**Interconnected Cities, Integrated Markets: Exploring the Impact of Transport Networks on Labor Market Integration in the Yangtze River Delta, China**

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**Abstract:**
This paper examines the impact of cities' network connections on regional labor market integration in megacity-regions. By applying a panel model to data for the Yangtze River Delta between 2014 and 2021, we analyze the impact of transport networks on labor market integration and explore the (potential) mechanisms in terms of network externalities. Our empirical analysis suggests a positive association between connectivity in transport networks and labor market integration. We also observe evidence of indirect effects: transport networks allow cities to benefit from network externalities associated with effective labor matching, specifically by reducing geographical distance restrictions and lowering matching costs, thus contributing to the increased integration of labor markets. We reflect on the broader implications of our empirical findings for regional development strategies and discuss possible avenues for further research.

**Keywords:** transport networks; labor market integration; network externalities; matching mechanism; wage convergence; China

## *1 Introduction*

Megacity-regions are increasingly understood as both sets of interconnected nodes and overlapping agglomeration economies (Amin & Thrift, 1992; Hall & Pain, 2006), where multiple urban centers generate economic benefits across spatially proximate and functionally linked areas. Among the multiplex linkages connecting cities, transport networks, as the backbone of infrastructure connections, are particularly important for regional development (Liu et al., 2016) – they can potentially facilitate economic growth (Huang et al., 2020), labor mobility (Hu et al., 2020), and regional integration through the free movement of goods, labor, and services (Bartz & Fuchs-Schündeln, 2012). Studies linking transport networks and regional integration are broadly understood in two interrelated ways: 1) One line of research examines integration through the formation and evolution of transport infrastructure. Cao et al. (2018), for instance, found that physical integration facilitated by transport infrastructure connections is a primary way of promoting regional integration. Similarly, Wang et al. (2022) revealed that the development of transport corridors can reflect how cities become integrated into regional systems. 2) Another strand of research focuses more explicitly on the effect of transport connectivity on market integration. Xu et al. (2019) found that railway networks enhance urban accessibility, thereby promoting market integration. More recently, Hu et al. (2023) and Liu et al. (2023) provided evidence that improved connectivity can facilitate the integration of commodity markets by expanding spatial access.

Despite the growing interest in transport networks and their role in regional integration, their relationship with the specific integration of labor markets has received relatively limited attention. Regional labor market integration (LMI), defined here as the free movement of labor, less restricted access to labor markets, and wage convergence, is nonetheless a vital pillar of overall regional integration (Zhao et al., 2017; Han & Sun, 2019; Wang & Zhang, 2024). LMI can be hypothesized to be closely related to transport networks because of the external benefits associated with enhanced market access and reduced transport costs (Tang et al., 2021). These virtuous effects are collectively captured by the notion of city network externalities, which refer to the benefits emanating from the extent to which cities are connected to other cities (Capello, 2000), including—but not limited to—improved labor matching, enhanced knowledge exchange, and expanded access to broader markets (Meijers et al., 2016). As a result, improved transport networks can contribute to LMI by promoting labor mobility and job matching within regional markets.

Paralleling these studies, an increasing number of policy documents have centered on enhancing the integration of labor markets through improved connectivity. One notable example in China is the state-orchestrated 'Outline of the Integrated Regional Development of the Yangtze River Delta (YRD).' Based on the presence of spatially proximate cities and densely interconnected networks (Cao et al., 2018), the formation of the YRD megacity-region has the potential to promote labor flows and potentially enhance LMI. Despite the growing interest in the link between transport networks and LMI in megacity-regions, a robust conceptual framework and detailed empirical evidence have been lacking. In particular, the underlying mechanism of this hypothesized link has yet to be explored.

Against this backdrop, in this paper, we aim to conceptualize and empirically examine how transport networks shape LMI in the YRD megacity-region. We focus specifically on passenger rail networks, as they are a significant means of intercity population movement in China (Jiao et al., 2017; Wang et al., 2020). Moreover, these networks provide a holistic representation of regional transport connectivity and capture complementary flows of labor and information, which are particularly relevant to labor market dynamics (Huang et al., 2020; Liu et al., 2023). We contribute to the state-of-the-art in three main ways. First, our analysis presents, for the first time, a conceptual framework linking transport networks and LMI, focusing on the 'matching' mechanism of network externalities. Second, we extend previous work on transport networks and regional market integration (e.g., Liu et al., 2023) by focusing specifically on labor markets and exploring the indirect ways through which network externalities influence LMI. Third, we enrich the LMI literature by linking network connectivity to wage differences between cities, thereby shifting the analytical focus from local socio-economic factors to intercity linkages, and from administrative units to functionally linked megacity-regions.

The remainder of this paper is organized as follows. We begin by reviewing the state-of-the-art in research on transport networks and LMI and linking it to the Chinese context. This is followed by an elaboration on our data and methods and, subsequently, an overview of the empirical results. We conclude our paper by discussing the main findings and directions for future research.

## *2 Research context, conceptual framework, and hypotheses development*

### 2.1 Megacity-regions in China: remnants of a fragmented labor market

Much of the debate over whether China's economic reform, initiated in 1978[1], has led to increased levels of market integration remains inconclusive. Several papers, including Young's (2000) analysis, argued that despite decades of reforms, China's regional markets remain largely fragmented, with fiefdoms controlled by local cadres. These fragmented markets include commodity and labor markets and have gained increasing attention from academic and policy circles. This interest is particularly pronounced in labor markets because of the negative implications associated with fragmentation, such as varied social welfare benefits and heightened spatial inequalities (Yuan et al., 2023).

Several socio-economic factors contribute to the fragmentation of China's regional LMI. First, geographical distances and disparities in transport infrastructure provisions affect the willingness and ability of labor movements (Han & Sun, 2019). Second, local institutional factors, exemplified by administrative borders and government control, may restrict population mobility and social service provisions. Additionally, the relative gaps between regions in population size, technological investment, human capital, and industrial output may lead to

[1] In 1978, China launched economic reform policies, which aimed at mitigating the control of the central government over the national economy and promoting Chinese cities to engage with foreign investments and the global market.

differences in employment opportunities and wage levels, as well as the fragmentation of labor markets (Yuan et al., 2023). In addition, a growing body of research has examined the trajectories of LMI, but most of this literature focuses on provincial or national scales. For example, Han and Sun (2019) used provincial wage data to examine LMI trends across 31 provinces. Using a refined city-level dataset, Yuan et al. (2023) examined the levels of cities' integration into provincial and national markets. These studies largely reflect integration dynamics confined within administrative boundaries, such as traditional regional-planning units of provinces (as in Wu, 2016), rather than the more functionally linked megacity-regions.

Market integration has gained momentum in China, with above all the relevance of megacity-regions as a scale of analysis receiving much attention. One of China's most apt policy specifications for megacity-regions are the so-called 'Urban Agglomerations' *(chengshiqun)*, defined as regions with densely interconnected cities and complementary economic profiles (Derudder et al., 2022). These regions are explicitly designed as new state spaces, operating alongside provinces in regional policymaking (Wu, 2016). Putting an explicit emphasis on the scale of megacity-regions is significant, as the complementarities and linkages arising from intercity interactions may generate positive outcomes (e.g., dense labor markets and cross-regional infrastructure provision) (Wang et al., 2019; Ji & Yuan, 2023). As such, market integration could be made possible by those cross-regional functional linkages and dense flows of people and information within the region. Despite this growing relevance, relatively few studies have explicitly examined LMI at this scale, except for Zhao et al. (2017), who analyzed LMI trends in the Jing-Jin-Ji megacity-region in China.

Previous LMI-focused studies in the Chinese context have two key limitations: 1) most studies focus on locally rooted factors, such as economic size and population density, within individual cities (Ke, 2015; Han & Sun, 2019). Limited attention has been paid to how non-local relations (e.g., cross-regional transport linkages and their associated externalities) shape market integration dynamics. 2) The units of analysis are often limited to administrative boundaries, leaving cross-regional market activities and LMI evolution in functionally linked megacity-regions largely unexplored. This study addresses these gaps by exploring how intercity transport networks facilitate the flow and (re)distribution of resources (labor and knowledge) that are essential for LMI in the YRD megacity-region.

### 2.2 Linking transport networks and labor market integration

Research on the LMI impact of transport networks is part of broader debates on how transport infrastructure shapes labor markets, such as promoting the integration of labor markets by facilitating labor flows and addressing inequalities (e.g., unemployment rates and welfare benefits) (Johansson et al., 2002). A large body of research has examined whether the improvements in transport infrastructure, such as the construction of high-speed railways, may affect labor flows and spatial employment patterns (Jiao et al., 2017; Liu et al., 2023). Liu et al. (2022), for instance, found that the expansion of rail networks promotes interregional population flows and integrated markets by spatial employment agglomeration. A related body of research has also indirectly explored market integration effects through the lens of the infrastructure network and its connectivity, which captures the patterns of intercity linkages (e.g., directness, geographical diversity, and density) (Wang et al., 2022). For example, dense transport infrastructure linkages between cities improve connectivity, potentially enhancing access to larger labor pools, and facilitating the movement of skilled labor and the information transmitted with them (Guirao et al., 2018; Yan et al., 2022).

However, relatively few studies have explored how transport connectivity and its associated network externalities collectively shape the integration of labor markets. Two key research gaps thus remain: 1) While many conceptual discussions suggest a purported link between transport networks and LMI through the lens of network externalities (e.g., Yuan et al., 2023), empirical studies explicitly examining this relationship are scarce. Most empirical studies have focused on the broader implications of transport network externalities (Tian et al., 2023), such as economic growth (Huang et al., 2020) and innovation performance (Tang et al., 2021). 2) Although prior research has tried to make sense of network externalities, they are often viewed as a vague and generalized form of economic advantage (e.g., Huang et al., 2020). Few studies have specified or tested the specific mechanisms—such as matching, learning, or sharing—through which transport networks shape regional dynamics, let alone examined their specific role in the integration of labor markets. This study addresses these gaps by focusing on a mechanism of matching, through which transport connectivity may enhance LMI. This will be discussed in detail in the following section.

### 2.3 'Matching' mechanism: Network externalities and labor market integration

A key building block of our conceptual framework is the notion of network externalities. As argued by Neal et al. (2021), the explanatory power of urban networks often lies in these externalities *per se*. Network externalities refer to the economic advantages that arise from cities' interconnection within broader networks, such as expanded market access, improved labor matching, and knowledge spillovers generated by face-to-face interactions (Capello, 2000; van Meeteren, 2016). This extends the geographical scale of agglomeration externalities, traditionally associated with benefits concentrating at a given location (Parr, 2002) through 'sharing', 'learning', and 'matching' mechanisms (Meijers et al., 2016). Particularly, our central focus is the 'matching' mechanism, which, as conceptualized by Duranton and Puga (2004), captures the benefits of dense pools of workers close to employers and effective job-worker matches. Below, we elaborate on both the direct effects of transport networks on LMI and the indirect ways through which network externalities operate, specifically focusing on the 'matching' mechanism (i.e., effective job-worker matching).

The impacts of transport networks and their associated externalities are much more specific and elaborate than simply instruments to promote labor flows. First, transport networks and their externalities can extend the geographical scope of agglomeration externalities, extending labor markets to a broader area (Tang et al., 2021). In larger labor markets, as described by Duranton and Puga (2004, p. 30), *'an increase in the number of agents trying to match improves the chances of matching.'* For example, Bastiaanssen et al. (2020) found that enhanced transport networks improve job-matching opportunities and employment rates by enabling workers to search for geographically dispersed jobs. In other words, transport networks can reduce distance-related restrictions, facilitating the movement of skilled labor, and the job information transmitted with them (Guirao et al., 2018; Yan et al., 2022). These face-to-face interactions foster information exchange and reduce uncertainties (e.g., about job requirements or work performance), therefore increasing the chances of productive job-worker matching over longer distances. This contributes to positive ex-ante effects on wage differences and the enhanced integration of labor markets (Johansson et al., 2002).

Second, intercity networks deliver 'synergies' (improved performance through effective interactions) and 'complementarities' (specialization in distinct urban functions) that yield productivity benefits (van Meeteren et al., 2016). For example, intercity interactions facilitated by transport networks create broader opportunities for people seeking specialized job openings in diverse locations (Guirao et al., 2018; Wang et al., 2019). Specifically, transport networks enhance job-matching probabilities by reducing the unit cost associated with labor-matching activities, such as time spent commuting, fare costs, and information searching costs (Hu et al., 2020). Lin (2017), for example, found that improved railway networks generate economic benefits, such as reduced commuting time and costs, thus promoting workforce flows across cities. Therefore, transport networks enable people to seek jobs that better align with their skills at lower costs, reducing wage differentials and enhancing LMI.

Taken together, we propose the following set of hypotheses:

*H1: Transport network connectivity has a direct and positive effect on LMI.*

*H2: Transport networks indirectly promote LMI by reducing distance-related restrictions on intercity mobility.*

*H3: Transport networks enhance LMI indirectly by lowering the costs associated with labor matching between cities.*

## *3 Study area, data, and methodology*

### 3.1 Study area

The Yangtze River Delta (YRD) is one of China's most economically developed megacity-regions, characterized by densely connected rail networks, concentrated populations, and industries (Zhang et al., 2020). However, there is no universally agreed-upon definition of the YRD's boundaries in academic and policy discussions. In our analysis, we follow the delineation put forward in the National Development Plan of the Urban Agglomeration in the

Yangtze River Delta (Figure 1), comprising 26 cities (prefecture-level and provincial-level cities[2]). In 2021, the YRD contained 11.75% of China's total population, generated 20.08% of the national GDP, and covered 2.21% of the country's total land area. The region's rail networks span over 12,000 kilometers, linking approximately 90% of its urban areas. These characteristics make the YRD a relevant case study for examining the relationship between transport networks and regional LMI. Notably, our study period (2014-2021) includes a critical external shock – the COVID-19 pandemic. In 2020, the YRD experienced significant economic and transport disruptions: the regional GDP growth rate declined by 51%, and intercity passenger volume dropped by 56% compared to 2019[3]. Table 1 provides an overview of key characteristics of the YRD cities, including railway frequencies (daily) and average wages[4] across 19 sectors in 2021.

Table 1 Specifications of cities in the YRD megacity-region (2021)

| City | Area (km$^2$) | POP (million) | GDP (billion yuan) | Rail frequencies | Average wage (yuan) |
|---|---|---|---|---|---|
| Shanghai | 6340 | 24.89 | 4321.5 | 1963 | 190044.6 |
| Nanjing | 6587 | 9.42 | 1635.6 | 1804 | 144070.9 |
| Wuxi | 4627 | 7.48 | 1400.3 | 1235 | 121597.1 |
| Changzhou | 4385 | 5.37 | 880.8 | 1189 | 118651 |
| Suzhou | 8657 | 12.85 | 2271.8 | 1325 | 143473 |
| Nantong | 8001 | 7.73 | 1102.7 | 160 | 108300.7 |
| Yancheng | 16972 | 6.71 | 661.7 | 100 | 94306.68 |
| Yangzhou | 6591 | 4.58 | 669.6 | 313 | 101574.4 |
| Zhenjiang | 3847 | 3.22 | 476.3 | 723 | 103255.5 |
| Taizhou | 5787 | 4.51 | 602.5 | 118 | 108143.4 |
| Hangzhou | 16850 | 12.20 | 1810.9 | 1383 | 147093.7 |
| Ningbo | 9816 | 9.54 | 1459.5 | 549 | 113945.8 |
| Jiaxing | 3915 | 5.52 | 635.5 | 696 | 93554.5 |
| Huzhou | 5820 | 3.41 | 364.5 | 354 | 106689.2 |
| Shaoxing | 8279 | 5.34 | 679.5 | 421 | 95173.04 |
| Jinhua | 10942 | 7.13 | 535.5 | 513 | 95434.21 |
| Zhoushan | 1440 | 1.17 | 170.4 | 0 | 102105 |

[2] China has established hierarchies for its territorial administrative divisions. The administrative designation as a 'city' in our analysis includes: (1) Provincial-level cities. In China, provinces, broadly comparable to states in the US, are the first-level administrative units. Provincial-level cities include municipalities and special administrative units directly under the jurisdiction of the central government (e.g., Shanghai). 2) Prefecture-level cities, the second-level administrative units in China, which are generally composed of an urban center and the smaller towns surrounding them (e.g., Suzhou in Jiangsu province).
[3] Statistics on the regional GDP growth rate and intercity passenger volume are drawn from official reports, including the 2020 YRD Economic Operation Report and the 2021 YRD Transport Industry Report.
[4] Average wage figures are reported in Chinese Yuan (RMB). For international comparison, we provide an approximate conversion using the average exchange rate of 1 USD = 6.45 RMB in the year of 2021, as reported by the National Bureau of Statistics of China. Based on this rate, the highest average wage was in Shanghai, at 190,044.6 RMB (approx. 29,480 USD); the lowest was in Anqing, at 78,012.53 RMB (approx. 12,095 USD); and the median city in terms of average wage was Wuhu, with 95,121.21 RMB (approx. 14,750 USD).

| | | | | | |
|---|---|---|---|---|---|
| Taizhou* | 9411 | 6.06 | 578.6 | 302 | 97080.06 |
| Hefei | 11445 | 9.47 | 1141.3 | 800 | 105704.8 |
| Chuzhou | 13516 | 3.99 | 336.2 | 277 | 88067.47 |
| Ma'anshan | 4049 | 2.16 | 243.9 | 273 | 100344.2 |
| Wuhu | 6026 | 3.67 | 430.3 | 582 | 95121.21 |
| Xuancheng | 12340 | 2.49 | 183.4 | 292 | 79532.79 |
| Tongling | 3008 | 1.63 | 116.6 | 244 | 90860 |
| Chizhou | 8399 | 1.33 | 100.4 | 230 | 83120.63 |
| Anqing | 13590 | 4.17 | 265.7 | 259 | 78012.53 |

**Sources:** National Bureau of Statistics, China's City Statistical Yearbook 2022, National railway ticketing system


Figure 1 Location of the Yangtze River Delta in China

## 3.2 Data

### 3.2.1 Railway frequencies

Passenger railway frequencies provide a pertinent proxy for regional transport connectivity (Liu et al., 2017). We incorporate both high-speed and conventional rails to measure the evolving connectivity of cities within the YRD's regional transport network[5].

[5] Trains include high-speed trains (passenger rail transport that operates at speeds above 250 km/h) and conventional trains

Since train schedules are relatively stable, we use national train frequencies for a fixed day in May for each year from 2014 to 2021[6]. Data were retrieved from the *Shengming* train timetable and cross-validated using the national online railway ticket system. We count each direct train once per inter-city pair, regardless of how many stations it stops at within the same city. In other words, for cities with multiple train stations, all train frequencies are aggregated in the same city. These station-level records are therefore aggregated to the city-level to construct a 26-by-26 matrix representing the number of intercity connections in each year.

#### 3.2.2 Average wage data

Average wages provide a baseline for assessing labor price convergence (Collin et al., 2019) and labor market integration (Zhao et al., 2017). Our analysis uses average wages for employees in the non-private sector across cities in the YRD from 2014 to 2021[7]. Given variations in job-skill requirements and wage rates across industries[8], we categorize the data into 19 sectors and calculate wage differentials separately for each sector[9].

All nominal wage data are sourced from the China Statistical Yearbook 2015-2022 (for data from 2014-2021). As nominal wages are influenced by different living costs over time, we adjusted the data using the Consumer Price Index (CPI) from 2013 to calculate *CPI-deflated wages* as a proxy for real wages[10]. While real-wage dispersion over the study period is somewhat lower than nominal wage dispersion, excluding cost-of-living interferences did not influence our core analysis of wage convergence.

### 3.3 Operationalization of variables

#### 3.3.1 Dependent variable: labor market integration

Earlier studies measuring LMI have employed either a single indicator, such as the

(passenger rail that operates at a speed less than 140 km/h).

[6] The timing of data collection is set to filter the impact of the seasonal influences on train frequencies, such as the weekends, summer/winter vacation for students and national holidays.

[7] We use wage data from the non-private sector for three main reasons: 1) Collecting wage data from the private sector at a regional scale is challenging due to the lack of reliable public data on private enterprises in many Chinese cities. 2) Workers, particularly high-skilled labor, are more likely to seek jobs in public sectors for job security or fringe benefits (e.g., work-based welfare), which could largely affect urban labor mobility and integration of labor markets. 3) Extant studies on the Chinese regional labor market mainly focus on non-private sector data, such as Zhao et al., (2017) and Han and Sun (2019), which measure labor market integration using this dataset.

[8] For example, based on data from the National Bureau of Statistics, in 2021, the average wage in the hotels and catering services sector stood at 53,631 RMB, which is only one-third of the average wage in the information transmission, computer service, and software sector, amounting to 201,506 RMB.

[9] According to the "Industrial Classification for National Economic Activities", the real wages of 19 sectors include Agriculture, forestry, animal husbandry and fishing; Mining; Manufacturing; Production and supply of electricity, gas and water; Construction; Transport, storage and post; Information transmission, computer service and software; Wholesale and retail trade; Hotels and catering services; Financial intermediation; Real estate; Leasing and business services; Scientific research, technical services and geological prospecting; Management of water conservancy, environment and public facilities; Services to households and other services; Education; Health, social securities and social welfare; Culture, sports and entertainment; Public management and social organization.

[10] To do so, we set the Consumer Price Index (CPI) for 2013 as the base year (CPI = 100) and constructed a year-on-year CPI index for subsequent years based on their relative ratios compared to previous years. We then deflated the nominal wage data to obtain real wages in each year accordingly. This adjustment allows us to mitigate the varied cost-of-living and ensure comparability of wage values across time and places.

unemployment rate (Bartz & Fuchs-Schündeln, 2012), or relative calculations, such as wage differentials (Prado et al., 2021). The latter approach is widely applied in earlier studies, which use relative wage differences to assess variations in labor prices and explore the integration of China's labor market (Han & Sun, 2019).

The theoretical rationale for linking wage difference to LMI is derived from Cournot's (1838) longstanding argument that *'the flow of information and labor will ensure that wages (for the same type of labor, employed under the same conditions) at different locations will 'tend to equality easily and quickly'* (Rosenbloom, 1996, p. 627). In essence, in an integrated labor market, information flows easily and rapidly between employers and workers across different places, and participants respond rapidly to employment signals, particularly, wage levels (Rosenbloom, 1996). As such, regional wage differences serve as a key reflection of whether regional labor markets tend to integrate (Collin, 2016).

Following Zhao et al. (2017), we construct average wage data as a three-dimensional panel dataset ($i \times k \times t$), representing the average wage of industrial sector $k$ in year $t$. Subsequently, we use the wage difference method to estimate LMI in three consecutive steps: (1) calculating the relative wage difference across 19 sectors in city $i$ in time $t$; after which (2) using the demean method to estimate wage differentials caused by market fragmentation; and finally (3) using standard deviations to measure LMI for each city.

Assume that $p_{it}^k$, $p_{jt}^k$ are the wages of sector $k$ in cities $i, j$ at time $t$. $Q_{ijt}^k$ denotes the wage difference between the city pair $(i, j)$ for sector $k$ at time $t$ (Eq. 1). First, we calculate the first-order wage difference $\left|\Delta Q_{ijt}^k\right|$ to reveal the relative wage difference as presented in Eq. 2. In our analysis, we calculate a total of 49,552 wage difference values[11].

$$Q_{ijt}^k = \ln\left(p_{it}^k\right) - \ln\left(p_{jt}^k\right) \tag{1}$$

$$\left|\Delta Q_{ijt}^k\right| = \left|\ln\left(\frac{p_{it}^k}{p_{jt}^k}\right) - \ln\left(\frac{p_{it-1}^k}{p_{jt-1}^k}\right)\right| = \left|\ln\left(\frac{p_{it}^k}{p_{it-1}^k}\right) - \ln\left(\frac{p_{jt}^k}{p_{jt-1}^k}\right)\right| \tag{2}$$

Second, we calculate the wage differentials $q_{ijt}^k$ resulting from different labor market conditions $\varepsilon_{ijt}^k$. We calculate the average wage $\left|\Delta\overline{Q_{ijt}^k}\right|$ to mitigate the potential bias related to the specific difference $a^k$, as expressed in Eq. 3:

$$q_{ijt}^k = \left|\Delta Q_{ijt}^k\right| - \left|\Delta\overline{Q_{ijt}^k}\right| = \left(a^k - \overline{a^k}\right) + \left(\varepsilon_{ijt}^k - \overline{\varepsilon_{ijt}^k}\right) = \left(\varepsilon_{ijt}^k - \overline{\varepsilon_{ijt}^k}\right) \tag{3}$$

Third, we use the standard deviation $Var(q_{ijt})$ to reveal the wage dispersion across all sectors resulting from the market fragmentation between city $i$ and $j$ in time $t$. This measure is used to calculate the degree of LMI as the reciprocal of labor market fragmentation in Eq. 4:

[11] Our analysis used a dataset comprising the wages of 19 different sectors across 26 cities over an 8-year period. This three-dimensional dataset enables us to calculate a total of 49,552 wage differential values. This included a combination of paired cities (represented by $C_{26}^2$ = 326), sector categories (19), and time periods (8). The calculation was performed by multiplying the corresponding quantities: 326 * 19 * 8 = 49,552.

$$LMI_{it} = \sqrt{\frac{1}{Var(q_{it})}} = \frac{\sum_{i\neq j}^{n-1} Var(q_{ijt})}{n-1} \quad (4)$$

where $LMI_{it}$ represents the level of labor market integration in city $i$ at time $t$, $n$ refers to the total number of cities in the region, and $n$-$1$ indicates the number of wage difference pairs involving city $i$.

### 3.3.2 Key independent variable: transport network connectivity

This research exclusively focuses on transport connections as a holistic proxy for regional network connectivity. They can embody and capture the population movements and, among other things, the flow of information (Wang et al., 2022). In particular, in China, rail connections serve as a significant means of people traveling between cities at the regional scale (Wang et al., 2019). Therefore, we use intercity rail connections to measure transport network connectivity.

To calculate the composite rail network connectivity, we assign weights of 0.33 and 0.67 to conventional and high-speed trains, respectively, based on their contributions to total passenger volume and railway connections (as in Zhao et al., 2022; Liu et al., 2023). Using these weighted averages, our measure of composite connectivity captures the relative significance of each type of railway connection in the regional network and intercity mobility (Eq. 5). Nodes correspond to the cities in the YRD, and edge weights represent the number of trains between city pairs. Our analysis uses degree centrality ($DC$) as the primary metric for intercity transport connectivity, which captures the direct links incident upon each city (Liu et al., 2017). The composite connectivity is computed as follows:

$$DC_i = \sum_{j\neq i} (0.67 \times HS_{ij} + 0.33 \times CT_{ij}) \quad (5)$$

where $DC_i$ denotes the degree centrality of city $i$, calculated as the weighted sum of all direct rail connections between city $i$ and other cities $j$ in the regional transport network. $HS_{ij}$ and $CT_{ij}$ represent the number of high-speed and conventional trains between city $i$ and $j$, respectively.

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### 3.3.3 Intermediate variables

**Commented [BD2]:** Mediating?

In this analysis, our central focus is on examining how transport networks influence LMI by focusing on two intermediary variables, i.e., time and cost, to explore the potential ways through which transport networks indirectly influence LMI.

(1) Time distance

Time distance is a key metric for addressing people's commuting choices (Hu et al., 2020). It captures the opportunity cost of commuting, such as the trade-off between commuting time and alternative uses of that time, and reflects the information costs of individual commuting decisions (Weiss et al., 2018).

Following Duan et al. (2020), we proxy time distance using the minimum travel time between cities. Based on train schedule data, the minimum travel time is calculated as the shortest duration of any direct train connection available in a day (excluding additional access times to train stations)[12]. The calculation of the average minimum travel time is provided in Eq. 6. In cases where city pairs were not linked by railways in earlier study years, we use Google Maps to estimate driving time. This methodological choice aligns with previous studies and our research objective of providing a holistic understanding of transport network connectivity and its externalities (Liu & Zhang, 2018)[13].

$$TIM_i = \frac{\sum_{j=1,j\neq i}^{N} min\ time_{ij}}{N} \tag{6}$$

where $TIM_i$ is the average minimum time from city $i$ to other cities within the region, $min\ time_{ij}$ denotes the minimum travel time for city pair $i$ and $j$. $N$ represents the total number of city pairs involving city $i$.

(2) Matching cost

Extant studies have linked transport networks and job-matching costs by measuring unit commuting costs (see Guirao et al., 2018; Hu et al., 2020). Following the method proposed by Lin (2017), we construct a cost matrix $\tau_{ij}$ incorporating both time and fare costs.

The *time cost*$_{ij}$, represents the monetary value that individuals are willing to pay to save time or the compensation they require for time lost. This metric is computed as the product of the unit value of time and the average commuting time (Eqs. 7 and 8).

$$Time\ cost_{ij} = unit\ value_{ij} * time_{ij} \tag{7}$$

$$Time_{ij} = 1\{time_{ij} \neq 0\} \frac{\sum_{1}^{n} time_{ij}}{n} \tag{8}$$

where $time\ cost_{ij}$ denotes the opportunity cost of time, and $unit\ value_{ij}$ represents the unit value of time for a city pair $i$ and $j$, determined by the average hourly wage[14] (Lin, 2017). $Time_{ij}$ refers to the average commuting time between cities $i$ and $j$. $n$ refers to the total number of trains between the city pair.

The $fare\ cost_{ij}$ represents the railway fare between city $i$ and $j$. Following Hu et al. (2020), we collect ticket prices from China's national online railway ticket system and calculate the

[12] The minimum travel time between cities provides a pertinent proxy for time distance and labor mobility, which is widely used to indicate the labor mobility changes caused by rail connections (e.g., Chen et al., 2017; Hu et al., 2020; Weiss et al., 2018). This calculation did not include additional access times (e.g., time taken to travel to and from railway stations), as our study exclusively focuses on intercity scale – railway connections and commuting time between cities, rather than within-city accessibility. This is consistent with previous research and ensures comparability across cities (e.g., Liu et al., 2018; Duan et al., 2020).

[13] While our primary focus is on rail networks, cities without direct rail connections can still benefit from regional connectivity through alternative modes, such as road networks, which contribute to spillover effects and market access (Lin, 2017; Chen, 2021). In addition, excluding these pairs would result in significant data loss and bias, particularly as many cities have rail connections due to the rapid and top-down expansion of transport infrastructure over time. Using road travel time ensures consistency and accounts for the dynamic nature of intercity network development (e.g., Liu & Zhang, 2018; Chen, 2021).

[14] To address potential endogeneity concerns, we use the average wage data from 2007, which precedes the construction of high-speed railways.

fare cost in Eq. 9. Ticket prices of second-class seats for high-speed rail and hard seats for conventional trains were used to calculate the average intercity commuting cost. These categories represent the most frequently chosen options, capturing the typical costs incurred by passengers (Li et al., 2020).

$$fare\ cost_{ij} = 1\{ticket_{ij} \neq 0\}\frac{\sum_{1}^{n} ticket_{ij}}{n} \tag{9}$$

where *fare cost*$_{ij}$ denotes the monetary cost of commuting, *ticket*$_{ij}$ is the average ticket price for a given city pair[15]. $n$ refers to the total number of trains between cities.

Based on the cost matrix $\tau_{ij}$, we compute the cost for each city by Eq. 10. To align with the weights applied in the composite transport matrix, we calculate the costs for high-speed rail and conventional trains separately and assign weights of 0.67 and 0.33, respectively[16].

$$COS_i = \frac{\sum_{j=1, j\neq i}^{N} \tau_{ij}}{N} \tag{10}$$

where $COS_i$ represents the total cost of traveling from city $i$ to other cities in the region, $\tau_{ij}$ denotes the cost between city $i$ and $j$. $N$ is the total number of city pairs involving city $i$.

### 3.3.4 Control variables

Our analysis includes a range of control variables known to potentially impact LMI. First, relative differences in regional development can lead to labor market fragmentation, such as variations in population size, industry outputs, and human capital levels (Chen & Xi, 2016). To quantify these regional disparities, we employ proxies including differences in total population, the share of tertiary output value to GDP, and the number of higher education students (Zhao et al., 2017). Second, government behavior may have a dual effect on labor markets, either constraining intercity labor mobility or enhancing the appeal of public services for the workforce (Han & Sun, 2019). To capture this effect, we include two variables: the share of government expenditure in GDP as a proxy for government intervention and the share of technology expenditure in GDP to reflect public service investments. Third, we include the share of employees in the tertiary industry to benchmark the employment structure of different industries, as it has been shown to enhance job opportunities for skilled labor and increase wage levels (Liu et al., 2022). Lastly, as administrative borders arguably restrict labor mobility by imposing additional costs (Yuan et al., 2023), we introduce a dummy variable to capture this potential effect. Cities adjacent to a provincial border are assigned a value of 1; otherwise, the value is 0. Table 2 summarizes the descriptive statistics for all variables in the year 2018

[15] We focused on second-class seats for high-speed rail and hard seats for conventional trains to calculate the average ticket prices as a proxy for intercity fare costs (Huang et al., 2016). These categories represent the most frequently chosen options for commuting trips, as they account for the majority of ticket choices in China's passenger railway system (Li et al., 2020; Chen et al., 2024). Ticket prices were collected from China's national online railway ticketing system, which provides real-time pricing for available seats.

[16] Cities that did not have train connections in previous years are instead connected by road networks accessible by cars. We measure commuting time between city pairs by car-driving time in Google Maps, and the monetary costs by fuel expenses associated with car travel. Specifically, we use an average fuel consumption rate of 0.075 L/km and a fuel price of 6.87RMB/L, both calibrated in 2010. Consequently, the fuel cost is calculated as the commuting distance multiplied by 0.515 RMB/km.

(the midpoint of the study period).

Table 2 Summary statistics of variables for the middle year of 2018 (N=26)

| Variable | Definition | Min | Max | Mean | SD | Data Source |
|---|---|---|---|---|---|---|
| LMI | Labor market integration | 8.82 | 16.26 | 12.30 | 1.05 | City Statistical Year Book 2015-2022 (2014-2021 data) |
| DC | Degree centrality | 0 | 1057.32 | 317.41 | 311.58 | Shengming Train Timetable; National Railway Ticket System |
| POP | Difference in the population size (million) | -4.44 | 9.78 | 0.04 | 2.51 | City Statistical Year Book 2015-2022 (2014-2021 data) |
| IND | Difference in the share of tertiary industry output (%) | -12.65 | 21.15 | 0.11 | 7.72 | City Statistical Year Book 2015-2022 (2014-2021 data) |
| HUM | Difference in the number of higher education students (thousand) | -44.21 | 56.34 | 0.09 | 28.59 | City Statistical Year Book 2015-2022 (2014-2021 data) |
| TEC | Share of technology expenditure in GDP (‰) | 2.94 | 18.25 | 6.48 | 3.52 | City Statistical Year Book 2015-2022 (2014-2021 data) |
| GOV | Share of government expenditure in GDP (%) | 6.03 | 21.75 | 9.78 | 3.18 | City Statistical Year Book 2015-2022 (2014-2021 data) |
| EMP | Share of employees in the tertiary industry (%) | 16.57 | 68.88 | 41.44 | 13.24 | City Statistical Year Book 2015-2022 (2014-2021 data) |
| BOR | Provincial border | 0 | 1 | 0.5 | 0.51 | National Administrative Division Inquiry Platform |
| TIM | Minimum commuting time (min) | 72.92 | 242.56 | 96.63 | 53.07 | Shengming Train Timetable; National Railway Ticket System |
| COS | Total cost (yuan) | 112.28 | 268.05 | 158.28 | 40.73 | Shengming Train Timetable; National Railway Ticket System |

### 3.4 Methods

#### 3.4.1 Benchmark panel model

Linear regressions with period and group fixed effects are widely used to estimate causal effects. In this analysis, we performed a Hausman test for the panel model selection procedure (chi-square = 15.38, p-value = 0.0334), which indicated that the fixed-effects model outperforms the random-effects model. Given this, we employed a two-way (i.e., individual and time) fixed effect model to investigate the impact of transport networks on LMI.

$$LMI_{it} = \delta + \alpha DC_{it} + \beta X_{it} + \gamma_i + \delta_i + \varepsilon_{it} \quad (10)$$

where $LMI_{it}$ is the level of labor market integration of city *i* in year *t*, $DC_{it}$ is the degree centrality, $X_{it}$ denotes a set of control variables, $\gamma_i$ is the time-fixed variable, $\delta_i$ is the individual fixed effect, and $\varepsilon_{it}$ is the random error term of the model.

In our empirical analysis, we address a range of econometric issues. First, panel unit test results (Appendix A) confirm the stability of relationships between variables. Second, the Variance Inflation Factor (VIF) and Wooldridge test results (Appendix B) suggest that multicollinearity and serial correlation among the explanatory variables are not a concern. Finally, to address potential endogeneity – arising from reverse causality or omitted variables – we employed instrumental variables (IVs) and dynamic generalized method of moments (GMM) models (Ullah et al., 2018) (Appendix C provides details on how we dealt with endogeneity).

### 3.4.2 Path analysis by structural equation modeling (SEM)

Traditional regression techniques primarily focus on estimating the direct causal effects of predictor variables on the dependent variable. However, they are less effective in capturing the indirect pathways or the mechanisms through which these relationships operate (Ullman & Bentler, 2012). To address this limitation, following the study of Li et al. (2018), we adopt SEM for path analysis. As a multivariate statistical technique, SEM is an effective approach for testing the complex relationships among variables by maximum likelihood estimation (Ullman & Bentler, 2012). This approach offers several advantages: (1) a comprehensive framework for exploring both direct and indirect relationships between variables while accounting for potential covariances; (2) clear identification of causal pathways and mediating effect; (3) standardized coefficients for indirect effect and goodness-of-fit statistics; and (4) the inclusion of bootstrapping tests to validate the robustness of indirect effects (Yang & Liu, 2023). However, few studies have applied SEM to investigate the mechanism of linking transport networks and labor market performance.

In this study, we adopt SEM to examine the hypothesized effect of transport networks on LMI, focusing on the mediating role of labor matching. The underlying theoretical hypotheses of the proposed model are that transport networks promote LMI both directly and indirectly by reducing distance restrictions and matching costs (as discussed in Section 2.1). Figure 2 illustrates these hypothesized effects, with solid lines representing direct relationships and dashed lines denoting indirect relationships. Our analysis focuses on the structural model, as defined by Ullman and Bentler (2012), which incorporates observed variables to conduct path analysis, i.e., examine the presence of indirect effects[17]. In addition, we employ a bootstrapping

[17] The SEM includes two parts: (1) the measurement model, which indicates the constructs between latent and observed variables, and (2) the structural model, which tests the relationships between variables. According to the definitions in Ullman and Bentler (2012), the exclusive inclusion of measured variables in the structural model is called path analysis. In our analysis,

test with 5,000 iterations to validate the robustness of potential mediating pathways[18].

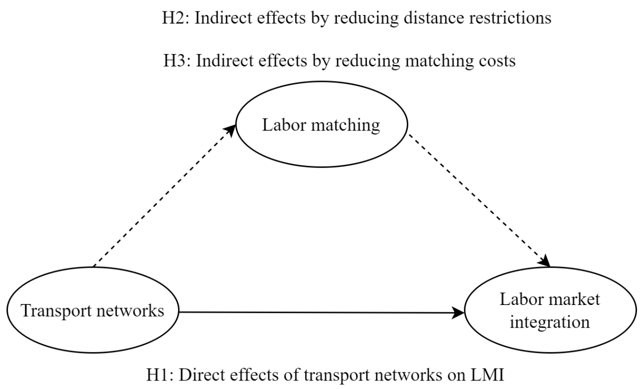


Figure 2 Direct and indirect effects in SEM

### *4 Results*

### 4.1 The link between transport networks on LMI

We structure our discussion of the results around Table 3. Model 1 includes only a set of exogenous control variables. Model 2 extends the two-way fixed effect model with the inclusion of degree centrality (*DC*), and Model 3 introduces the interaction term *DC*COV*. The $R^2$ values for Models 1-3 indicate that approximately 54% of the variance in LMI is explained by transport networks and other socio-economic attributes. This level of explanatory power is consistent with previous studies examining railway infrastructure and market integration (Hu et al., 2023). This suggests that LMI may also be shaped by socio-economic factors that are difficult to observe, such as local market conditions or intra-sectoral activities. The coefficients of control variables generally exhibit expected signs, with all variables, except for *TEC*, demonstrating statistical significance. Furthermore, the signs of control variables remain consistent across all specifications, aligning with the conclusions of Han and Sun (2019).

Turning to the critical variable of interest, the coefficient of *DC* exhibits a statistically significant positive effect (Models 2 and 3). This indicates that, on average, for every one-unit increase in transport network connectivity (*DC*), the level of LMI increases by approximately 0.002 units, holding other factors constant. Although the magnitude may appear relatively small, this reflects the positive effects of regional connectivity in general: enhanced transport network connectivity is associated with increased LMI. In other words, cities with more

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we focus on the observed variable and structural model that examined path analysis with indirect effects.

[18] The bootstrapping test is a valid and robust approach for testing mediating effects (see Hayes, 2009; Zhao et al., 2010). It can generate a bias-corrected confidence interval (e.g., 95% CI), enabling inferences to be drawn regarding the significance of indirect effects in the sampled population. Specifically, if zero falls outside the lower and upper bounds of the confidence interval, it suggests a significant indirect effect.

connections experience increased labor mobility and reduced wage differences. Our first hypothesis (*H1*) is therefore accepted. The results align with Hu et al. (2020), supporting the positive impact of transport networks on labor mobility and labor market performance.

Table 3 Regression results of the panel model

| Variables | Model (1) | Model (2) | Model (3) |
|---|---|---|---|
| DC | | 0.0022(0.0005)*** | 0.0021(0.0005)*** |
| POP | -0.1016(0.0342)** | -0.1088(0.0281)*** | -0.1192(0.0297)*** |
| IND | -0.0222(0.0114)* | -0.030(0.0144)* | -0.0287(0.0142)* |
| TEC | 0.0516 (0.0415) | 0.0451(0.0456) | 0.0407(0.0443) |
| GOV | -0.0567(0.029)* | -0.0623(0.0313)* | -0.0607(0.0294)* |
| EMP | 0.04329(0.0138)** | 0.0393(0.0158)** | 0.0372(0.0145)** |
| HUM | -0.0093(0.0028)** | -0.0073(0.0026)** | -0.0080(0.0024)** |
| BOR | -0.5904(0.2264)* | -0.7210(0.3355)* | -0.7163(0.3497)* |
| DC*COV | | | 0.0004(0.0001)** |
| Time effect | YES | YES | YES |
| 2015 | 0.5701(0.0228)*** | 0.5040(0.0322)*** | 0.5223(0.0283)*** |
| 2016 | -0.0651(0.0552) | -0.1166(0.0578)* | -0.0665(0.0303)* |
| 2017 | -1.2152(0.0737)*** | -1.4408(0.0777)*** | -1.3792(0.0524)*** |
| 2018 | -0.2378(0.0714)** | -0.4874(0.0681)*** | -0.4218(0.0448)*** |
| 2019 | -1.0708(0.1754) *** | -1.3811(0.1853)*** | -1.2802(0.1396)*** |
| 2020 | -1.8769(0.1533)*** | -2.2216(0.1627)*** | -2.1389(0.1197)*** |
| 2021 | -0.6397(0.1779)*** | -0.5167(0.1120)*** | -0.3084(0.1405)** |
| Constant | 9.6656(0.3312)*** | 9.4093(0.4690)*** | 9.6240(0.3970)*** |
| $R^2$ | 0.5390 | 0.5479 | 0.5499 |
| F-statistic | 127.8*** | 152.83*** | 53.66*** |
| Obs. | 208 | 208 | 208 |

Notes: 1) Significance: 0.01 (***), 0.05 (**), and 0.1 (*).

2) Driscoll-Kraay standard errors of parameter estimates are reported in parentheses.

In addition, the F-statistics (p-value=0) and significant coefficients of time variables in Model 3 indicate the relevance of time-trend effects, i.e., the presence of unobserved effects over time. In our analysis, time trends negatively influence LMI throughout the study period, except for 2015. The positive time effect in 2015 reflects a period of economic stability and rapid expansion of transport infrastructure. This generally indicates improved regional infrastructure and virtuous conditions for boosting economic activities and labor market dynamics. In contrast, the significant negative time effect in 2020 captures the economic and social disruptions caused by the pandemic, such as restrictions on population mobility, which negatively influenced intercity worker flows and labor market performance (Cui et al., 2022). While the pandemic's effect extended beyond 2020, its most pronounced impact on population mobility is reflected in that year (Cui et al., 2021; Zhang et al., 2023).

Notably, as evident in Models 1 and 2, the adverse effects of external shocks, particularly those associated with the pandemic, become more pronounced. We introduced an interaction term (*DC∗COV*) to account for these specific circumstances to examine how transport networks influence resilience during external shock. The positive and significant coefficient suggests that transport connections mitigated some of the pandemic's adverse effects by enabling cities to adapt and maintain a degree of connectivity. This finding highlights the resilience-enhancing role of transport networks, as observed in previous studies (e.g., Freckleton et al., 2012; Zhang et al., 2023). Put differently, despite restrictions on population movements, transport networks contribute positively to economic stability and LMI.

In addition, we conducted IV regression and GMM models to address the endogeneity and perform robustness checks (Appendix C). Our results indicated that the two-way fixed effect model remains consistent across different specifications for our key variable, confirming its suitability for interpreting our findings.

### 4.2 Path Analysis: capturing the indirect effect of the labor matching mechanism

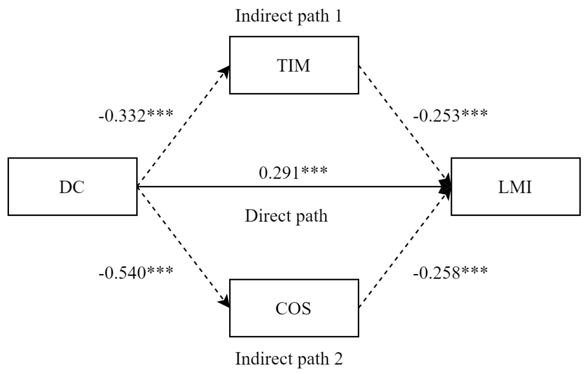
Based on the observed causal links between transport networks and LMI, we examine the underlying mechanisms through which transport networks influence LMI. The proposed structural model is evaluated through two hypothesized paths, i.e., reducing the distance restriction and the matching cost. We begin by evaluating the model fit indices, which, as Kline (2023) suggested, are essential for validating the proposed model. The fit indices in Table 4 fall within acceptable ranges, indicating that the structural model effectively captures the relationship between transport networks and LMI (Li et al., 2018; Huang et al., 2022).

Table 4 Results of the model fit

| Type | Model fit index | Critical value | Actual value |
|---|---|---|---|
| Absolute fit | $Chi^2/df$ (Chi-square divided by degrees of freedom) | ＜3 | 1.594 |
| | GFI (Goodness-of-fit index) | ＞0.90 | 0.969 |
| | AGFI (Adjusted goodness-of-fit index) | ＞0.90 | 0.964 |
| | RMSEA (Root mean squared error of approximation) | ＜0.08 | 0.049 |
| Incremental fit | NFI (Normed fit index) | ＞0.90 | 0.987 |
| | RFI (Relative fit index) | ＞0.90 | 0.925 |
| | IFI (Incremental fit index) | ＞0.90 | 0.969 |

| | | | |
|---|---|---|---|
| | TLI (Tucker-Lewis index) | ＞0.90 | 0.974 |
| | CFI (Comparative fit index) | ＞0.90 | 0.969 |
| Parsimonious fit | PGFI (Parsimonious goodness of fit index) | ＞0.50 | 0.964 |
| | PNFI (Parsimonious normed fit index) | ＞0.50 | 0.965 |
| | PCFI (Parsimonious comparative fit index) | ＞0.50 | 0.966 |

Given the robust model performance, we analyze both the direct and indirect effects of transport networks on LMI. The path analysis results are summarized in Table 5 and are visually represented in Figure 3. For the direct effect, the significantly positive coefficient of the impact path *(DC→LMI)* indicates that transport networks exert direct positive influences on LMI, reaffirming Hypothesis 1.




All coefficients are standardized. RMSEA = 0.05, GFI = 0.97, CFI = 0.98, TLI = 0.96

Figure 3 Path analysis: direct and indirect effects of transport networks on LMI

Turning to the indirect effects, we examine whether transport networks enhance LMI through two mediators: reducing time distance (*TIM*) and mobility cost (*COS*). For indirect path 1, transport networks significantly reduce the time distance between cities (*DC→ TIM*: standardized coefficient = -0.332, $p < 0.001$). Reduced commuting time enhances job mobility and increases LMI (*TIM→LMI*: standardized coefficient = -0.253, $p < 0.001$). Based on the standardized path coefficients, a one-unit increase in transport network connectivity results in an indirect positive effect of 0.084 units on LMI by reduced time distance (calculated by multiplying the coefficients of sub-paths: -0.332 and -0.253). This highlights the presence of indirect path 1 *(DC→TIM→LMI)*: by reducing commuting times, transport networks allow workers to find jobs over long distances, improving job accessibility and job-matching opportunities, contributing to increased labor flows and LMI. These findings broadly align with previous research (e.g., Liu et al., 2018; Duan et al., 2020), emphasizing the role of rail networks in reducing distance-related barriers and increasing labor mobility and LMI

(Johansson et al., 2002). Therefore, Hypothesis 2 is accepted.

For indirect path 2, transport networks reduce labor-matching costs (*DC→COS*: standardized coefficient = -0.540, p < 0.001), and this reduction contributes to increased LMI (*COS→LMI*: standardized coefficient = -0.258, p < 0.001). Every unit increase in transport network connectivity indirectly improves LMI by 0.139 units through reduced labor-matching costs (calculated by multiplying the coefficients of sub-paths: -0.540 and -0.258). This suggests that transport networks enhance job-matching probabilities and align employment opportunities more effectively by reducing costs, thus reducing wage differences and enhancing market integration. These results support the argument that well-connected cities provide better matching opportunities, as discussed by Meijers et al. (2016). Our Hypothesis 3 is, therefore, accepted.

Table 5 Results of path analysis and hypotheses tests

| Hypothesis | Path | Coefficient [a] | SE. | CR. | Result |
|---|---|---|---|---|---|
| H1 | DC→LMI | 0.291 | 0.011*** | 3.533 | Supported |
| H2 | DC→TIM | -0.332 | 0.015*** | -5.072 | Supported |
| | TIM→LMI | -0.253 | 0.013*** | -3.626 | Supported |
| H3 | DC→COS | -0.540 | 0.197*** | -9.227 | Supported |
| | COS→LMI | -0.258 | 0.012*** | -3.296 | Supported |

Note: *p < 0.001; [a] Standardized path coefficient; S.E.: standard error; C.R.: composite reliability

We conducted bootstrap estimates to validate the indirect effects using 5,000 bootstrap samples (Wood, 2005; Ullman & Bentler, 2012). Table 6 indicates that the confidence intervals (CIs) for both indirect paths (i.e., the 95% bias-corrected CI and the 95% percentile CI) do not include zero. This confirms that the indirect effects are statistically significant and robust. These results further substantiate our findings that transport networks influence LMI by reducing distance restrictions and lowering matching costs.

Table 6 Results of bootstrapping tests

| Influence Path | Indirect effect | Bootstrap SE. | Bias-corrected 95% CI | | | Percentile 95% CI | | |
|---|---|---|---|---|---|---|---|---|
| | | | Lower | Upper | P | Lower | Upper | P |
| DC→TIM→LMI | 0.084 | 0.019 | 0.032 | 0.138 | 0.002 | 0.031 | 0.136 | 0.002 |
| DC→COS→LMI | 0.139 | 0.027 | 0.041 | 0.237 | 0.003 | 0.030 | 0.236 | 0.003 |

## *5 Discussion and conclusions*

### 5.1 Main findings

Uneven interconnections in transport networks are arguably one of the many elements explaining why some cities thrive while others do not (Meijers et al., 2016). Although previous studies have examined the role of transport networks in shaping cities' economic performance (e.g., Huang et al., 2020; Hu et al., 2020; Liu et al., 2022), limited research has explored the link between transport networks and LMI, especially the underlying mechanism of this dynamic. This led us to the following questions: Will a city's transport network connectivity translate into higher LMI? And how can this be explained through the mechanism of network externalities?

This paper contributes to extant studies by addressing these questions within the context of the YRD megacity-region in China. Specifically, we constructed a conceptual framework linking transport networks and LMI through both direct and indirect pathways (i.e., the mechanism of 'matching'), proposing three research hypotheses and scrutinizing them empirically. Our main findings are that:

(1) Transport networks have a direct positive effect on LMI. This finding is supported by both the fixed effect model and the SEM approach, demonstrating that transport network connectivity enhances labor mobility and market access, which can contribute to an increased level of LMI. This positive effect remains robust, irrespective of time-varying trends and external shocks.

(2) Transport networks exert indirect effects on LMI through effective job-matching. Specifically, transport networks influence LMI by reducing geographical distance restrictions and the costs associated with job-seeking and matching activities. The results of the structural model collectively corroborate our key finding that labor matching is an important mechanism mediating the link between transport networks and LMI. Our findings, echoing Meijers et al.'s (2016) research on network externalities, provide evidence that the externalities generated by transport networks – through the matching mechanism – significantly influence LMI dynamics. This highlights the explanatory potential of transport networks and their externalities. Rather than simply quantifying network externalities in economic exercises, we delve into the benefits arising from cities' interconnection within transport networks and highlight how cities can potentially leverage these benefits to promote LMI within the region.

## 5.2 Theoretical and policy implications

Some theoretical and policy implications of the main findings are worth exploring. First, improvements in transport infrastructure endow cities with broad benefits related to increased market access and job mobility, particularly in megacity-regions (Wang et al., 2019). Second, network externalities extend beyond transport infrastructure and may emerge in different types of networks – such as firms, innovations, and trade networks – to generate economic benefits through 'sharing' and 'learning'. As such, policy attention should focus on enhancing cities' interconnection in a wide variety of networks (Burger & Meijer, 2016), ranging from physical infrastructure to knowledge exchange. Finally, we reflect on the practices in the YRD. The main impetus of market integration lies in transport network connectivity. This calls for policy attention to the 'integrated regional transport networks' anchored in its cities, such as promoting cost-efficient passenger transport systems and integrating intercity railways for regional commuting flows.

### 5.3 Future research directions

Future research can build on and address some of the limitations of our study. First, this study exclusively focuses on transport networks. Future research could extend the focus to examine a much wider variety of linkages (e.g., firm and technology) and explore other network externalities mechanisms (e.g., 'sharing' and 'learning') (Duranton & Puga, 2004). Second, our conceptual framework, tailored explicitly to network connections and the 'matching' mechanism, could potentially simplify the link between transport networks and market integration. This implies that an over-stretched focus on 'network externalities' may shroud the relations better explained by other concepts. Future inquiries should, therefore, explore different theoretical lenses to enrich the analyses. Third, we adopt the widely used non-private sector wage data to measure LMI trends; however, this may not fully capture urban labor market dynamics, particularly in private firms. Future studies can use alternative data sources, such as survey data, to examine inter-sectoral dynamics. A related limitation is the wage difference method. Although widely used in LMI studies, wage differences do not explicitly account for institutional arrangements, such as Hukou-related restrictions, which affect market integration. Future research could explore these dimensions by qualitative methods to analyze labor market performance. While this study captures the holistic patterns of intercity commuting through railway networks, future studies could extend our work by incorporating commuting time distributions and potential threshold effects, and by employing alternative catchment-based accessibility models using individual-level mobility data.

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