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IS LABOUR PRODUCTIVITY HIGHER IN TRANSIT ORIENTED DEVELOPMENT AREAS? A STUDY OF BEIJING

GUOWEI LYU*, LUCA BERTOLINI** & KARIN PFEFFER***

*College of land science and technology/Center of Land Policy and Law, China Agricultural University, Beijing, 100193, China. Email: g.lyu@cau.edu.cn

**Department of Geography, Planning and International Development Studies/Amsterdam Institute for Social Science Research, University of Amsterdam, NC Amsterdam, the Netherlands. Email: l.bertolini@uva.nl

***Department of Urban and Regional Planning and Geo-Information Management, University of Twente, Enschede, 7500 AE, the Netherlands. Email: k.pfeffer@utwente.nl

ABSTRACT

Transit oriented development (TOD) advocates enhancing public transport connectivity, clustering urban development around public transport nodes and creating station areas with high-density, diverse land uses and pedestrian- and cycling-friendly environments. While this urban development approach is expected to have positive effects on the urban economy, the impacts of TOD strategies on economic efficiency are yet to be empirically examined. This study operationalised economic efficiency as labour productivity; developed a methodology to investigate how labour productivity is distributed at the local level, to explore the relationships between TOD characteristics and the clustering of labour productivities across different types of industries within a city; and applied it to the case of Beijing, China. The results show that in most cases the distribution of labour productivity has no significant association with TOD characteristics. However, in certain consumer-service-related economic sectors (i.e. wholesale and retail; accommodation and catering; and culture, sports, and entertainment) labour productivity is on average significantly higher in an area with stronger transit-oriented development characteristics. Furthermore, within the conceptual framework of agglomeration economies, the paper identified specific TOD characteristics that are related to the clustering of the higher level of labour productivities in certain industry sectors. These outcomes provide insights for developing more focused TOD strategies, aimed at enhancing the clustering of labour productivities in the identified industries around the existing metro station areas in Beijing.

Key words: Transit oriented development; labour productivity; agglomeration economies; hotspot analysis; spatial regression; Beijing

INTRODUCTION

Transit oriented development (TOD) advocates for the integration of transport and land use systems by enhancing public transport connectivity and clustering urban developments around public transport nodes and creating areas with high-density, diverse land

uses, and pedestrian- and cycling-friendly environments (Bertolini & Spit 1998; Cervero *et al.* 2004; Dittmar & Ohland 2004). It is recognised as a strategy that can potentially enhance the urban economy by reducing transportation costs (e.g. Mudigonda *et al.* 2014; Nahlik & Chester 2014); by offering opportunities for land value capture

(e.g. Cervero *et al.* 2004; Renne 2008; Cervero & Murakami 2009; Mathur & Ferrell 2009; Bartholomew & Ewing 2011; Duncan 2011); and by stimulating employment (Belzer *et al.* 2011; Schuetz 2015), company setup and relocation (Iseki & Jones 2014; Noland *et al.* 2014; Zheng *et al.* 2016), or industry net income (Seo *et al.* 2013). However, is TOD also related to the economic efficiency of regions and areas? The theory suggests that the economy of a region (e.g. a country or a metropolitan area) with better-integrated transport and land use systems should be more efficient (with all other variables remaining unchanged). For example, labour productivity, a frequently used indicator to measure economic efficiency (Broersma & Oosterhaven 2009; Fedderke & Bogetić 2009; Reggiani *et al.* 2011), is typically higher and clustered in developed countries. However, how, within a city, an area's labour productivity is related to the area's attributes of transit oriented development (including both transport and land use characteristics), and how this differs per economic sector, is not highlighted in the literature. The aim of this paper is to contribute to filling this knowledge gap in this underexplored area of TOD research.

In order to answer this question, we developed a methodology to assess the values and the clustering of labour productivities in different types of area for different types of industries, in particular by exploring the relationships between TOD characteristics of station areas and the clustering of labour productivities in certain industries. The methodology was applied to the case study of metro TOD in Beijing, China. In our analysis, TOD characteristics include transport features, land use features, and features of transport land use relationships of both local metro station areas and metro station areas within the one-hour travel catchment of local metro station areas. The paper is structured as follows. The next section discusses the theoretical grounding of the relationship between TOD characteristics of station areas and the clustering of labour productivity in these areas, followed by a presentation of the contextual background of the case of Beijing in the next section. Then, the paper outlines the methodology used to measure the clustering

of labour productivities in the different industries at the local station area level and to explore the relationships between TOD characteristics of station areas and the clustering of labour productivity in the identified significantly associated industries. The final section closes with a summary of the findings, potential policy implications, reflections on the limitations of the study, and suggestions for future research.

THEORETICAL BACKGROUND

Labour productivity can be defined as the ratio between a volume measure of output (e.g. expressed as gross domestic product, gross value added, or sales) and a measure of input (i.e. labour use, expressed as total number of work hours or total employment) (Schreyer 2001; Al-Matari *et al.* 2014). The positive link between agglomeration economies and productivity has been well established (Ciccone 2002; Fujita & Thisse 2002; Rigby & Essletzbichler 2002; De Bok & Van Oort 2011). The impacts of agglomeration on productivity are hypothesised to come in the form of localisation economies of firms 'generated by the proximity of firms producing similar goods' (Fujita & Thisse 2002, p. 267; Marshall 2013), and urbanisation economies 'defined by all the advantages associated with the overall level of activity prevailing in a particular area' (Fujita & Thisse 2002, p. 267; see also Jacobs 1969; Glaeser *et al.* 1992), for example, the advantages caused by the existence of public goods, economies of scale in the size of markets, and inter-sector interactions. Previous studies have shown that the effects/mechanisms of agglomeration economies vary depending on the type of industry and the geographical context. Based on regional data in Europe, Brühlhart and Mathys (2008) find that the manufacturing sector exhibits negative localisation effects and positive urbanisation effects on labour productivity, whereas financial services benefit from localisation economies, but not from urbanisation economies. Furthermore, they find no statistically significant evidence of agglomeration effects on labour productivity in the industry sectors of

construction, wholesale and retail, hotel and restaurants, transport and communication services, and other market services. Based on Canadian cities' manufacturing data, Baldwin *et al.* (2008) find instead localisation economies to be important for productivity in manufacturing. Jofre-Monseny *et al.* (2014) examine the locations of new manufacturing firms in Spain at the city level, and find that localisation economies are higher in manufacturing industries employing workers with industry-specific skills while urbanization economies are higher in knowledge-intensive manufacturing. Focusing on the creative industry in cities in Italy and Spain, Lazzeretti *et al.* (2012) conclude that both urbanisation and localisation economies play important roles in the clustering of this sector. In some contexts, scholars find that specialisation (part of localisation economies) has even negative effects on employment growth (e.g. Bishop & Gripaios 2010 based on regional data of Great Britain on 23 economic sectors; Paci & Usai 2008 based on regional data of Italy on 34 sectors; de Vor & de Groot 2010 based on industry site data within a city on 11 sectors). Others found that diversity (Jacobian cluster, or part of urbanisation economies) has positive effects in the sectors of advertising (e.g. Bugge 2011 based on firm-level data within a city) and retail (e.g. Nilsson 2016 based on firm-level data in Sweden). In sum, the effects/mechanisms of agglomeration economies differ geographically (including across geographical scales, e.g., Burger *et al.* 2007), and across industries, and hence the same rules do not always apply to all contexts. This makes it interesting to enquire into industry-specific effects/agglomerations in the context of Beijing. In particular, at the station area level, we expect that there is a potential for the labour productivity of firms located in an area with stronger transit oriented development features (including both transport and land use characteristics) (i.e. with a higher level of spatial opportunities within reach, or location-based accessibility: Geurs & van Wee 2004) to be higher and clustered due to one or more of the following agglomeration economies-enhancing factors: (1) the higher transport connectivity characterising a TOD area can give firms access to larger

labour, customer, and supplier markets, and to more diverse urban services, which magnifies the effects of urbanisation economies (Graham 2007; Venables 2007); (2) the density and diversity of developments characteristic (Jacobs 1969; Ciccone & Hall 1996; Cervero & Kockelman 1997; Quigley 1998) of both local metro station areas and metro station areas within the travel catchment of local metro station areas can reduce the transport or transaction costs between firms (intra/inter industry sectors) and between firms and customers, which mainly magnifies the effects of urbanisation economies, and in some cases, it can shape conditions for skill/knowledge spill-overs and the development of social capital, which mainly magnifies the effects of localisation economies (Jofre-Monseny *et al.* 2014); and (3) the higher spatial connectivity within TOD areas resulting from developments oriented towards transportation interchanges and higher internal walkability can enhance interactions between firms and customers (increasing customer exposure to products and services) and between workers in different firms (enabling inter-firm learning and innovation processes; Chatman & Noland 2011), which mainly magnifies the effects of localisation economies.

Transport, land use and urban design-related factors are not the only factors that explain labour productivity differences between geographic areas. Other relevant, area-related factors include the availability of information and communication technology (Jorgenson & Vu 2010), the overall degree of innovation (Kurt & Kurt 2015), the institutional environment (Nicoletti *et al.* 2003), and the position in the global economy (Malick 2013). Within the same city, this study assumes that the effects of these other factors can be viewed as spatially correlated errors in the explanatory regression model.

THE CONTEXT OF BEIJING

Beijing is one of the main Chinese metropolises, home to 21.5 million residents, with 86.4 per cent urban population and 1,385.6 km² urban built-up environment in 2014 (Beijing Municipal Statistics Bureau 2015; Ministry of

housing and urban-rural development of China 2014). In 2014, the metro served 10 million passengers each workday, with 18 lines, 268 stations and 527 km of track in operation (Beijing Infrastructure Investment Corporation Limited 2015; Beijing Mass Transit Railway Operation Corporation Limited 2015). In 2015, in the Beijing built-up area, around half of the total number of passengers travelled by public transport, and among the passengers that travelled by public transport, around half travelled by metro (Beijing Transportation Research Centre 2017). With respect to travel purpose, in 2014, 85.1 per cent of the total trips by metro were for commuting to and from work, 5.1 per cent of the total trips by metro were for commuting to and from study, and 6.7 per cent of the total trips by metro were for other urban life, for example, visiting, shopping, recreation and entertainment (Ma *et al.* 2017). Based on these data, we can conclude that the metro system considerably supports the urban daily life of the residents, commuters and visitors of Beijing, which we might expect has, in turn, some impact on the labour productivity of firms located at the metro stops.

In order to facilitate economic development, TOD strategies focused on the metro system have been proposed – and implemented – in Beijing for years. According to the Beijing Urban Master Plan 2004–2020, TOD strategies are promoted as a tool to facilitate urban growth and restructure the urban spatial form (Beijing Municipal Government 2003). At that time, TOD strategies were officially considered as one of the key tools to conserve urban land use (Beijing municipal commission of urban planning 2009). Furthermore, the official Beijing Urban Master Plan 2016–2030 (Beijing Municipal Commission of Planning and Land Resource Management 2017) uses labour productivity as an important indicator for measuring the efficiency of Beijing's economy. It aims at increasing labour productivity across the city from 196,000 Chinese Yuan per worker in 2015 to 230,000 Chinese Yuan per worker in 2020; however, it does not propose a specific strategy as to how to reach this goal. This paper seeks to provide actionable insights by examining the relationship between TOD characteristics of station areas and the clustering of labour productivity in these areas.

METHODOLOGY

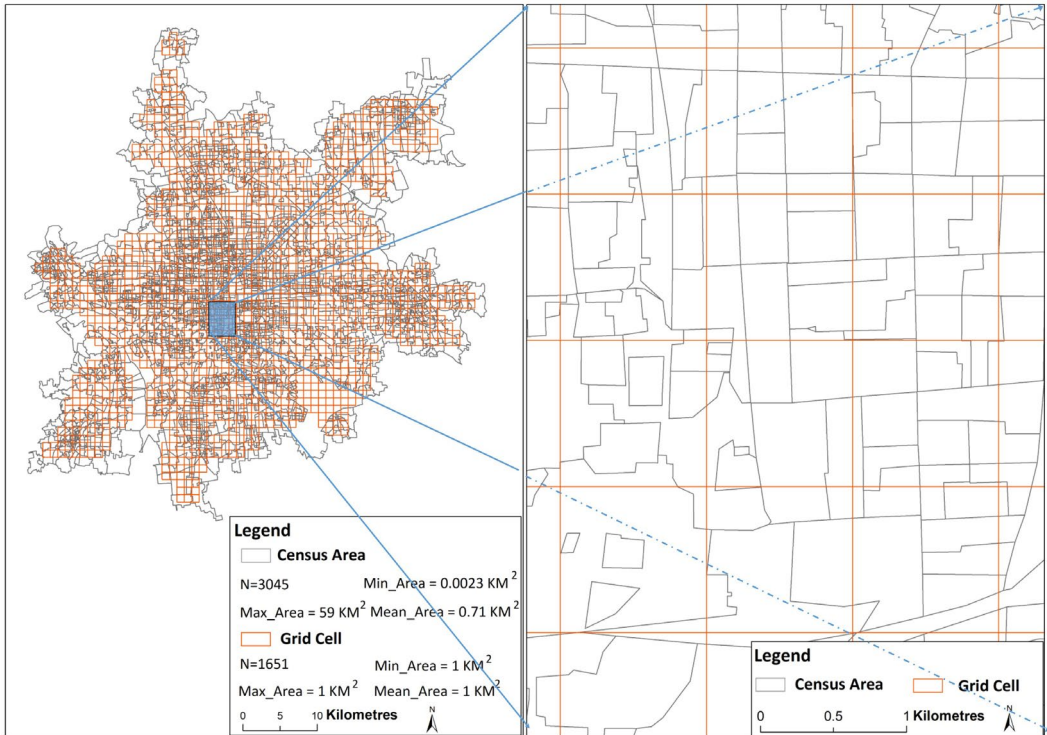
The methodological objectives of the paper are set out as follows: to measure the labour productivity of urban areas in Beijing; to assess the clustering of 'hot' and 'cold' spots of labour productivities; to identify three types of grid cells and assess the TOD characteristics that are theoretically related to labour productivity; and to explore, with a spatial regression model, the relationships between the clustering of labour productivity in a station area and the TOD characteristics of the station areas (including both the TOD characteristics of the station area and of the station areas within a one-hour travel catchment of the station area).

Measuring labour productivity of areas – Labour productivity can be defined as the ratio between a volume measure of output (e.g. gross domestic product, gross value added or sales) and a measure of input (e.g. total number of work hours or total employment) (Schreyer 2001; Al-Matari *et al.* 2014). Following the limitations of data availability, labour productivity of an area in this study is expressed as the ratio of sales (operating revenues) to the number of workers employed in the area (see Al-Matari *et al.* 2014).

The study covers the entire built-up area of Beijing (the boundary uses open access data from Yang *et al.* 2013), divided into 1,651 comparable grid cells (1 km by 1 km). Given the modifiable areal unit problem (Openshaw 1984), the choice of grid cells at different spatial scales may influence the results of the analysis. The 1 km² scale was selected because it (1) can sufficiently distinguish between three types of urban areas (see details below) and (2) is close to the average size of the spatial units in the original dataset of economic indicators.

The dataset on economic indicators was retrieved from Beijing's web application depicting the third economic census of 2014, including the census area boundaries and economic attributes (Beijing Municipal Statistics Bureau 2016) (see Figure 1). It presents data at local area level, which is the most disaggregated and complete economic census data for public use. In the built-up area of Beijing, there are 3,045 census areas (average size 0.71 km²).

Furthermore, an area's labour productivity was explored across different types



Note: The economic census data in Beijing is not localised at the individual workplace level, but at the irregularly-shaped census zone level (see Figure 1). In order to homogenize these heterogeneous geographical units, in support of comparison and computation, the data was transferred to grid cells.

Source: Beijing's web application depicting the third economic census of 2014 (Beijing Municipal Statistics Bureau 2016).

Figure 1. Local area level of the economic census boundaries and grid cells in the built-up areas of Beijing. [Colour figure can be viewed at wileyonlinelibrary.com]

of industries, categorised according to the Sectorial Classification System (Standardization Administration of the People's Republic of China 2011). Some sectors, such as agriculture, scientific research, and polytechnic services as well as international organisations, were dropped due to lack of census data. The following industry types were examined: entire industry (ENTI, this is not a sum based on the values of the different types of sectors, but a synthetic indicator for the industry as a whole that is used in the economic census database); mining quarrying (MINI); manufacturing (MANU); utilities (supply of water, gas, electricity, heat, etc.) (UTIL); construction (CONS); wholesale and retail (WHOL); transport, storage, and postal services (TRAN); accommodation and catering (ACCO); information transfer, software

and information technology services (INFO); finance (FINA); real estate (REAL); resident, repair, and other services (RESI); education (EDUC); health care and social work (HEAL); culture, sports, and entertainment (CULT); public administration, social insurance, and social organizations (PUBL).

Based on the boundaries of the economic census data and the locations of grid cells (see Figure 1), this study computed sales and the number of employees within each grid cell, using the geographic information system ArcGIS 10.3.1, desktop platform. First, we calculated sales density (M_1) and employment density (M_2) in each census area using the following equation:

$$Density_{i-j-M} = \frac{M_Values_{i-j}}{Surface_areas_j}, \quad (1)$$

$Density_{i,j,M}$ is the M (M_1 sale or M_2 employment) density of the census area j in industry type i ; $M_Values_{i,j}$ is the value of M in industry type i in the census area j , (e.g. $M_I_Values_{i,j}$ is the sales in the industry type of i in the census area j , which can be directly retrieved from the third economic census dataset of Beijing in 2014); $Surface_areas_j$ is the surface area of census area j , which was geometrically calculated in ArcGIS 10.3.1.

Second, the study calculated the spatial overlap of census areas and grid cells within ArcGIS, producing 9,767 new sub-areas across the 1,651 grid cells (Figure 1). Third, the paper re-aggregated $M_Values_{i,k}$ within each grid cell using the following equation:

$$M_Values_{i,k} = \sum_{k-s} Density_{i,j,M_k-s} \times Sub_area_{j,k-s}, \quad (2)$$

$M_Values_{i,k}$ is the M value in the industry type of i in cell k ; $Density_{i,j,M_k-s}$ is the M density in industry type i of the sub-area s that is simultaneously located in census area j and cell k (assuming $Density_{i,j,M_k-s} = Density_{i,j,M}$); $Sub_area_{j,k-s}$ is the surface area of the sub-area s that is simultaneously located in census area j and cell k ; $\sum k-s$ is the sum of sub-area(s) located in cell k .

Given that $M_I_Values_{i,k}$ represents the total sales in industry type i in cell k and that $M_2_Values_{i,k}$ represents the total number of employees in industry type i in cell k , labour productivity of industry type i for cell k can be calculated using the following equation:

$$Labour\ productivity_{i,k} = \frac{M_I_Values_{i,k}}{M_2_Values_{i,k}}. \quad (3)$$

‘Hot’ and ‘cold’ spot analysis: measuring clustering of labour productivities of areas (grid cells) – In order to investigate the spatial pattern of labour productivity across different industries at the grid cell level, the study applied the hotspot analysis (using ArcGIS 10.3.1) to the labour productivities of grid cells in the different sectors. Labour productivities of grid cells for selected industry types are reported in Figure 2 as an illustration: the entire industry

(for its synthetic value); accommodation and catering (an example of an industry type with positive association with TOD characteristics); manufacturing (as an example of an industry type with non-existent association with TOD characteristics); and mining quarrying (as an example of an industry type with small number of total grid cells where firms exist).

The hotspot analysis presumes the presence of spatial autocorrelation of labour productivities: similar values of labour productivities are not randomly distributed but rather agglomerate in a location. However, the geographical scale of the cluster (agglomeration) of labour productivity is expected to vary for different economic sectors because the scale effect of agglomeration economies in each economic sector varies. Thus, prior to conducting the hotspot analysis, the study applied incremental spatial autocorrelation (Esri 2016b), using Global Moran’s I statistic (Goodchild 1986; Anselin 1996), to measure spatial autocorrelation of labour productivity in a specific industry sector for a series of distances and to derive their corresponding z-scores. The z-scores reflect the intensity of spatial clustering, and statistically significant peak z-scores indicate distances where the spatial processes that promote clustering are most pronounced. Based on this analysis, the study identified the distance within which the labour productivities of an economic sector are expected to be spatially autocorrelated. This distance was used to determine the weight matrix between grid cells, which provided the basis for the hotspot analysis.

Next, hotspot analyses of the labour productivities of grid cells for different types of industries were performed, based on their corresponding weight matrix. Hotspot analysis can detect statistically significant spatial clusters of high values (hotspots) and low values (cold spots) using the Getis-Ord G_i^* statistic (Getis & Ord 1992; Ord & Getis 1995; Esri 2016a; O’Sullivan & Unwin 2010) by applying the following formula:

$$G_i^* = \frac{\sum_{j=1}^n W_{i,j} x_j - \bar{X} \sum_{j=1}^n W_{i,j}}{\sqrt{\frac{\sum_{j=1}^n x_j^2 - n(\bar{X})^2}{n}} * \sqrt{\frac{[n \sum_{j=1}^n W_{i,j}^2 - (\sum_{j=1}^n W_{i,j})^2]}{n-1}}}, \quad (4)$$

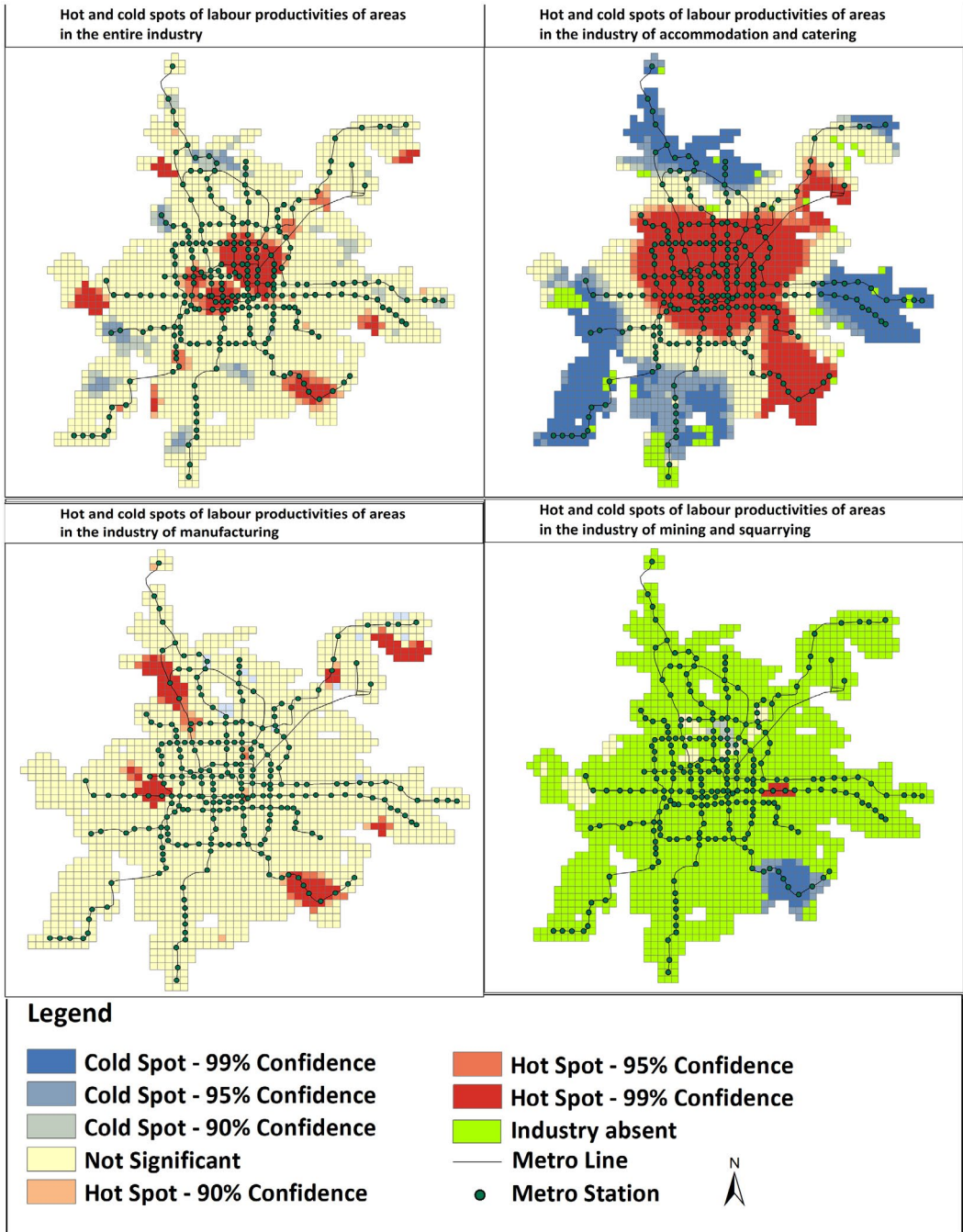


Figure 2. Hot and cold spots of labour productivities of grid cells for selected industry types, illustrative of different degrees of association between clustering of productivity and TOD characteristics of areas: entire industry (reference), accommodation and catering (positive association), manufacturing (no association), mining and quarrying (small number of cells). [Colour figure can be viewed at wileyonlinelibrary.com]

where x_j is the labour productivity value for the grid cell j ; $W_{i,j}$ is the spatial weight between the centroid of grid cell i and j (determined by the corresponding clustering distance identified by incremental spatial autocorrelation analysis). Here $W_{i,j}=1$ if the Euclidean distance between grid cell i and j is within this clustering distance, and all cells within that distance are considered as neighbours, otherwise $W_{i,j}=0$. The total number of grid cells (where a labour productivity exists, compare Figure 2) is indicated by n , and \bar{X} is the mean value of labour productivity for the total of all grid cells (n grid cells). The local sum of labour productivities for a grid cell and its neighbours ($\sum_{j=1}^n W_{i,j} x_j$) is compared proportionally to the sum of labour productivities for the total grid cells ($\bar{X} \sum_{j=1}^n W_{i,j}$). Due to the definition of the spatial weight in this case, the average labour productivity for a grid cell and its neighbours is compared to the average of labour productivities for all grid cells. When the local sum (in this case, also mean value) is different from the expected local sum (also mean value) and when that difference is too large to be the result of random chance, a statistically significant G_i^* results. The G_i^* statistic returned for each grid cell is a z-score. For statistically significant positive z-scores, a larger z-score means a more intense clustering of high values (hotspots). For statistically significant negative z-scores, the smaller the z-score the more intense the clustering of low values (cold spots).

Identifying three types of urban areas and assessing TOD characteristics – This subsection identifies three types of urban areas, according to their proximity to transit stations, and assesses the TOD characteristics of station areas that are theoretically related to labour productivity, based on the dataset of Lyu *et al.* (2016). Past studies have delineated a TOD precinct according to its geographical distance from a transit stop. Most European researchers (e.g. Bertolini 1999; Reusser *et al.* 2008) propose a 700 m Euclidian distance from a transit stop, while most American studies use a range of $\frac{1}{4}$ mile (400 m) to $\frac{1}{2}$ mile (800 m) (e.g. Austin *et al.* 2010; Atkinson-Palomb & Kuby 2011). These European and American TOD area boundaries are based on the acceptable walking distance from a transit stop (assuming walking as the main access and egress mode and 10 minutes

as an acceptable walking time). Furthermore, some studies have proposed that segments up to 1,500 m (Schütz 1998) include a secondary area that might profit from the transit connection. Empirical evidence shows that some walking trips to a transit node are generated in this secondary area (Daniels & Mulley 2013; El-Geneidy *et al.* 2014). Based on the abovementioned TOD studies, the paper defined TOD cells as those located within 700 m Euclidian distance from a metro stop (comparing their respective centroids). Furthermore, cells that are between 700 m and 1,500 m Euclidian distance from a centroid of a metro stop are defined as TOD secondary cells (SC). As beyond 1,500 m only a few walking trips to a transit stop might take place, they are identified as non-TOD cells. Based on this method, the study identified three types of urban areas: 375 TOD grid cells, 548 TOD secondary grid cells (SC), and 728 non-TOD grid cells.

We further assessed the TOD characteristics of grid cells that overlapped with one or more centroid(s) of metro station(s), defined as TOD cells. Our measurements of the specific components of TOD are based on the work of Lyu *et al.* (2016). Their TOD indicators were generated from 94 TOD indicators in the literature and opinions from local TOD experts. Additionally, we set the following adoption and adaptation rules: adopted and adapted indicators should be theoretically relevant for the clustering of labour productivity of an area along the lines discussed in the theoretical background section. See Table 1 for all adoptions, adaptations and the corresponding reasons (the footnotes provide more information regarding the computation of the indicators). The dataset in this section is adapted from (Lyu *et al.* 2016).

Relating TOD characteristics to the clustering of labour productivity – This subsection first summarises the mean values of G_i^* s in three types of urban areas across different industries and identifies in which industries labour productivities are significantly higher/ clustering in TOD grid cells. Next, it uses spatial regression analysis to explore the relationships between TOD characteristics and the clustering of labour productivities (i.e. G_i^* values) in the identified industries.

Table 1. *Adoptions and adaptations of TOD indicators according to their theoretical relevance to labour productivity.*

Original indicators based on Lyu <i>et al.</i> (2016)	Adopt or adapt (indicator abbreviation)	Reason ^a
Number of directions served by metro	Adopt (NDM)	<i>Transport connectivity</i> of an area, relevant to urbanisation economies (UE)
Number of directions served by bus	Adopt (NDB)	<i>Transport connectivity</i> , relevant to UE
Daily frequency of metro services	Adopt (DFM)	Waiting times in stations, relevant to UE
Number of stations within 20 minutes of travel by metro	Adopt (NSM)	<i>Transport connectivity</i> to metro network, relevant to UE
Travel times to major employment and activity centres by metro ^b	Adopt (TCM)	<i>Transport connectivity</i> to urban centres, relevant to UE
Car-parking capacity	Adopt (CPC)	<i>Transport connectivity</i> , relevant to UE
Average distance from station to jobs in the station area	Adopt (DSJ)	<i>Proximity</i> of economic establishments to metro station within a station area, relevant to UE
Average distance from station to residents in the station area	Adapted as the averaged value of average distances from station to jobs (economic establishments) of all station areas within a one-hour travel catchment ^c (ADJ) Adopt (DSR)	<i>Proximity</i> of economic establishments to metro station for all station areas within a one-hour travel catchment, relevant to UE
Length of paved footpaths of a station area	Adapted as the averaged value of average distances from station to residents of all station areas within a one-hour travel catchment (ADR) Adopt (LFS)	Proximity of labour and (or) customers to metro station, relevant to UE
Intersection density (number of intersections in a station area)	Adopt (NIS)	Proximity of labour and (or) customers to metro station for all station areas within a one-hour travel catchment, relevant to UE
Average block size ^d of a station area	Adopt (BSS)	Walkability of a station area, relevant to localisation economies (LE)
Walk Scores ^e of a station area	Adopt (WSS)	Same with LFS
Number of residents of a station area	Adopt (NRS)	Same with LFS
Number of jobs ^f within a station area	Adapted as the average number of residents of all station areas within a one-hour travel catchment (ANR) Adopt (NJS) Adapted as the average number of jobs (economic establishments) for all station areas within a one-hour travel catchment (ANJ) Adopt (NWR)	Density of labour and (or) customers within a station area, relevant to UE Density of labour and (or) customers of all station areas within a one-hour travel catchment, relevant to UE <i>Density</i> of establishments within a station area, relevant to UE <i>Density</i> of establishments of all station areas within a one-hour travel catchment, relevant to UE
Number of workers in retail, hotel and catering within a station area	Adapted as the average number of workers (economic establishments) in retail, hotel, and catering for all station areas within a one-hour travel catchment (AWR)	<i>Density</i> of establishments in the economic sector of retail, hotel, and catering within a station area, relevant to UE/LE (depending on the explained variable) Density of establishments in the economic sector of retail, hotel, and catering of all station areas within a one-hour travel catchment, relevant to UE/LE

Table 1. (Continued)

Original indicators based on Lyu <i>et al.</i> (2016)	Adopt or adapt (indicator abbreviation)	Reason ^a
Number of workers in education, health, and culture within a station area	Adopt (NWE)	Density of establishments in the economic sector of education, health, and culture within a station area, relevant to UE/LE
Number of workers in public administration and services within a station area	Adapted as the average number of workers (economic establishments) in education, health, and culture for all station areas within a one-hour travel catchment (AWE) Adopt (NWP)	Density of establishments in the economic sector of education, health, and culture of all station areas within a one-hour travel catchment, relevant to UE/LE
Degree of functional mix ^g of a station area	Adapted as the average number of workers (establishments) in public administration and services for all station areas within a one-hour travel catchment (AWP) Adopt (DMS) Adapted as the average degree of functional mixes for all station areas within a one-hour travel catchment (ADM)	Density of establishments in the sector of public administration and services within a station area, relevant to UE/LE Density of establishments in the sector of public administration and services of all station areas within a one-hour travel catchment, relevant to UE/LE Diversity of economic establishments and households within a station area, relevant to UE

Notes: ^athe key words in Italics refer to the key concepts in the theoretical section.

^bMeasured as the average travel time (unit: minute) to top-ten most dense station areas by employment in Beijing by metro (by counting the number of economic establishments per station area, see more in Lyu *et al.* 2016).

^cA one-hour travel catchment is the surface area covered within one-hour travel time by means of public transport (including walking) from a departure grid cell to any other grid cell within the built-up area of Beijing. The average index within one-hour travel time catchments aims to approximately estimate the network effects of TOD characteristics. The travel times by public transport are based on Google Maps Distance Matrix API. The departure time was set at 7:00 in the morning Beijing local time on Wednesday, 9 November 2016. We set a travel time of one hour because the average commute time for all passengers by public transport in Beijing during peak hours is about one hour (Beijing transportation research centre 2015).

^dThe total length of the street network in a station area is calculated (unit: kilometre).

^eWalk Score is a number between 0 and 100 that measures the walkability of a location (available at www.walkscore.com).

^fThe calculation was based on all the economic establishments. The calculations of the numbers of workers in retail, hotel, and catering; in education, health, and culture; and in public administration and services were based on the numbers of their corresponding types of economic establishments.

^gThe calculation was based on the number of establishments in different sectors (number of establishments in retail, hotel, and catering; in education, health and culture; and in public administration and services), and the number of housing units in a station area. The degree of functional mix = $1 - ((a - b/d) - (a - c/d)) / 2$, with $a = \max(\text{the three types of establishments and housing})$, $b = \min(\text{the three types of establishments and housing})$, $c = \text{average (the three types of establishments and housing)}$, and $d = \text{sum}(\text{the three types of establishments + housing})$. The data was adapted from Lyu *et al.* (2016).

According to Getis and Ord (1992), a G_i^* (z-score) value near zero indicates that: (1) the detected values (here the labour productivity values) are nearly randomly distributed (i.e. no apparent spatial clustering); or (2) the detected values are close to the average value of the total grid cells (\bar{X}); or both. On the other hand, a G_i^* value of less than -1.65 indicates the clustering of low values (cold), while a value above $+1.65$ denotes high values (hot) (confidence level of 90% or higher). The paper summarises the mean values of G_i^* s in three types of urban areas across different industries (see Table 2). It shows that for most industry sectors labour productivities are either: (1) distributed nearly randomly in each type of urban area; or (2) close to the average labour productivity for all grid cells (or both). In other words, for the majority of industry sectors the distribution of labour productivities has no significant association with TOD. However, Table 2 also shows that within certain industry sectors (i.e. wholesale and retail; accommodation and catering; and culture, sports, and entertainment) the labour productivities of TOD grid cells are on average significantly higher than the average labour productivities for all grid cells within their corresponding industry sectors.

In order to explore how TOD contributes to the clustering of labour productivities in certain industry sectors, we first conducted a regression analysis using the ordinary least square (OLS) method, with the TOD indicators (Table 1) as explanatory variables and G_i^* values in three identified industry sectors (Table 2, in bold) as the separate dependent variables. Since we found that the residuals of OLS regressions are spatially autocorrelated (because some omitted factors were not considered into the OLS model, see discussion in the theoretical background section), we applied spatial error regression models (SERM) to correct such biases (Anselin 2004). The explanatory variables in SERMs were selected stepwise according to the Akaike information criterion. Our regression observations are TOD grid cells that overlapped with one or more centroid(s) of metro station(s) (also see Figure 2). The number of observations is slightly smaller than the number of metro stations (268), since a

Table 2. The mean values of G_i^* s in three types of urban areas for the different industries.

Industry type	Area type		
	Non_TOD	SC	TOD ^a
ENTI	-0.31	-0.06	0.66
MINI	-0.11	-0.11	0.02
MANU	-0.03	-0.01	0.05
UTIL	-0.03	-0.05	0.17
CONS	-0.44	0.28	0.47
WHOL	-1.32	0.63	3.01
TRAN	0.03	0.07	-0.19
ACCO	-0.63	0.46	2.21
INFO	-0.23	0.13	0.51
FINA	-0.23	-0.04	0.38
REAL	0.12	-0.11	-0.18
RESI	0.02	-0.05	-0.02
EDUC	-0.16	0.12	0.21
HEAL	-0.23	0.31	0.47
CULT	-0.98	0.4	1.83
PUBL	-0.02	-0.01	-0.15

Notes: Industry types: entire (ENTI); mining quarrying (MINI); manufacturing (MANU); utilities (supply of water, gas, electricity, heat, etc.) (UTIL); construction (CONS); wholesale and retail (WHOL); transport, storage, and postal services (TRAN); accommodation and catering (ACCO); information transfer, software, and information technology services (INFO); finance (FINA); real estate (REAL); resident, repair, and other services (RESI); education (EDUC); health care and social work (HEAL); culture, sports, and entertainment (CULT); public administration, social insurance, and social organizations (PUBL).

^aValues in bold indicate that the mean values of G_i^* s for the area type are greater than $+1.65$, suggesting the clustering of high labour productivity values.

few centroids of metro stations are located in the same grid cell (in these cases, the TOD variables of the observation were based on the closest metro station area), and a few grid cells might be lacking G_i^* values for the identified industries.

The results of the SERMs (Table 3) show how TOD characteristics may explain the spatial difference of the clustering of labour productivities in the identified industries. Certain TOD characteristics, by magnifying the effects of urbanisation economies, are significantly related to the clustering of higher labour productivities in certain industries. These include: the area's location-based

Table 3. Results and diagnostics of the regression models.

Explanatory variable	Wholesale and retail (N = 261)		Accommodation and catering (N = 258)		Culture, sports, and entertainment (N = 254)	
	Beta of OLS (1)	Beta corrected by SERM (1)	Beta of OLS (2)	Beta corrected by SERM (2)	Beta of OLS (3)	Beta corrected by SERM (3)
Constant	-13.2	-1.11	73.51**	1.51**	-51.10*	-10.66**
NDM	0		0.04		0.08	
NDB	0.01		0		0	
DFM	0		0		0	
NSM	0.04		-0.04		-0.06*	
TCM	-0.11**	-0.03**	-0.11**	-0.02**	-0.09**	-0.04**
GPC	0.01		0.02		0.03**	
DSJ	0.01**		0.003*		0	
ADJ	-0.02**	-0.01**	-0.01		-0.03**	
DSR	0		0		0	
ADR	0.02	0.01**	0.01**		0.03**	0.01**
LFS	0		0		0	
NIS	0.02**		0		-0.01**	
BSS	-0.0002*		0		0.0001**	
WSS	-0.01		-0.01		0	
NRS	0		0		0	
ANR	-0.0004**		-0.0002**		-0.0003**	0.00002**
NJS	-0.01*		0		0	
ANJ	0.09**		0.06**	-0.02** ^{a,b}	0.03**	
NWR	0		0		0	
AWR	-0.18**		-0.13**	0.02**	-0.07**	
NWE	0.01	0.002**	0.01**	0.002**	0.02**	
AWE	0.09**		0.04**	0.04**	0.03*	
NWP	0.02**		0.01**		0	
AWP	-0.11**		-0.05**		0	
DMS	12.99		-2.15		-5.2	5.94**
ADM	17.11		-77.96**	0.97**	58.86**	0.93**
Lambda(λ)		0.98**				
Diagnostic		0.97		0.98		0.93
R-squared	0.73		0.80		0.73	

Table 3. (Continued)

Explanatory variable	Wholesale and retail (N = 261)		Accommodation and catering (N = 258)		Culture, sports, and entertainment (N = 254)	
	Beta of OLS (1)	Beta corrected by SERM (1)	Beta of OLS (2)	Beta corrected by SERM (2)	Beta of OLS (3)	Beta corrected by SERM (3)
Akaike information criterion	1,336.89	818.94	1,087.02	599.60	1,046.17	766.21
Global Moran's I ^a	0.54	0.23	0.41	0.08	0.43	0.06

Notes: Variable abbreviation description (we only name the significant variables in SERMs, for the rest see Table 1): Travel times to major employment and activity centres by metro (TCM); Averaged value of average distances from station to jobs (economic establishments, derived from Baidu Maps and gathered by Lyu *et al.* 2016) for all station areas within a catchment (ADJ); Averaged value of average distances from station to residents for all station areas within a catchment (ADR); Number of residents in a station area (NRS); Average number of jobs (economic establishments) for all station areas within a catchment (ANJ); Average number of workers (economic establishments) in retail, hotel, and catering for all station areas within a catchment (AWR); Number of workers (economic establishments) in education, health, and culture within a station area (NWE); Average number of workers (economic establishments) in education, health, culture for all station areas within a catchment (AWE); Degree of functional mix for a station area (DMS). The dependent variables are separately Gi*s in the three identified industry sectors and explanatory variables are TOD components.

^aThe residuals of the OLS models are highly autocorrelated at the Euclidean distance of 3,000 m (sensitivity analyses, i.e. incremental spatial autocorrelation analyses, were applied). Thus, we set 3,000 m as the distance threshold. Global Moran's I values were based on this weight matrix.

^bInterestingly, the Beta value of the variable of average number of jobs (economic establishments) for all station areas within a catchment (ANJ) is negative for the industry sector accommodation and catering, although it is positively correlated to the dependant variable (Pearson's correlation coefficient between ANJ and Gi*: 0.56**). By stepwise backward elimination of the significant variables in SERM (2), we found that the negative sign of ANJ became positive when we removed AWR and AWE. This suggests that the negative sign of ANJ in SERM (2) does not indicate de-densification of firms in all industries. Associating ANJ with a higher AWR and AWE, a lower ANJ might imply that the average proportion of economic establishments in all station areas within a catchment in the economic sectors retail, hotel, and catering; and education, health, and culture is higher, which can positively relate to the clustering of labour productivity in the accommodation and catering industry.

*Significant level: $p < 0.10$. **Significant level: $p < 0.05$.

accessibility to city centres (negative association with ‘travel times to major employment and activity centres by metro’ (TCM)); density in certain industry sectors and diversity of development in a metro station area (positive association with ‘number of workers (economic establishments) in education, health, and culture within a station area’ (NWE) and positive association with ‘degree of functional mix for a station area’ (DMS)) or along metro networks (positive association with ‘average number of workers (economic establishments) in education, health, culture for all station areas within a catchment’ (AWE)); and certain adjacent development patterns along metro networks (negative association with ‘averaged value of average distances from station to jobs (economic establishments, derived from Baidu Maps and gathered by Lyu *et al.* 2016, for all station areas within a catchment’ (ADJ) and positive association with ‘averaged value of average distances from station to residents for all station areas within a catchment’ (ADR)).

Furthermore (see SERM (2) in Table 3), density of economic establishments in the sectors of retail, hotel, and catering for all station areas within a one-hour travel catchment (AWR) (a location-based accessibility measure), by magnifying the effects of localisation economies, might induce the clustering of higher labour productivities in the sector of accommodation and catering.

Some TOD characteristics do not show any significant association with the clustering of labour productivity in the identified sectors. The lack of significance of walkable connections between firms and/or households in an area (as expressed by the indicators ‘length of paved footpaths of a station area’ (LFS), ‘intersection density’ (NIS), ‘average block size of a station area’ (BSS), and ‘Walk Scores of a station area’ (WSS)) might be due to the fact that the identified (examined) sectors are not knowledge-related economic sectors, and therefore skill/knowledge spill-overs-enhancing factors (here, walkability) are not main factors driving the clustering of labour productivity. The analysis also shows the lack of significance of the transport connections of an area (as expressed by the indicators ‘number of directions served by metro’

(NDM), ‘number of directions served by bus’ (NDB), ‘daily frequency of metro services’ (DFM), ‘number of stations within 20 minutes of travel by metro’ (NSM), and ‘car parking capacity’ (CPC)). The reason might be that what matters to the clustering of higher labour productivity are not just transport connections, but rather the urban density or diversity that the transport connections give access to, as represented by the land use features of station areas with the one-hour travel catchment. This finding is consistent with the literature that stresses that accessibility (combining transport and land use characteristics) rather than just connectivity (only entailing transport characteristics) drives economic productivity (Melo *et al.* 2017; Otsuka 2018; Credit 2019).

CONCLUSION AND DISCUSSION

This study sought to explore the relationships between TOD characteristics of metro station areas and the clustering of labour productivities in these areas, taking Beijing as a case study. Different from findings in some geographical contexts (e.g. Baldwin *et al.* 2008; Brühlhart & Mathys 2008; Bishop & Gripiaios 2010), we find, at the station area level, for the majority of industry sectors, the distribution of labour productivity has no significant association with the TOD characteristics of station areas. However, for certain consumer-service-related economic sectors – wholesale and retail; accommodation and catering; and culture, sports, and entertainment – labour productivity is on average significantly higher in an area with stronger TOD characteristics (see Table 2 and Table 3).

In particular, the study finds that the effects of transport connectivity on labour productivity should not be considered alone, but together with the spatial opportunities transport connectivity gives access to. This is consistent with the general conceptual framework of urbanisation economies (Jacobs 1969; Glaeser *et al.* 1992; Fujita & Thisse 2002; De Bok & Van Oort 2011), and with more specific literature on the relationships between accessibility and productivity (Melo *et al.* 2017; Otsuka 2018; Credit 2019). In our

analysis this is on the one side empirically captured by the lack of significance of NDM, NDB, DFM, NSM, and CPC, that is, the indicators of the transport connectivity alone. On the other side, it is captured by the significance of the advantages of a better accessibility to urban centres and of how much urban density is accessed within one-hour travel: negative significance of the indicator 'travel times to major employment and activity centres by metro' (TCM), positive significance of AWE, namely, the indicator of urban densities in another economic sectors accessed within one-hour travel.

Furthermore, the study shows a significant association between the clustering of labour productivity and density and diversity of developments in a station area (e.g. positive significance on NRS (i.e. the overall labours/customers), NWE (i.e. economic establishments in the certain sector), and DMS (i.e. the diversity of the station area)). Such an association can also be conceptualised within the framework of urbanisation economies (Jacobs 1969; Glaeser *et al.* 1992; Nilsson 2016).

Finally, the mechanism of localisation economies (Marshall 2013) can be used to explain positive associations between the labour productivity in the sectors of accommodation and catering, and the density of establishments in the economic sectors of retail, hotel, and catering of all station areas within a one-hour travel catchment (AWR) (see SERM (2) in Table 3).

Taken together, these outcomes provide insights for developing more focused TOD strategies (e.g. emphasising density in certain sectors and diversity of development within a TOD area), aimed at enhancing the clustering of higher labour productivities in the identified industries around the existing metro station areas in Beijing. At the same time, the study warns that for other economic sectors, no associations between TOD characteristics and the clustering of labour productivities might be expected, requiring a highly selective approach in the search for synergy between urban planning strategies and labour productivity.

Several limitations qualify the study's findings. First, our methodology is a novel attempt to explore the relationships between TOD

characteristics and the clustering of labour productivities in several industries within one analytical framework. This is an exploratory study which does not explain why the relationship between labour productivity and TOD seems absent in activity sectors like finance (Brühlhart & Mathys 2008). Future work can shed light on the role that accessibility and other TOD-characteristics play in these sectors. In the future, more sophisticated models that consider other theoretically relevant factors (e.g. degrees of agglomeration effects for firms in the same industry sector but located in different parts of the city, e.g. in the centre or in the periphery) could be explored. Second, the findings about the relationships between TOD characteristics and the clustering of labour productivities, as well as the associated policy implications, might be constrained by the specific characteristics of the Beijing case (e.g. the by and large mono-centric distribution of service-related activities, the relatively well-developed metro network, etc.). Therefore, it would be interesting to explore such relationships and policy implications in other contexts, and the paper has developed a replicable methodology for such studies. Third, the cross-sectional, correlational nature of our analysis does not allow for the exploration of relationships of causality. In order to address this issue, in the future, it would be interesting to conduct a longitudinal study (see e.g. Levinson 2008) to explore potential causality relationships between changes in different TOD characteristics (as resulting from TOD strategies) and the clustering of labour productivities over time. Fourth, our study only focuses on metro-based TOD; TOD based on other transit modes (e.g. railway, bus rapid transit) could be examined in the next step. Fifth, our methodology showed the contributions (i.e. benefits) of different TOD components to the clustering of labour productivities, but it did not consider the relative costs of strategies aimed at adjusting each TOD component. Future research could develop a methodology that includes a costs and benefits analysis of policy interventions, which could reveal trade-offs – and also potential synergies – between different components of TOD policies. Sixth, the study

relied on publicly available spatial and statistical datasets: TOD data of Lyu *et al.* (2016) and Beijing's economic census data (Beijing Municipal Statistics Bureau 2016). A drawback is that the level of detail or bias of these datasets, for example, including the way labour productivity has been measured, might influence the reliability of the results.

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