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Spatial spillovers of agglomeration economies and productivity in the tourism industry: The case of the UK

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A R T I C L E I N F O

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A B S T R A C T

This research investigates the direct and (indirect) spatial spillover effects of agglomeration economies on the productivity of the tourism industry. With increasing concerns about the persistence of low (labour) productivity in tourism across many developed economies, there is an urgent need to address this productivity challenge. Using major under-exploited UK microeconomic panel data, spatial econometric modelling is employed to estimate the effects of agglomeration economies on productivity. Findings reveal the significant effects of agglomeration economies on productivity within a specific region, but also significant spatial spillover effects across neighbouring regions, suggesting the possibility of productivity convergences. Competitive and complementary effects of agglomeration economies on productivity are identified.

1. Introduction

Productivity in tourism is an important measure of performance, growth and competitiveness at a firm, sector and regional level (Battisti & Iona, 2009; Yang, 2016). Productivity contributes in the long-term to national economic growth and living standards by enhancing the effectiveness and efficiency of the workforce and production (Grönroos & Ojasalo, 2004). Unsurprisingly, therefore, productivity is one of the key foci of tourism management systems. However, after the 2008 global financial crisis, productivity levels have sharply fallen globally and productivity growth has been stagnant in developed economies and, more recently, in emerging economies (OECD, 2015). This has had negative implications on lower paid and highly labour-intensive sectors, such as tourism, which has exacerbated the sectoral and regional differences in productivity, heightened productivity concerns in national economic strategies and challenged the global (sustainable) development goal of decent work and economic growth (Gal & Egeland, 2018, p. 1456; Thompson et al., 2016). In particular, the low level of labour productivity in tourism has been a historical issue in the tourism industry especially due to high labour turnover and low retention rates (Robinson et al., 2014; People1st, 2017). Labour productivity is an important measure as the growth of the gross value-added (GVA) of an industry can be significant but GVA per employee, or hours worked, can be low – as in the case of the UK tourism industry (People1st, 2017). This prolonged period of low or stagnant productivity growth has renewed attention on the analysis of productivity. Yet, there are still substantial gaps in our understanding of productivity in tourism, one of which, agglomeration, i.e. the geographical concentration of firms, is addressed in this paper.

The agglomeration of tourism firms can improve their productivity via place-specific externalities such as labour pooling and knowledge spillovers (Hanson, 2001). As a result, proximate firms are most often likely to possess similar productivity levels, a phenomenon known as spatial dependence. These agglomeration economies are particularly important in tourism because production and consumption are highly localised, and goods and services are inseparable in time and space (Majewska, 2017). Tourism demand and supply are spatially concentrated in a specific place, i.e. cluster, and the tourism product or experience is produced by a complex set of producers and suppliers (Jackson & Murphy, 2002; Michael, 2003). Additionally, the tourism industry is highly labour-intensive with considerable potential for the exchange of (intangible) knowledge and ideas via personal interaction. This makes spatial proximity an important factor for effective knowledge spillovers at a destination level (Shaw & Williams, 2009). Such agglomeration economies can also exert spillover effects across regions, which can potentially contribute to regional convergence or divergence of

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productivity (Yang & Wong, 2012). However, there have been few previous studies of such spillover effects in tourism, and the nature and extent of agglomeration in the tourism industry is largely assumed and uncertain (Baldwin & Martin, 2004; Capone, 2015).

Therefore, this research aims to investigate the impact of agglomeration economies on labour productivity (hereafter productivity will refer to labour productivity, unless otherwise stated) of the tourism industry using spatial econometric modelling. The research objectives are: first, to examine the impact of agglomeration economies, in the form of labour market pooling and knowledge spillovers, on tourism productivity within a region (direct effect); second, to estimate the spatial spillover effects of agglomeration economies on tourism productivity across neighbouring regions (indirect effect); and, third, to estimate the spatial spillover effects of productivity in one region on the productivity of neighbouring regions, and vice a versa, to examine the potential of regional productivity growth. Although spatial econometric modelling has been utilised in tourism research (e.g. Yang & Wong, 2012), to the best of the researchers' knowledge, this is the first attempt to utilise such techniques to analyse the impacts of agglomeration economies on tourism productivity. A key advance is that traditional econometric models have not been able to measure the potential spillover effects of agglomeration economies due to the lack of specific measures of spatial interactions. In addition, major under-exploited micro-level datasets will be used to conduct the analysis, the first time that they have been utilised in tourism productivity studies.

This research will focus on the UK tourism industry because it has the weakest productivity performance amongst the G7 countries – output per hour worked was 16.3% below than of the rest of the G7 in 2016 (Sidhu, 2016). The low productivity level in the tourism industry compared to other industries in the UK has been a long-term issue – there is a 31% gap between the industry and the economy as a whole, and a 53% gap with manufacturing (People1st, 2017). However, there are few robust empirical studies on tourism productivity; existing studies are mostly in the context of the manufacturing industry or the general economy, which includes both manufacturing and services (e.g. Graham & Kim, 2008; Melo & Graham, 2014), but not specifically tourism. Additionally, the latest UK government Industrial Strategy has highlighted the need to boost national productivity levels via tackling low productivity but highly labour-intensive sectors, such as tourism, and regional disparities in productivity across the UK (HM Government, 2017). Thus, addressing the low productivity levels in the UK tourism industry is vital to the competitiveness of the industry but also of the whole economy.

The next section reviews the literature on productivity in tourism and agglomeration economies, and the subsequent research hypotheses based on this review. Then the methods and data will be discussed, outlining the empirical models, variables, unit of analysis and the micro-level secondary data sources that are utilised. Finally, the empirical findings of the estimation models will be discussed in order to identify the direct and indirect effect of agglomeration economies on tourism productivity. The final section presents the conclusion and limitations of the research, which will suggest new agendas for further research.

2. Literature review

The relevant generic (non-tourism) and tourism literature on productivity and agglomeration economies are reviewed in this section. Most of the published literature focusses on developed economies and urban environments, unless specifically stated and referenced otherwise. Additionally, the relevant research hypotheses will be stated throughout the review.

2.1. Productivity in tourism

Productivity has been and is currently still regarded as a long-term driver of economic growth and key to raising national living standards and the competitiveness of the economy (Grönroos & Ojasalo, 2015). Productivity reflects the effectiveness and efficiency of how inputs are utilised to produce outputs. There are two main types of productivity measures: total factor productivity (TFP) and single factor productivity (e.g. labour productivity). TFP measures the ratio of output to different inputs, which are labour, capital and residual (technological change), whereas single factor productivity measures the output per specific input (Syverson, 2011). Such measures portray the various factors of productivity: e.g. physical, human and – increasingly researched – environmental capital (Lannelongue et al., 2017), innovation and technology (Serrano-Domingo & Cabrer-Borrás, 2017). TFP is conceptually a stronger measure as it considers all the inputs of productivity, but it is technically challenging to aggregate the complete set of factors, due to data limitations, as in this research. Thus, this paper focusses on labour productivity, which is a key measure of performance in many industries, particularly in tourism due to its highly labour-intensive and intangible nature (Park et al., 2016).

Labour productivity in tourism is different from the traditional concept of productivity, which originated in manufacturing. The interaction between the supplier and consumer is central to the delivery of tourism services so that the efficiency and effectiveness of labour is essential in service quality, customer satisfaction and, ultimately, productivity of the labour but also the firm (Grönroos & Ojasalo, 2004; Nachum, 1999). It is therefore a major concern that there is a long-term slowdown in productivity growth in developed economies, including the traditional low growth sectors like tourism, retailing, construction and administrative services (Kim et al., 2007; Martin et al., 2017). Tourism is well-known for being a low value-added and (labour) productivity sector owing to its transient, seasonal, temporary and low-skilled workers and high levels of labour turnover (Battisti & Iona, 2009). With rising costs and limited resources, labour recruitment and skills shortages constitute major challenges in the industry. The subsequent large gap in labour productivity levels between tourism and other sectors of the economy has been a persistent concern as it affects the sector's competitiveness and the survival of individual firms, especially given the impacts of the growing digital economy (Battisti & Iona, 2009; Blake et al., 2006).

Labour productivity depends on various factors such as competition, human capital, and innovation and management practices. Non-tourism researchers and practitioners have defined competitiveness through productivity, highlighting the significant role of competition on firm productivity (Martin & Sunley, 2003; Porter, 1998). Competition can drive out low productivity firms and enhance the growth of high productivity firms within the market (Van Reenen, 2010), but fierce competition can reduce profit margins which has been observed in the tourism industry due to the growth in online sales and the sharing economy (Ahmad & Schreyer, 2016; Zervas et al., 2016 in hotels). Yet, competition can lead to greater managerial efforts to enhance labour productivity.

Human capital is also a key determinant of labour productivity as the quality of labour (i.e. skills, knowledge and work experience) influences the efficiency and effectiveness of the workforce in the generic literature (Syverson, 2011). Human capital is one of the key resources in tourism firms which tend to be highly labour-intensive while the intangible nature of the industry implies that skilled and knowledgeable workers are vital to service quality and delivery, which ultimately impacts on productivity (Brown & Dev, 2000). However, in tourism, a large share of employees is low-skilled or unskilled, casual and seasonal. This highlights the importance of management of recruitment, rewarding and training to increase human capital in the tourism industry (Madera et al., 2017; Úbeda-García et al., 2014). However, there is contradictory evidence about the effects of training and human resource management on productivity in tourism (cf. Cho et al., 2006).

Additionally, there are several studies that investigated the relationship between environmental capital and productivity (Delmas & Pekovic, 2013; Lannelongue et al., 2017). However, tourism studies are limited on this topic. Yet, with growing attention on environmental issues and sustainability, environmental (or natural) capital is likely to be seen as a major driver of tourism productivity, but this paper focusses on agglomeration.

Knowledgeable workers can contribute to innovation which can improve productivity levels further. Positive association between innovation and productivity has been well-established in the literature, in particular the role of information technology in pushing the boundaries of tourism productivity (Joppe & Li, 2016). Yet, the operationalisation and effectiveness of innovation on tourism productivity is contested as there is limited research in this area due to measurement issues relating to tourism innovation.

An alternative determinant of labour productivity, which is relatively under-researched in tourism, is location and, in particular, spatial agglomeration. It is theorised that firms that locate in a cluster (or agglomeration) have higher levels of labour productivity because clusters generate place-specific external economies of scale, i.e. agglomeration economies (Rosenthal & Strange, 2004; Majewska, 2015 in tourism), but also diseconomies (continued in section 2.2). Although the effects of agglomeration are assumed to be important in the tourism sector, there has been relatively limited research on the topic which partly reflects secondary data limitations. The paper aims to address this research gap by utilising a neglected (in tourism) source of micro-level secondary data.

2.2. Agglomeration economies

The productivity of tourism firms can benefit from agglomeration economies. This concept originates from economic geography and was introduced by Alfred Marshall (1920). Generic studies on the relationship between agglomeration and productivity emerged in context of the manufacturing industries (Glaeser & Maré, 2001; Rosenthal & Strange, 2004), where the findings have identified significant implications for productivity and positive impacts on firm and regional performance and growth (Martin & Sunley, 2003; Porter, 1998). This is because close proximity between related and unrelated firms reduces search and transportation costs, whether that is from the customer's perspective (demand-side agglomeration) or the firm's perspective (supply-side agglomeration) (McCann & Folta, 2009). In the context of tourism, Chung and Kalnins (2001) and Kalnins and Chung (2004) focused on demand-side agglomeration and found that agglomeration increases demand in the US lodging industry, especially in rural markets where subsequent search cost reduction can be more effective. Asymmetric contributions to demand-side agglomeration were identified in the study; high-resource firms avoid markets with high numbers of low-resource incumbent firms, leading to adverse selection and firms avoiding co-locating. In other words, firms not only benefit from agglomeration economies and spillover effects, but also contribute to them, which supports the generic research by Shaver and Flyer (2000). However, robust empirical findings are very limited in the context of supply-side agglomeration and tourism, which this research contributes to.

Marshall's (1920) agglomeration economies provide an economic rationale for why specialised industries and firms localise in a specific area. He categorises them into three elements – input-output linkages, labour market pooling and knowledge spillovers – which enhance firm performance in clusters (Martin & Sunley, 2003). It is also important to acknowledge agglomeration diseconomies, which are the negative externalities, such as spatial inequalities of growth and wages and high competition and price wars (McCann & Folta, 2009), which can cause alternative effects on productivity. However, these studies are not in the context of tourism. This study particularly examines labour market pooling and knowledge spillovers, focussing on supply-side agglomeration effects (ibid.) in the tourism-context. Input-output linkages, which refer to the ease of sharing inputs and outputs due to the proximity of suppliers, producers and consumers within a cluster, are excluded in this study due to secondary data limitations.

It is acknowledged that there is a lack of tourism studies on agglomeration economies, and thus the following sections will mostly focus on the generic literature, while gaps relating to the tourism literature will be identified.

2.3. Labour market pooling

Flexible and diverse labour market pooling can allow more efficient allocations of labour within a cluster, which is especially important following demand and/or productivity shocks. This is due to the lower search and relocation costs incurred by firms in close proximity, and better information about new opportunities, but also because workers can leave firms that are less productive and move to firms with better productivity prospects (Combes & Duranton, 2006; Glaeser, 2010). A large pool of labour also generates benefits for firms and employees as it improves the possibility of job matches and facilitates adjustments to shocks in the local labour market (Melo & Graham, 2014). This can enhance productivity and attract more skilled workers to the locality (Glaeser, 2010). However, the nature of the locality is likely to be important. Specifically, tourism clusters (and destinations) can be found in both urban and rural areas (Hall, 2005; Krugman, 1991; Novelli et al., 2006), with research on the latter being limited.

Past studies have found that labour market pooling in clusters plays a significant role in productivity (Helsley & Strange, 1990; Krugman, 1991; Overman & Puga, 2008, pp. 1–14). Positive effects of labour market pooling have been identified in the manufacturing industry (Andersson & Loof, 2011; Mariotti et al., 2010). Abel et al. (2012) identified that metropolitan areas with substantial human capital stock increase productivity in manufacturing. However, questions remain as to how productivity gains relate to the range of labour skills. This is especially relevant to tourism firms which suffer from skills shortages; the sector is well-known for its low-skilled, diverse and flexible workforce (People1st, 2015). Yet, the significance of agglomeration is partially derived from the quality and diversity of the local labour market. Heterogeneous skills and requirements within a labour market pool can also enable greater sorting, which consequently drives higher productivity and wage levels (Andini et al., 2012; Wheeler, 2006).

However, increased wages and costs related to an increase in labour pooling within a cluster can have negative effects on tourism productivity (Yang, 2016). The general literature suggests there is a trade-off between labour pooling and poaching, i.e. the loss of workers due to labour market competition (Combes & Duranton, 2006). Rival firms can access a firm's internal knowledge as a result of poaching, thereby creating incentives to increase wages to retain human capital within the firm (ibid.). This can lead to detrimental effects on productivity. However, such studies have mostly been in the manufacturing industry-context. Yet, with high labour turnover rates in tourism, labour poaching within a cluster arguably can lead to a reduction in tourism productivity, but there has hitherto been a lack of research on this topic. Thus, the following hypothesis will be tested:

Hypothesis 1. There is a significant direct effect of labour market pooling on the labour productivity of tourism firms within a spatial unit.

2.4. Knowledge spillovers

The movement of labour across firms and industries within a cluster can enact significant knowledge spillovers (Rosenthal & Strange, 2004). Spatial proximity between firms makes knowledge transfer and spillovers easier which forms a basis for innovation and learning (Boschma, 2005). Localised clusters of similar and related firms form a local milieu or learning region that facilitates knowledge spillovers and stimulates learning and innovation, ultimately boosting the productivity of firms but also of the cluster (Boschma & Ter Wal, 2007; Iammarino & McCann, 2006). Studies based on manufacturing have examined knowledge spillovers via research and development expenditure and patent citations (Döring & Schnellenbach, 2006; Henderson, 2007). However, enhanced learning within clusters is also possible via social networks, mutual relationships, shared interactions and language, knowledge about other firms and their competencies, and trust (Bathelt et al., 2004). This does indicate the impact of social capital on knowledge spillovers and, by implication, productivity (Brien et al., 2012; Sainaghi & Baggio, 2014).

Of particular importance is that tourism productivity depends on the embedded and embodied knowledge of labour (Yang & Wong, 2012), unlike in manufacturing. Knowledge in tourism is strongly tacit in nature, and new knowledge and ideas learnt and shared between individuals in the workplace can generate innovation at the firm level, increasing the competitiveness and productivity of both the firm and workers (Weidenfeld et al., 2010; Zhang et al., 2015). Human capital is created through learning by observation and imitation which is more easily realisable in geographically concentrated areas owing to greater transparency and proximity (Shaw & Williams, 2009). In such a learning environment, the movement of experienced labour across cluster firms accumulates human capital and knowledge spillovers are prominent, which can influence productivity (Joppe, 2012; Weidenfeld et al., 2014). It has been argued that tourism employees are more likely to share incremental knowledge while employees from different sectors are more likely to share uncommon knowledge (Shaw & Williams, 2009). The sharing of knowledge based on similar products is relatively more important than radical new knowledge in tourism (Hjalager, 2002; Weidenfeld et al., 2010). Thus, knowledge in tourism is more likely to be transferred via experienced labour from within the tourism sector.

However, it is important to acknowledge that knowledge does not spillover only in one direction (Mariotti et al., 2010). Knowledge can flow in and out, which can cause positive and negative effects on firm and labour productivity. Additionally, when firms are in spatial proximity, it does not mean that these firms will interact and that such interactions are positive spillovers (ibid.). Firms may absorb but also lose knowledge, which may result in a negative net balance. Thus, knowledge spillovers can have negative implications for productivity. Moreover, individuals may not share knowledge as they perceive a loss in sharing that knowledge (Yang, 2008 in tourism). Thus, there are winners and losers in relation to agglomeration economies, which can influence the impact on productivity (Shaver & Flyer, 2000).

Nevertheless, learning by observation and imitation within the workplace and subsequent labour movement within a cluster can generate significant knowledge spillovers, positively influencing labour productivity in tourism. Hence, the following hypothesis is proposed:

Hypothesis 2. There is a significant direct effect of knowledge spillovers on the labour productivity of tourism firms within a spatial unit.

2.5. Spatial spillover effects

The spatial spillover effects of agglomeration and productivity can further contribute towards regional productivity growth (Yang & Wong, 2012). These refer to externalities that are locally bound in nature (Capello, 2009). This is because locating a firm near other firms means that the firm can take advantage of the spatial spillover effects from the other firms in the neighbourhood, enhancing efficiency and productivity (Barros, 2005).

Productivity spillover effects across spatial regions can lead to regional growth effects. There have been a number of regional studies of overall uneven economic growth (Martin et al., 2017) but in tourism, despite the marked spatial dependence in productivity across the UK and its tourism industry, there has been very little research on the effects of productivity spillovers across regions. In tourism, competition effects can contribute significantly toward productivity spillovers between neighbouring regions as they tend to attract similar visitor market segments, driving strong competition (Yang & Wong, 2012). Thus, spatial spillover effects can enhance the labour productivity of firms, sectors and regions (Campos, 2012). However, previous researchers have emphasised the contradiction between convergence and agglomeration because convergence effects may result in diminishing returns in a cluster and lead to divergence (Delgado et al., 2014). Yet, it has been found that agglomeration plays a complementary role with convergence between spatial units generating economic growth (ibid.).

The agglomeration effects that can be acquired when in close proximity offer substantial advantages to the firms within the cluster due to these spillover effects. The spatial spillover effects of agglomeration economies, i.e. labour market pooling and knowledge spillovers, have been studied in regard to regional productivity in the general literature. Positive spillover effects of human capital on productivity growth between spatial regions in the manufacturing industry were identified (Fingleton & López-Bazo, 2006; Rosenthal & Strange, 2008). However, other studies have inferred negative spillover effects of human capital as there could be limited available labour in the neighbouring regions or substitution or competition effects of educated labour between the neighbouring regions (Olejnik, 2008). This may suggest that intra-cluster advantages are more significant than inter-cluster advantages (LeSage & Fischer, 2008).

Similarly, spatial spillover effects of knowledge on productivity have been evident in previous general studies, where significant effects were identified between competing firms and cooperation between close regions (Döring & Schnellenbach, 2006). Knowledge spillovers between neighbouring regions or agglomerations can enhance productivity via external linkages and networks (Bathelt et al., 2004). Yet, excessive external spillovers can threaten the long-term value and survival of the agglomeration (ibid.). Overall, positive labour and knowledge externalities have been identified as supporting regional spillover and productivity effects (Huang & Zhang, 2017; Ramos et al., 2010).

In tourism, workers are likely to move between local regions for better employment and higher wages, which may suggest spatial spillovers of labour and knowledge based on proximity, product and market similarity (Weidenfeld et al., 2010). However, the majority of the aforementioned studies in the previous paragraphs are not from the tourism literature. There is no tourism productivity study known to the researchers that examines the spillover effects of agglomeration economies and productivity across regions and how this can potentially generate regional growth. These effects can be estimated through spatial econometric techniques (Yang & Wong, 2012), which this research will adopt. Based on the literature, the following hypotheses are proposed regarding spatial spillover effects:

Hypothesis 3. There is a significant spatial spillover effect of the labour productivity of tourism firms across spatial units.

Hypothesis 4. There is a significant spatial spillover effect of labour market pooling on the labour productivity of tourism firms across spatial units.

Hypothesis 5. There is a significant spatial spillover effect of knowledge on the labour productivity of tourism firms across spatial units.

Overall, tourism studies on agglomeration and regional development are evident in the existing scholarship (e.g. Jackson & Murphy, 2006; Santos Estêvão & Ferreira, 2009; Weidenfeld et al., 2014), but there has been a lack of focus on the mechanisms and economies of agglomeration, and especially how these impact on productivity within and across spatial units. The impact of agglomeration economies in the tourism industry have largely been implied from the presence of clusters; the actual implications are unknown. Moreover, tourism productivity studies have ignored the effects of the external spatial factors, which can be considered a significant research gap despite tourism being place and space bound (Majewska, 2015).

3. Model and data

3.1. Spatial Durbin panel model

Spatial econometric techniques can deal with spatial data, accounting for spatial autocorrelation but also spatial spillover effect in the modelling framework (Chhetri et al., 2017). A failure to account for spatial autocorrelation can produce bias and inefficient parameter estimates due to the spatial interaction amongst the data (Arbia, 2014). A spatial Durbin panel model (SDM) is proposed to capture and estimate the impact of agglomeration economies on the labour productivity of tourism firms in the UK. The model includes the spatially lagged terms of the dependent and explanatory variables unlike the traditional panel model (Elhorst, 2014). The static SDM is specified as follows:

$$Y_{it} = \rho_{it} WY_{it} + X_{it}\beta + WX_{it}\theta_{it} + u_i + \varepsilon_{it} \tag{1}$$

where Y_{it} denotes an $N \times 1$ vector of the dependent variable for spatial unit i ($i = 1, \ldots, 373$) at time t ($t = 2006, \ldots, 2016$), X_{it} is the $N \times 5$ vectors of explanatory variables, β represents the corresponding 5×1 estimate parameters. W is the row-standardised $N \times N$ spatial weights matrix, describing the spatial arrangement for the spatial units, ρ_{it} and θ_{it} are the spatial parameters, and lastly, ε_{it} is an $N \times 1$ vector of independently and identically distributed error terms with zero mean and variance, while u_i denotes the time-invariant spatial specific effects.

The dynamic spatial panel model is proposed to capture the dynamic structure of agglomeration and its effects on labour productivity of tourism firms. This is an extension to the static spatial panel model, and it includes the time-lagged dependent variable in addition to other explanatory variables (Elhorst, 2012). The dynamic SDM can therefore analyse both the spatial autocorrelation between spatial units and the dynamic structure over time. The inclusion of both the spatially and temporally lagged dependent variable reduces the potential bias caused by omitted variables. The model is specified as follows:

$$Y_{it} = \tau_{it} Y_{it-1} + \rho_{it} WY_{it} + X_{it}\beta + WX_{it}\theta_{it} + u_i + \varepsilon_{it} \tag{2}$$

where Y_{it-1} denotes the time-lagged dependent variable and τ_{it} is the response parameter.

The spatial weights matrix, W, determined in this research is the queen contiguity-based spatial weights matrix for both the static and dynamic model. This is because the spatial weights matrix is required to be symmetrical, but the distance-based (e.g. k nearest neighbour) weights matrix is asymmetrical and thus is unsuitable in the dynamic setting. The queen contiguity weights matrix, which defines a neighbour when spatial units share a common border or single common point, is used. This means that any borderless spatial unit (i.e. island) needs to be removed.

The spatial Hausman test is conducted to determine the fixed-effect (FE) or random-effect (RE) model approach and maximum-likelihood estimation is used to estimate the model (Belotti et al., 2017). In spatial models, the spatial interactions indicate various spatial spillover effects between regions and can be estimated, which is one of the objectives of this research.

3.2. Variables and unit level

The variables of the models are shown in Table 1.

The dependent variable Y_{it}, labour productivity, is measured as total GVA at basic price of tourism firms over total tourism labour worked hours in a spatial unit. GVA at basic price is defined as the difference between output at basic prices and intermediate consumption at purchase prices.

The explanatory variables, X_{it}, are as follows:

- location quotient, x_{1t}, represents the degree of agglomeration of tourism firms in a spatial unit. There are various measurements of the degree of agglomeration such as employment density (Marco-Lajara et al., 2016), local Gini coefficient (Gabe & Abel, 2012) and local Moran's I (Majewska, 2017), but this research uses location quotient as it is a simple measure of the degree of geographical agglomeration and industrial specialisation of a region which is commonly used in tourism studies (Capone, 2015). However, it does not reveal the spatial patterns of clustering; yet, the use of spatial econometrics accounts for the spatial patterns, and thus the location quotient measure is suitable for this research.
- skilled labour pool, x_{2t}, is the share of tourism employees with National Vocational Qualifications (NVQ) level 1 to 5, or equivalent qualifications amongst the total tourism employees in a spatial unit. The NVQ are work-based qualifications, which recognise the skills and knowledge that an individual requires to do a job. This is a proxy for labour market pooling under the concept of agglomeration economies and it can be argued to be more appropriate to use NVQ compared to educational qualifications such as higher education degrees (Melo & Graham, 2014; Potter & Watts, 2014) as the incumbent tourism workforce is relatively low skilled and new skills and training tend to be attained via their job. This means that vocational qualifications are more accessible to the tourism workforce.
- formal entry qual, x_{3t}, is the share of tourism employees with jobs that require formal qualifications for entry amongst the total tourism employee in a spatial unit. This is a proxy for high-skill jobs and thus labour market pooling (Graham and Melo, 2009). The measure has been included in the model based on the ONS Standard Occupational Classification (SOC), which accounts for competence acquired through non-school qualifications, training and work experience and information on job entry requirements, all of which are important in tourism. Despite, the SOC data being personal rather than sectoral level, it was considered more extensive than any other data that measure skills amongst the limited data available in this area.
- last job in tourism, x_{4t}, is the share of employees who had a previous job in tourism amongst the total number of employees in a spatial unit. This is a proxy for knowledge spillover in relation to the concept of agglomeration economies. Knowledge in tourism is strongly tacit in nature, and knowledge transfer and spillovers usually occur between individuals through different forms of learning experience (Cooper, 2006; Shaw & Williams, 2009). There is considerable evidence in the tourism literature that the movement of knowledgeable and experienced workers between firms can be considered a channel of knowledge spillovers (Yang, 2008, 2010). These individuals learn from each other by observation and imitation, bringing knowledge from different localities via the movement from one job or department to another, generating and sharing knowledge (Smith, 2001). Thus, this variable can proxy knowledge spillovers within and across firms within a spatial unit.

Table 1
Summary of variables.

Code		Name	Description
Y_{it}		labour productivity	GVA at basic price over total tourism labour worked hours
X_{it}	x_{1t}	location quotient	Ratio of tourism employment to total employment in a spatial unit against the ratio of total tourism employment to total employment
	x_{2t}	skilled labour pool	Share of tourism employees with NVQ level 1–5 or equivalent qualification(s)
	x_{3t}	formal entry qual	Share of tourism employees with jobs that require formal qualification(s) for entry
	x_{4t}	last job in tourism	Share of employees who have had a previous job in tourism
	x_{5t}	non-tourism labour productivity	GVA at basic price over total non-tourism labour worked hours

- non-tourism labour productivity, x_{5t}, is the labour productivity of non-tourism sectors, measured by the GVA at basic price of non-tourism firms over total non-tourism labour worked hours in a spatial unit. This controls for the changes in the local economy of a spatial unit.

This research defines a spatial unit as a *local authority district* (LAD). Spatial data are usually in the forms of lines, points or polygons (shapes). Spatial data used in this research are in the form of polygons, representing each LAD. The reason to select the LAD unit rather than the Nomenclature of Territorial Units for Statistics (NUTS) is because the NUTS areas are formulated by grouping unitary authorities (NUTS3), counties or council areas (NUTS2) or are the country itself (NUTS1) (ONS, 2017). The diversely defined spatial units mean that each NUTS unit varies in size substantially (Vojtech & Pavlina, 2014). Additionally, given that this research only examines the UK, a more localised spatial unit is preferred.

Travel-to-work-areas (TTWAs) are functional economic areas that represent local labour market areas but they are highly variable in spatial scale and substantially larger than LADs which suggests that spatial spillover effects that occur within TTWAs are not captured (ONS, 2019c). Due to their larger scale, many TTWAs are also likely to include multiple clusters: this applies especially to London and other major metropolitan areas (ibid.). This undermines their value for analysing the mechanism of agglomeration economies and their spillover effects and implies that TTWAs work better in some areas than others, which is problematic in research which analyses Great Britain as a whole. This is especially the case in differentiating rural and urban clusters as the former are likely to be 'lost' to the analysis, constituting the 'ring' of semi-rural or rural areas linked to the core by journey to work flows. In contrast, the LADs are far more effective at capturing both rural and urban clusters.

LADs reflect administrative boundaries and they are increasingly considered to be reasonable approximations of local labour market areas, despite not being specifically designed to capture journey to work flows, as with TTWAs (UKCES, 2014). Moreover, the Office for National Statistics (ONS) annual local area database, which is central to this study, is based on LADs, which aims to capture economically-active respondents. Finally, as administrative areas, LADs can be considered more practical in terms of implementing place-based strategies of agglomeration. Using LADs ensures the consistency of using one type of spatial unit; yet, it should be acknowledged that the boundaries of LADs are arbitrary in many ways (ONS, 2019b).

3.3. Data

Major microeconomic UK datasets were employed to extract the necessary data required to construct the variables of the specified models – Table 2. These datasets required secure access, which one of the researchers had privileged access to (there is a vetting procedure followed by training), and thus hitherto has been little used by tourism researchers. The datasets are available by individual, firm/enterprise, industry and region over time from 1998 to 2016. Due to a methodological break in 2005 for one of the key datasets, only panel data from 2006 have been used in this study. The three datasets in Table 2 were linked together using individual enterprise and region codes. Data processing will be further discussed later in the section.

Table 2
Summary of data sources.

	Variable name	Source[a]
Labour productivity of tourism firms	labour productivity	ABS ARD APS
Degree of clustering of tourism firms	location quotient	APS
Labour market pooling	skilled labour pool formal entry qual	
Knowledge spillover	last job in tourism	
Labour productivity of non-tourism firms	non-tourism labour productivity	ABS ARD APS

[a] Data citation: ONS (2012, 2018); ONS. Social Survey Division (2018).

Data have been obtained from the UK Data Service (UKDS); the main data source is the ONS. ONS is the UK's largest independent producer of official statistics related to the economy, population and society at the national, regional and local level (ONS, 2019a). This research used the UKDS Secure Lab which provides privileged access to data that are entitled to secure access as they are too detailed, sensitive or confidential to be made open access (UK Data Service, 2019). All data collection, preparation and analysis were undertaken in the Secure Lab.

Data at the local unit level in England, Wales and Scotland (Great Britain) were used. Northern Ireland has been neglected due to poor data coverage. Data were available for all 380 LADs (i.e. spatial units) in Great Britain but, given that this research uses a contiguity-based spatial weights matrix, six island LAD units were excluded as they do not share any borders with another LAD unit – Isles of Scilly, Isle of Wight, Isle of Anglesey, Eilean Siar, Orkney Islands, Shetland Islands. The City of London LAD unit was also excluded due to insufficient data coverage of the tourism sector. Henceforth, the total number of (unmodified) LADs used in the analysis was 373.

The measure of labour productivity was constructed by aggregating micro-level data from the Annual Respondent Database (ARD) covering the period from 2006 to 2008 and Annual Business Survey (ABS) covering the period from 2009 to 2016. From the ARD and ABS, GVA at basic price was estimated to construct the output measure of labour productivity. The measures of location quotient and agglomeration economies (i.e. labour market pooling and knowledge spillover effects) were constructed by aggregating individual-level data from the Annual Population Survey (APS) covering the period 2006 to 2016. The number of employees was aggregated by sector and spatial unit for each year to generate the location quotient variable. Raw data on individual qualifications, SOC codes, sum of worked hours from the main and/or second job (i.e. input measure of labour productivity) and the Standard Industry Classification codes for the individual's previous job were aggregated by industry and spatial unit. Other variables of interest, such as voluntary termination (i.e. labour turnover), training redundancy and on-the-job training (proxy for knowledge spillovers), were accessible but due to poor data coverage, they were excluded in the final model. After merging the data from the ARD and ABS with the APS, for each LAD (a total of 373), given the panel time period of 11 years (from 2006 to 2016), there were 4103 observations in total.

There were a limited number of missing values in the dataset. Substantial efforts have been made to pool data from different sources and after aggregating the data, missing values were imputed using multiple expectation-maximisation imputation to substitute the missing values. Multiple imputation reduces bias compared to other methods of imputation such as listwise deletion or mean imputation (Honaker et al., 2018). Using expected-maximisation with bootstrapping algorithm, it ensures efficiency and robustness in imputing missing values across multiple variables, including time-series data (ibid.). The majority of the variables are in natural logarithm (indicated as 'ln()') to analyse the relationship between labour productivity of tourism firms and the explanatory variables. This makes it easier to interpret and also increases the model fit overall. The data holds geographical information, which is suitable for spatial analysis.

3.4. Descriptive statistics

The descriptive statistics of the variables are presented in Table 3, showing the mean value, standard deviation (Std. Dev.) overall, between and within and the range values. The standard deviation (between) illustrates the unit-level averages for every unit, i.e. variations between

Table 3
Descriptive statistics of variables (2006–2016).

Variable	Mean	Std. Dev.	Std. Dev. (between)	Std. Dev. (within)	Range	VIF
labour productivity	1.15	0.58	0.20	0.54	16.63	–
location quotient	1.00	0.15	0.13	0.07	1.36	1.01
skilled labour pool	2.36	0.98	0.58	0.78	7.55	1.63
formal entry qual	1.95	0.91	0.59	0.70	7.94	1.62
last job in tourism	1.29	0.61	0.37	0.49	5.75	1.03
non-tourism labour productivity	2.76	0.67	0.36	0.57	9.70	1.01

N = 4103 n = 373, T = 11.

LADs, and (within) presents the variation over time within the units.

Observing the descriptive statistics, the average labour productivity is 1.15, with a standard deviation of 0.58. Labour productivity varies more over time than between the LADs as the standard deviation (within) is greater than the standard deviation (between). Similarly, the remaining variables vary more over time than between the LADs, which may suggest the significant temporal effects of agglomeration economies on labour productivity. However, the variation of the location quotient is greater between the LADs than over time, which implies that the degree of clustering of tourism firms does not change much over this time frame even though labour productivity does change over time. The variance inflation factor (VIF) is consistently well below 3, confirming the absence of multicollinearity.

4. Findings

4.1. Spatial dependence

Given the focus on spatiality, it is important to test for spatial interaction, i.e. dependence or autocorrelation, in the data. First, tests for cross-sectional dependence in the panel model were conducted. The Breusch-Pagan Lagrange Multiplier (LM) test and Breusch-Godfrey/Wooldridge test have been tested based on the FE model (Bivand et al., 2008; Wooldridge, 2010). The test statistics (84,148 and 258.21, respectively) show that cross-sectional dependence is significant at the 1% level.

Given that the cross-sectional dimension of the data is spatial, i.e. each cross-sectional unit refers to a spatial unit, there is a need to consider the spatial dimension of data. Thus, locally robust LM diagnostic tests for spatial dependence were generated to confirm the spatial dependence, i.e. cross-sectional dependence including the spatial dimension of the data expressed by the spatial weights matrix (W = queen) (Anselin et al., 1996). These tests show whether the spatial dependence is on the spatially lagged dependent variable or error term – Table 4.

Both the LM tests for the spatial lag and error dependence are significant, which leads to the examination of the robust LM test statistics. The robust LM test for spatial lag dependence is statistically significant at the 10% level, whereas the robust LM test for spatial error dependence

Table 4
Locally robust LM test for spatial lag and error dependence.

	W = queen
LM test for spatial lag dependence	29.937***
Robust LM test for spatial lag dependence	2.936*
LM test for spatial error dependence	27.639***
Robust LM test for spatial error dependence	0.638

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

is statistically insignificant. This supports that the presence of spatial dependence is on the lag of the dependent variable.

Figs. 1 and 2 illustrates the spatial dependencies of labour productivity in the UK. Figs. 1 and 2 present the tourism labour productivity (in log form) of each LAD in 2006 and 2016, respectively. Both maps show that the local regions are influenced by the neighbouring LADs as LADs in proximity show similar levels of productivity. The darker the shade, the higher the productivity level, and the circled LADs present clusters of high labour productivity. In addition, the more distant from the darker shades of LADs, the lighter the shade, reflecting lower levels of productivity in those distant LADs. Both figures not only present the variations of labour productivity across different LADs in the UK but also the spatial dependence on labour productivity. This further supports the selection of the SDM, and thus spatial panel modelling is required to examine the effects of agglomeration economies on tourism labour productivity, which is presented in the following section.

4.2. SDM estimations

The static and dynamic SDMs are generated to estimate the impact of agglomeration economies on the labour productivity of tourism firms in all 373 LADs in Great Britain from 2006 to 2016. Table 5 presents the coefficient estimates and Table 6 presents the marginal impact measures which are crucial to interpreting the direct and indirect (spatial spillover) effects of agglomeration economies on labour productivity. It is argued that the coefficient estimates of spatial models are often interpreted incorrectly as if they are simple partial derivatives (Golgher & Voss, 2016). Thus, despite the hypothesis testing being based on the estimated coefficients presented in Table 5, more accurate interpretations of the effects are based on the impact measures in Table 6, which this research follows.

To determine whether to use the FE or RE model estimations, the spatial Hausman test was conducted: the test statistic of 106.27 is positive and statistically significant, suggesting that the FE model is preferred to the RE. In addition, FE models are generally more suitable than RE models in spatial econometrics because, for spatial data, adjacent regions are located in fixed areas, e.g. all regions in a country, and because the FE model reduces the potential bias caused by omitted variables (Elhorst, 2014; LeSage & Pace, 2009).

The spatially and temporally lagged dependent variable, *W*ln(labour productivity)* and *ln(labour productivity)*$_{t-1}$ respectively, are both statistically significant, which suggests significant implications of space and time for the relationship between agglomeration economies and productivity. As shown in Figs. 1 and 2, in 2006, three circled regions including North West (e.g. Craven and Lancaster), West Midlands, and London/South East (e.g. Reigate and Banstead) show higher levels of labour productivity. In 2016, however, the regions of Scotland (e.g. Aberdeenshire), East Midlands (e.g. Lincolnshire) and East (e.g. Essex, Suffolk, and Norfolk) have been observed as clusters presenting higher labour productivity. In addition to the statistical estimations of temporal lagged dependence, it shows the changes of productivity levels in the spatial distributions over time (see Figs. 1 and 2). The dynamic SDM further reduces the potential bias caused by omitted variables and improves the explanatory power (Li et al., 2016). Thus, the analysis will mainly focus on, and the hypothesis testing will be based on, the dynamic SDM. The model diagnostics presented in Table 5 further support this. The log-likelihood is higher for the dynamic model compared to the static model, which suggests that the dynamic model has a better model fit. Both the AIC and BIC estimates are smaller for the dynamic model, which further confirms its better fit than the static model. Overall, the results show that there is a better model fit when considering the spatial and time lags of the dependent variable.

First, looking at the direct coefficient effects of the explanatory variables, i.e., the effects of the variables on labour productivity within a LAD, the dynamic model shows some variations when considering the time dimension of the data, taking a time lag of one year. The degree of

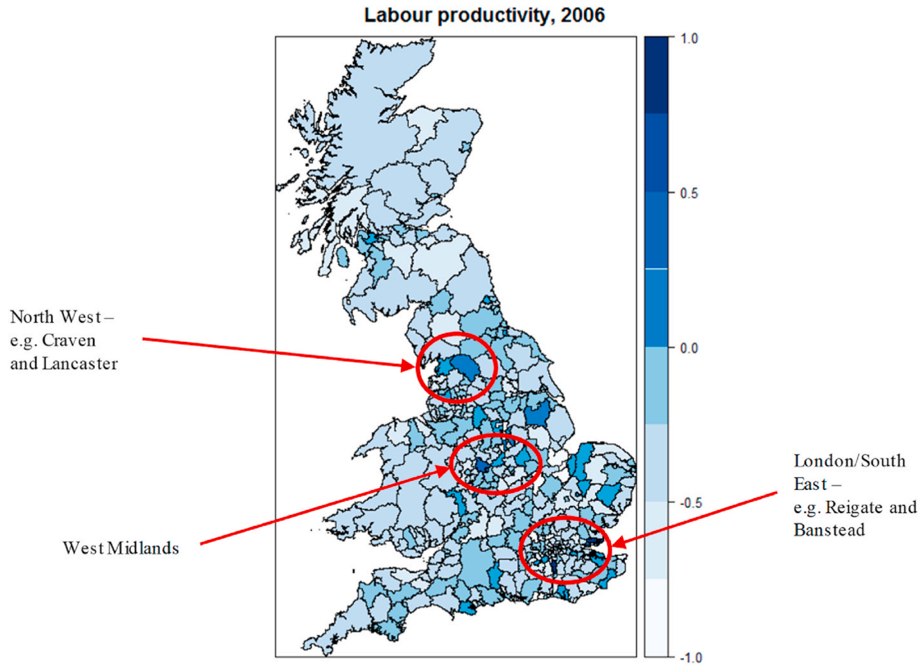

Fig. 1. Map of logged tourism labour productivity in the UK, 2006

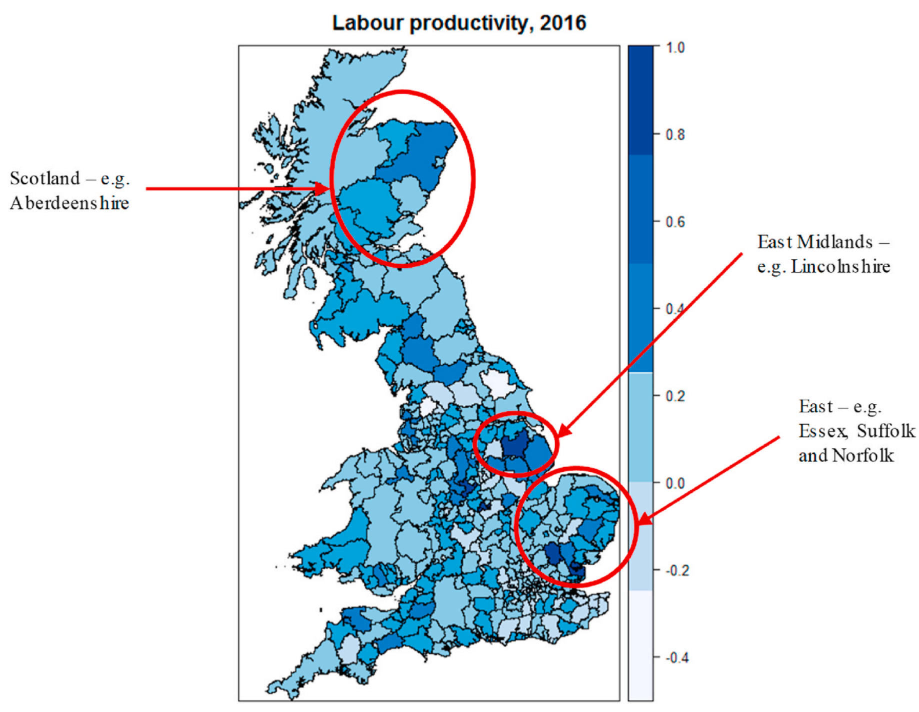

Fig. 2. Map of logged tourism labour productivity in the UK, 2016

clustering of tourism firms is negatively associated with labour productivity within a LAD – a one per cent increase in the degree of clustering decreases labour productivity by 0.248%. Regarding the role of agglomeration economies in the labour productivity of tourism firms within a LAD, the labour market pooling components show positive associations. A one per cent increase in the skilled labour pool increases productivity by 0.049% and is statistically significant. However, the variable *ln(formal entry qual)*, which proxies the share of high-skill jobs in a LAD, is significantly negative, implying a decrease in productivity by 0.102% for every one per cent increase in the share of high-skilled jobs (McCann & Folta, 2009). Based on these proxy labour market pooling measures, Hypothesis 1 is partially supported. The effects of knowledge spillovers on productivity within a LAD is positive but statistically insignificant, and Hypothesis 2 is therefore rejected, posing questions as to whether this is due to the difficult-to-transfer firm-specific embedded nature of knowledge, or to the lack of new knowledge transferred by such labour mobility given the strong alternative possibilities of knowledge transfer via observation in the sector. Lastly, the labour productivity of non-tourism sectors, which controls for the regional effect, is positive and significant, implying that the change in

Table 5
SDM coefficient estimations.

Dependent variable: ln(labour productivity)		Static	Dynamic
Time-lagged effect	ln(labour productivity)$_{t-1}$	–	0.266***
Degree of clustering	ln(location quotient)	−0.242***	−0.248***
Labour market pooling	ln(skilled labour pool)	0.076***	0.049***
	ln(formal entry qual)	−0.114***	−0.102***
Knowledge spillover	ln(last job in tourism)	0.008	0.004
Control variable	non-tourism labour productivity	0.015*	0.023**
Dependent variable	W*ln(labour productivity)	0.607***	0.485**
Degree of clustering	W*ln(location quotient)	0.086	0.036
Labour market pooling	W*ln(skilled labour pool)	0.215***	0.120***
	W*ln(formal entry qual)	0.041*	0.018
Knowledge spillover	W*ln(last job in tourism)	0.045***	0.072***
Control variable	W*non-tourism labour productivity	0.006	0.046***
Model diagnostics			
	Observations	4103 (n = 373; T = 11)	3730 (n = 373; T = 10)
	R-squared	0.124	0.405
	Log-likelihood	−297.76	−110.57
	AIC	619.52	247.15
	BIC	695.35	328.06
	Hausman test	106.27***	

Note: W = queen; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

the productivity of tourism within a LAD is not sector-specific but is in line with the rest of the local economy; regional effects influence productivity, posing questions as to whether these are related to tangible resources such as infrastructure or intangible such as entrepreneurial culture.

Second, the spatial spillover effects refer to the spatially lagged dependent and explanatory variables (expressed as *W*(variable name)*). Subsequent coefficient estimates refer to the effect of the variable on labour productivity across LADs. In the dynamic model, the coefficient of the spatial spillover of labour productivity is 0.485; if there is a one per cent increase in labour productivity in the neighbouring LADs, then the labour productivity will increase by 0.485% in the focal LAD. This shows statistically significant spillover effects of labour productivity across neighbouring regions and time, supporting Hypothesis 3. Existing research has claimed that local regions with a similar visitor economy attract similar customers and spatial proximity may therefore lead to significant productivity spillover effects across the regions (Yang & Wong, 2012). This has been illustrated in section 4.1 where the spatial dependence of labour productivity was highlighted across the UK, showing how LADs are influenced by neighbouring LADs, and the regional differences have been accounted for by the fixed effects in the model. The degree of clustering of tourism firms is positive when considering its spillover effect over space and time (0.036% increase in labour productivity) but is statistically insignificant. It is important to acknowledge that markets can extend across more than one LAD, given LADs are administrative units. Thus, the spillover effects of *ln(location quotient)* may be unclear, and this may be due to the different, and sometimes contradictory, impacts of different types of spillover effects.

Regarding the spatial spillover effects of agglomeration economies over time, a one per cent increase in the skilled labour pool will increase labour productivity by 0.120%, which is statistically significant. Unlike the direct effect, the spatial spillover effect of *ln(formal entry qual)* is positive when considering its effect across neighbouring regions, but statistically insignificant. Similar to Hypothesis 2, Hypothesis 4 is partially supported. Complementary effects of local labour markets on the labour productivity of tourism firms within the region can be generated through such spillover effects. The spatial spillover effects of knowledge are also shown to have complementary effects of a 0.072% increase in productivity for every one per cent increase in knowledge spillover across neighbouring LADs and time, unlike its direct effects. This supports Hypothesis 5. That the spatial spillover knowledge effects are significant, while the direct effects are insignificant, may reflect either being able to access different types of knowledge from different types of firms in neighbouring LADs, or stronger alternative knowledge transfer mechanisms (e.g. social networks) across compared to within LADs. Thus, significant spatial spillover effects of agglomeration economies on the labour productivity of tourism firms are evident.

Due to these spatial spillover effects, spatial feedback loop effects (LeSage & Pace, 2009) are estimated, which identify the average effect of the explanatory variables (X) on the dependent variable (Y) of a region to its neighbouring regions, vice a versa. The coefficients of the SDM models do not directly reflect the marginal effects of X on Y, which can lead to misleading inference (ibid.) – this can explain the inconsistent coefficient estimates between the direct and spatial spillover effects in Table 5. Table 6 shows the direct, indirect and total effect of each variable on labour productivity, along with the inferential statistics; these estimations infer more accurate interpretations of the spillover effects.

For the static model, only the long-run impact measures were estimated; for the dynamic model, both the long-run and short-run impact measures were estimated. The short-run effects imply the effects of the change in X on Y at time *t*, whereas the long-run effects imply the effects on Y at time *T,* as it goes to infinity, of a change in X, which remains through all times to *T* (Doran & Fingleton, 2018). Consistent with theory, the short-run effects appear to be smaller than the long-run effects because it takes time for the benefits of agglomeration to be developed within a cluster as it flows through different firms and entities (McCann & Folta, 2009). Thus, the long-run effects allow the full direct and indirect spillover effects to be realised; the following analysis and discussion will mainly focus on the long-run effect of the dynamic model.

Looking at the long-run effects of the dynamic model, the direct effects are larger than the coefficient estimates in Table 5, suggesting significant feedback effects as they pass via neighbouring LADs back to the focal LAD. The direct effect measures the average effect of the

Table 6
Impact measures: direct, indirect and total effects.

	Static			Dynamic					
	Long-run			Long-run			Short-run		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
ln(location quotient)	−0.251***	−0.131	−0.382	−0.378***	0.483	−0.861*	−0.261***	−0.154	−0.415**
ln(skilled labour pool)	0.123***	0.615***	0.738***	0.112***	0.566***	0.679***	0.068***	0.259***	0.328***
ln(formal entry qual)	−0.118***	−0.066	−0.184***	−0.155***	−0.181*	−0.335***	−0.107***	−0.055	−0.162***
ln(last job in tourism)	0.017*	0.121***	0.138***	0.028*	0.281***	0.309***	0.014	0.135***	0.149***
non-tourism labour productivity	0.017***	0.036	0.054**	0.050***	0.226***	0.275***	0.031***	0.102***	0.133***

Note: W = queen; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

change in X on Y, including the feedback via the neighbouring LAD and back to the focal LAD. Consistent with the coefficient estimates, the direct effect of the degree of clustering on productivity is significantly negative. With an increase in the degree of clustering of tourism firms within a spatial area, there may be an increase in localised market competition, a form of agglomeration diseconomies, which may reduce productivity (McCann & Folta, 2009). Competition for scarce local resources, i.e. labour and land, can also increase the costs of firms in a local area, putting pressures on prices, which has further detrimental effects on productivity. However, it is not just competition which is important, because firms may also benefit from collaborative behaviour via agglomeration economies, e.g. knowledge spillovers, or positive spatial spillover effects, which can generate greater efficiency and productivity (Viladecans-Marsal, 2004). Asymmetric contributions to agglomeration can also generate mixed agglomeration impacts on productivity (Shaver & Flyer, 2000), and require further investigation.

Regarding the direct effects of agglomeration economies on the labour productivity of tourism firms, a one per cent increase in the skilled labour pool increases productivity by 0.112% and is statistically significant. This supports the general findings in the extant literature of the positive association between skilled labour pool and productivity based on the likelihood of better labour matches within a locality (e.g. Rosenthal & Strange, 2004). In contrast, the variable *ln(formal entry qual)*, which proxies the share of high-skill jobs in a LAD, is significantly negatively related to the labour productivity of tourism, which may be associated with the negative effects of higher labour costs on productivity (McCann & Folta, 2009). This may also reflect the high skills mismatch within the local areas, especially because the tourism industry has a large share of low-skilled jobs. Yet, the heterogeneity of the labour force makes it difficult to disentangle this relationship, given the key role that may be played by human resource management practices (Madera et al., 2017). A diverse pool of skilled labour, in terms of the level of qualifications, can improve labour productivity, but the associated cost should also be considered.

One key difference between the direct effect and coefficient estimates is that the knowledge spillover variable is statistically significant when taking into consideration the feedback effect. The impact measures are considered to provide a more accurate interpretation of the spatial effects (Golgher & Voss, 2016), and suggest that an increase in the share of employees who have had a previous job in tourism in the neighbouring LADs significantly increases the labour productivity of tourism in the focal LAD. The literature contends that knowledge spillovers tend to be highly tacit in tourism, and that much of the knowledge is job-related and highly relevant with individuals drawing insights from previous work experiences (Yang, 2008, 2010). This further supports the positive effects of intra-cluster knowledge exchange on firm innovation (Bathelt et al., 2004), ultimately impacting on the productivity of tourism firms in the LAD.

Interesting findings can be seen from the indirect effects. These measure the average effects of the change in X of the focal region on the Y of neighbouring regions, or X of neighbouring regions on the Y of the focal region. There are no significant spillover effects of the degree of clustering on labour productivity. The *ln(skilled labour pool)* variable is positively significant, suggesting significant complementary effects of a skilled labour pool across neighbouring regions, which can boost labour productivity (and is consistent with e.g. Melo & Graham, 2014; Wixe, 2015). The spillover effects of labour market pooling can significantly contribute to productivity growth across neighbouring LADs, perhaps indicating the importance of being able to draw on a larger regional labour pool to help address local skilled labour shortages. This further suggests the potential movement of labour across localities or labour markets in close proximity, whether that is daily commuting or economic migration to specific local regions. Yet, the *ln(formal entry qual)* variables are negative and statistically significant. The high costs related to high-skilled jobs and the high labour mismatch, which tourism firms struggle to tackle, can be observed here again (McCann & Folta, 2009). Both complementary and competition effects of labour market pooling across neighbouring LADs can be suggested. The neighbouring effects of a skilled labour pool can significantly improve the labour productivity of tourism firms in the forms of enlarged regional labour pools, which can help enhance labour allocation and matching across a wider geographical boundary. Yet, labour heterogeneity and management effects may complicate this relationship at the regional scale, as well as within clusters.

The indirect effect of knowledge spillover is statistically significant and positive on labour productivity in the long-run. Knowledge can spillover globally (inter-cluster knowledge) and locally (intra-cluster knowledge), which also influences the degree of impact on productivity. Bathelt et al. (2004) argued that knowledge can spill over to other firms in inter-cluster transfers. Intra-cluster knowledge (local buzz) allows opportunities for firms to interact closely to tackle various spontaneous situations, and inter-cluster knowledge (global pipeline) allows firms to form knowledge-enhancing relations with external firms (ibid.), which can lead to significant implications for productivity. Moreover, Weidenfeld et al. (2010) examined the overall process of knowledge transfer and innovation in a visitor attraction area, Cornwall, and innovation was found to be relatively easily imitated by neighbouring attractions, especially those with similar tourism products, while labour mobility was found to be important for innovation. Thus, spatial spillover effects of knowledge across the LADs can significantly enhance the labour productivity of tourism firms in the UK over time.

The total effect refers to the sum of the direct and indirect effects, measuring the average effect of the change in X of the focal region on the Y of all the focal and neighbouring regions. The dynamic model shows greater significant positive effects than the static model, suggesting the importance of time in the effects on productivity. Compared to the long-run impact measures, the short-run measures show similar outcomes, but lower magnitude effects. This supports McCann and Folta's (2009) argument that the value of agglomeration grows over time regarding the supply-side agglomeration effects. Given that only the dynamic model can derive the short-run effects, the direct effects further confirm the existence of feedback effects as the estimates are larger than the coefficient estimates. Differences from the long-run effects are the direct effect of the knowledge spillover variable, which is statistically insignificant but significant in the indirect effect, and the *ln(formal entry qual)* variable, which is significant in the direct effect but not in the indirect effect. Yet, the total effects of these two variables on tourism productivity are significantly positive, implying significant spatial spillovers of agglomeration economies on labour productivity overall.

In summary, the findings from the SDM estimations have shown significant impacts of agglomeration economies on the labour productivity of tourism firms within a LAD, but also across neighbouring LADs. Both complementary and competition effects of the variables where evident, which support the existing theoretical literature on agglomeration (e.g. Porter, 1998; Peiró-Signes et al., 2014 in hotels). Furthermore, the long-run marginal effects of agglomeration economies are greater than the short-run effect on the labour productivity of tourism within and across neighbouring regions; this emphasises the need to take a long-run perspective on how agglomeration economies affect productivity. In reality, both positive and negative externalities will be at work, and the benefits of close locational proximity must outweigh the localised competition within neighbouring firms to have a net positive effect on productivity (Yang, 2012). Supported by many scholars, location is considered to be one of the most influential factors on performance in the tourism industry (Adam & Mensah, 2014).

5. Conclusion

This research has applied spatial panel models to investigate the impact of agglomeration economies on the productivity of tourism firms across LADs in the UK. It provides theoretical and practical but also methodological contributions, via the building of the dataset used in the estimation of the model contributions, to the still limited understanding of this topic in tourism.

This paper has addressed the theoretical gap in the tourism literature in terms of the operationalisation of agglomeration economies. This is one of the first attempts to apply spatial modelling techniques, which are readily applicable to other destinations and contexts beyond tourism, to analyse the impact of agglomeration economies on the productivity of tourism firms. Specifically, the impact of skilled labour pooling and knowledge spillovers was confirmed as positive effects on productivity as anticipated (Abel et al., 2012; Rosenthal & Strange, 2004). In contrast, when considering the share of high-skilled jobs within a region and its influence on productivity, the findings of this research have inferred negative effects on tourism productivity. This may relate to the high costs of high-skilled jobs in tourism or the possibility of labour poaching within the region or industry (Combes & Duranton, 2006), a topic on which further research is needed.

Additionally, this paper is the first substantial study of the spatial spillover effects of agglomeration economies and labour productivity across space and time in tourism studies. It has unpacked the complex set of effects of agglomeration and spatial spillover effects, with empirical findings supporting significant spatial spillover effects of both labour market pooling and knowledge and labour productivity between regions. This may lead to regional productivity growth in the UK tourism industry. Given privileged access to major under-exploited micro-level panel data, both static and dynamic spatial panel models were estimated to gain a better understanding of the impact of agglomeration economies on tourism productivity across space and time. The significance of the time-lagged effect of labour productivity and the long-run marginal effects of agglomeration economies on labour productivity within and across neighbouring regions, makes it important for researchers, not just in tourism but beyond, to adopt a long-run perspective on how agglomeration economies can affect productivity across space.

In terms of practical contributions, the sectoral dimension of the productivity problem in the UK was highlighted in the modern Industrial Strategy (HM Government, 2017), stating that some of the biggest opportunities for raising productivity come in sectors that have lower productivity levels, such as tourism. This makes the research timely in providing empirical evidence of the potential economic effects of agglomeration for tourism businesses (e.g. hotels, restaurants, travel agencies and attractions) and insights into the significance of agglomeration economies and the possible spillover effects that can help address the low level of productivity across the UK. This can be in the form of tourism clusters or zones, which the UK Tourism Sector Deal will introduce (HM Government, 2019), creating business networks or communities to share knowledge and resources in improving productivity at a firm, sectoral and regional level. This can further suggest the impact of diversification of the tourism industry on labour productivity via different sectors within tourism. These practical or policy insights, although developed specifically in a UK case study, are likely to have broader application, at least to other developed countries and service industries.

This research faces some limitations, which requires further research. Firstly, the dataset was limited to the UK, which may limit the generalisability of the results. Further research is recommended across other developed and developing economies to explore the spillover effect of agglomeration economies and tourism productivity. Secondly, due to data unavailability, control variables regarding market characteristics were not available at this scale. Additionally, due to limited choice of spatial units based on the secondary data, the spatial units were not always coterminous with tourism and labour markets. Lastly, local estimations could have further shown the spatial variations in the effects of agglomeration and tourism productivity at each local level (i.e. LAD). Thus, spatial and/or temporal local models, such as geographically weighted regression models, need to be further examined to capture such local effects.

Declaration of authors' contributions

Yoo Ri Kim: Conceptualisation, Methodology, Data curation, Formal analysis, Lead author; Allan M Williams: Conceptualisation, Writing – contribution to different drafts; Sangwon Park: Conceptualisation, Overall research design, Writing – contribution to different drafts; Jason Li Chen: Methodology, Writing – contributing to writing up of technical and analytical issues.

Impact statement

The UK has the weakest productivity performance amongst the G7 countries, and the regional and sectoral dimension of the productivity problem in the UK has been highlighted in the government's Industrial Strategy. Lower productivity levels, such as in tourism, provide some of the main opportunities for increasing productivity. This research identifies the potential economic effects of agglomeration on tourism businesses and provides insights into how agglomeration economies and related spatial spillovers contribute to highly uneven territorial productivity differentials. Significant agglomeration effects imply that tourism clusters or business communities can enable knowledge and resource sharing to improve productivity at the firm, sector and regional level. Addressing the low productivity level of the tourism industry can strengthen its competitiveness but also that of other complementary sectors and the general economy.

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