Interconnected Track and Tech: The Impact of Multiplex Transport and Technology Networks on Labor Market Integration in the Yangtze River Delta, China

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Abstract

Despite growing scholarly attention to the role of urban networks in explaining regional integration dynamics, a more explicit focus on the multiplexity of infrastructure- and knowledge-based networks is required for understanding the nuanced ways in which cities regionally integrate. Applying a panel model to data for the Yangtze River Delta for the period 2014-2021, we juxtapose the impacts of transport and technology connections on labor market integration. To this end, we abstract both types of connections into a two-layer network and explore their (potential) interplays. Our analysis reveals that while transport networks show a positive correlation with labor market integration, technology networks demonstrate a complex U-shaped effect. We also find evidence for nuanced interactions in the multiplex network: 1) cities' connectivity in both networks leads to a U-shaped effect on labor market integration due to the dominant role of technology connections; 2) cities' interdependencies within the two-layer network lead to synergy effects, specifically manifested as increased integration of labor markets. We reflect on the broader implications of our findings for regional development strategies and discuss possible avenues for future research.

Keywords: transport networks; technology networks; multiplexity; labor market integration; network externalities; synergy effect

1 Introduction

Cities are increasingly understood as both agglomeration economies and interconnected nodes (Amin & Thrift, 1992; Meijers et al., 2016). These city networks are inherently multiplex, comprising multifunctional, multidirectional, and multiscalar flows (Burger et al., 2014). Among these linkages, transport and technology networks are particularly salient (Guan et al., 2022): cities are fundamentally connected through transport infrastructures and, above all, knowledge exchanges (Devriendt et al., 2010). These connections are not only pertinent proxies for regional connectivity but also have the potential to facilitate economic growth and market integration through the free movement of goods and labor (Liu et al., 2023). Specifically, transport linkages function as primary conduits for the movement of people and goods (Wang et al., 2022); while technology linkages—less spatially constrained—are instrumental in promoting the exchange of knowledge and innovative ideas essential to integration processes (Cao et al., 2018).

In both academic and policy discussions, these two imperfectly different yet interrelated linkages—physical infrastructure and intangible knowledge—are increasingly viewed as fundamental for labor market integration (LMI), a key dimension of broader integration (Lu & Mao, 2020). LMI is defined here as the free movement of labor, less restricted access to labor markets, and wage convergence (Zhao et al., 2017; Ma et al., 2023). Conceptually, a growing body of literature has closely linked LMI analysis to improved transport connections and facilitated technology linkages between cities (Tang, 2021; Ma et al., 2023), particularly through the lens of 'network externalities' (Capello, 2000). For example, transport networks are hypothesized to promote LMI by enhancing labor mobility and extending access to larger labor pools (Johansson et al., 2002). The LMI impact of technology networks can be understood through uneven knowledge diffusion that affects job matching and wage differences (Mujia et al., 2019). The importance of these linkages in LMI has also been highlighted in policy circles, for instance, China's state-orchestrated *'Outline of the Integrated Regional Development of the Yangtze River Delta (YRD) 2019'* identifies infrastructure linkages and knowledge flows as pivotal for integrated labor markets.

Crucially, focusing on a single type of network to explain LMI potentially risks oversimplifying the complex and interdependent nature of urban systems. Cities are increasingly connected within overlapping transport and technology networks that may mutually enhance each other. This, in its broadest sense, reflects the essence of how cities coexist and interact through infrastructure and knowledge linkages (Wang et al., 2023). These overlapping flows may collectively give rise to what Meijers (2005, p. 765) has termed ‘regional synergies’: the regional whole may become more than the sum of its parts. For instance, cities connected by transport networks allow people to travel/commute with intangible knowledge (Xiao et al., 2022), while technology linkages promote face-to-face interactions that, in turn, create needs for tangible trips (Devriendt et al., 2010). Such interdependencies are best captured through a so-called *multilayer* network framework, where each flow is specified as a distinct yet interconnected layer of the broader network (Wang et al., 2023). Focusing on their combined effects and potential synergies can help to get a handle on multiplex network interactions (Derudder, 2021), particularly for capturing nuanced relationships between transport-technology network interactions and LMI dynamics.

Despite growing interest in the links between these overlapping networks and LMI, a robust conceptual framework and detailed empirical corroboration on their relationships (or the lack thereof) have been missing. Existing studies either view these networks as broad manifestations of integration (Cao et al., 2018) or focus on the implications of a single type of linkage (Liu et al., 2023). In particular, how these networks function both individually and collectively in shaping LMI has, to the best of our knowledge, not yet been explicitly examined. Against this backdrop, we build on recent claims (e.g., Lu & Mao, 2020) emphasizing the importance of transport and technology networks in the integration of labor markets. While other factors, such as capital flows, may also shape LMI, we focus exclusively on these networks due to their dual relevance: they serve as salient proxies for embodying the movement of labor and knowledge and have been highlighted as key enablers of LMI in both theoretical discussion and policy agenda—making them especially pertinent to our analysis.

This study aims to address *three* interrelated research questions:

1) To what extent do cities’ transport and technology networks affect LMI individually?
2) How do cities’ combined transport-technology networks influence LMI collectively?
3) Do cities’ interactions in the multilayer network generate synergistic effects on LMI?

To address these questions, we examine the effects of transport and technology networks on LMI in the YRD megacity-region in 2014-2021. Based on the presence of spatially proximate cities and dense networks interconnecting them (Cao et al., 2018), megacity-regions have emerged as critical units for promoting LMI due to the potential benefits associated with their formation (e.g., cross-regional infrastructure) (Cao et al., 2018). We focus exclusively on the YRD due to its economic prominence, dense linkages, and the central role in the regional planning agenda. Although the study period (2014-2021) is partly shaped by data availability, it also roughly coincides with China’s broader initiatives for ‘New Urbanization’ and the YRD’s integrated development.

By doing so, we do not claim these networks are the only or most critical drivers of LMI; rather, we focus on how these key forms of intercity linkages shape labor market dynamics. This extends an emerging body of literature that examines the alleged benefits of networked development in promoting regional integration, particularly in megacity-regions. More specifically, our study contributes to the state-of-the-art in *four* main ways: 1) Conceptually, we (re)frame LMI as a process shaped by complementary flows, moving beyond the traditional focus on locally-rooted socioeconomic factors or a single-dimensional network. 2) Theoretically, we build on the work of Burger et al. (2014) on urban multiplexity by examining the mechanisms of network externalities, and we extend the notion of regional synergies (Meijers, 2005) to the context of interlayer interactions—an aspect that remains less explored. 3) Methodologically, our analysis presents, for the first time, a two-layer network capturing transport and technology connections to assess their interdependencies at the regional scale. 4) Empirically, by juxtaposing the LMI effect of transport-technology networks, we extend the work of Liu et al. (2025), which examined LMI changes in the YRD but limited their analyses to a single type of technology linkages.

The remainder of this paper is organized into four sections. Section two elaborates on the literature linking transport and technology networks to LMI and specifies four hypotheses. Section three elaborates on our data, variables, and model specifications. In Section four, we report the empirical results. Section five concludes the paper with a discussion of our findings, policy implications, and possible avenues for future research.

2 Hypotheses Development: linking transport and technology networks to LMI

Transport and technology networks play distinct yet potentially reinforcing roles in shaping LMI: the former reduces spatial frictions and facilitates labor mobility (Wang et al., 2022), while the latter enables the diffusion of intangible knowledge and skills (Liu et al., 2025). A growing body of research has highlighted their respective roles and potential interactions in regional performance. For instance, Cao et al. (2018) compared spatial structures of transport and knowledge networks to explore their roles in regional integration. Similarly, Guan et al. (2022) found partial coupling between transport and technology transfer networks, revealing their structural interdependence in regional development. Extending this line of work, we theorize how these two interdependent network layers may shape LMI in different yet possibly synergistic ways.

Our theoretical framework linking transport and technology networks to LMI builds on two related notions: 1) network externalities and 2) the synergies these offer. Network externalities refer to the economic benefits emanating from cities' interconnection (Capello, 2000), which extend agglomeration benefits across networks of cities through mechanisms of 'sharing', 'matching', and 'learning' (Meijers et al., 2016). These benefits are particularly evident as cities become increasingly connected within multiplex networks, where overlapping connections generate economic benefits more than the sum of their individual contribution, embodying the rise of regional 'synergies' (cf. Meijers, 2005, p. 765). By focusing on these mechanisms, we present a detailed elaboration of how infrastructure- and knowledge-based linkages shape regional LMI, both individually and collectively.

2.1. The role of transport networks (externalities) in LMI

The literature focusing on the links between transport networks and LMI generally focuses on either of two dimensions: (1) the role of transport infrastructure and the associated connectivity (Derudder et al., 2014), and (2) network externalities arising from transport linkages (Huang et al., 2020).

The first strand focuses on how improvements in transport infrastructure enhance LMI performance. Early contributions, such as Johansson et al. (2002), highlighted that improved transport networks can reduce wage disparities and enhance employment opportunities, thereby promoting LMI. This body of research also explored how transport connectivity—such as geographical diversity and density—shapes regional labor movement (Wang et al., 2022). For instance, Liu et al. (2022) argued that dense transport linkages can potentially enhance access to larger labor pools. Similarly, transport connectivity is found to facilitate face-to-face interactions and the flow of job information, thereby enhancing labor mobility and LMI (Zimmermann, 2009).

A second line of inquiry focuses on transport network externalities, particularly through the lens of the matching mechanism. As conceptualized by Duranton and Puga (2004), this captures the benefits of worker-employer proximity for effective job-worker matching. For example, transport network externalities can extend agglomeration benefits by reducing distance restrictions (Hu et al., 2020; Liu et al., 2023) and facilitating geographically scattered job searches (Huang et al., 2020; Tang et al., 2021). A related strand of research focuses on the reduction of mobility costs, for instance, Lin (2017) and Tveter (2021) found that transport networks enhance labor mobility and matching opportunities by reducing commuting time and costs.

As a corollary, transport networks and their externalities lead to positive ex-ante effects on wage differences and enhanced LMI (Johansson et al., 2002). Therefore, our first hypothesis is that *cities' increased transport network connections are positively related to the integration of labor markets.*

2.2 The link between technology networks and LMI

Research on technology networks and LMI is part of broader discussions on how technological change and skill enhancement shape regional labor markets. For example, Dawid et al. (2012) demonstrated that enhanced LMI is closely related to technology diffusion and skill development facilitated by regional labor flows. Central to this process is the learning mechanism, where knowledge exchanges stretch and spill-over across cities/regions to foster skill development (Cao et al., 2023). This, in many (if not most) cases, involves face-to-face interactions in relation to 'the acquisition of skills by workers and their learning about new technologies' (Duranton & Puga, 2004, p. 2).

Technology connections, in this context, enable workers to engage in knowledge-intensive activities and upgrade their skills (Acemoglu, 2002). However, their effects on LMI are uneven. Limited technology diffusion may lead to wage disparities and restricted labor flows due to rising demand for skill-biased labor (Wang & Yin, 2016). In contrast, dense technology linkages promote broader knowledge spillovers and more opportunities to (in)directly learn and adapt to new technologies (Fang et al., 2008). This process of accumulating and (re)combining knowledge bases can facilitate technology spillovers to less-skilled labor, which may ultimately enhance labor force participation and reduce wage disparities (Antonelli & Gehringer, 2017). Similarly, as argued by Mujia et al. (2019), increased learning activities and specific job-related skill development can contribute to enhanced LMI.

Taken together, the relationship between technology networks on LMI may be nonlinear: limited technology connections may 'polarize' labor markets due to uneven learning opportunities, while dense linkages can enhance learning effects, thus reducing wage disparities and enhancing LMI. Despite this potential link, limited studies have explicitly examined the LMI effects of technology networks, except for a recent study by Liu et al. (2025), who identified a U-shaped relationship between technology cooperation linkages and LMI in the YRD megacity-region. Given this, our second hypothesis is that: *cities' technology network connections have a 'U'-shaped effect on the integration of labor markets.*

2.3 Multiplex transport-technology networks and LMI

Crucially, these networks do not operate in isolation. Emerging research on urban multiplexity (Burger et al., 2014) highlights that different types/layers of connections can interact, potentially generating synergistic effects. In the context of LMI, the co-evolution of transport and technology linkages may collectively facilitate deeper integration than either network could separately. For instance, Lu and Mao (2020) discussed how the interplay between infrastructure linkages and knowledge flows can purportedly contribute to regionally integrated markets. Building on this, our exploration focuses on two dimensions: 1) how the 'co-existence' of transport and technology connections (i.e., combined effects); and 2) how interdependencies between these networks (i.e., interactive effects) can add up to LMI changes.

Cities with overall high connectivity in regional networks often function as key hubs for the aggregation and diffusion of people, goods, and knowledge (Burger et al., 2014), generating increased economic benefits (Hu et al., 2020). Specifically, cities connected by both dense transport and technology networks become the major market, where labor and knowledge are (re)combined and (re)distributed (Guan et al., 2022). As ‘networks of agglomerations’, they attract a concentration of information and talents while reducing mobility and information-searching costs (Tang et al., 2021). As such, cities’ connections in these overlapping networks can enhance access to labor pools and exchange of skills and information, thereby promoting labor mobility and LMI (Lu & Mao, 2020). Our third hypothesis, therefore, is: *the combined effect of cities’ transport and technology network connections contributes to the increased levels of LMI.*

Beyond the co-existence of these linkages, cities’ interconnection in overlapping transport and technology networks may increasingly stretch across cities/regions, leading to (potential) interdependencies that reinforce each other (Zhao et al., 2017). For example, transport connections allow people to travel/commute with knowledge and information (Xiao et al., 2022), while dense technology networks can facilitate the needs for tangible trips and face-to-face interactions—crucial for knowledge sharing and skill acquisition (Devriendt et al., 2010). As such, cities’ interdependencies in these complementary networks can deliver synergistic benefits, such as additional job-matching and learning opportunities (Hu et al., 2020), which can reduce wage differences and promote LMI (Liu et al., 2025). Given this, our fourth hypothesis is: *cities’ interdependencies in the multiplex networks are positively related to LMI.*

3 Study Area, Data, and Methodology

3.1 Study area

In our analysis, we draw on the delineation put forward in the National Development Plan of the Urban Agglomeration in the YRD (Fig. 1), which comprises 26 cities[1]. This delineation is recognized as a territorial framework for capturing broad regional integration. As of 2021, the YRD contained 11.75% of China’s total population, contributed to 20.08% of the national GDP and 30.01% of the national granted patents and R&D expenditures, while only covering 2.21% of the total land area.

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[1] This delineation includes 26 cities: Shanghai, Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yancheng, Yangzhou, Zhenjiang, Taizhou (Jiangsu), Hangzhou, Ningbo, Jiaxing, Huzhou, Shaoxing, Jinhua, Zhoushan, Taizhou (Zhejiang), Hefei, Wuhu, Ma’anshan, Tongling, Anqing, Chuzhou, Chizhou and Xuancheng.

Fig.1 Location of the YRD region

3.2 Operationalization of variables

3.2.1 Dependent variable

Earlier studies measuring LMI have employed either a single indicator (e.g., the unemployment rate) or relative calculations, such as wage differentials (Collin et al., 2019). The latter approach is grounded in the idea that barriers to labor flows may lead to significant disparities in labor market performance across places. Previous studies used relative wage differences to assess variations in labor prices and examine the trajectories of China's LMI (Zhao et al., 2017; Han & Sun, 2019; Liu et al., 2025).

Following previous studies, our analysis uses relative wage differences to measure 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 real 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 city pair (*i, j*) for sector *k* at time *t*. First, we calculate the first-order of wage difference to reveal the relative wage difference in Eq. 1. We calculated a total of 49,552 relative wage differences.

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

Second, we use the demean method to calculate the real wage differentials q_{ijt}^k resulting from different conditions in fragmented markets ε_{ijt}^k.

$$q_{ijt}^k = \left|\Delta Q_{ijt}^k\right| - \left|\overline{\Delta Q_{ijt}^k}\right| = \left(a^k - \overline{a^k}\right) + \left(\varepsilon_{ijt}^k - \overline{\varepsilon_{ijt}^k}\right) = \left(\varepsilon_{ijt}^k - \overline{\varepsilon_{ijt}^k}\right) \tag{2}$$

And third and finally, we used the standard deviation $Var(q_{ijt})$ to reveal the wage dispersion and calculate LMI:

$$LMI_{it} = \sqrt{\frac{1}{Var(q_{it})}} = \frac{\sum_{i\neq j}^{n-1} Var(q_{ijt})}{n-1} \qquad (3)$$

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

3.2.2 Key independent variables

(1) Transport network connections

Transport connections, exemplified by rail connections, typically serve as tangible conduits for facilitating the movement of people, goods, and, implicitly, the exchange of information (Liu et al., 2023). Therefore, we use railway frequencies, including high-speed and conventional rail, to measure a city's transport connectivity. Given the relative stability of train schedules, we use national train frequencies recorded on a fixed day in May between 2014 and 2021. Data on train frequencies were sourced from the *Shengming* timetable and corroborated through the national railway ticket system.

Our analysis constructs transport networks by assigning weights of 2/3 to high-speed rail and 1/3 to conventional trains (Zhao et al., 2022). In Figure 2, nodes correspond to cities in the YRD, and the edge weights represent the number of trains between city pairs. We measure network connections by normalized degree centrality (*DC*) as independent variables.

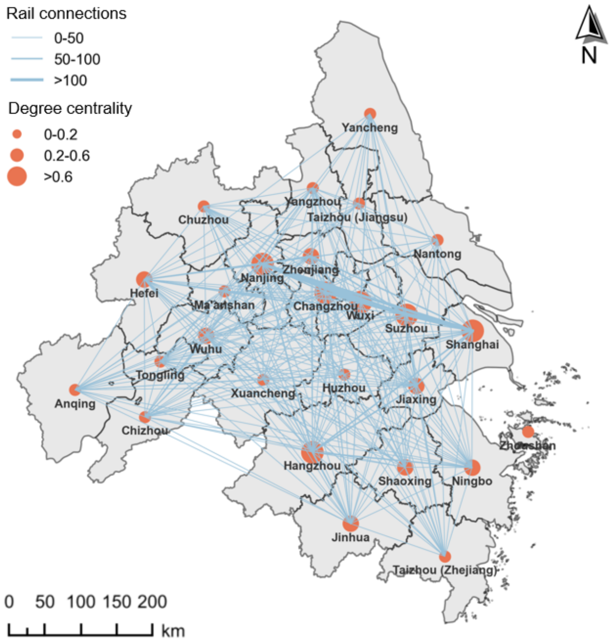

Figure 2 The intercity transport network in the YRD (2021)

(2) Technology network linkages

Patents are often used for capturing knowledge flows and technological diffusion. The transfer of patents is, among other things, crucial in capturing technology linkages between cities (Liu et al., 2025). We sourced patent transfer data from the Incopat Global Patent Database, and geocoded addresses of each patent and assigned these to cities accordingly (excluding the patent transfer within the same city). We then calibrated the data through random sampling and cross-validation, excluding patents with missing addresses or detailed information. We finally collected 203,915 records of patent transfers.

We constructed intercity technology networks, with nodes representing cities in the YRD, and edges indicating the number of patents transferred between city-pairs (Figure 3). We calculate the normalized DC to capture the intercity technology linkages and reveal the potential for the (re)combination of knowledge bases (Cao et al., 2023).

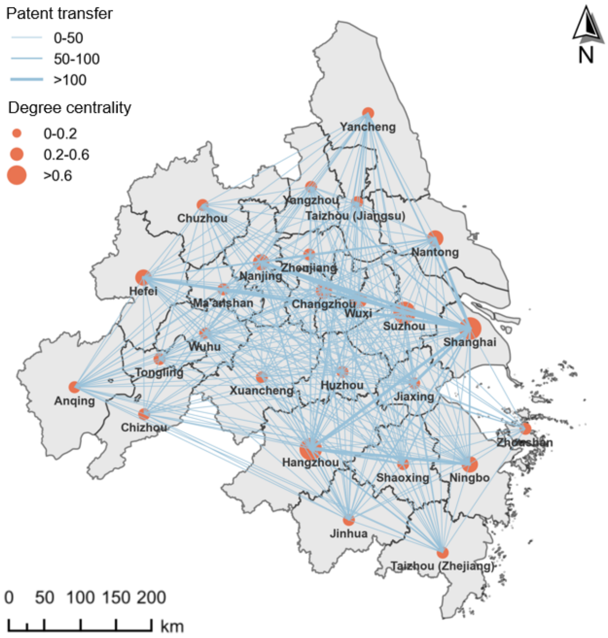

Figure 3 The intercity technology network in the YRD (2021)

(3) Mapping interactions in a multilayer framework

Multilayer networks, defined by multiple networks anchored in a shared set of nodes (Higham et al., 2022), can embody and capture the multidimensional interactions between cities. In our analysis, the multilayer network consists of transport and technology edges, linking the same set of cities (nodes) in the YRD. Both layers are linked through shared nodes, allowing for the analysis of both intra-layer and inter-layer interactions. Fig. 4 schematically illustrates the network using a binary representation, with transport and technology layers shown in blue and orange, respectively. Dashed lines indicate links in both layers; solid lines represent intra-layer connections, and gray lines denote overlaps across layers.

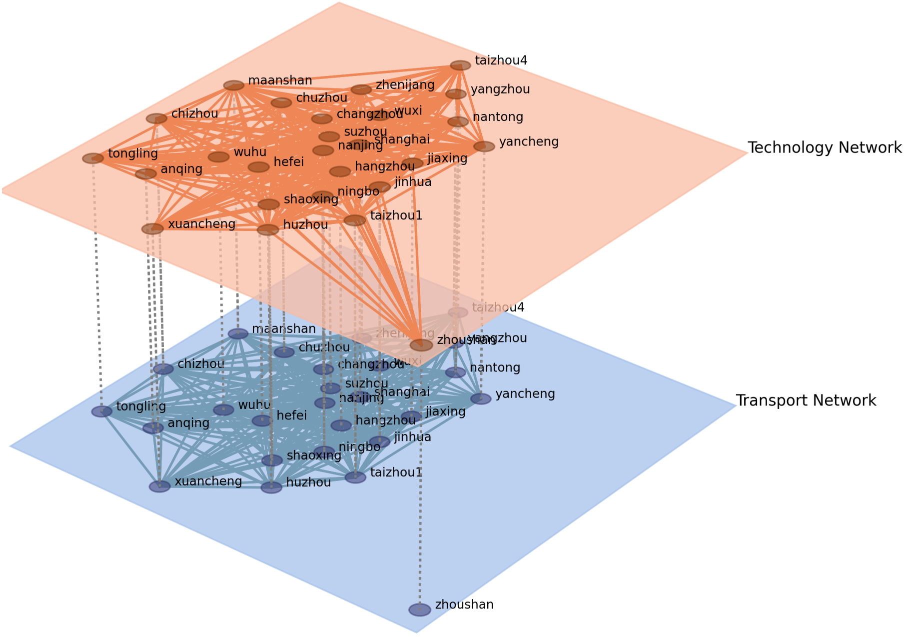

Fig. 4 Schematic illustration of the multilayer network

Following the methods of Hu et al. (2020), we examine the correlation between layers using correlation methods and conditional probability. The results of correlation coefficients indicate that cities' transport and technology linkages are closely correlated, irrespective of varied specifications (Appendix A). Our examination of conditional probabilities (Appendix B) indicates strong interdependencies between layers, suggesting that one type of connection can mutually reinforce another.

Based on their observed interrelations, we used an aggregated measure of degree centrality tailored for multilayer networks, as proposed by Basaras et al. (2017), to provide a general sense of nodal connectivity across layers (Figure 5).

$$ADC_i = \frac{1}{M}\sum_{l=1}^{M}\frac{a_{il}}{N_l - 1} \quad (4)$$

where a_{il} represents the degree of node i within layer l. N_l denotes the number of nodes in layer l, and M is the number of layers in the multiplex network.

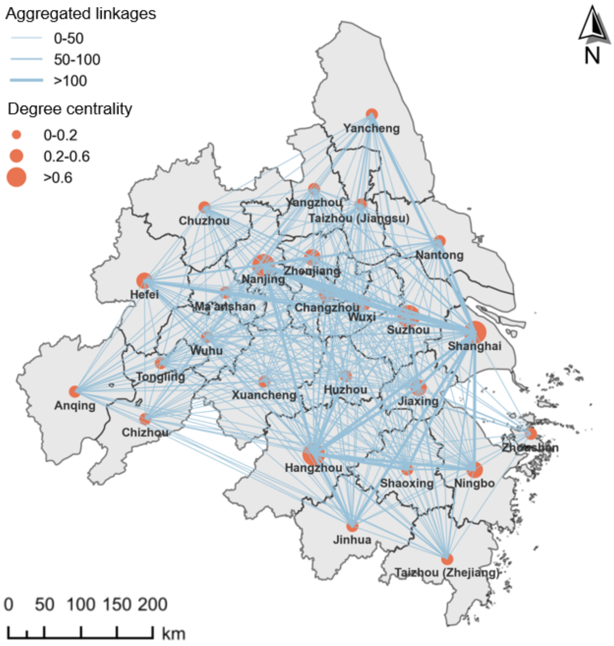

Figure 5 Aggregated networks of the YRD cities in 2021

Given the inter-layer interactions, we further examine cities' interdependencies across layers. Following Hu et al. (2020), we introduce the so-called node interdependence to quantify the presence and length of shortest paths linking node pairs. Node interdependence λ_i is defined as:

$$\lambda_i = \frac{1}{N^{[M]}} \sum_{j \neq i} \frac{\varphi_{ij}}{\sigma_{ij}} \tag{5}$$

where $N^{[M]}$ is the total number of cities in network $G^{[M]}$. σ_{ij} is the number of shortest paths and φ_{ij} sums of the ratio of links within the shortest paths that exist in both layers. λ_i, ranging between 0 and 1, with higher values indicating enhanced connectivity across layers, i.e., increased interactions across transport-technology linkages.

3.2.3 Control variables

Our analysis includes a set of control variables known to potentially impact LMI. First, economic size, measured by GDP, is associated with increased employment opportunities (Han & Sun, 2019). Second, differences in total population and in the number of higher education students to quantify disparities in human capital. Third, the importance of the tertiary industry by its output value to GDP (Zhao et al., 2017). Lastly, two related indicators for proxying government behaviors: the share of government expenditure in GDP as the extent of government intervention, and the share of technology expenditure in GDP to reflect public investment. Descriptive statistics for variables in 2018 (the middle year) are reported in Table 1.

Table 1 Summary statistics of variables in 2018 (N=26)

Variable	Definition	Min	Max	Mean	SD
LMI	Labor market integration	8.82	16.26	12.30	1.05
RDC	Degree centrality of transport networks	0	1	0.30	0.29
PDC	Degree centrality of technology networks	0.01	1	0.34	0.26
ADC	Aggregated degree centrality	0.02	1	0.33	0.26
NOD	Node interdependence	0.16	0.98	0.64	0.21
GDP	Gross domestic product (trillion yuan)	0.07	3.27	0.69	0.69
IND	Share of tertiary industry (%)	16.57	68.88	41.44	13.24
TEC	Share of technology expenditure in GDP (%)	0.29	1.82	0.65	0.35
GOV	Share of government expenditure in GDP (%)	6.03	21.75	9.78	3.18
POP	Difference in the size of population (million)	-4.44	9.78	0.04	2.51
HUM	Difference in the number of higher education students (ten thousand)	-4.42	5.63	0.01	2.86

3.3 Analytical strategy

We specify a panel model with period and group fixed effects to measure the effects of multiplex networks on LMI. Our model selection commenced with a Hausman test, the results of which (chi-square = 29.04, p-value = 0.0103) suggested that the fixed-effects model outperforms the random-effect model. Given this, we employed a two-way fixed-effect model for the analysis:

$$LMI_{it} = \delta + \alpha NC_{it} + \beta X_{it} + \gamma_i + \delta_i + \varepsilon_{it} \tag{6}$$

where LMI_{it} is the level of integration of city *i* in year *t* within the region, NC_{it} represents the network connections, X_{it} denotes a set of control variables, γ_i and δ_i denote the time-and individual fixed effects, respectively, and ε_{it} is the random error term.

However, the inclusion of network-derived variables (e.g., degree centrality) may violate core assumptions of regression analysis: the interdependence of observations (e.g., the DC of city i is influenced by city *j*, and vice versa). To address this concern, we used the bootstrapping method with 5000 replications, assigning measures of accuracy to regression estimates. We also addressed key econometric challenges. Unit-root tests and VIF analysis suggest no evidence of non-stationarity or multicollinearity. Analyses for cross-sectional independence, heteroscedasticity, and autocorrelation supported the fixed-effect model with corrected standard errors. A critical concern is potential endogeneity arising from reverse causality and/or omitted variables. This, above all, can be addressed by the Generalized Method of Moments (GMM) model.

4 Results

4.1 Varying impacts on LMI: transport networks vis-à-vis technology networks

We structure our discussion of the impact of transport and technology networks on LMI around Table 2. In Model 1, the coefficients for most control variables – except for *GDP* and *TEC* – are statistically significant with the expected signs. Specifically, the difference in the population size (*POP*), human capital (*HUM*), and government control (*GOV*) are negatively associated with LMI. The share of tertiary industry (*IND*) contributes to reduced wage differences and increased LMI, corroborating the findings of Han and Sun (2019).

Focusing on our key variables of interest, we observe that coefficients for both transport (*RDC*) and technology networks (*PDC*) are statistically significant, albeit in different directions. Model 2 shows a positive association between transport connections and LMI, suggesting that enhanced transport connections reduce wage differences, echoing Hu et al. (2020), who found that transport connections facilitate labor mobility and mitigate wage disparities.

Conversely, technology networks and LMI (Model 3) reveal a somewhat nuanced U-shaped relationship, corroborated by the UTEST estimation (Appendix C). This indicates that limited technology spillovers can lead to 'polarization' in regional labor markets (e.g., job concentration in knowledge-intensive industries and intercity wage differences). However, as technology spillovers become increasingly widespread, the benefits of knowledge exchanges—such as job-skill enhancement and increased employment opportunities—begin to outweigh the downsides, thereby facilitating wage convergence. These findings broadly align with previous research (e.g., Wang & Yin, 2016). Therefore, our first (*H1*) and second (*H2*) hypotheses are accepted.

Table 2 Results of the regression analysis

Variables	Model (1)	Model (2)	Model (3)	Model (4)
RDC		2.29(1.01)*		2.15(1.02)*
		[1.06]*		[1.06]*
PDC			-2.97(0.73)***	-2.98(0.73)***
			[1.10]***	[1.11]***
PDC^2			4.59(1.81)**	4.41(1.73)**
			[1.81]**	[1.81]**
GDP	0.13(0.14)	0.24(0.27)	0.33(0.24)	0.43(0.23)
	[0.49]	[0.49]	[0.49]	[0.50]
IND	0.05(0.01)***	0.05(0.01)***	0.05(0.01)**	0.05(0.01)***
	[0.02]**	[0.01]***	[0.01]***	[0.02]***
TEC	0.41(0.46)	0.36(0.51)	0.57(0.48)	0.53(0.52)
	[0.69]	[0.69]	[0.69]	[0.69]
GOV	-5.32(2.41)*	-4.11(1.81)*	-6.32(2.68)*	-5.13(2.34)*
	[2.60]*	[2.01]*	[2.87]*	[2.54]*
POP	-0.12(0.01)***	-0.12(0.01)***	-0.12(0.01)***	-0.12(0.01)***

	[0.06]**	[0.06]**	[0.06] **	[0.06]**
HUM	-0.09(0.03)**	-0.08(0.03)**	-0.08(0.03)**	-0.07(0.03)**
	[0.04]*	[0.04]*	[0.04]*	[0.03]*
Constant	11.02(0.25)***	10.23(0.47)***	11.67(0.31)***	10.95(0.53)***
	[0.65]***	[0.97]***	[0.72]***	[0.95]***
R^2	0.54	0.54	0.56	0.57
F-statistic	60.08***	265.37***	49.32***	206.27***
Obs.	208	208	208	208
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

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

2) Driscoll-Kraay standard errors in parentheses; Bootstrap standard errors in brackets.

4.2 The impact of multiplex networks on LMI

The main added value of our research is the ability to focus on the joint dynamics of both networks: how does the interplay between transport and technology networks affect LMI? In this section, we aim to capture the combined and interactive effect of multiplex networks on LMI changes.

4.2.1 The combined impact on LMI: which network dominates?

In our investigation of multiplex networks, the combined network effect (*ADC*) exhibits a U-shaped relationship with LMI, as confirmed by the UTEST estimation (Appendix C). Interestingly, the joint effect of multiplex networks on LMI closely resembles that of technology networks. Our Hypothesis 3 is, therefore, not accepted. A plausible explanation lies in the potentially ‘dominant’ role of technology connections. As Burger et al. (2014) argued, different types of networks do not necessarily yield identical economic implications. Notably, technology transfer, less spatially constrained than physical linkages (Cao et al., 2018), is arguably more effective in fostering skill development and reducing wage disparities. To investigate this, we compared the effects of transport and technology networks (Table 2) and employed a random forest algorithm to assess their relative importance in predicting LMI changes. We found that, all else being equal, technology networks have a more pronounced impact on LMI, corroborating our observation of their dominant role.

More specifically, cities’ overall connections in multiplex networks adversely affect LMI, suggesting that job-access effects facilitated by cities’ transport connections may be (partially) offset by the ‘polarization’ associated with technology linkages. This trend, however, reverses as overall connections intensify. As workers adapt more easily to new technologies and leverage improved connectivity, they tend to seek jobs better aligned with their enhanced skills in broader labor markets.

Table 3 Regression results of the panel model

Variables	Model (1)	Model (2)	Model (3)
ADC	-2.82(0.64)***		-2.80(0.59)***
	[0.75]***		[0.75]***
ADC^2	5.15(1.63)**		5.25(1.63)**
	[1.82]**		[1.98]**
NOD		0.82(0.17)***	0.86(0.26)***
		[0.18]***	[0.27]***
GDP	0.23(0.28)	0.10(0.29)	0.19(0.30)
	[0.48]	[0.48]	[0.48]
IND	0.05(0.01)***	0.05(0.01)***	0.05(0.01)**
	[0.01]**	[0.01]***	[0.01]***
TEC	0.55(0.46)	0.44(0.43)	0.59(0.41)
	[0.69]	[0.69]	[0.68]
GOV	-6.67(3.13)*	-6.14(2.95)*	-7.55(3.62)*
	[3.27]	[3.02]*	[3.74]*
POP	-0.12(0.01)***	-0.12(0.01)***	-0.12(0.01)***
	[0.05]**	[0.05]***	[0.04] **
HUM	-0.09(0.03)**	-0.09(0.03)**	-0.09(0.03)**
	[0.04]*	[0.04]*	[0.05]*
Constant	11.67(0.27)***	11.65(0.13)***	12.31(0.23)***
	[0.52]***	[0.43]***	[0.65]***
R^2	0.56	0.54	0.57
F-statistic	48.97***	404.54***	62.33***
Obs.	208	208	208
City FE	YES	YES	YES
Year FE	YES	YES	YES

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

2) Driscoll-Kraay standard errors in parentheses; Bootstrap standard errors in brackets.

4.2.2 The interactive effect on LMI

To explore the interactive effect of multiplex networks in more detail, we begin by scrutinizing the role of cities' interdependencies in shaping LMI. In Table 3, cities' interdependencies (*NOD*) are positively associated with LMI (Model 3). This suggests that as cities become more interconnected through transport and technology connections, their growing interdependencies can lead to positive synergies, i.e., the increased levels of LMI.

Specifically, cities connected by dense transport connections benefit from enhanced labor flows across broader markets, providing conduits for face-to-face interactions. Technology connections can facilitate knowledge exchange, interpersonal communication, and learning processes, thereby stimulating the need for job searching and commuting trips. Collectively, these networks manifest interdependent and complementary roles in reducing wage differences and promoting LMI. This finding supports the presence of synergies in multiplex networks (Meijers, 2005). Our hypothesis 4 is therefore accepted.

To ensure the robustness of these findings, we employed GMM models to address potential endogeneity concerns (Appendix D). The results remain consistent across different model specifications, lending credibility to our findings.

5. Conclusions

Cities are increasingly embedded in a complex web of networks, where the multifaceted connections are arguably one of many elements to explain their economic dynamism (Meijers et al., 2016). Despite a growing literature highlighting the critical roles of transport and technology networks in shaping market integration (e.g., Andersson et al., 2023; Cao et al., 2018), limited attention has been given to how their interactions influence the integration of labor markets. In this study, *theoreticall*y, we contribute to the emerging literature by linking transport-technology networks to LMI through the network-related mechanisms (i.e., network externalities and synergies); *empirically,* extending a recent study of Liu et al. (2025) on technology cooperation and LMI, *we* juxtaposed the impact of transport and technology linkages on LMI, both individually and collectively, within the YRD region.

Our main findings are that:

(1) Transport networks are positively related to LMI, aligning with the earlier findings on transport connectivity and LMI (Johansson et al., 2002); while technology networks exhibited a ‘U’-shaped effect on LMI, echoing previous discussions on the heterogeneous impact of network linkages (Burger et al., 2014).

(2) The combined effect of cities’ networks on LMI follows a ‘U’-shaped trend, with the potentially dominant role of technology linkages (Cao et al., 2018).

(3) Crucially, interactions in the multiplex transport-technology network generate positive synergies (Guan et al., 2022), highlighting that cities’ interactions in complementary network layers can translate into synergistic effects on LMI.

These findings highlight the need to conceptualize city networks as multilayered and interdependent urban systems (Hu et al., 2020). This also emphasizes the explanatory potential of both infrastructure and technology linkages as instrumental for shaping the broader integration (Liu et al., 2025). While intercity transport and technology connections are often discussed in parallel (e.g., Guan et al., 2022), our results indicate that they are related to LMI in different ways. This supports the recent discussions to account for network multiplexity (Meijers et al., 2016) and to develop an analytical framework capable of embodying and capturing cities’ interdependencies across network layers (Higham et al., 2022).

The empirical focus explored in our paper—China’s Yangtze River Delta (YRD) megacity-region—has been the subject of recent studies examining its network development (e.g., Cao et al., 2018; Zhang et al., 2020). Our findings extend this strand of literature by providing evidence on the links between multiplex networks and market integration in the YRD, and the theoretical mechanisms underlying this association. Complementing the study by Liu et al. (2019), which measured synergies through local socio-economic factors, our analysis highlights how synergies embedded in intercity linkages can be internalized to shape regional labor markets.

Our main findings can be relevant to policy narratives. First, for an integrated market, the main impetus lies in the integrated and networked framework anchored in its cities. Policy strategies on promoting market integration should prioritize enhancing both physical infrastructure connectivity and technology linkages. Second, different types of network externalities can translate into a form of regional capital, facilitating the movement of human capital and the exchange of knowledge (Liu et al., 2023). Third, interdependencies between cities are crucial in determining the presence of synergies in regional networks. Policy initiatives are therefore suggested to foster cross-regional interactions that link infrastructure and innovation linkages with/beyond the region.

Our study has of course some limitations. First, rail connections and patent transfer are admittedly less-than-perfect proxies for transport and technology networks. Future work could include a broader variety of linkages (Meijers et al., 2016). Second, although our theoretical lenses—network externalities and synergies—offered tailored frameworks, they may oversimplify the broader dynamics of networks and regional integration. Alternative perspectives, such as complementarities and cooperation (Capello, 2000; Liu et al., 2025), may reveal other important mechanisms. Third, future studies could extend our study by applying an econometrics-based framework for both inter- and intra-regional connections, and generalize the findings based on locally-rooted factors.

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Appendix

Appendix A Correlation between transport and technology networks

Table 1 Correlation between transport and technology network

	PCC	SCC	QAP
2014	0.628	0.661	0.494
2015	0.667	0.642	0.427
2016	0.672	0.612	0.572
2017	0.713	0.709	0.596
2018	0.774	0.729	0.675
2019	0.703	0.715	0.653
2020	0.830	0.727	0.728
2021	0.861	0.768	0.718

*Correlation coefficients of Pearson (PCC), Spearman's rank (SCC) and Quadratic Assignment Procedure (QAP). P-value is lower than 0.001.

Appendix B Interactions between transport and technology networks

We employ conditional probability to assess interlayer interactions. This value ranges from 0 to 1, with a higher value suggesting a higher likelihood of connections in one layer given its presence in another.

Table 2 The conditional probability between two networks

	P (technology | transport)	P (transport | technology)
2014	0.917	0.715
2015	0.916	0.718
2016	0.897	0.671
2017	0.916	0.670
2018	0.930	0.675
2019	0.940	0.701
2020	0.955	0.732
2021	0.901	0.833

Appendix C Results of UTEST estimation

UTEST results confirm U-shaped effects: for technology networks (PDC), the turning point is 0.2945 within the range [0.0153, 1]; for multiplex networks (ADC), it is 0.3737 within [0.0140, 1].

Table 3 Results of UTEST estimation

	PDC		ADC	
	Lower bound	Upper bound	Lower bound	Upper bound
Interval	0.0153	1	0.0140	1
Slope	-1.5839	4.0026	-1.7793	3.0984
Extreme/Turning point	0.2945		0.3737	

Appendix D Dealing with endogeneity

We use system GMM with one-period lagged variables as internal instruments. Results align with fixed-effects estimates, reinforcing the robustness of our findings.

Table 4 Results of GMM estimations

Variables	One-step GMM		Two-step GMM	
	Model 1	Model 2	Model 3	Model4
L1.LMI	0.23(0.10)**	0.16(0.08)**	0.21(0.07)***	0.21(0.05)***
L1.RDC	2.12(1.21)*		1.41(0.76)*	
L1.PDC	-3.34(1.88)*		-3.20(1.49)**	
L1.PDC^{2}	6.88(3.19)**		6.13(3.03)**	
L1.ADC		-7.70(2.20)***		-6.23(1.52)***
L1.ADC^{2}		9.86(4.28)**		7.77(2.64)***
L1.NOD		1.82(0.98)*		1.80(1.04)*
GDP	1.03(0.56)*	1.05(0.56)*	0.70(0.48)	0.68(0.30)**
IND	0.04(0.12)	0.03(0.01)**	0.02(0.02)	0.02(0.01)***
TEC	0.36(0.23)	0.31(0.49)	0.19(0.22)	0.63(0.36)*
GOV	-0.84(1.37)	-4.46(3.28)	-1.49(3.71)	-4.93(2.12)**
POP	-0.11(0.06)*	-0.06(0.07)	-0.07(0.05)	-0.01(0.06)
HUM	-0.21(0.09)**	-0.17(0.09)*	-0.18(0.08)**	-0.16(0.07)**
Time Effect	YES	YES	YES	YES
AR (1)	0.004	0.004	0.002	0.005
AR (2)	0.432	0.621	0.442	0.533
Sargan test	0.219	0.846	0.219	0.832
Hansen test	0.318	0.870	0.318	0.898
No. of instruments	25	25	25	25
Observations	182	182	182	182

Notes: 0.01 (***), 0.05 (**), and 0.1 (*). Standard errors are reported.