of HSR connection on technological diversity in China, city-level panel data from 2004 to 2017 is collected. The cities in this study include four provincial and 15 subprovincial cities, 16 provincial capitals, and 249 ordinary prefecture-level cities. The data includes three parts. First, a city-level statistical dataset, obtained from China City Statistical Yearbooks. Price-relevant indicators are transformed into constant 2000 pricing using a province-level price index. The data for the province-level price

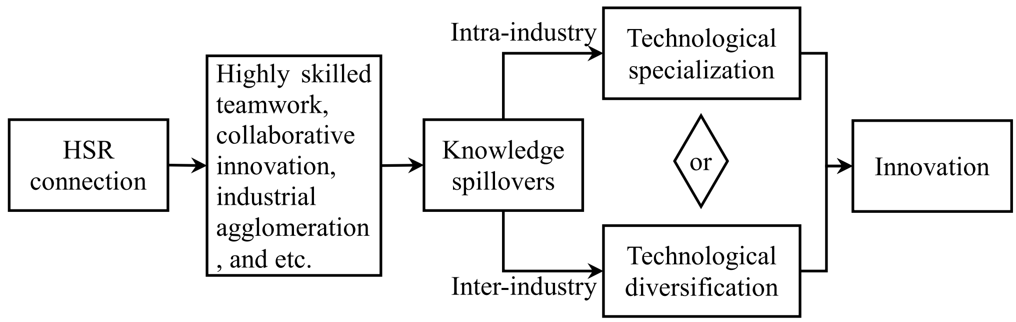

Fig. 1. The roadmap of HSR connection affecting innovation.

index are from China Statistical Yearbooks. Second, information regarding whether a city is connected to HSRs is from the Chinese Research Data Services Platform. Third, the invention patent applications dataset, including basic information for each patent, such as name, types, applicants, address, IPC code, application date, public announcement date, and other relevant details, which comes from the China National Intellectual Property Administration.

Variables

The dependent variable is technological diversity. Referencing previous research (Choi & Lee, 2021; Kim et al., 2016; Zabala-Iturriagagoitia et al., 2020), we measure it using the Shannon−Wiener diversity index, calculating technological diversity as follows:

$$TD_{it} = \sum_k p_{ikt} \ln\left(\frac{1}{p_{ikt}}\right) \quad (1)$$

where i, k, and t denotes cities, four-digit industries, and year, respectively. p_{ikt} is the share of four-digit industry k's patent stock to total patent stock in city i in year t.

The patent stock is calculated by applying the perpetual inventory method to the patent count of four-digit industries referencing Park and Park (2006). The patents of four-digit industries in each city and year are obtained by merging the four-digit industry codes and the invention patent applications dataset using the recently issued Table of Reference Relationship between International Patent Classification and National Economic Industry Classification (2018). A higher diversity index value indicates more even distribution of patents across four-digit industries, thus the higher the technological diversity.

One of the advantages of the Shannon−Wiener index as compared to other diversity indices, such as Simpson's index (Chiu et al., 2008; Garcia-Vega, 2006), is that it avoids the influence of scale effects. More specifically, the minimum of TD_{it} is zero if all patents are concentrated in a specific industry, and the maximum of TD_{it} is ln$N$ when patents are evenly distributed across four-digit industries, where N is the number of four-digit industries. However, the Simpson's diversity index is measured by subtracting the Herfindahl −Hirschman Index (HHI) from 1, where HHI will continuously decrease with the increase in the number of industries.

Fig. 2 presents the spatial distribution of technological diversity in China. Note that the number of red blocks increases over time. In addition, yellow blocks are always located in western China from 2004 to 2017, but red blocks are primarily located in eastern China. A lot of blue blocks in central China convert into red blocks. These results indicate that the technological diversity between four-digit industries is roughly increasing over time and cities with relatively high technological diversity are along HSR lines. However, whether HSR connection leads to a rise or decline in technological diversity remains unclear, because it requires further comparison of the trends between the HSR group and the non-HSR group.

The independent variable of interest is HSR connection. Referencing Gao and Zheng (2020), Chen (2021), and Hanley et al. (2022), HSR equals 1 if a city has an HSR station and 0 otherwise, which is described as follows:

$$HSR_{it} = \begin{cases} 1, \text{city } i \text{ has a HSR station in year } t; \\ 0, \text{city } i \text{ yet has no HSR station in year } t. \end{cases} \quad (2)$$

Fig. 3 presents the changes of technological diversity based on HSRs. The technological diversity (TD_{it}) in HSR cities is higher than that in non-HSR cities, but the upward trend in non-HSR cities is more rapid than that in HSR cities.

Finally, some city-level characteristics that may affect technological diversity and HSRs are considered. Referencing Gao et al. (2020), Wang and Cai (2020), Kuang et al. (2021), and Chen (2021), the control variables include (1) population size, which is measured by the residential population; (2) population density, which is measured by the residential population per square kilometer; (3) financial development, which is measured by the ratio of bank credit to GDP; (4) foreign investment, which is measured by the ratio of foreign direct investment to GDP; (5) public expenditure, which is measured by the ratio of government expenditure to GDP; (6) industry structure, which is measured by the share of tertiary industry value-added; (7) road infrastructure, which is measured by road length; and (8) industry scale, which is measured by the employment of manufacturing and the value-added of secondary industry. To avoid contemporaneous correlation and heteroskedasticity problems, a one-year lag for all control variables is taken, with logarithm form is taken for some variables.

The descriptive statistics of all variables are reported in Table 1.

Identification strategy

The DID method is a widely used tool for estimating the treatment effect of HSR connection (e.g. Chen, 2021; Gao et al., 2020; Gao & Zheng, 2020; Hanley et al., 2022; Hiroyasu et al., 2017; Wang & Cai, 2020). As with previous research, we take HSR connection as a quasi-natural experiment. The treated group is cities with at least one HSR station, and the control group is cities that have no HSR station from 2004 to 2017. The econometric model is as follows:

$$TD_{it} = \beta_0 + \beta_1 HSR_{it} + \mathbf{Z}'\gamma + \lambda_i + \mu_t + \varepsilon_{it} \quad (3)$$

where TD_{it} represents the technological diversity between four-digit industries in city i and year t, HSR_{it} represents HSR connection, $\mathbf{Z}$ represents the vector of control variables, λ_i and μ_t are city and year fixed effects, respectively, ε_{it} is random disturbances, and β_0, β_1, and $\boldsymbol{\gamma}$ are the coefficients to be estimated. A positive β_1 indicates that HSR connection leads to technological diversification, while a negative β_1 indicates that HSR connection leads to technological specialization.

A parallel trends assumption is a necessary precondition for causal inference using the DID method. Referencing Beck et al. (2010), Gao

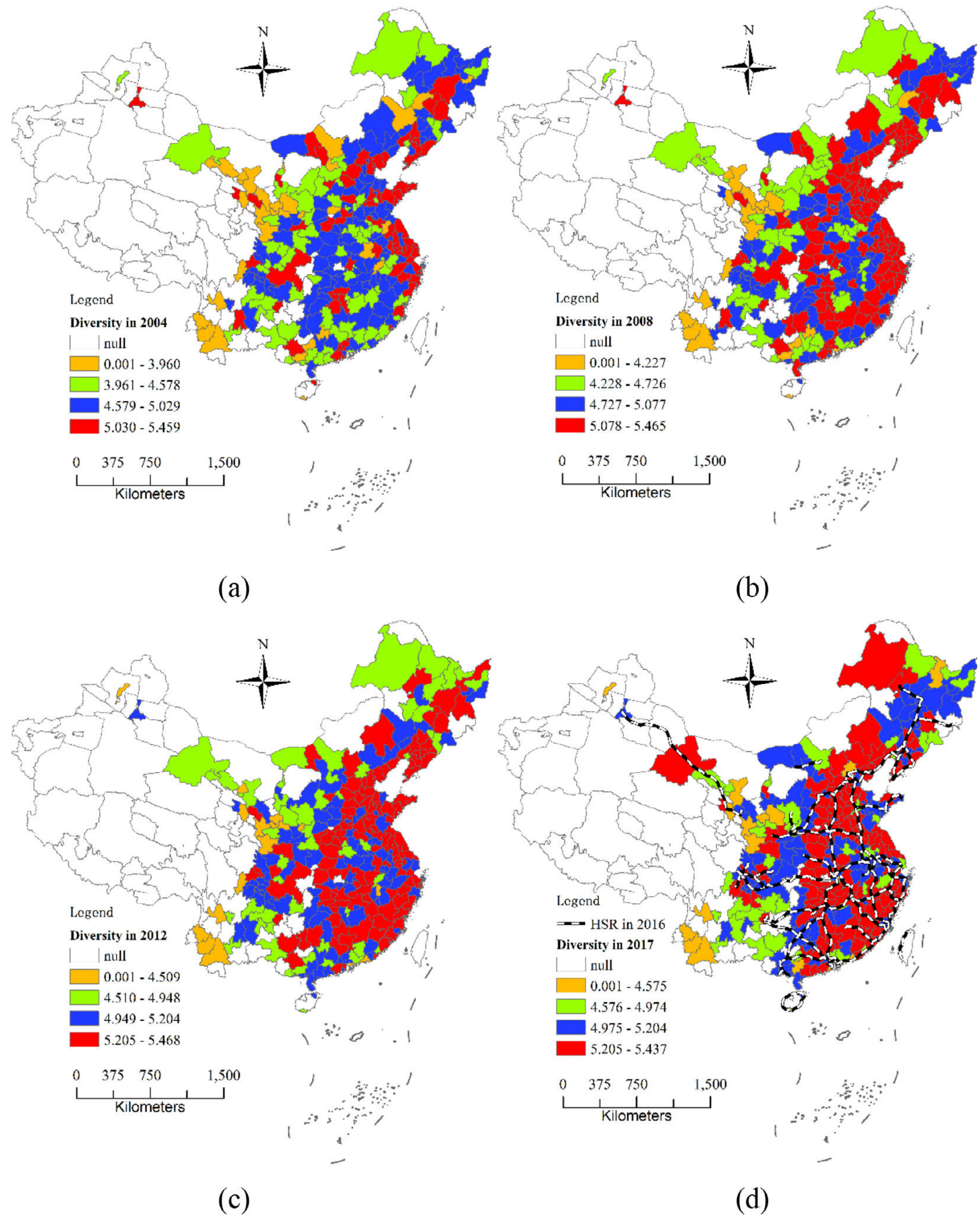

Fig. 2. The dynamics of technological diversity in China

Note: (a) is the map of technological diversity in 2004; (b) is the map of technological diversity in 2008; (c) is the map of technological diversity in 2012; (d) is the map of technological diversity in 2017, and the map of HSR lines in 2016 is from Li (2016).

et al. (2020), and Chen (2021), we test whether there are common pretrends between the HSR and non-HSR groups as follows:

$$TD_{it} = \beta_0 + \sum_{T} (\alpha_T \times HSR_{io+T}) + \mathbf{Z}'\gamma + \lambda_i + \mu_t + \varepsilon_{it} \tag{4}$$

where $T = (-11, \ldots, 9)$ denotes the years relative to the HSR station opening. If the coefficients α_T are statistically insignificant in the pre-intervention period ($T < 0$), then the common pretrends are satisfied.

To address the endogeneity issues caused by the nonrandom selection of HSR stations, we employ IV regressions to estimate the causal effect of HSR connection on technological diversity. The method includes two-stage regressions, which are as follows:

$$\text{Stage 1}: HSR_{it} = \beta_0 + \varphi_1 IV_{it} + \mathbf{Z}'\gamma + \lambda_i + \mu_t + \varepsilon_{it} \tag{5}$$

$$\text{Stage 2}: TD_{it} = \beta_0 + \phi_1 \widehat{HSR}_{it} + \mathbf{Z}'\gamma + \lambda_i + \mu_t + \varepsilon_{it} \tag{6}$$

where IV_{it} is the instrumental variables for HSR connection, and in the second stage, $\widehat{HSR}_{it}$ is the fitted value of HSR_{it} in the first stage.

Referencing previous research (Banerjee et al., 2020; Chen, 2021; Gao et al., 2020; Hornung, 2015), the straight-line strategy is used to construct the IV for HSR connection. In 2004, the HSR blueprint consisting of Four North–South Lines and Four East–West Lines was planned, in which 30 cities were selected as HSR nodes, which is the foundation for constructing the IVs for HSR connection. While the planned HSR blueprint is correlated with the actual HSR lines, it does not directly affect present outcomes; thus, a potential HSR

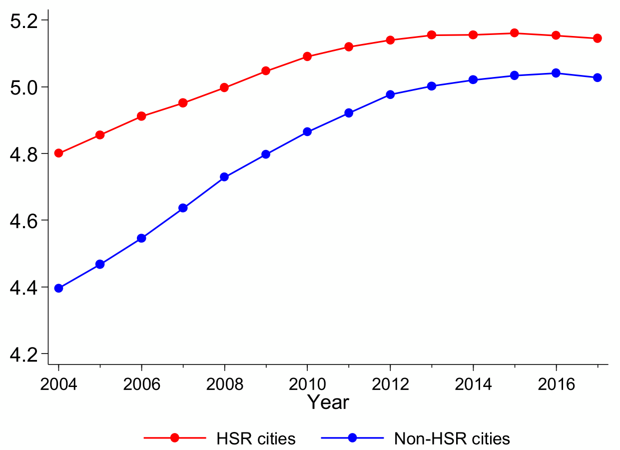

Fig. 3. The changes of technological diversity.

connection (PHSR) could be constructed by the planned HSR blueprint, taking 1 if a city is passed through by the planned HSR blueprint and 0 otherwise. The IV for HSR connection is as illustrated by Fig. 4.

To capture the time-variation of HSR connection, we construct a pseudo opening time using the actual opening time of the nearest planned route, where 1 is taken if both node cities of the nearest planned route have HSR stations and 0 otherwise. For example, the actual opening time of Changsha and Guiyang was in 2009 and 2014, respectively. The straight-line of Changsha–Guiyang passes through Loudi and Huaihua; thus, the pseudo opening time of the two cities is 2014.

Empirical results

Baseline regressions

Table 2 presents the baseline regression results. Column (1) is the regression result excluding the control variables in Eq. (4), revealing that the treatment effect of HSR connection on technological diversity is −0.118. Columns (2)–(4) present the regression results when adding the control variables stepwise. The treatment effect of HSR connection declines as more control variables are added into the model, but the coefficients of HSR connection remain statistically significant at the 1% level. As shown in column (4), the coefficient of HSR connection declines when further controlling for the share of tertiary industry value-added, road length, the number of manufacturing employees, and the value-added of secondary industry. The adjusted treatment effect of HSR connection on technological diversity is −0.063, indicating that HSR connections lead to a reduction in technological diversity in HSR cities.

The regression coefficients from Eq. (5) are presented in Fig. 5, revealing that the pretrends are not statistically significant at the 5% level. The results indicate that there are no systematic differences in technological diversity between HSR cities and non-HSR cities before connecting to HSRs. Meanwhile, technological diversity decreases annually after connecting to HSRs. The downward trend in coefficients means that the negative effect of HSR connections on technological diversity strengthens over time.

Overall, the baseline regression results indicate that HSR connection has a significant role in explaining the changes in technological diversity between HSR cities and non-HSR cities. Our results confirm the technological specialization effect of HSR connection. As argued by Caviggioli et al. (2020), specialty matching of highly skilled migrants is an important mechanism in explaining why migration leads to technological specialization. Accordingly, a possible explanation for our findings may be that HSR connection accelerates intra-industry knowledge spillovers, such as highly skilled teamwork, talent migration, and collaborative innovation.

To comprehensively validate the path in Fig. 1, we also estimate the impacts of HSR connection on innovation and knowledge spillovers. The results are presented in Table 3. Columns (1) and (2) are the regression results of changes in granted invention patents per capita and invention patent applications per capita based on HSR connection. Connecting to HSRs leads to a 0.230 increase in granted patents and 1.021 patent applications per 10,000 persons. Columns (3) and (4) report the result of changes in industrial agglomeration and changes in co-authored patent applications per capita based on HSR connection. The HHI of two-digit industry employment significantly increased by 0.007 and the number of co-authored patent applications per 10,000 persons significantly increased by 0.444. The

Table 1
Descriptive statistics.

Variable	Non-HSR group			HSR group			Difference [a]
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	
Technological diversity between four-digit industries	1302	4.818	0.435	2674	5.049	0.340	−0.230***
Technological diversity between two-digit industries	1302	2.976	0.291	2674	3.086	0.183	−0.110***
The number of granted invention patents per 10,000 persons	1302	0.180	0.381	2674	0.734	1.658	−0.554***
The number of invention patent applications per 10,000 persons	1302	0.739	1.416	2674	2.856	6.226	−2.117***
Industrial agglomeration measured by the HHI of two-digit industry employment	1302	0.160	0.056	2674	0.174	0.080	−0.014***
The number of co-authored invention patent applications per 10,000 persons	1302	0.290	0.534	2674	1.096	2.218	−0.806***
ln(The residential population), lagged 1 year	1302	5.568	0.693	2674	5.974	0.673	−0.406***
ln(The residential population per square kilometer), lagged 1 year	1302	5.158	0.934	2674	5.982	0.859	−0.824***
The ratio of bank credit to GDP, lagged 1 year	1302	0.720	0.359	2674	0.870	0.538	−0.151***
The ratio of foreign direct investment to GDP, lagged 1 year	1208	1.128	1.322	2630	2.585	2.603	−1.457***
The ratio of government expenditure to GDP, lagged 1 year	1302	19.424	11.616	2674	14.033	7.117	5.392***
Share of tertiary industry value-added, lagged 1 year	1302	0.347	0.077	2674	0.379	0.090	−0.032***
ln(Road length), lagged 1 year	1287	5.703	0.808	2655	6.320	0.999	−0.617***
ln(The number of manufacturing employees), lagged 1 year	1292	1.285	1.015	2656	2.234	1.147	−0.950***
ln(The value-added of secondary industry), lagged 1 year	1302	14.379	0.981	2674	15.127	1.076	−0.748***
ln(Increased market potential) (lnΔMP)	1302	0	0	2674	3.223	3.931	−3.223***
Technological concentration measured by HHI	1302	0.017	0.009	2674	0.015	0.006	0.003***
Potential HSR connection (PHSR)	1302	0.043	0.203	2674	0.571	0.495	−0.528***

Notes: [a] student's *t*-test on the difference of means between non-HSR group and HSR group.
*** indicates significance at 1%.

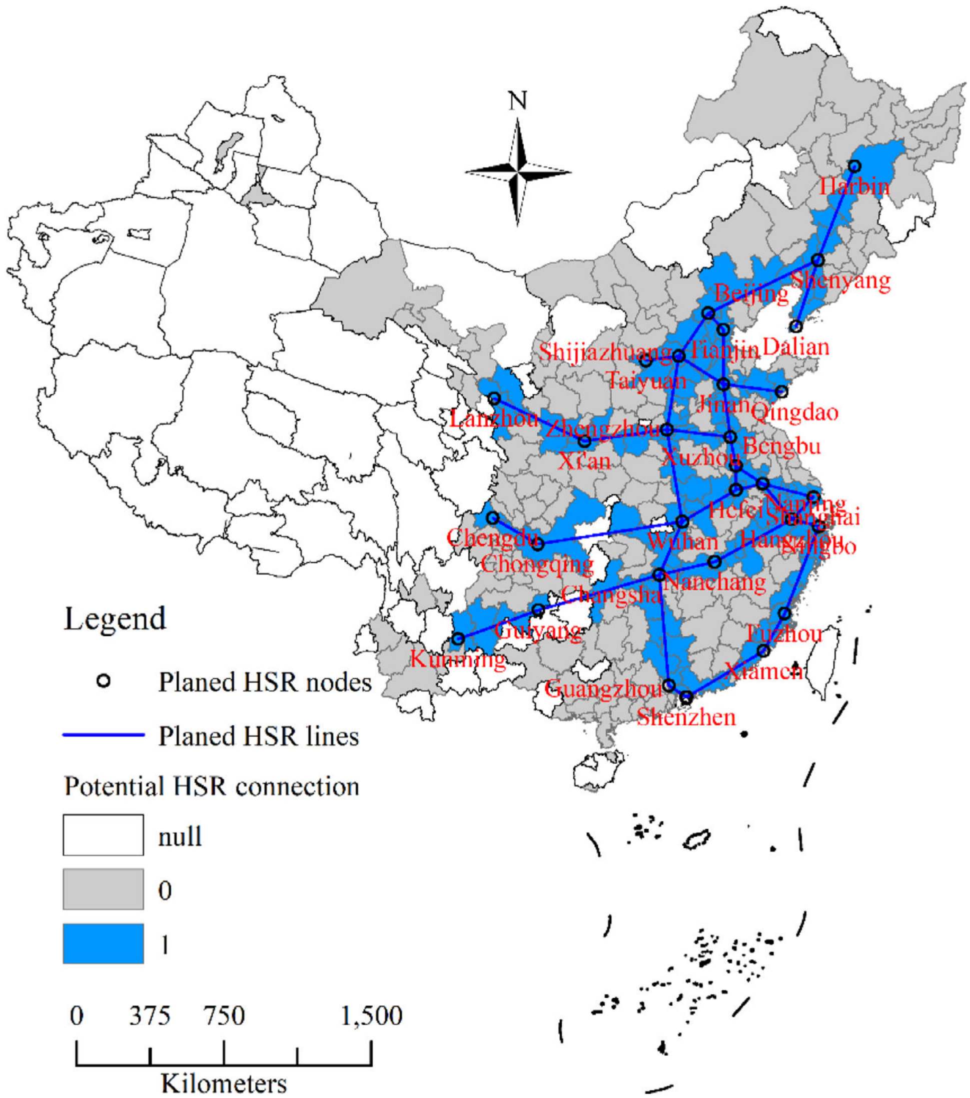

Fig. 4. The IV for HSR connection.

results of Table 3 validate that HSR connection has positive effects on innovation and knowledge spillovers.

Robustness check

The coefficient of HSR connection may be biased due to outlier samples and measurement errors. Table 4 reports various robustness check results. First, we exclude four provincial cities from the samples. As shown in column (1), the treatment effect of HSR connection on technological diversity is −0.059, which is very close to the coefficient in the baseline regressions. Second, we employ a market potential approach to estimate the impact of HSR connection on technological diversity. As shown in column (2), the effect of increased market potential caused by HSR connection on technological diversity is also statistically significant. Third, we measure the concentration of patent stock across four-digit industries by HHI. As shown in column (3), the treatment effect of HSR connection on technological concentration is statistically positive. Finally, we re-calculate the technological diversity by Shannon−Wiener diversity index using two-digit industry patent data, and column (4) shows that HSR connection significantly reduces technological diversity by −0.031. These robustness check results support the basic findings of baseline regressions.

Table 5 reports the IV regression results. The first-stage results in columns (1) and (3) show that our IVare highly correlated with HSR connection. The Kleibergen−Paap rk Wald F statistics for weak identification are greater than 10. The null hypothesis of weak IV is rejected. We also test the correlation between PHSR and technological diversity, and the coefficients of changes in technological diversity on PHSR in the preintervention period are statistically insignificant, indicating that the exclusion restriction is not violated. The results are not reported here, but available upon request.

Column (2) is the result when all cities participate in the regression, showing that the coefficient of HSR connection is greater than that in baseline regressions, but HSR connections overall have a statistically significant and negative effect on technological diversity. Column (4) is the results excluding the 30 node cities. The coefficient of HSR connection becomes smaller, but remains statistically significant and negative. Overall, the IV regression results indicate that connecting to HSRs has a causal effect on technological specialization for HSR cities. The IV regression results support the findings of our baseline regressions as well.

Heterogeneity

Does the impact of HSR connection on technological diversity differ between core and peripheral cities? To answer this question, we

Table 2
Baseline regression results.

	(1) Tech. diversity	(2) Tech. diversity	(3) Tech. diversity	(4) Tech. diversity
HSR connection	−0.118***	−0.117***	−0.083***	−0.063***
	(−5.863)	(−5.832)	(−4.439)	(−3.532)
ln(The residential population)		−0.179**	−0.158*	−0.228**
		(−2.074)	(−1.877)	(−2.485)
ln(The residential population per square kilometer)		0.158*	0.128	0.186**
		(1.780)	(1.502)	(2.043)
The ratio of bank credit to GDP			−0.057*	−0.003
			(−1.791)	(−0.132)
The ratio of foreign direct investment to GDP			0.005	0.005
			(0.932)	(1.109)
The ratio of government expenditure to GDP			0.010***	0.013***
			(3.593)	(4.329)
Share of tertiary industry value-added				0.523*
				(1.944)
ln(Road length)				0.006
				(0.220)
ln(The number of manufacturing employees)				−0.015
				(−0.674)
ln(The value-added of secondary industry)				0.348***
				(6.115)
Constant	5.005***	5.150***	5.092***	−0.318
	(920.087)	(15.528)	(15.827)	(−0.335)
Year FEs	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes
Observations	3976	3976	3838	3811
# of cities	284	284	284	283
Within R^2	0.039	0.042	0.079	0.158

Notes: the table report coefficients and robust clustered t-value from regression of changes in technological diversity between four-digit industries on HSR connection and changes in control variables.
* indicates significance at 10%.
** indicates significance at 5%.
*** indicates significance at 1%.

group cities by population size, administrative hierarchies, and geographical locations, presenting the results in Table 6.

Columns (1) and (2) show that connecting to HSRs exerts a greater reduction effect on technological diversity in large cities than small and medium-sized cities. The coefficient of HSR connection in large cities is −0.220 and statistically significant at the 1% level, but it is not significant in small and medium-sized cities.

Columns (3) and (4) present the regression results grouped by administrative hierarchies. In cities with high administrative hierarchies, which include provincial cities, subprovincial cities, and provincial capitals, the coefficient of HSR connection is −0.325 and statistically significant at the 1% level; however, the coefficient of HSR connection in ordinary prefecture-level cities is only −0.035, far less than the former.

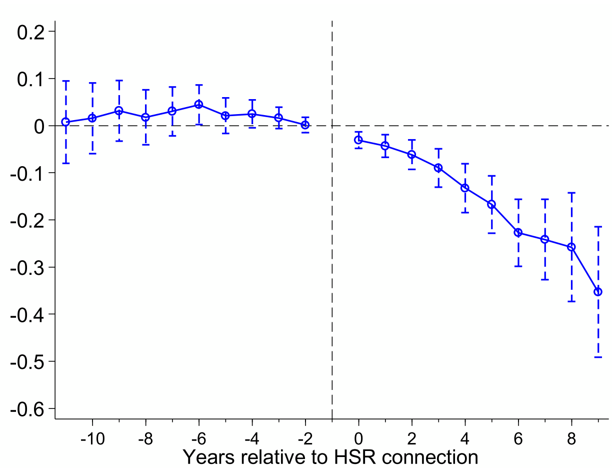

Fig. 5. The changes of technological diversity before and after connecting to HSRs.

Columns (5) and (6) are the regression results grouped by geographical location. The results show that HSR connection leads to a reduction in technological diversity by −0.121 in cities located in eastern China, but it only leads to a reduction by −0.050 in cities located in central and western China.

The results in Table 6 indicate that the technological specialization effect of HSR connection is asymmetric between core and peripheral cities. The asymmetric coefficients indicate that connecting to HSRs has greater backwash effect than spread effect. Specifically, HSR connection is conducive to intra-industry knowledge spillovers between core and peripheral cities, but the benefits core cities receive are greater. The possible explanations for this finding are twofold. First, the knowledge use capability of core cities is higher than that of peripheral cities, which results in core cities benefiting more, even if the mutual knowledge spillovers are symmetric. Second, HSR connection accelerates the movement of innovation resources (i.e., knowledge, skilled talent, and venture capital) from peripheral cities to core cities.

Does connecting to HSRs lead to competing clusters in the cities along HSR lines? To answer this question, we focus on the five longest HSR lines in China, including the Beijing–Hong Kong line, the Lanzhou–Xinjiang line, the Shanghai–Kunming line, the Beijing–Shanghai line, and the Harbin–Dalian line. Column (1) in Table 7 demonstrates that the technological specialization effect of HSR connection in the five longest lines is greater than that in other HSR cities. Specifically, as shown in columns (2)–(5), connecting to HSRs reduces the technological diversity in the cities along HSR lines, and the effect size is greater than the average (−0.063) in the four longest HSR lines. The Lanzhou–Xinjiang line, which is the longest HSR line located in western China, is an exception. The result is presented in column (6), in which the coefficient of HSR connection is statistically

Table 3
HSR-innovation nexus and knowledge spillovers.

	(1) Granted patents per capita	(2) Patent applications per capita	(3) Industrial agglomeration	(4) Co-authored patent applications per capita
HSR connection	0.230***	1.021***	0.007***	0.444***
	(3.427)	(3.519)	(2.741)	(4.743)
Constant	10.174***	20.920	0.115	6.712
	(2.605)	(1.326)	(0.879)	(1.318)
Control variables	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes
Observations	3811	3811	3811	3811
# of cities	283	283	283	283
Within R^2	0.141	0.126	0.174	0.165

Notes: the table reports coefficients and robust clustered t-value from regression of changes in the number of granted invention patents per 10,000 persons, changes in the number of invention patent applications per 10,000 persons, changes in the industrial agglomeration measured by the HHI of employment, and changes in the number of co-authored patent applications per 10,000 persons on HSR connection.
* indicates significance at 10%.
** indicates significance at 5%.
*** indicates significance at 1%.

Table 4
Robustness check results: outlier samples and measurement errors.

	(1) Provincial cities excluded	(2) Market potential approach	(3) Tech. concentration measured by HHI	(4) Tech. diversity between two-digital industries
HSR connection	−0.059***		0.001***	−0.031***
	(−3.298)		(2.854)	(−2.932)
ln(ΔMP)		−0.008***		
		(−3.445)		
Constant	−0.334	−0.330	0.151***	1.294**
	(−0.355)	(−0.346)	(4.629)	(2.308)
Control variables	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes
Observations	3755	3811	3811	3811
# of cities	279	283	283	283
Within R^2	0.156	0.158	0.111	0.053

Notes: columns (1)-(2) report coefficients and robust clustered t-value from regression of changes in technological diversity between four-digit industries on HSR connection or changes in increased market potential caused by HSR connection; 4 provincial cities (Beijing, Tianjin, Chongqing and Shanghai) excluded in column (1); the increased market potential caused by HSR connection is taken in column (2); columns (3) and (4) report coefficients and robust clustered t-value from regression of changes in technological concentration measured by HHI and changes in technological diversity between two-digit industries on HSR connection.
*indicates significance at 10%.
** indicates significance at 5%.
*** indicates significance at 1%.

Table 5
IV regression results.

	All sample		Node cities excluded	
	HSR	Tech. diversity	HSR	Tech. diversity
PHSR × Pseudo opening time	0.411***		0.381***	
	(13.007)		(11.053)	
HSR connection		−0.365***		−0.191***
		(−5.332)		(−2.601)
Constant	1.512		1.899*	
	(1.452)		(1.784)	
Control variables	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes
Observations	3811	3811	3391	3391
# of cities	283	283	253	253
Weak identification	169.177		122.164	
Within R^2	0.156		0.129	

Notes: columns (1) and (3) report coefficients and robust clustered t-value from first stage regression of HSR connection on instrument variable (PHSR × Pseudo opening time); columns (2) and (4) report coefficient and robust clustered t-value from second stage regression of changes in technological diversity between four-digit industries on the fitted HSR connection in first stage.
* indicates significance at 10%.
** indicates significance at 5%.
*** indicates significance at 1%.

Table 6
Heterogeneity by cities with different population size, administrative hierarchies and geographical locations.

	(1) Large cities	(2) Small and medium-sized cities	(3) Cities with high administrative hierarchies	(4) Cities with low administrative hierarchies	(5) Cities in eastern China	(6) Cities in central and western China
HSR connection	−0.220***	−0.004	−0.325***	−0.035*	−0.121***	−0.050**
	(−8.734)	(−0.190)	(−9.450)	(−1.842)	(−4.721)	(−2.000)
Constant	1.145	0.252	1.131	−0.502	0.056	0.852
	(0.961)	(0.274)	(0.839)	(−0.552)	(0.050)	(0.786)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2182	2820	1667	3335	2267	2735
# of cities	164	212	127	249	170	206
Within R^2	0.282	0.081	0.301	0.126	0.226	0.077

Notes: the table reports coefficients and robust clustered t-value from regression of changes in technological diversity between four-digit industries on HSR connection; large cities refer to the cities with urban residential population more than 1 million in 2014, otherwise small and medium-sized cities; cities with high administrative hierarchies refer to provincial cities, subprovincial cities and provincial capitals, and the cities with low administrative hierarchies refer to the ordinary prefecture-level cities; the geographic division of eastern China, central China and western China is according to China National Bureau of Statistics.
* indicates significance at 10%.
** indicates significance at 5%.
*** indicates significance at 1%.

Table 7
Heterogeneity by cities along different HSR lines.

	(1) Five longest lines	(2) Beijing-Hong Kong line	(3) Shanghai-Kunming line	(4) Beijing-Shanghai line	(5) Harbin-Dalian line	(6) Lanzhou-Xinjiang line
HSR connection	−0.025	−0.147***	−0.114***	−0.256***	−0.280***	−0.039
	(−1.073)	(−2.939)	(−2.654)	(−5.561)	(−5.877)	(−0.258)
HSR connection × Main lines	−0.086***					
	(−2.661)					
Constant	−0.308	1.080	1.252	1.247	1.446	1.602
	(−0.327)	(0.789)	(0.945)	(0.942)	(1.102)	(1.182)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3811	1555	1499	1457	1317	1259
# of cities	283	119	115	112	102	99
Within R^2	0.168	0.123	0.100	0.215	0.138	0.051

Notes: the table reports coefficients and robust clustered t-value from regression of changes in technological diversity between four-digit industries on HSR connection and its interaction term with main lines; the length of each HSR line comes from Li (2016); main lines is a dummy variable whether a city is along the five longest HSR lines.
*indicates significance at 10%.
**indicates significance at 5%.
*** indicates significance at 1%.

insignificant. Thus, the answer to the question is that HSR connection primarily strengthens technological specialization in the cities along the Beijing−Hong Kong line, the Shanghai−Kunming line, the Beijing −Shanghai line, and the Harbin−Dalian line.

Does HSR connection enhance the initial advantages of a city that is more technologically diverse? To answer this question, we test whether cities with higher or lower technological diversity in the initial year (2004) tend to be more technologically specialized after connecting to HSRs. As shown in columns (1) and (2) of Table 8, the coefficient of HSR connection in cities with low initial technological diversity is 0.036 and statistically insignificant, but is −0.189 and statistically significant in cities with high initial technological diversity. An interaction term is introduced in column (3), revealing that the coefficient of interaction of HSR connection with initial technological diversity is statistically significant and negative. The results of Table 8 indicate that HSR connection leads to more technological specialization in cities with initially high technological diversity, rather than initially specialized cities.

Concluding remarks

Through estimating the impact of HSR connection on technological diversity in China, this study investigates whether HSR connection leads to technological diversification or specialization. The technological diversity between four-digit industries for each city is measured using the Shannon−Wiener diversity index. The IV for HSR connection is constructed using a straight-line strategy. Both DID and IV regressions are employed to identify the causal effect of HSR connection on technological diversity. The main conclusions are as follows.

First, HSR connection is conducive to technological specialization rather than technological diversification. The empirical evidence applying the DID method and IV regressions confirms that connecting to HSRs leads to a reduction in technological diversity. The reduction in technological diversity resulting from HSR connection is about 0.063, on average. This finding may be explained by the knowledge spillover effect within industries. A similar finding was obtained by Caviggioli et al. (2020), and explained by specialty matching of highly skilled migrants.

Second, the technological specialization effects of HSR connection are heterogeneous between different city groups. We confirm that connecting to HSRs has a greater specialization effect on core cities than peripheral cities, and leads to competing clusters in the cities along the four longest HSR lines. In addition, HSR connection has a greater specialization effect in cities with a high initial technological diversity, rather than initially specialized cities; therefore, HSR connection has an important role in innovation geography and spatial knowledge spillovers.

Despite the acknowledged role of technological diversification and specialization in economic activities, its relationship with transportation improvement remained unexplored in existing literature.

Table 8
Heterogeneity by cities with different initial technological diversity.

	(1) Cities with low initial diversity	(2) Cities with high initial diversity	(3) Tech. diversity
HSR connection	0.036	−0.189***	1.802***
	(1.475)	(−8.792)	(11.476)
HSR connection × Initial diversity			−0.385***
			(−12.162)
Constant	1.006	1.302	1.323
	(1.018)	(1.214)	(1.533)
Control variables	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
City FEs	Yes	Yes	Yes
Observations	2483	2519	3537
# of cities	188	188	282
Within R^2	0.053	0.257	0.311

Notes: initial diversity is the technological diversity between four-digit industries of each city in 2004; cities with low initial diversity refer to the cities with the technological diversity in 2004 less than the median, otherwise cities with high initial diversity; column (3) is the result from regression of changes in technological diversity between four-digit industries on HSR connection and its interaction term with initial diversity, certainly, the samples in 2004 are dropped in this column.
*indicates significance at 10%.
**indicates significance at 5%.
*** indicates significance at 1%.

The study investigating whether HSR connection leads to technological diversification or technological specialization is associated with the literature regarding the HSR−innovation nexus, also offering fresh evidence that HSR connection affects innovation through intra-industry knowledge spillovers. In addition, the heterogeneous impacts of HSR connection on technological diversity between different city groups provide new insight for understanding the relationship between transportation improvement and innovation.

Authorship contribution statement

Jun Chen: Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing - Original Draft, Visualization, Project administration, Funding acquisition. *Guangzhen Guo*: Validation, Writing - Review & Editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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