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Impact of high-speed rail on the mismatch of labor and industry allocations: Evidence from Chinese cities in 2000-2019

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ABSTRACT

The uneven development of China can be reflected by the mismatch of labor and industry distributions (MLIS) in terms of spatial structure. Industries usually agglomerate in large cities where a strict household registration system causing high barriers with respect to population and labor entry. Infrastructures that reduce the cost of labor and technology mobility, as represented by high-speed rail (HSR), are possible improvement to regulate such distortions as the two agglomerated into opposite directions. This paper focuses on the impact of HSR on MLIS using a large panel dataset comprising 285 Chinese cities in 2000–2019. A difference-in-difference analysis is introduced to carried out empirical analyses. This paper finds that HSR can significantly mitigate the MLIS in prefecture level cities, but not in cities above prefecture level. The heterogeneous effects of HSR are then discussed with respect to industries and MLIS types. Further mechanism tests show that HSR's mitigating effect on MLIS comes from the employment effect and the innovation effect. Finally, policy recommendations are provided on HSR investment to improve China's uneven development from the perspective of synergy labor and industry distributions.

1. Introduction

The uneven development strategies are often adopted by developing countries at the start of their economic take-off, facing the shortage of both capitals and foreign exchanges. China followed a similar path at the beginning of her economic reform and opening-up to agglomerate industries in the coastal areas. However, this uneven strategy has inevitably led to the development imbalances among cities and regions, the spatial structure of which can be reflected as the mismatch between the distributions of industries and labor. The local labor supply in the industry agglomerated cities cannot adequately respond to their labor demand, thus requiring labor supply from other cities to fill the gap. Such mismatch reflects unequal opportunities for economic development as the labor forces facing higher unemployment risks in cities other than the industry agglomerated ones. At the same time, such mismatch results in a loss of overall efficiency, as factors like labor forces need to migrate over long distances from cities with lower industrial agglomeration to the higher ones.

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The overall efficiency loss is further exacerbated by the distortions caused by the policies like the household registration system. China's city size and industrial agglomeration go in the same direction, in other words, industries are prioritized agglomerated in large cities, followed by small and medium-sized cities. However, household registration barriers increase with the size of the city (An et al., 2022), which result in the agglomeration of population and labor at odds with the size of the city and thereby goes in the opposite direction of industrial agglomeration. Such barriers cause industrial agglomeration and labor agglomeration in the opposite direction, resulting in factor allocation distortion. This distortion can lead to widening development imbalances with exacerbated loss of efficiency in special allocation of factors.

Infrastructures have been recognized as a tool that can regulate such distortions in the New Growth Theory, thus being expected to mitigate the costs of labor migration towards industry agglomerated cities and promote balanced development. High-speed rail (HSR) project is one of such infrastructures in China dedicated to improving the efficiency of population and technology communication by building an efficient network to connect the urban nodes across the country. China has built the longest and largest HSR network worldwide, with a total length of over 40,000 km by the end of 2021, accounting for more than two-thirds of the world's total.[1] China is ambitiously planning to expand the network to 70,000 kilometers by 2035.[2] This has led to extensive discussions on the evaluation of HSR's economic benefits, especially with regard to economic development, industrial agglomeration, population agglomeration and labor migration (Yao et al., 2020).

Although the economic contributions of HSR are commonly recognized, some studies have pointed out that HSR may produce a siphoning effect leading to the deprivation of factors like labor forces in developing cities by developed cities (Deng et al., 2019) thus forming a clustering shadow detrimental to the development of the former and widening the development gap between poor and prosperous cities (Diao, 2018). The pressures of the uneven development are magnified today as China faces the aging and negative population growth issues (Bairoliya & Miller, 2021; Zhan et al., 2021). In 2020, the proportion of persons over 65 in the total population was 13.50% compared to 11.90% in 2010, while the natural population growth rate had fallen to only 0.15% compared to 0.48% in 2010.[3] This makes local governments increasingly competitive for the population resources, particularly for the working age. As a result, concern about HSR's potential impacts on labor loss has attracted the attention of policy makers and academic researchers.

A separate discussion on HSR's effect on the agglomeration of industry or labor may lead to entirely different conclusions. The localized improvement brought about by HSR may lead to a global loss of efficiency when HSR singularly promotes one of these agglomeration but does not have a corresponding effect on the other. This paper studies the impact of HSR on China's uneven development from the perspective of synchronized agglomerations of industries and labor. Cai and Zhang (2012) propose a new perspective on this topic, which is to compare the degree of mismatch between the share of industry and the share of labor. A larger mismatch implies a higher development imbalance in China, which leads to labor underemployment and inefficient allocation of industries and labor forces. Drawing on this research, this paper studies the impact of HSR on the mismatch of labor and industry shares (MLIS) at city- and industry- levels. On this basis human capital differences and heterogeneity treatment effects are further discussed. A series of robustness checks are introduced to support findings including a pre-trend test, two placebo tests, the retest with the replacement of explanatory variables and a PSM-DID analysis.

The main findings are as follows: (1) HSR is conducive to reducing MLIS in the prefecture level cities. (2) The role of HSR is heterogeneous across industries and types of MLIS. (3) The mechanisms of HSR's effect on MLIS include the employment effect and the innovation effect. These findings disapprove the concern that HSR could decrease labor forces or increase MLIS. These findings can help the local and central governments to optimize the HSR investment decisions based on industrial structure and labor agglomeration status thus balancing China's regional development. Considering that the uneven strategy is commonly adopted in developing countries, the uneven development and the problems it has brought about that China has experienced can also be relevant to other developing countries when achieving economic take-off.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature and developing theoretical mechanism hypotheses. Section 3 introduces a theoretical framework to study the impact of HSR on MLIS and uses a time-varying DID model to carry out empirical analyses. Two mechanisms are discussed in Section 4, namely the employment effect and the innovation effect. Section 5 loosens the assumption of homogeneous labor by taking into account the role of higher education. An event study is also used to test the pre-trend of dependent variables, a prerequisite of the DID design. Four kinds of robustness tests are presented in Section 6, namely the DID estimators with heterogeneous treatment effects, two placebo tests and the retest using the space-time compression variable to measure the role of HSR. Section 7 concludes with policy implications.

2. Literature review

Infrastructure investments are important productive government expenditures (Arrow & Kurz, 1970; Barro, 1990; Keynes, 1973), which are widely supported to promote economic development (Barro & Sala-i-Martin, 1992; Shioji, 2001) by enhancing technology spillovers (Barro & Sala-i-Martin, 2003), increasing specialization(Bougheas et al., 2000), and facilitating growth (Duggal et al., 1999; Finn, 1993). China's HSR is one of these infrastructures dedicated to building connections between the country's major cities and other

[1] Sources: People.cn, high-speed railway mileage doubled in five years (*in Chinese*). URL:cpc.people.com.cn/n1/2021/0131/c64387–3201 7825.html.

[2] Sources: China Railway, Outline of Powerful Nation Railway Advance Planning in the New Era (*in Chinese*). URL:www.china-railway.com.cn/xwzx/rdzt/ghgy/gyqw/202008/t20200812_107636.html.

[3] Sources: National Bureau of Statistics, the Seventh National Census Bulletin. URL:www.stats.gov.cn/tjsj/tjgb/rkpcgb/.

cities along the railway (Fang et al., 2023; Liu et al., 2021; Yao et al., 2019b, 2019a, 2022). The impact of HSR on China's industrial agglomeration has gained wide discussion (Tian et al., 2023; Zhou & Zhang, 2021). China's uneven development and household registration system make the allocations of industries and labor forces inadequate. A labor force faces the barriers of spatial distances and household registration systems when migrating from her place of birth to developed cities where industries congregate. HSR is expected to potentially reduce rather than increase regional development disparities, which is a critical requirement for China to reach her ambitious goal of high-quality sustainable economic development in the coming decades. There are considerable studies interested in assessing the economic benefits of HSR. In terms of the topic of this paper, the relevant literatures are those discussing the impact of HSR on labor and industry agglomerations and the urban development in China.

On the one hand, one determinant of MLIS is a city' labor share. Existing research on the impact of HSR on population and labor agglomeration has produced two different perspectives on whether HSR benefits or harms the small cities after its operation. Some studies argues that HSR produces a significant siphoning effect or agglomeration shadow, that is, it accelerates the loss of labor and population in small and medium-sized cities (Cao et al., 2013; Niu et al., 2021). Feng et al. (2023) says that HSR significantly agglomerates China's high-skilled labor forces into the eastern region, while the northeastern and central-western regions face the risk of regional brain drain. Deng et al. (2019) finds that the population migration accelerated by HSR has significant negative impacts on shrinking cities characterized by persistent population decreases. In addition, Dong et al. (2021) find that China's HSR significantly promotes industry agglomeration, but has a non-significant positive effect on population agglomeration.

However, there is also literature that points to the positive contribution of transportation infrastructure to population and labor agglomeration. Wang et al. (2019) point out that HSR inhibits long-term population migration using the panel data set of 26 cities in China's Yangtze River Delta urban agglomeration, in other words it promotes the population to stay in their hometowns (Heuermann & Schmieder, 2019), which is conducive for the developing small cities avoiding their population and labor forces being siphoned. Reverse urbanization, whereby firms and production activities move to the periphery of large cities, can contribute to more even distributions of labor and industry (Yin et al., 2015). Han et al. (2023) finds that HSR significantly promotes the agglomeration of population in counties using a panel data set comprising 1838 Chinese counties in 2003–2018, and the mechanism that generates this positive effect comes from labor mobility. Lin (2017) supports that HSR can increase urban employment by expanding market access. The debate on the positive and negative effects of HSR on population and labor agglomerations has not yet drawn a unanimous view, and further research on this topic can provide more empirical evidences. Accordingly, this paper proposes the following mechanism hypothesis:

H1: Employment effect is one of the mechanisms by which HSR affects MLIS.

On the other hand, another determinant of MLIS is a city' GDP share. Technological progress is widely regarded as an important contributor of GDP growth, and transportation infrastructure is thought to be conducive to knowledge creation and diffusion by increasing opportunities for face-to-face cooperation. This role of high-speed rail has gained attention as a new transportation infrastructure that is particularly capable of reducing travel times between cities. Dong et al. (2020) suggest that researchers in China's second-tier cities become more efficient with HSR operation, and their collaborations with scientists in big cities increase the quantity and quality of their research, which accelerates the generation and dissemination of innovations. Wang et al. (2022) carry out empirical studies using patent data and find that HSR played a significant and positive role in stimulating the intensity of collaborative activities in technological innovation. Gao and Zheng (2020) conduct an innovation survey on manufacturing firms in China's Yangtze and Pearl River Deltas and empirically find that HSR operation promotes firms' innovations in peripheral regions, which works more effectively in the Yangtze River Delta and increases over time. Li et al. (2023) argue that HSR facilitates the mobility of high skilled labors and promotes the growth of innovation output, which helps cities to become more economically resilient. Accordingly, this paper proposes the following hypothesis:

H2: HSR can contribute to GDP growth and thus have an impact on MLIS by promoting innovation effects.

To sum up, there are many discussions in existing studies about the impact of HSR on industry or labor agglomeration, which have not drawn unanimous conclusions. However, the directions of industry agglomeration and labor agglomeration might be inconsistent or even opposite due to the distortion caused by the household registration system, that is, the cities with higher industrial agglomeration tend to have stricter restrictions on population and labor agglomeration. This non-synergy makes HSR may exacerbate China's global imbalances and overall efficiency losses if HSR single-handedly promotes the industry or labor agglomeration without having a correspondingly effective impact on the other, although it may provide localized improvements. The impact of HSR on the synchronized agglomerations of labor and industry has not yet been fully studied, which is precisely the focus of this paper.

3. Analyses on HSR and MLIS

3.1. Set-up

Referencing Krugman (1991a), this paper introduces a simplified two-city model, where the economic system is supposed to consist of two cities, i.e., City M and City N. A representative labor force in City M can consume tradeable goods and non-tradeable housing by allocating her own income. For simplicity, the subscript t indicating year is omitted. The total output Y and the total labor force L are the sum of the output and labor forces in each of the two cities:

$$Y = Y_M + Y_N, L = L_M + L_N \tag{1}$$

Labor is assumed to be homogeneous. Then, per labor GDP (y) of the economic system is:

$$y = Y/L = (Y_M/L_M)(L_M/L) + (Y_N/L_N)(L_N/L) \tag{2}$$

Define per labor GDP as y_i=Y_i/L_i (i = M,N), the GDP share as s_i=Y_i/Y (i = M,N), and the labor share as q_i=L_i/L (i = M,N). Clearly, s_M+s_N= 1, q_M+q_N= 1. Then Eq. (2) can be rewritten as:

$$y = y_M s_M + y_N s_N \tag{3}$$

China's uneven regional development has resulted in uneven labor productivity. This paper assumes the initial labor and industry distributions as that city N has lower labor productivity than city M. An Edgeworth Box[4] is introduced to display such spatial distributions (Fig. 1). Any point in the 45° line can be treated as an optimum distribution that there is no imbalance in the system. Clearly, all points on the 45° line satisfy s_M=q_M and s_N=q_N. In this equilibrium, a city's share of output in a given industry is equal to its share of labor in that industry. It is important to note that the shares of different industries within a city are not required to be equal. This ensures a city can specialize in a typical industry, with all labor employed in that industry.

However, Chinese cities walk away from the equilibrium in the 45° line under China's uneven development pattern. Define the growth rate of the systems per labor GDP as γ^{y}=$\dot{y}/y$, then:

$$\begin{aligned}\gamma^{y} &= \frac{dy/dt}{y} = \frac{(\dot{y}_M q_M + y_M \dot{q}_M) + (\dot{y}_N q_N + y_N \dot{q}_N)}{y} \\ &= \left(\frac{\dot{y}_M}{y_M}\right)\left(\frac{y_M}{y}\right)\left(\frac{L_M}{L}\right) + \left(\frac{\dot{y}_N}{y_N}\right)\left(\frac{y_N}{y}\right)\left(\frac{L_N}{L}\right) + \left(\frac{y_M}{y}\right)\left(\frac{\dot{q}_M}{q_M}\right) q_M + \left(\frac{y_N}{y}\right)\left(\frac{\dot{q}_N}{q_N}\right) q_N \\ &= \frac{Y_M}{Y}\gamma^{y}{}_M + \frac{Y_N}{Y}\gamma^{y}{}_N + \frac{Y_M}{Y}\gamma^{q}{}_M + \frac{Y_N}{Y}\gamma^{q}{}_N \\ &= s_M\gamma^{y}{}_M + s_N\gamma^{y}{}_N + s_M\gamma^{q}{}_M + s_N\gamma^{s}{}_N\end{aligned} \tag{4}$$

where γ^{y}_{i} and γ^{q}_{i} (i = M,N) denote the growth rates of per labor GDP and the labor share. Based on Eq. (4), the growth rate of per labor GDP can be promoted by two components: (1) the growth rates of per labor GDP in each city, and (2) contribution of labor allocation G= $s_M\gamma^{q}_{M} + s_N\gamma^{q}_{N}$.

The first order condition of the left- and right-hand sides of the equation q_M+q_N= 1 with respect to t yields:

$$\gamma^{q}{}_M q_M + \gamma^{q}{}_N q_N = 0 \Rightarrow \gamma^{q}{}_N = -\frac{q_M}{q_N}\gamma^{q}{}_M \tag{5}$$

Combining Eqs. (4) and (5), G can be rewritten as:

$$G = \gamma^{q}{}_M\left(\frac{s_M}{q_M} - \frac{s_N}{q_N}\right) \tag{6}$$

For the social planer, labor can be reallocated to increase per labor GDP growth of the economic system as long as $G>$ 0. It is only when s_N=q_N and s_M=q_M that $q_N/s_N \equiv q_M/s_M$, i.e. $G \equiv 0$. In other words, the most ideal labor allocation condition is represented by the 45° line when each city's industry share equals it labor share. However, there is in fact a mismatch between the distributions of labor and industry under China's uneven development. China's HSR can significantly reduce the time cost of labor mobility and thus potentially become an improvement to reconcile this mismatch. The following empirical analyses focuses on this issue.

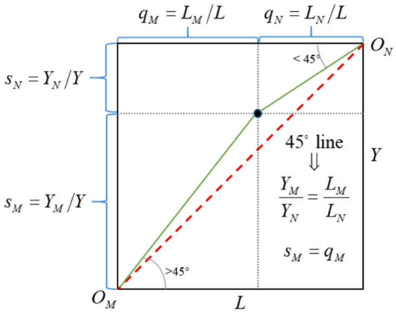
3.2. MLIS variable and empirical models

Cai and Zhang (2012) suggest that the mismatch of industry and labor distributions can provide a new perspective to measure the uneven development of China. Following this idea, this paper defines MLIS in each industry as the difference between the output share (the share of city's GDP with respect to the samples' total) and labor share (the share of a city's labor forces with respect to the samples' total).

$$\begin{aligned} &MLIS_{ijt} = s_{ijt} - q_{ijt} \\ &s_{ijt} = \frac{Y_{ijt}}{\sum_i Y_{ijt}}, q_{ijt} = \frac{L_{ijt}}{\sum_i L_{ijt}}\end{aligned} \tag{7}$$

where $MLIS_{ijt}$ denotes the absolute value of the difference between city i's labor share and output share in sector j and year t. s_{ijt} denotes the output share, calculated by dividing the GDP in sector j and city i into the GDP in sector j in all sample cities. q_{ijt} denotes city i's labor share, calculated by dividing the employees in sector j and city i into the employees in sector j in all sample cities. Specifically, the employees used in this paper are those employed in urban legal entity and private sector as well as the self-employed persons in urban areas. A direct study on the values of industrial outputs or the number of employees would ignore the endowment differences and

[4] The Edgeworth box was first introduced by Edgeworth and Pareto developed it into the boxed form, and it is one of the foundational theories of the economics of welfare which is often used in graphical displays of general equilibrium. Therefore, this paper introduces the Edgeworth box to display the distributions of output and labor.



Note: Labor force allocation starts at point O_M in City *M*, while starts at O_N in City *N*.

Fig. 1. An Edgeworth box showing the spatial distributions of labor and industry.

comparative advantages in different cities with different industry structures. Therefore, this paper adopts structural indicators to compare the differences in the shares of output and labor. It is obvious that MLIS can be rewritten as labor productivity if the minus sign in the formula is replaced by the division sign and the denominator and numerator are exchanged. The MLIS shall be reduced as long as the labor productivity of each industry converges among the cites, even if the industrial structure and resource endowment. This will not be affected by different resource endowments and industrial structures because the reduction of MLIS does not mean that each place has to have the same industrial structures.

A time-varying DID model is used to study the impact of HSR on MLIS as:

$$MLIS_{ijt} = \beta_0 + \beta_1 hsr_{it} + \beta_2 \ln w_{i,t0} \times year_t + \beta_3 \ln h_{i,t0} \times year_t + \beta_4 \ln gov_{it} + \beta_5 \ln med_{it} + \beta_6 \ln edu_{it} + \beta_7 \ln avi_{i,t-1} + \beta_8 \ln road_{it} + city_i + year_t + \varepsilon_{it} \quad (8)$$

where hsr_{it} is a DID term equals 1 when city *i* is connected by HSR in year *t,* and 0 otherwise. Considering that HSR' effect may take some time to manifest, hsr_{it} takes the value of 1 when HSR is put into operation in the first half of year *t*; otherwise, $hsr_{it}= 0$ and $hsr_{i,t+1} = 0$ when HSR is put into operation in the second half of year *t.*

With reference to Ahlfeldt and Feddersen (2018), Qin (2017) and Yao et al. (2020), this paper controls some variables that are commonly used. Specifically, w_{it} denotes individual income, measured by the per capita urban disposable income.[5] h_{it} denotes house prices to control the impact of house prices on labor forces. Some studies point out that HSR can have an impact on individual incomes and house prices. This paper uses the base year variables $w_{i,t0}$ and $h_{i,t0}$ interacting with year dummies, i.e. $w_{i,t0} \times year_t$ and $h_{i,t0} \times year_t$, as the control variables to avoid bias in estimation.[6] gov_{it} controls for government intervention, represented by government expenditures except those on science, technology and education. med_{it} denotes the number of hospital beds per capita, representing the local healthcare conditions. edu_{it} controls educational conditions and human capital stocks, measured by students enrolled in higher education. $road_{it}$ and avi_{it} control the impact of other transportation infrastructures, where the former measured by the surface areas of city roads and the latter measured by a dummy variable which equals to 1 when city *i* has at least one airport and 0 otherwise. $city_i$ and $year_t$ control the city- and time- fixed effects (FE), respectively. The estimation errors cluster at city level.

In addition, this paper further uses the space-time compression effect variable $\ln td_{it}$ as a proxy of the dummy variable hsr_{it} to denote the role of HSR for robustness checks referring to Yao et al. (2020). And this paper also tests two mechanisms of HSR, i.e. the employment effect and the innovation effect by introducing the mechanism variables including the number of employees in each industry and the number of patents filed by each city. These variables will be used in Sections 4–6.

3.3. Variables and data

The sixth and so far the last train's speed increase of the traditional rail system in China was implemented in April 2007. The operating speeds of different types of traditional rail transport have remained relatively stable ever since then. HSR has been in operation and a national HSR network has been progressively built since 2008. Considering the panel data availability and the need for sufficient pre-HSR time period, this paper uses a large panel dataset comprising 285 Chinese cities at and above the prefecture level in 2000–2019 to conduct empirical analyses. According to the calculation rule proposed in Eq. (8), this paper counts the numbers of cities operate HSR for the first time in each year during the sample period as shown in Fig. 2.

According to China's standards, the HSR lines are the railways with a design speed of no less than 350 km/h. The Beijing-Tianjin Intercity Railway launching in 2008 is the first HSR that meets this standard. In fact, China's first experimental HSR line is the

[5] The data on per capita wages are available in the Yearbooks but not used as the measure of incomes. This is because the data on wages at city level are those of employees working in state-owned, urban, joint-stock, and foreign-invested establishments. Whereas those employed in private and township enterprises and urban self-employed workers are excluded. Therefore, this paper uses the per capita urban disposable income to estimate individual income. Sources: National Bureau of Statistics of China, http://www.stats.gov.cn/ztjc/ztsj/sjzsj/sjz2006/200801/t20080111_61160.html.

[6] Many thanks to the anonymous reviewer for this suggestion.

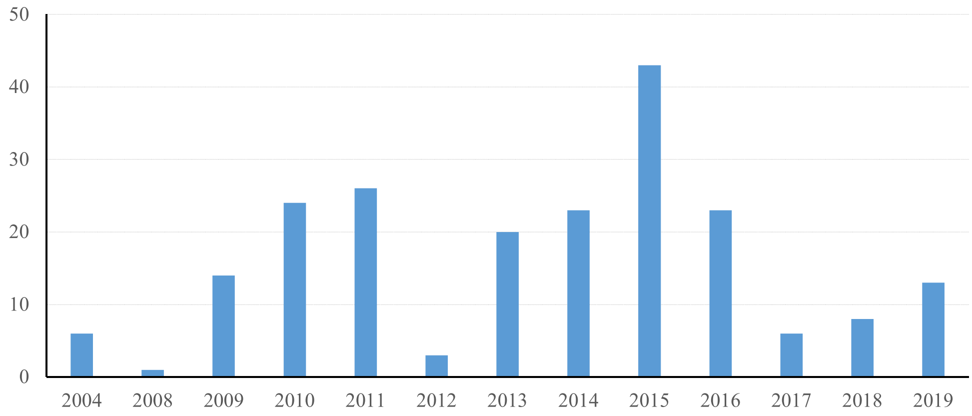


Fig. 2. The numbers of cities operate HSR for the first time in each year.

Qinhuangdao-Shenyang High-speed Railway being into operation since October 2003. However, the design speed of this line is only 250 km/h lower than China's standard, leading to controversy in existing studies as to whether it is China's first HSR or not. Based on the most prudent considerations, the empirical analyses in this paper treat this line as a HSR line and marks the first year with HSR operation of the six cities along the line as 2004 (because it was put into operation in the second half of 2003). But these six cities are excluded from the sample in the pre-trend test in Section 5.2 and the placebo test in Section 6.2.

City-level data are obtained from *China City Statistical Yearbook* 2001–2020 including per capita urban disposable income, government expenditures, hospital beds, students enrolled in higher education, airport infrastructures, retail sales of consumer goods and local government revenue. Data on road areas are from *China Urban Construction Statistical Yearbook*. Data on house prices are from the municipal bureau of statistics. Data on HSR are collected from China Railway ' Gaotie.cn.[7] Table 1 reports the definitions and descriptive statistics of each variable.

3.4. Empirical findings

Based on Eq. (8), this section carries out the DID analyses using the 285 sample cities' panel dataset. It is common view that HSR's effect works mainly in the secondary and tertiary industries, therefore the analysis in this paper focuses on the two industries. While industry heterogeneities are considered, the type heterogeneities of MLIS are also under concern. There are in fact two types of MLIS: (1) the GDP ratio is higher than the labor ratio, i.e., $s_i > q_i$ and (2) the GDP ratio is lower than the labor ratio, i.e., $s_i < q_i$ according to Eq. (7). The absolute values of the second type of MLIS are used when focusing on this group. In this way HSR's effects on different types of MLIS can be consistent, that is, when the coefficients of HSR are negative mean that HSR can help to reduce MLIS.

Table 2 presents the results of HSR on MLIS with the two types of mismatch in two industries taken into account. Columns (1) and (2) show that HSR significantly reduced the first type of MLIS in the secondary, while such effect also works on the second type in the tertiary industry as in Column (6). In addition to the role of HSR, some control variables also have impacts on MLIS. Road infrastructures are found to have exacerbated MLIS, contrary to HSR. The core difference between the two infrastructures is that HSR is currently dedicated to passenger transportation while the latter carries more than 80% of China's freight traffic. The quest for cheaper transportation costs for intermediate goods promotes the agglomeration of firms to the core cities thus exacerbating the mismatch between labor and industry distribution. Residential income and house prices can significantly mitigate MLIS, which may due to the fact that firms need to take into account the cost paying for labor and land and may make relocation decisions to areas with sufficient labor supplies. This may push industrial reallocated into where labor agglomerated thus synergizing the spatial distributions of them. Local government intervention, on the other hand, can widen the MLIS. Such impacts may due to the local governments in the industry agglomerated cities usually impose a high barrier on household registration to restrict the inflow of population and labor, thus exacerbating the mismatch between labor and industry distributions.

A key prerequisite of the validity of the DID design is that the control group can serve as a valid counterfactual sample for the treatment group. China's imbalances in cities may affect the validity, especially when the administrative level of cities creates opposite forces on labor and industry agglomerations. Therefore, this paper further divides the sample cities into two groups, i.e. cities above prefecture level and prefecture level cities. The results of cities above prefecture level are reported in Table 3, showing no significant effect of HSR on MLIS either in the two industries or the two types. The results in Table 4, on the other hand, show that HSR can reduces the MLIS in the prefecture level cities, and the effect of HSR works significantly on the first type of MLIS in the secondary industry and the second type of MLIS in the tertiary industry.

On the basis of these findings, the following mechanism analyses and further discussions focuses on these two types of the prefecture level cities.

[7] URL: https://www.12306.cn/ and www.gaotie.cn/.

Table 1
Variable definition and descriptive statistics.

Variable	Definition	Obs.	Mean	Std.
$MLIS_{it}^{S}$	the difference between the labor share (the share of a city's labor forces with respect to the samples' total) and output share (the share of city's GDP with respect to the samples' total) in the secondary industry (‰)	5441	1.80	3.02
$MLIS_{it}^{T}$	the difference between the labor share and output share in the tertiary industry (‰)	5441	1.64	3.72
$adMLIS_{it}^{S}$	the $MLIS_{it}^{S}$ moderated by human capital, with the labor share multiplies the ratio of students enrolled in higher education to local population (‰)	5441	-0.99	9.81
$adMLIS_{it}^{T}$	the $MLIS_{it}^{T}$ moderated by human capital	5441	-0.74	8.18
hsr_{it}	DID term, which equals 1 if city *i* is connected by HSR in year *t,* and 0 otherwise	5700	0.24	0.43
$\ln td_{ikt}^{hsr}$	space-time compression effect, which equals the time difference between city *i* and *k* before and after HSR operation when city *i* is connected by HSR in year *t,* and 0 otherwise	5700	1.09	2.01
$\ln w_{it}$	the logarithm of per capita urban disposable income (*yuan*)	5156	9.73	0.59
$\ln w_{i,t0}$	the logarithm of per capita urban disposable income in the base year (*yuan*)	5700	8.79	0.28
$\ln h_{it}$	the logarithm of house prices (*yuan*/m^2)	4939	8.04	0.67
$\ln h_{i,t0}$	the logarithm of house prices in the base year (*yuan*/m^2)	5700	7.06	0.37
$\ln gov_{it}$	the logarithm of government expenditures except those on science, technology and education	5700	11.83	5.10
$\ln med_{it}$	the logarithm of hospital beds per capita (beds/10,000 persons)	5634	9.34	0.75
$\ln edu_{it}$	the logarithm of students enrolled in higher education	5690	9.98	1.87
$\ln road_{it}$	the logarithm of road surface area (10,000 m^2)	5568	6.69	1.06
avi_{it}	dummy variable equals to 1 when city *i* has an airport and 0 otherwise	5700	0.41	0.49
$\ln sl_{it}$	the logarithm of employees in the secondary industry of city *i* and year *t* (10,000 persons)	4837	11.81	1.02
$\ln tl_{it}$	the logarithm of employees in the tertiary industry of city *i* and year *t* (10,000 persons)	4838	12.04	0.79
$\ln pa_{it}$	the logarithm of the number of patents filed by city *i* in year *t*	5688	6.42	1.99

Table 2
Results of HSR's impact on MLIS in the 285 sample cities.

Industry	Secondary			Tertiary		
Type	—	$s_i>q_i$	$s_i<q_i$	—	$s_i>q_i$	$s_i<q_i$
Column	(1)	(2)	(3)	(4)	(5)	(6)
hsr_{it}	-0.3263 * *	-0.2897 *	-0.2151	-0.0555	0.0345	-0.1512 * *
	(0.128)	(0.162)	(0.159)	(0.068)	(0.115)	(0.061)
$\ln w_{i,t0}$	-0.3041 * **	-0.1501 * *	-0.2404 * **	-0.0433 *	-0.0550	-0.0474
	(0.054)	(0.065)	(0.055)	(0.025)	(0.038)	(0.030)
$\ln h_{i,t0}$	-0.1745 * **	-0.1868 * *	-0.1579 * **	-0.0980 * **	-0.1536 * **	-0.0546 * *
	(0.048)	(0.075)	(0.056)	(0.032)	(0.049)	(0.025)
$\ln gov_{it}$	0.2999 * *	0.4757 * **	0.1198	0.1437	0.5609 * **	-0.0281
	(0.147)	(0.153)	(0.142)	(0.111)	(0.178)	(0.078)
$\ln med_{it}$	-0.1837	0.5600	-0.1805	0.1029	0.4396	-0.0347
	(0.376)	(0.480)	(0.379)	(0.248)	(0.434)	(0.221)
$\ln edu_{it}$	0.0134	0.0895	0.0698	0.0850 *	0.0817	0.0421
	(0.079)	(0.111)	(0.082)	(0.045)	(0.055)	(0.044)
$\ln road_{it}$	0.3737 *	0.6706 * *	0.1440	0.2079	0.5692	0.0957 *
	(0.203)	(0.324)	(0.125)	(0.129)	(0.350)	(0.050)
avi_{it}	0.1120	0.0871	0.0101	0.1087	0.2685 * *	-0.0212
	(0.112)	(0.149)	(0.114)	(0.067)	(0.135)	(0.049)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5363	2859	2504	5363	2450	2913
Adj. R^2	0.805	0.853	0.757	0.930	0.941	0.765

Notes: 1. Robust standard errors cluster at city-level are in parentheses. 2. * ** $p < 0.01$, * * $p < 0.05$, * $p < 0.1$.

4. Analyses of mechanisms

This section analyzes the mechanisms by which HSR reducing MLIS. There are many discussions in the existing literature on the economic benefits of HSR, according to which this paper proposes two possible mechanisms in Section 2, i.e. the employment effect and the innovation effect. The corresponding mechanism variables for each mechanism are introduced and their cross-product terms with the DID term hsr_{it} are used to conduct mechanism analyses. Specifically, the mechanism variables are centered when building the cross-product terms.

4.1. The employment effect

Based on the composition of the MLIS indicators, an increase in the labor force may also have an impact on them. China's HSR has been dedicated to passenger transportation and has reduced the time cost of labor mobility, which facilitates labor forces' migration to cities with higher industry agglomeration thus decreasing MLIS. HSR can also enhance inter-city technology spillovers to promote the

Table 3
Results of HSR's impact on MLIS in the cities above the prefecture level.

Industry		Secondary			Tertiary	
Type	—	$s_i>q_i$	$s_i<q_i$	—	$s_i>q_i$	$s_i<q_i$
Column	(1)	(2)	(3)	(4)	(5)	(6)
hsr_{it}	-0.1917	0.0543	-0.4221	0.4726	0.2931	-0.4323
	(0.452)	(0.912)	(0.347)	(0.435)	(0.420)	(0.786)
$\ln w_{i,t0}$	-0.9481 * **	-0.8072 * *	-0.6429	-0.1136	-0.1096	-1.8445 * *
	(0.242)	(0.324)	(0.443)	(0.179)	(0.164)	(0.717)
$\ln h_{i,t0}$	-0.0695	0.0593	-0.1852	-0.1110	-0.1878	0.6063
	(0.217)	(0.275)	(0.300)	(0.130)	(0.116)	(0.500)
$\ln gov_{it}$	0.9619	1.5751 *	0.0588	0.7334	1.9752 * **	-1.0849
	(0.581)	(0.870)	(0.673)	(0.632)	(0.433)	(0.593)
$\ln med_{it}$	1.9411	5.2556	1.2044	1.6260	2.9482 *	-0.6217
	(2.468)	(5.449)	(1.535)	(2.117)	(1.585)	(2.235)
$\ln edu_{it}$	0.4119	-1.2155	1.1927 *	1.0933 *	2.0371 *	0.5558 *
	(0.700)	(2.494)	(0.618)	(0.561)	(1.141)	(0.288)
$\ln road_{it}$	2.1211	5.2342	0.9781	1.7962	2.0837 *	-1.3418
	(2.064)	(3.134)	(1.063)	(1.070)	(1.203)	(0.877)
avi_{it}	-0.0962	-1.0446 * *	128.1241 * **	-0.7326 *	1.9088	-0.6127
	(0.348)	(0.479)	(35.415)	(0.371)	(24.144)	(0.662)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	667	305	362	667	521	146
Adj. R^2	0.839	0.820	0.779	0.910	0.926	0.756

Notes: 1. Robust standard errors cluster at city-level are in parentheses. 2. * ** $p < 0.01$, * * $p < 0.05$, * $p < 0.1$.

Table 4
Results of HSR's impact on MLIS in the prefecture level cities.

Industry		Secondary			Tertiary	
Type	—	$s_i>q_i$	$s_i<q_i$	—	$s_i>q_i$	$s_i<q_i$
Column	(1)	(2)	(3)	(4)	(5)	(6)
hsr_{it}	-0.3883 ***	-0.3671 ***	-0.2515	-0.0771	-0.0574	-0.0934 *
	(0.114)	(0.125)	(0.182)	(0.053)	(0.086)	(0.054)
$\ln w_{i,t0}$	-0.2406 ***	-0.0935 *	-0.1749 ***	-0.0395 **	-0.0614 **	-0.0320
	(0.049)	(0.049)	(0.039)	(0.018)	(0.026)	(0.023)
$\ln h_{i,t0}$	-0.1279 **	-0.0994 **	-0.1487 **	-0.0219	-0.0395	-0.0194 *
	(0.051)	(0.039)	(0.075)	(0.014)	(0.025)	(0.011)
$\ln gov_{it}$	0.2437	0.5228 ***	0.1496	0.0799	0.3318 ***	0.0670
	(0.150)	(0.170)	(0.159)	(0.059)	(0.126)	(0.045)
$\ln med_{it}$	-0.2530	0.3479	-0.3724	0.1033	0.1667	0.1629
	(0.351)	(0.266)	(0.530)	(0.125)	(0.198)	(0.127)
$\ln edu_{it}$	-0.0079	0.0522	0.0160	0.0382	0.0104	0.0198
	(0.065)	(0.074)	(0.061)	(0.027)	(0.027)	(0.033)
$\ln road_{it}$	0.2096 *	0.3672 **	0.0525	0.0774	0.1360	0.1038 **
	(0.122)	(0.169)	(0.098)	(0.069)	(0.152)	(0.047)
avi_{it}	0.1066	0.0658	0.0013	0.0908	0.2017	-0.0198
	(0.115)	(0.148)	(0.111)	(0.063)	(0.136)	(0.051)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4696	2554	2142	4696	1929	2767
Adj. R^2	0.753	0.850	0.740	0.910	0.945	0.753

Notes: 1. Robust standard errors cluster at city-level are in parentheses. 2. * ** $p < 0.01$, * * $p < 0.05$, * $p < 0.1$.

economic growth in prefecture level cities (Yao et al., 2020) thus enabling them to create more jobs and decreasing the MLIS. This paper tests the employment effect on MLIS using the secondary and tertiary industry employees, i.e. sl_{it} and tl_{it}, as mechanism variables. Table 5 reports the results of the first mechanism test. The employment effect significantly reduces the first type of MLIS, i.e. output share > labor share, which is effective in both secondary and tertiary industries. In other words, HSR can indirectly contribute to the first type of MLIS in the tertiary industry through the employment effect, even though its direct effect is insignificant. These findings support that the employment effect is an important mechanism of HSR's effect on MLIS.

4.2. The innovation effect

According to the composition of MLIS indicators, they can also be affected by the increases in GDP of each industry, because a higher GDP means that the city has a larger industrial scale that can provide more employment opportunities. The operation of HSR can promote intercity communication and cooperation, helping to generate and disseminate new knowledge and technologies, thereby

Table 5
Results of the mechanism test with respect to the employment effect.

Industry	Secondary		Industry	Tertiary	
Type	$s_i > q_i$	$s_i < q_i$	Type	$s_i > q_i$	$s_i < q_i$
Column	(1)	(2)	Column	(3)	(4)
$\ln sl_{it} \times hsr_{it}$	-0.6303 ***	-0.7215	$\ln tl_{it} \times hsr_{it}$	-0.3683 **	-0.0833
	(0.152)	(0.526)		(0.143)	(0.133)
$\ln sl_{it}$	-0.2700 *	-0.7208 ***	$\ln tl_{it}$	0.2754	0.4559 *
	(0.161)	(0.181)		(0.215)	(0.254)
hsr_{it}	-0.2490 **	0.0294	hsr_{it}	0.0628	-0.0853
	(0.107)	(0.125)		(0.078)	(0.052)
$\ln w_{i,t0}$	-0.0025	-0.0655 *	$\ln w_{i,t0}$	-0.0617 **	-0.0519 **
	(0.049)	(0.037)		(0.024)	(0.022)
$\ln h_{i,t0}$	-0.1055 ***	-0.1754 **	$\ln h_{i,t0}$	-0.0347	-0.0373 ***
	(0.038)	(0.073)		(0.026)	(0.011)
$\ln gov_{it}$	1.1637 ***	0.2743	$\ln gov_{it}$	0.4694 **	0.0967 *
	(0.323)	(0.274)		(0.213)	(0.050)
$\ln med_{it}$	0.2820	0.1321	$\ln med_{it}$	0.0864	0.0027
	(0.245)	(0.541)		(0.191)	(0.117)
$\ln edu_{it}$	0.0445	0.0354	$\ln edu_{it}$	-0.0160	-0.0012
	(0.051)	(0.076)		(0.031)	(0.026)
$\ln road_{it}$	0.3075 **	0.0262	$\ln road_{it}$	0.1390	0.0659 *
	(0.146)	(0.099)		(0.144)	(0.035)
avi_{it}	0.0722	-0.1158	avi_{it}	0.2913 *	-0.0401
	(0.157)	(0.103)		(0.155)	(0.044)
City FE	Yes	Yes	City FE	Yes	Yes
Year FE	Yes	Yes	Year FE	Yes	Yes
Observations	2210	1850	Observations	1636	2425
Adj. R^2	0.881	0.751	Adj. R^2	0.952	0.801

Notes: 1. Robust standard errors cluster at city-level are in parentheses. 2. * ** $p < 0.01$, * * $p < 0.05$, * $p < 0.1$.

promoting GDP growth. This is the second mechanism by which HSR may affect the MLIS, i.e., the innovation mechanism. Considering that patents are important outcomes of innovation activities, this project uses the number of patents filed in each city to create a new variable pa_{it}, which is then introduced to empirically analyze whether the innovation mechanism has a significant impact. The results reported in Table 6 show that the innovation mechanism works significantly by which HSR reduces the first type of the MLIS in the secondary industry (column 1). Even though this mechanism does not have a significant impact on the MLIS in the tertiary industry, the reduction effect of the HSR on the second type of it is still significant after controlling for the mechanism variable. These findings are consistent with those of Yuan and Li (2021).

5. Two further discussions

5.1. Control the quality of labor forces

The above discussions in Sections 3 and 4 are based on the assumption that the qualities of labor forces are homogeneous across cities. This sub-section relaxes this assumption by introducing a new variable ad_{it}, defined by dividing the number of students enrolled in higher education into the number of residents. This is because higher education is widely considered to be beneficial for human capital development and labor quality improvement (Angrist & Krueger, 1999). Then ad_{it} is used to recalculate the adjusted MLIS as $adMLIS_{ijt}$ of city i in sector j and year t as follows:

$$\begin{aligned} adq_{ijt} &= ad_{it} \times L_{ijt} \Big/ \sum_i ad_{it} \times L_{ijt} \\ ad_{it} &= edu_{it}/pop_{it} \\ adMLIS_{ijt} &= \left(ad_{it} q_{ijt} - s_{ijt}\right) \times 100\% \end{aligned} \tag{9}$$

The results with the use of $adMLIS_{ijt}$ are reported in Table 7. With the labor quality taken into account, HSR significantly decreases the first type of MLIS in the secondary as well as the second type of MLIS in the tertiary industry. These are consistent with the results in Table 4, supporting the robustness of the above findings.

5.2. An event study

It is a necessary prerequisite for the validity of the DID design that the pre-trends of the treatment and control groups should follow similar development trends (Wooldridge, 2010). This sub-section carries out an event study (Qin, 2017) to test whether the prerequisite is satisfied as:

Table 6
Results of the mechanism test with respect to the innovation effect.

Industry	Secondary		Tertiary	
Type	$s_i > q_i$	$s_i < q_i$	$s_i > q_i$	$s_i < q_i$
Column	(1)	(2)	(3)	(4)
$\ln pa_{it} \times hsr_{it}$	-0.1131 ***	-0.1337	0.0117	-0.0033
	(0.035)	(0.091)	(0.016)	(0.023)
$\ln pa_{it}$	0.1637 **	-0.0037	0.1243 *	0.0681 *
	(0.081)	(0.080)	(0.065)	(0.037)
hsr_{it}	-0.0965	0.0191	-0.1009	-0.0952 **
	(0.110)	(0.130)	(0.074)	(0.047)
$\ln w_{i,t0}$	-0.0657	-0.1236 ***	-0.0643 **	-0.0356
	(0.045)	(0.039)	(0.025)	(0.025)
$\ln h_{i,t0}$	-0.0687 **	-0.1281 **	-0.0444 *	-0.0147
	(0.033)	(0.061)	(0.025)	(0.011)
$\ln gov_{it}$	0.4547 ***	0.1615	0.2933 **	0.0647
	(0.170)	(0.166)	(0.127)	(0.043)
$\ln med_{it}$	0.3464	-0.3503	0.0947	0.1383
	(0.243)	(0.497)	(0.191)	(0.129)
$\ln edu_{it}$	0.0178	0.0153	0.0105	0.0133
	(0.061)	(0.060)	(0.027)	(0.032)
$\ln road_{it}$	0.4042 **	0.0591	0.1144	0.0981 **
	(0.166)	(0.094)	(0.155)	(0.045)
avi_{it}	0.0287	0.0025	0.2126	-0.0229
	(0.148)	(0.100)	(0.135)	(0.050)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2543	2142	1918	2767
Adj. R^2	0.857	0.748	0.945	0.754

Notes: 1. Robust standard errors cluster at city-level are in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7
Results of education-adjusted MLIS (DV=$adMLIS_{it}$).

Industry	Secondary	Tertiary
Type	$s_i > q_i$	$s_i > q_i$
Column	(1)	(2)
hsr_{it}	-0.9713 * **	-0.4282 * **
	(0.214)	(0.108)
$\ln w_{i,t0}$	-0.3405 * *	-0.0600
	(0.133)	(0.048)
$\ln h_{i,t0}$	-0.2328 * **	-0.0742 * *
	(0.073)	(0.034)
$\ln gov_{it}$	0.1652	-0.1366
	(0.256)	(0.096)
$\ln med_{it}$	0.6406	0.3950 *
	(0.549)	(0.232)
$\ln road_{it}$	0.3965 *	0.1264
	(0.234)	(0.079)
avi_{it}	0.1466	0.1767 * *
	(0.206)	(0.083)
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	2554	2774
Adj. R^2	0.740	0.589

Notes: 1. Robust standard errors cluster at city-level are in parentheses. 2. * ** $p < 0.01$, * * $p < 0.05$, * $p < 0.1$.

$$MLIS_{ijt} = \beta_0 + \sum_{k=-9}^{9} \alpha_k hsr_i * 1\{age_{it} = k\} + \beta_x X_{it} + city_i + year_t + \varepsilon_{it} \quad (10)$$

where hsr_i equals 1 when city i is connected by HSR and 0 otherwise. $1\{age_{it}= k\}$ is an event time indicator equal to 1 when $age_{it}= k$ and 0 otherwise. age_{it} denotes how many years before/after the implementation of HSR, for example, city i was connected by HSR for the first time in 2011, then $age_{i,year2011}= 1$, $age_{i,year2012}= 2$, and $age_{i,year2010}= -1$. The earliest HSR line with a speed of 350 km/h or more is the Beijing-Tianjin Intercity Railway,[8] which is put into operation since August 1, 2008. According to the calculation rules introduced in Section 3, the first year of HSR operation in the cities along this route is labeled as 2009 because it launched in the second half of the year. Then these cities have at most 9 periods before HSR operation during the sample period. This paper tests the nine years prior to HSR implementation (*before*9, *before*8…*before*1) as well as the nine years after HSR operation (*after*1, *after*2…*after*9). The control group of the event study comprising the cities without HSR and the samples being in the period longer than 9 years before or after HSR operations. X_{it} denote the control variables same as in Eq. (8). The period *before*1 is taken as the baseline year and thus omitted according to Qin (2017).

Fig. 3 presents the results of event studies in the secondary and tertiary industries, respectively. None of the α coefficients are significantly different from zero prior to HSR operation, supporting the validity of the DID design. Fig. 3a suggests that HSR's effect on the first type of MLIS in the secondary remains after HSR operation. Fig. 3b supports significant reducing effect of HSR on the second type of MLIS in the tertiary industry at least in the first three years of its operation.

6. Robustness checks

6.1. DID estimators with heterogeneous treatment effects

According to (de Chaisemartin & D'Haultfœuille, 2020), the DID design of this paper is essentially a linear regression with time- and city- fixed effects, which identifies weighted sums of the average treatment effects with weights that may be negative thus biasing the estimates. To test whether the negative weights causes bias in the estimations, this section introduces the estimators proposed by de Chaisemartin & D'Haultfœuille (2020). Table 8 reports the results with heterogeneous treatment effects in the prefecture level cities. The results in Column (1) and (2) show that the sum of negative weights are around − 0.0214 and − 0.0143 with respect to the first type of MLIS in the secondary industry and the second type of MLIS in the tertiary industry, respectively, indicating that the bias caused by this issue are within acceptance. To sum up, the results in this section to some certain extent support the validity of the DID design with respect to the prefecture level cities.

6.2. A placebo test with virtual time when HSR being into operation

Considering the potential bias caused by endogeneity, Sections 6.2 and 6.3 conduct placebo tests on the operation time of HSR and the samples with HSR operation, respectively. It indicates that the endogeneity due to reverse causations or sample selection bias do cause biased estimates if the virtual operation time variable or the virtual operation city variable is conducive on MLIS reduction; otherwise, it can be said that the estimates in this paper are unbiased and consistent to some certain extent.

This sub-section first considers a common suspicion about the endogeneity arising from the inverse causality. Specifically, cities may have been selected to become HSR-connected cities because they possessed a better match between labor and industry distributions, which can lead to a misestimating of the role of HSR. Referring to Granger (1969), this paper conducts a counterfactual test, also known as a placebo test, to see *whether the cause occurred before the effects, rather than the other way round*. As stated in Section 5.2, no city operated HSR before 2008 except those along the Qinhuangdao-Shenyang High-speed Railway. Further considering that the construction process of HSR takes at least two years, this paper sets 2001–2005 as the virtual time window and sets a virtual launch time in the year 2005 to carry out a placebo test. A dummy time variable $after_t$ is introduced which equals 1 in 2005 and 0 otherwise. A DID design is introduced to perform the placebo test as follows:

$$DV_{it} = \beta_0 + \beta_1 hsr_i \times after_t + \beta_x X_{it} + city_i + year_t + \varepsilon_{it} \tag{11}$$

where DV_{it} denote $MLIS_{ijt}$. hsr_i is a dummy variable equals 1 when city i is a city connected by HSR and 0 otherwise. $after_t$ is the dummy time variable. X_{it} denote the control variables same as in Eq. (8).

Table 9 reports the results of the placebo test with virtual time when HSR being into operation. None of the coefficient of $hsr_i \times after_t$ is significantly different from zero, supporting that the endogeneity by reverse causations does not significantly affect the consistency of the coefficients.

6.3. A placebo test randomizing cities with HSR operation

This sub-section takes another placebo test to test the endogeneity arising from sample selection bias and/or omitted variable bias. The coefficients of HSR are not unbiased estimators if there are some factors that can affect MLIS are not included in the regression and

[8] It should be noted that the Qinhuangdao-Shenyang High-speed Railway was the first trial run high-speed rail line in China, which was put into operation in October 2023. However, there is a controversy in the existing research about whether this train is a HSR line or not because its operating speed is lower than China's HSR standard of 350 km/h. For the most prudent consideration the empirical analyses in this paper treat it as a HSR line but exclude these samples in the parallel trend test and the robustness test in Section 6.2.

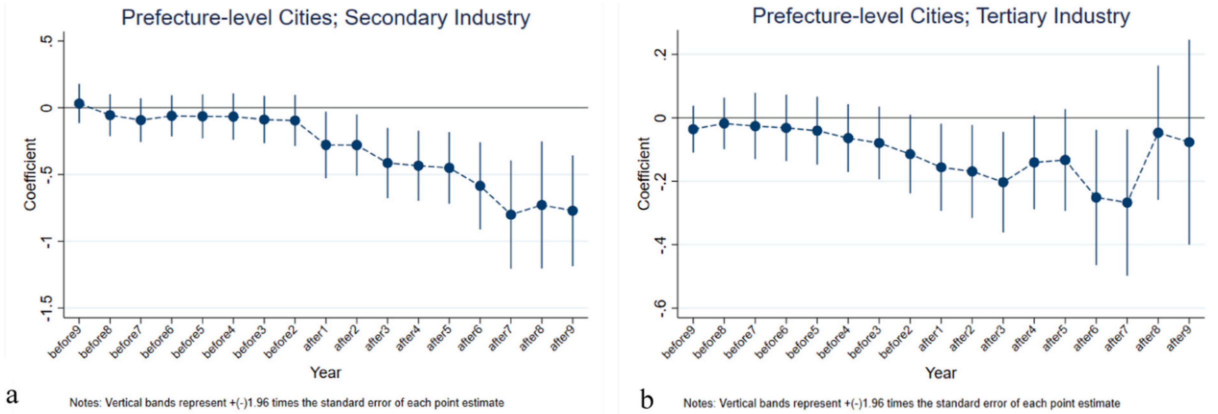


Fig. 3. a. Results of the secondary industry when $s_i > q_i$. Fig. 3b. Results of the tertiary industry when $s_i < q_i$. Fig. 3. Results of the event study in the prefecture level cities.

Table 8
Results of DID estimators with heterogeneous treatment effects of the prefecture level cities.

Industry	Secondary	Tertiary
Type	$s_i > q_i$	$s_i < q_i$
Column	(1)	(2)
positive weight	526	460
sum of the positive weights	1.0214	1.0122
negative weight	33	13
sum of the negative weights	-0.0214	-0.0122
estimate	-0.0806	-0.0638
SE	0.0647	0.0341
control variables	Yes	Yes

Table 9
Results of the placebo test with virtual time when HSR being into operation.

Industry		Secondary			Tertiary	
Type	—	$s_i > q_i$	$s_i < q_i$	—	$s_i > q_i$	$s_i < q_i$
Column	(1)	(2)	(3)	(4)	(5)	(6)
$hsr_i \times after_t$	-0.0721	-0.0726	-0.0156	0.0120	-0.3413	-0.1728
	(0.059)	(0.083)	(0.084)	(0.056)	(0.263)	(0.178)
$\ln w_{i,t0}$	-0.1483 ***	-0.1789 ***	-0.0811	-0.0521 *	-0.1091 *	0.1464
	(0.052)	(0.055)	(0.079)	(0.031)	(0.061)	(0.178)
$\ln h_{i,t0}$	0.1827 ***	0.2252 ***	0.0856	0.0676 *	0.1181	0.0461
	(0.065)	(0.069)	(0.100)	(0.040)	(0.085)	(0.038)
$\ln gov_{it}$	0.0127 ***	0.0135 **	0.0190 **	-0.0013	0.1230	0.0635 **
	(0.005)	(0.006)	(0.008)	(0.004)	(0.122)	(0.028)
$\ln med_{it}$	0.6481	0.4909	0.8937	0.3129	-0.2422	0.4738
	(0.440)	(0.400)	(0.797)	(0.330)	(0.335)	(0.338)
$\ln edu_{it}$	-0.0296	-0.0501	0.0089	-0.0083	-0.0276	0.0186
	(0.047)	(0.123)	(0.027)	(0.043)	(0.078)	(0.055)
$\ln road_{it}$	0.2889 **	0.2366 *	0.3835 *	0.0951	0.0010	0.0910
	(0.120)	(0.127)	(0.222)	(0.085)	(0.094)	(0.088)
avi_{it}	0.0367	0.0239	-0.0188	0.1100	0.0967	0.0646
	(0.217)	(0.203)	(0.427)	(0.111)	(0.211)	(0.089)
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	1178	646	532	1178	480	698
Adj. R^2	0.955	0.952	0.958	0.956	0.978	0.843

Notes: 1. Robust standard errors cluster at city-level are in parentheses. 2. * ** $p < 0.01$, * * $p < 0.05$, * $p < 0.1$.

these implied factors for some reason happens to exist only in cities in with HSR. To deal with this issue, this paper randomly selects half of the prefecture level cities to construct a virtual HSR treat group and repeats the experiment 500 times to observe the virtual effect on MLIS.

Fig. 4 reports the results of the experiments with random selections showing that the estimates of the virtual effect on MLIS follow a

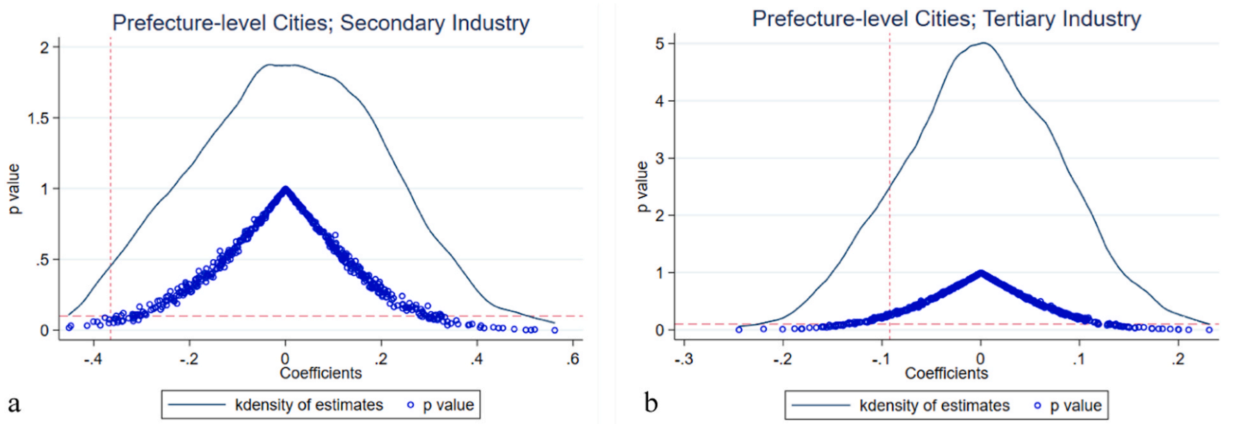


Fig. 4. a. Results of the secondary industry when $s_i > q_i$. Fig. 4b. Results of the tertiary industry when $s_i < q_i$. Fig. 4. Results of the placebo test randomizing cities with HSR operation.

normal distribution with a mean of zero in both the secondary and the tertiary industries. The estimates reported in Table 4 are added to the graphs as dashed lines parallel to the vertical axis, and it can be seen that the virtual estimates are significantly different from the actual estimates. These findings support that the endogeneity does not significantly affect the empirical analysis in this paper to obtain unbiased and consistent estimates.

6.4. Using the space-time compression as a proxy of the dummy variable hsr_{it}

It is a common practice to use the dummy variable hsr_{it} to denote HSR operation (Wan et al., 2016; Zhang et al., 2018). However, it cannot reflect the strength and mechanism of HSR's impact. The space-time compression of HSR has been regarded as a key mechanism (Yao et al., 2020). Shortened inter-city travel times can facilitate inter-city spatial interactions (Liu et al., 2019; Jiao et al., 2020). Referring to Yao et al. (2020), variable $\ln td_{ict}$ is defined denoting the space-time compression of HSR on city i and its growth center c:

$$\ln td_{ict} = \ln\left[\left(traveltime_{ict}^{nohsr} - traveltime_{ict}^{hsr}\right)^{hsr_{ict}}\right] \tag{24}$$

where $traveltime_{ict}^{hsr}$ and $traveltime_{ict}^{nohsr}$ denotes the shortest train travel times from city i to its growth center c with and without HSR, respectively. For each prefecture level city i, the growth center is the closest cities above prefecture level including municipalities, sub-provincial cities and provincial capital. td_{ict} equals the space-time compression when both city i and center c are under HSR operation; otherwise, $td_{ict} = (traveltime_{ict}^{nohsr})^0 = 1$ thus $\ln td_{ict} = 0$.

The results reported in Table 10 show that HSR's space-time compression effect significantly decreases the MLIS in the prefecture level cites in both the two industries. These are consistent with the results in Section 3 (Table 4), supporting the robustness of the previous findings.

6.5. A propensity score matching differences-in-differences analysis (PSM-DID)

The DID design used in this paper is a time-varying DID, this is due to the fact that the construction of HSR in China is a gradual process as there being cities for the first time connected by HSR in each year after 2008 (as shown in Fig. 2 in sub-Section 3.3). This may lead to biased estimates of HSR's effect due to sample imbalances. This paper further introduces a PSM-DID analysis to select matched treatment and control groups and re-test the impact of HSR. Table 11 reports the results of the PSM-DID analysis supporting HSR's significant impact on mitigating MLIS in both the secondary and tertiary industries. And the results of the balance test for the matched samples are reported in Table 12. The t-test biases of the control variables are all less than the empirical value of 10, indicating that there is no systematic difference between the matched treatment and control groups.

7. Conclusion and policy implications

The uneven development is a structural problem in China, spatially reflected as the non-synergistic agglomerations of labor and industry. Industries agglomerated in large cities where strict barriers to household registration are often imposed to limit population and labor agglomeration. The distortions caused by the policies lead to a mismatch between the spatial distributions of labor and industry, exacerbated by the conflicting direction of agglomeration. Such a mismatch results in overall efficiency loss and exacerbated uneven development. Reducing the cost of labor mobility may be an improvement that can bridge this mismatch. China's HSR is one of such infrastructures that can reduce the time cost of labor force motilities and thus being expected to optimize the spatial allocations of labor and industry.

Table 10
Results of HSR's impact on MLIS in the prefecture level cities using lntd_{ict} to replace hsr_{it}.

Industry		Secondary			Tertiary	
Type	—	$s_i > q_i$	$s_i < q_i$	—	$s_i > q_i$	$s_i < q_i$
Column	(1)	(2)	(3)	(4)	(5)	(6)
hsr_{it}	-0.0872 ***	-0.0901 ***	-0.0541	-0.0194	-0.0159	-0.0235 **
	(0.024)	(0.026)	(0.037)	(0.012)	(0.020)	(0.011)
ln$w_{i,t0}$	-0.2404 ***	-0.0948 *	-0.1737 ***	-0.0392 **	-0.0609 **	-0.0319
	(0.049)	(0.049)	(0.039)	(0.018)	(0.026)	(0.023)
ln$h_{i,t0}$	-0.1271 **	-0.0965 **	-0.1493 **	-0.0216	-0.0391	-0.0193 *
	(0.051)	(0.039)	(0.075)	(0.014)	(0.025)	(0.011)
lngov_{it}	0.2439	0.5252 ***	0.1494	0.0801	0.3309 **	0.0678
	(0.150)	(0.169)	(0.159)	(0.059)	(0.126)	(0.046)
lnmed_{it}	-0.2421	0.3526	-0.3664	0.1057	0.1697	0.1652
	(0.351)	(0.265)	(0.528)	(0.125)	(0.197)	(0.127)
lnedu_{it}	-0.0064	0.0516	0.0175	0.0385	0.0102	0.0204
	(0.065)	(0.075)	(0.061)	(0.027)	(0.028)	(0.034)
ln$road_{it}$	0.2097 *	0.3684 **	0.0517	0.0775	0.1368	0.1035 **
	(0.122)	(0.168)	(0.098)	(0.069)	(0.151)	(0.047)
avi_{it}	0.1150	0.0673	0.0112	0.0920	0.2006	-0.0177
	(0.116)	(0.146)	(0.115)	(0.063)	(0.135)	(0.051)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4696	2554	2142	4696	1929	2767
Adj. R^2	0.753	0.850	0.740	0.910	0.945	0.753

Notes: 1. Robust standard errors cluster at city-level are in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11
Results of the PSM-DID analysis.

Industry		Secondary			Tertiary	
Indicator	coefficient	z / t statistics	p-value	coefficient	z / t statistics	p-value
Column	(1)	(2)	(3)	(4)	(5)	(6)
hsr_{it}	-2.70	9.05	0.000	-2.12	5.26	0.000
ln$w_{i,t0}$	0.00	0.81	0.417	0.00	0.81	0.417
ln$h_{i,t0}$	0.00	-0.06	0.949	0.00	-0.06	0.949
lngov_{it}	1.26	23.89	0.000	1.26	23.89	0.000
lnmed_{it}	-0.65	-9.23	0.000	-0.65	-9.23	0.000
lnedu_{it}	0.17	5.41	0.000	0.17	5.41	0.000
ln$road_{it}$	0.17	3.64	0.000	0.17	3.64	0.000
avi_{it}	-0.74	-13.03	0.000	-0.74	-13.03	0.000

Notes: 1. Robust standard errors cluster at city-level are in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12
Results of the balance tests after the PSM-DID.

Indicator	t-test bias	t	p > t
Column	(1)	(2)	(3)
hsr_{it}	-1.40	-0.31	0.757
ln$w_{i,t0}$	-6.10	-1.30	0.194
ln$h_{i,t0}$	0.60	0.70	0.486
lngov_{it}	6.90	1.67	0.095
lnmed_{it}	3.60	1.02	0.307
lnedu_{it}	-1.00	-0.23	0.818
ln$road_{it}$	-0.20	-0.04	0.968
avi_{it}	-1.40	-0.31	0.757

Notes: 1. Robust standard errors cluster at city-level are in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

This paper discusses the role of HSR on MLIS (the mismatch of labor share and industry share), using a large panel dataset comprising 285 Chinese cities in 2000–2019. A DID design is used to analyze whether HSR improves MLIS in different cities and industries. The empirical analyses find that HSR significantly reduces the MLIS in prefecture level cities while this effect is insignificant in cities above prefecture level. In addition to administrative level heterogeneity, the effect of HSR is also found to be heterogeneous with respect to different industries and types. This paper identifies two types of MLIS according to whether the GDP share is larger than the labor share and finds that HSR mainly improves the first type of mismatch in the secondary industry and the second type of mismatch in the tertiary industry. The mechanism of HSR's effect on MLIS comes from two mechanisms, namely the employment effect and the innovation effect.

Further discussions consider the moderation of labor quality by human capital accumulation and find that the impact of HSR remains effective. A series of robustness checks supports the empirical results, including a pre-trend test, DID estimators with heterogeneous treatment effects, two placebo tests with virtual HSR operation time and samples, the retest using HSR's space-time compression effect variable to replace the dummy variable and a PSM-DID analysis.

The above findings can draw some policy implications. Firstly, HSR can significantly shorten the time cost of labor migration while promoting economic development, thus being conducive to improving the spatial allocation of labor and industry. Therefore, HSR can be helpful to improve the efficiency of the local governments with large secondary industry output shares but insufficient labor shares as well as those with sufficient labor shares but insufficient tertiary industry output shares. Secondly, HSR's employment promotion mechanism and innovation mechanism can significantly improve the MLIS in cities with insufficient labor. Further expansion of HSR infrastructure investment can bring about improved spatial allocation efficiency of factors in regions with industry agglomeration, thus improving the overall efficiency of factor allocation.

It is useful to note some limitations of this study. One is that the objects of this studies are the employees employed in urban legal entity and private sector as well as the self-employed persons in urban areas. Informal employment groups are not included in this study due to the availability of data. In fact, there is a certain scale of informal employees in China, a significant portion of which is comes from the migrant population, and this group is also affecting the local labor supply and the spatial allocation efficiency. It is an important and worthwhile further expansion to break through the data limitations and study the impact of HSR on the migrant population and informal employment and the role of these on MLIS. The other limitation is that the assumption that labor is homogeneous may not uphold. This paper uses the number of students enrolled in higher education as a proxy to represent labor quality due to data limitations. Students enrolled in other kinds of education should have been taken into consideration, such as secondary vocational education. However, these data are not constantly available and hence are not used in this study.

CRediT authorship contribution statement

Fanjie Fu: Methodology. **Xiaoqian Zhang:** Data curation. **Jing Fang:** Conceptualization. **Shujie Yao:** Data curation. **Jinghua Ou:** Formal analysis.

Declaration of Competing Interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

Data Availability

Data will be made available on request.

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