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ABSTRACT

Assessing agglomeration economies in a spatial framework with endogenous regressors

This paper is concerned with the influence of agglomeration economies on economic outcomes across British regions. The concentration of economic activity in one place can foster economic performance due to the reduction in transportation costs, the ready availability of customers and suppliers, and knowledge spillovers. However, the concentration of several types of intangible assets can boost productivity as well. Thus, using an interesting dataset which proxies regional productivity, we will assess the relative importance of agglomeration and other assets, controlling both for endogeneity and for spatial autocorrelation at the same time. Our results suggest that agglomeration has a definite positive influence on productivity, although our estimates of its effect are dramatically reduced when spatial dependence and other hitherto omitted variables proxying intangible assets are controlled for.

JEL Classification: C21, J34, R10, R11 and R12
Keywords: agglomeration economies, endogeneity, intangible assets and spatial autocorrelation

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Assessing agglomeration economies in a spatial framework with endogenous regressors

April 2009

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1. Introduction

The research programme of the New Economic Geography (FUJITA (1988), KRUGMAN (1991), FUJITA et al. (1999)), investigates the sources of imbalances in economic performance across regions and countries, focusing its analysis on centripetal and centrifugal forces that determine the distribution of economic activity across space. Within this research programme the studies by CICCONE and HALL (1996) and CICCONE (2002) stand out as focussing on the measurement of agglomeration economies.

In this paper, we attempt to analyze this effect on labour productivity in the NUTS3[1] regions of Great Britain. Our investigation includes several novelties. First of all, it uses a new dataset to measure economic outcomes and productivity, that is, GVA per job filled (WOSNITZA and WALKER, 2008). It has the advantage of avoiding a number of the measurement errors that have afflicted other productivity data sets. Second, as a proxy for the agglomeration of economic activity, our study uses a concept elaborated by RICE et al. (2006), that of "economic mass". Thirdly, we rely on the hypothesis that the mere location of individuals and firms within a specific space cannot be the only source of aggregated increasing returns. Thus, we think that the qualitative characteristics of each region are also important in explaining economic outcomes. Hence, departing from the model by CICCONE (2002) and following BODE's (2004) suggestions, we have included several modifications in order to control for a wider range of private returns beyond individuals' location and to allow for a broader variety of social returns or externalities within the region as well. Finally, we take account of the effect of externalities that take place across – as well as within – regions: that is, we take very full account of spatial autocorrelation.

The way in which we have chosen to go about our study is basically as follows: we will start by estimating our model by OLS, both with and without including sources of private and social returns within regions, in addition to agglomeration *per se*. However, several sources of endogeneity could arise from these first estimates. It could be the case that the concentration of employees leads to better economic outcomes or, on the contrary, that better economic outcomes attract more workers to live in a given region due to higher wages. If the latter occurs, estimation by OLS will yield inconsistent estimates. To deal with this problem, we will conduct our estimation using

[1] NUTS corresponds to the French acronym for "*nomenclature d'unités territoriales statistiques*", and refers to administrative divisions within Europe for statistical purposes.

2SLS. The existence of externalities *across* regions would in any case lead to the OLS estimates being biased and inconsistent. To our knowledge, there are few papers which have estimated the agglomeration effect taking account at the same time of these two sources of inconsistency. In fact, as stressed by FINGLETON and LE GALLO (2008), applied spatial econometrics has almost neglected the effects of other endogenous variables, although their presence is common in every empirical work.

We will therefore explore stage by stage which of these three features –and to what extent - is a source of bias in the agglomeration elasticity if not controlled for.

Another novelty of our study refers to spatial econometrics techniques. We do not only consider a spatial lag of our dependent variable as an explanatory variable, but also check for residual autocorrelation once this spatial lag has been included. If necessary, we can estimate our model by feasible generalized spatial two-stages least squares (FGS2SLS), as suggested in KELEJIAN and PRUCHA (K-P) (1998). Indeed, if there are significant spatially autocorrelated explanatory variables aside from the spatial lag and their effects are not fully controlled by means of its inclusion, their absence would tend to induce a spatially non-random pattern of residuals which has to be taken into account. We have modified the K-P estimator in order to include the possibility of controlling for other sources of endogeneity (in our case, the reverse causality between agglomeration and economic outcomes). As far as we know, no papers exist which deal with the estimation of the agglomeration effect, taking into account both two-way causation and spatial autocorrelation by means of a spatial lag and a spatially autocorrelated error term, and to do this will be, therefore, one of the main contributions of the paper.

Our results do suggest that agglomeration economies are significant in determining productivity, although our estimates of their size is somewhat reduced when the intangible asset endowments which characterize the knowledge-based economy are introduced, and are dramatically diminished when spatial dependence is controlled for. The paper is organized as follows: section 2 reviews the theoretical and empirical literature on agglomeration economies; section 3 presents our model and some data issues; section 4 outlines the OLS estimates of our baseline specification, while section 5 deals with 2SLS estimations to cope with endogeneity problems. Finally, section 6 concludes.

2. Background

Broadly understood, the study by CICCONE and HALL (1996) highlights the idea that density of economic activity is a source of enhanced productivity gains due to the effect of spatial externalities leading to increasing returns within regions. Three main sources have been put forward to understand why improved aggregated economic results may come about from the agglomeration of economic activity. On the one hand, easier access to suppliers and customers, in the presence of transportation costs that rise with distance, will surely lead to better outcomes for the firm, holding input endowments and technology constant – since, quite simply, "the ratio of output to input will rise with density" (CICCONE and HALL, 1996, p. 54). Secondly, the concentration of economic activity would imply thicker and larger input markets, so ones that are more efficient in terms of market matching. Thus, the concentration of producers in one location would bring about a large and diverse provision of certain inputs (ROSENTHAL and STRANGE, 2004), which could be characterized by strong scale economies in input production. Finally, the concentration of economic activity results in more intensive and frequent knowledge spillovers, given that firms can learn from others when they are sharing a common space. More recently, other important sources of agglomeration economies have been put forward as well, such as natural advantages, home market effects (HANSON, 2005), consumption opportunities (GLAESER et al., 2001), and rent-seeking (ADES and GLAESER, 1995).

According to the seminal study by CICCONE and HALL (1996), density is crucial for explaining the variation of productivity. Indeed, a doubling of employment density will lead to a 6% increase of average labour productivity. CICCONE (2002) enlarged the scope of his previous work by estimating agglomeration effects for the NUTS3 regions of France, Germany, Italy, Spain, and the UK with a model in which the concentration of production is the main source of agglomeration economies. This study suggests substantial agglomeration effects in Europe, with estimated elasticities of around 4.5%, which do not differ significantly across countries.

The empirical literature concerned with the effect of agglomeration economies on economic performance has grown enormously since the seminal paper by CICCONE and HALL (1996) for the US and some useful surveys (ROSENTHAL and STRANGE, 2004; DURANTON, 2007) already exist. In broad terms, the majority of studies obtain elasticities between 0.01 and 0.20, using different proxies for agglomeration and for economic outputs and both at an aggregate level or at plant level – although results under 0.10 are preponderant - so a doubling of city or region size leads to an increase in productivity between 1% and 10% (GRAHAM, 2007)[2]. Although somewhat later than for the US case, a growing literature estimating agglomeration effects for Europe has sprung up as well – in addition to CICCONE (2002).

Hence, CINGANO and SCHIVARDI (2004) and COMBES et al. (2008) stress the importance of human capital –the later ones focusing their attention on the endogenous nature of human capital. Panel data techniques and dynamics are suggested in BLIEN et al. (2006), BRÜLHART and MATHYS (2008) and BRÜLHART and SBERGAMI (2009). Stressing the role of diseconomies when dealing with agglomeration effects on economic outcomes are GRAHAM (2007) and BRÜLHART and SBERGAMI (2009), whilst the former study highlights large differences in the estimated agglomeration effect dependent upon the economic sector analysed – from elasticities around 0.04 for manufacturing sectors up to values of 0.18 for certain service sectors. Finally, BAPTISTA (2003), FINGLETON (2003) or RICE et al. (2006) are interesting references for the British case.

3. Methodology and some data issues

3.1. The model

For our purposes, we start from the approach by CICCONE (2002), who develops a fruitful theoretical model to be empirically tested of a production function in region s of the form:

$$y = Q_s f(l \cdot H, k; Y_s, A_s) = Q_s ((l \cdot H)^{\beta} k^{1-\beta})^{\alpha} \left(\frac{Y_s}{A_s} \right)^{(\lambda-1)/\lambda} \qquad (1)$$

where y is the output per hectare, l the number of workers per hectare, H the average level of human capital, k the amount of physical capital used in the hectare; Q_s is the

[2] For the case of the US, the review by ROSENTHAL and STRANGE (2004) supports a range of agglomeration economies estimates of between 3% and 8%.

index of TFP in the region; and Y_s and A_s denote total production and total hectares of the region respectively; α captures returns to capital and labour on the hectare, β is a distribution parameter, and $(\lambda-1)/\lambda$ is the parameter which captures spatial externalities arising from the concentration of economic activity - in this case, density of production (Y_s/A_s). Here, based on our theoretical considerations, we will introduce a few modifications to be empirically tested. Basically, we consider that this specification fails to represent a great variety of individual returns that might foster economic outcomes as well, leading to an omitted variables problem. Further, it does not resolve the question of what kind of externalities affect output and, therefore, labour productivity (BODE, 2004). Our main hypothesis is that the mere concentration of economic activity cannot be the sole determinant of productivity differentials across regions.

The economic literature has recently started to shift its focus of analysis: from the impact of physical inputs (labour and physical capital) to the impact of intangible ones. This shift of focus has become even more important since the advent of the so-called knowledge-economy. Our theoretical model will include several kinds of intangible endowments, which will allow us to control for a wider variety of private returns which derive from the accumulation of these intangible inputs. At the same time, it will let us control for a broader range of social returns or externalities which follow from the accumulation of endowments – however, we are concerned about the difficulty of empirically differentiating at an aggregate level between these two sources of increasing returns, that is, private and social returns. Here, we limit our inputs to those of knowledge, human capital, and entrepreneurial culture[3]. Where these sources of productivity are not controlled for, the estimation of the agglomeration effect could be biased upward.

The literature has widely stressed the role played by human skills in determining regional economic outcomes (MORETTI, 2004; CICCONE and CINGANO, 2003; COMBES et al., 2008). The hypothesis behind these contributions is twofold. On the one hand, it relies on the assumption that, even given equal technologies among regions, there exist differences between areas concerning the ability of individuals to make that technology

[3] We are concerned about the omission of other kinds of intangible asset, such as relational capital, social capital, territorial capital, cognitive capital, intellectual capital, and the like. We assume, however, that our 3 types of intangible assets are taking into account to a certain extent the possible effects of these unidentified intangible assets on productivity.

productive (FINGLETON, 2003). On the other hand, human capital spillovers increase aggregate productivity beyond the effect of this capital on individuals' productivity. Thus, an increase of the overall level of human capital of each region leads to higher levels of productivity (MORETTI, 2004)[4]. However, human capital could be acquired both in the educational system and while working. Therefore, the occupational composition of the region is important too (CICCONE and CINGANO, 2003) and may well bias the density parameter upward if not controlled for appropriately.

In a similar way as human capital endowments, differential access of each region to knowledge could explain productivity differentials across regions as well, *ceteris paribus* (FINGLETON, 2003). Actually, the access to innovation and new technologies, and to the processes and individuals that generate them –in broad terms, knowledge capital - is rooted in the so-called theories of endogenous economic growth. We hypothesize that private returns of knowledge and knowledge externalities arise both from knowledge inputs – that is, R&D efforts and the number of employees working in high-technology industrial sectors, and from knowledge outputs, that is to say, patents.

In addition, as AUDRETSCH (2002) and ROSENTHAL and STRANGE (2004) suggest, the entrepreneurial or business culture of a region could boost economic performance as well. Indeed in HM TREASURY (2001), we find that entrepreneurial activity is regarded as a key driver of productivity growth in the economy. The creation and enlargement of firms is associated with the introduction of new technologies, innovative production processes, and increased competitive pressure on the other firms in a given market, providing them with strong incentives to further innovate and adopt new technologies (GLAESER et al., 1992). Thus, we will include both the amount of new entrepreneurial projects set up in a given region, and the overall growth of firms during the whole period, in order to take account not only of the business culture of the region, but also its success.

Given all the former arguments, we should assume, contrary to CICCONE's (2002) model, that this set of intangible assets enters the production function affecting directly the total factor productivity index - Q_s - of each region, in order to capture a greater variety of private returns and externalities. These considerations lead us to a new TFP measure like

[4] See MORETTI (2004) for a detailed review of theories and empirical studies on human capital and human capital externalities.

$$Q_s = Q_s(Q, H_s, O_s, RD_s, MAN_s, PAT_s, E_s, S_s) \tag{2}$$

where Q are the determinants of TFP which do not differ at a NUTS3 level. H_s and O_s are educational and occupational human capital indicators respectively, RD_s an indicator of knowledge efforts, MAN_s an indicator of high-tech manufacturing knowledge, and PAT_s an indicator of knowledge outputs; E_s is an entrepreneurship capital indicator, and S_s an entrepreneurship success indicator, all of them within the region s. So going back to equation (1), the final model would be

$$y = Q_s(Q, H_s, O_s, RD_s, MAN_s, PAT_s, E_s, S_s) \cdot f(l, k, Y_s, A_s) \tag{3}$$

which actually follows the form of

$$y = Q_s(\cdot) \cdot (l^{\beta} k^{1-\beta})^{\alpha} \left(\frac{Y_s}{A_s} \right)^{(\lambda-1)/\lambda} \tag{4}$$

where $Q_s(\cdot)$ is the total factor productivity index affected for a wider range of private and social returns aside from those derived from the agglomeration of the economic activity. In order to make this function estimable, we can turn it into an aggregate regional production function of the form:

$$Y_s = y \cdot A_s = A_s Q_s(\cdot) \left(\left(\frac{L_s}{A_s} \right)^{\beta} \left(\frac{K_s}{A_s} \right)^{1-\beta} \right)^{\alpha} \left(\frac{Y_s}{A_s} \right)^{(\lambda-1)/\lambda} \tag{5}$$

where output, labour and capital (Y_s, L_s, K_s) correspond to their quantity in each region instead of in each hectare. Rearranging and solving for labour productivity, yields:

$$Y_s = A_s^{1-\alpha\lambda} Q_s(\cdot)^{\lambda} L_s^{\alpha\lambda} \left(\left(\frac{K_s}{L_s} \right)^{1-\beta} \right)^{\alpha\lambda} \tag{6}$$

$$\frac{Y_s}{L_s} = \left(\frac{L_s}{A_s}\right)^{\alpha\lambda-1} Q_s(\cdot)^{\lambda} \left(\left(\frac{K_s}{L_s}\right)^{1-\beta}\right)^{\alpha\lambda} \tag{7}$$

As stressed by CICCONE (2002), at low levels of regional disaggregation, data on the quantity of physical capital do not exist. To cope with this disadvantage, we will follow CICCONE (2002) and we will assume that the rental price of capital is the same within every NUTS1 region. Hence, from equation (1) can be derived the capital-demand function, $K_s = \frac{\alpha(1-\beta)}{r} Y_s$, where r is the rental price of capital in each larger region. Thus, the developments carry on in the following way:

$$\frac{Y_s}{L_s} = \left(\frac{L_s}{A_s}\right)^{\alpha\lambda-1} Q_s(\cdot)^{\lambda} \left(\left(\frac{\alpha(1-\beta)}{r} Y_s\right)^{1-\beta} L_s^{-(1-\beta)}\right)^{\alpha\lambda} \tag{8}$$

$$\left(\frac{Y_s}{L_s}\right) = \left(\frac{L_s}{A_s}\right)^{\theta} \Omega_s Q_s(\cdot)^{\omega} \tag{9}$$

where $\theta = \frac{\alpha\lambda - 1}{1-\alpha\lambda(1-\beta)}$ and measures the net effect of regional employment density on regional productivity – that is to say, higher outcomes minus the detrimental effect on productivity due to congestion, contamination, pollution and resources squandering, crime rates, higher house rents, and so on; $\Omega_s = \left(\frac{\alpha(1-\beta)}{r}\right)^{\frac{1}{1-(1-\beta)\alpha\lambda}}$ and is a constant which only depends on the rental price of capital in a larger region, and $\omega = \frac{\lambda}{1-\alpha\lambda(1-\beta)}$. Taking logs, and assuming that the productivity term, $Q_s(\cdot)$, enters in a logarithmic form, yields:

$$\log\left(\frac{Y_s}{L_s}\right) = \log\Omega + \theta(\log Agglomeration_s) + \phi_0 \log Q + \phi_1 \log H_s + \phi_2 \log O_s + \\ + \phi_3 \log RD_s + \phi_4 \log MAN_s + \phi_5 \log PAT_s + \phi_6 \log E_s + \phi_7 \log S_s + \\ + \phi_8 \log H_s \cdot \log RD_s + \phi_9 \log H_s \cdot \log MAN_s + \phi_{10} \log H_s \cdot \log PAT_s + \varepsilon_s \quad (10)$$

where ε_s is a random error term. As can be seen, interactions between educational human capital and each dimension of knowledge capital are included[5]. Regional dummies will be included also to capture both differences in exogenous TFP not explained in the model $(\phi_0 \log Q)$ -which are assumed to be marginal- and specially $\log\Omega$, because differences in physical capital or its rental price could be captured by allowing for spatial fixed effects for larger regions (CICCONE, 2002). Thus, a dummy for large regions (NUTS1) will replace $\phi_0 \log Q + \log\Omega$. Next, $\phi_i = \omega \cdot \delta_i$, and δ_i are the elasticities of TFP with respect to its determinants, where $i = 1,...10$ for the coefficients of the 7 indicators for intangible assets and cross-products.

3.2. Data

Productivity is defined as GVA per filled job for the period 2001 to 2005 and, as local data are prone to exhibit lumpiness from year to year, we compensate for this by using the average of the five years' productivity figures –the same applies for the explanatory variables. The literature has widely used either wages and earnings, or GVA per head or employee, to proxy regional productivity. However, productivity measures should include more than wages or salaries, but also allow for profits, for instance. Thus, WOSNITZA and WALKER (2008) decompose GVA per head in British regions, following the OECD methodology, into four elements, that is, productivity –actually GVA per job filled, which is calculated on a workplace basis instead of on a residence basis-employment rate, commuting rate, and activity rate. Taking as a measure of productivity this GVA per job on a workplace basis allows us to avoid some of the potential

[5] Human capital and knowledge capital could play a complementary role in determining economic outcomes. Indeed, the higher the amount of knowledge in a given economy –whatever its dimension - the larger will be the returns of human capital on productivity, since individuals will be provided with a wider variety of 'existing ideas' to be used in the production process. Besides, the larger the amount of human capital in a given region, the higher will be the returns of each dimension of knowledge on productivity, due to a better transformation of these ideas into new ones.

distortions of GVA per head or employee, particularly in cities that receive a significant number of commuters, or have low economic activity rates.

To proxy the concentration of economic activity in order to explain the effect of agglomeration on productivity, we will use the concept of "economic mass", due to RICE et al. (2006). This measure is based on the total population (or employment) of a given area which is located within a series of driving time bands around the centre of each NUTS3 area[6]. Thus, we do not understand agglomeration as population per hectare within a given administrative region, but as population in a band or isochrone of certain minutes' travel by car. According to the authors, this measure is an economically more meaningful proxy for agglomeration than the more traditional measure of employment density in the own or neighbouring regions. British NUTS3 areas are small enough, with boundaries determined administratively rather than economically, that travel time bands will capture the effective potential population (or jobs filled in our case) available for each area. Further, by including more than one travel time band, we will capture not only own area effects, but also cross-region effects, so we will be able to assess the scope of the agglomeration effect as well[7].

It is worth noting that intangible assets are hard to define and measure, basically due to a lack of consensus on what they exactly are. What is more, they tend to be a multidimensional concept, which we will try to take account in our proxies and, therefore, in our estimations. Information about the construction of each variable and the data sources are given in the appendix. We will assume that these variables will be completely exogenous, since they will pre-date our period of analysis, 2001-2005 –data for these variables will pertain to the period 1996-2000.

Table 1 sets out the variables used in this study with information on their variation across the regions of the UK. It is easy to see that differences across regions are important, as for the case of our dependent variable, which varies from £22,761 per

[6] Data on travel times (and distances as well) were calculated using Microsoft Autoroute 2002. We are very grateful to Patricia Rice and Anthony Venables for providing us with these data. To adapt our data to travel time data provided by Rice and Venables, the regions of Eilean Siar (Western Isles), Orkney Islands, and Shetland Islands have been excluded. Moreover, the following areas have been aggregated: East Cumbria and West Cumbria; South and West Derbyshire and East Derbyshire; North Nottinghamshire and South Nottinghamshire; Isle of Anglesey and Gwynedd; Caithness, Sutherland and Ross and Cromarty, Inverness and Nairn and Moray, Badenoch and Strathspey, Lochaber, Sky, Lochalsh and Argyll and the Islands.

[7] As RICE et al. (2006) mention, the ideal situation would be to include several time bands of no more than 20 minutes each one, although it would introduce serious collinearity problems in the estimation. In our study, then, we have introduced two travel time bands of 60 minutes each, so two parameters, θ_{0-60} and θ_{60-120}, will be included in our regressions.

filled job in the Scottish Borders region up to the value for Inner London – West, of £46,594. Differences among regions are high for the explanatory variables as well, especially for the concentration of population and employment, applied patents, and employment in R&D.

[Insert table 1 about here]

3.3. Spatial structure of productivity: Exploratory analysis

Externalities or social returns could arise both from intangible capital and from physical endowments. When the sender and the receiver of these externalities are not in the same region, we should expect a correlation between explanatory variables in one region and the dependent variable of its neighbouring regions. Concretely, we assume that if our dependent variable shows some degree of spatial dependence, it would mean that this spatial autocorrelation summarizes a wide range of externalities across regions. This is why we turn now to the analysis of the spatial distribution of our dependent variable. We want to analyse whether there exists a relationship between the economic performance of one NUTS3 region in terms of GVA per job filled and the economic performance of neighbouring regions. If so, we should take account of this dependence in the estimation of our model. Otherwise, the estimates of the relationship between agglomeration (both of employees and intangible endowments) and GVA per job filled will be biased.

To check for spatial dependence we need to define a measure of proximity, which will be summarized in a nxn matrix of spatial weights, where $W = \{w_{ij}\}$. The most common definition of proximity is that of first order physical contiguity, that is, if two regions share the same administrative border $w_{ij} = 1$, and $w_{ij} = 0$ otherwise. Other contiguity criteria have been defined in the literature, such as commercial exchanges (CABRER-BORRÀS and SERRANO-DOMINGO, 2007) or technological proximity (MORENO et al., 2005). We will focus our attention in another definition of contiguity, somewhat more relevant for our purposes. Concretely, we will define $w_{ij} = \exp(-0.01 d_{ij})$, d_{ij} being the travel time by car between the centres of region i and region j. As PATTACCHINI and RICE (2007) stress, travel times between regions are a more economically meaningful measure of proximity than physical contiguity or physical distance. What is more, this measure should suffer less from some kind of reverse causality than other economically meaningful measures like technological proximity or commercial exchanges. A cut-off of 120 minutes is introduced, since interdependencies beyond 2 hours' travel time should be negligible.

Table 2 shows the values of Moran's I and Geary's c-statistics for GVA per job filled using various definitions of proximity, including contiguity, physical distance and variations of time-travel-dependent measures. Whilst there is some variation across the various measures, it is clear that spatial dependence is significant.

[Insert table 2 about here]

4. Baseline results

The aim of this section is to explore the extent to which the parameter estimates for the effect of agglomeration on productivity, proxied by total employment within each isochrone, are modified when other sources of private returns and externalities within each region are taken into account. In Table 3 we display the OLS estimates. We have reported, in a first stage (column (i)), estimates of the effect of agglomeration on productivity, using only the educational human capital location quotient as a control, as is done in much of the literature reviewed in section 2. In the subsequent columns we show the effects of including the additional variables suggested by the model discussed in Section 3 (column (ii)). Finally, we allow for interactions between educational human capital and knowledge – columns (iii) to (v). If the estimated coefficients on the interactions are positive, the effect of each dimension of knowledge on productivity will be larger, the larger the amount of educational human capital there is in a given regional economy. Similarly, the effect of this capital on productivity will be higher, the higher the amount of knowledge there is in that region. In the lower panel of table 3 we report the total semi-elasticities, adding the complementarity effect to the direct effect following the formulae set out. We tested the joint significance of both parameters –the direct effect and its indirect effect through the interaction; standard errors for the total semi-elasticities were calculated using the delta method (SERFLING, 1980).

Next, following CICCONE's (2002) article, we assume that the capital income share, $\alpha(1-\beta)$, equals 0.3, whilst the income share of land, $(1-\alpha)$, equals 0.015. The agglomeration parameter within the first 60 minutes travel time band, θ_{0-60} , is, according to our estimates of the restricted model, 0.059. To get an approximation of the elasticity of production density on total output, we use the fact that $\frac{\lambda-1}{\lambda}=1-\frac{\alpha+\alpha(1-\beta)\theta}{1+\theta}$, so the estimated parameter implies results for the coefficient which captures spatial externalities in CICCONE's (2002) model – a value of 5.3% for our sample. Moreover, when a (significant) parameter for the second travel time band is added, a total elasticity of 6.2% arises.

When the full extended model is estimated (columns (ii) to (v)) the adjusted R-squares increase by around 0.12 and 0.15, so those specifications explain a larger proportion of variance than the restricted one. Moreover, the implied elasticities of the density of production are around 4.07% and 4.26%, about 69% to 80% of those in column (i). What is more, for the case of the second travel time band, 60-120 minutes, the parameters are no longer significant or are only significant at 10%.

Interestingly enough, the majority of the variables included in our model are significant and with the expected sign. Educational human capital has a significant and positive impact on productivity, while knowledge inputs –that is, R&D and high-tech manufacturing employment- positively affect outcomes as well. The business culture of a region –i.e., entrepreneurship capital- has a significant effect on productivity, whilst its success has a strongly significant and positive impact. On the other hand, the occupational human capital indicator does not have a significant impact on productivity, although this situation could be partially explained due to social and institutional factors, and to labour market segmentations within high performing regions, since people in those regions demand low-productivity services to be located inside. Knowledge outputs, that is to say, applied patents according to their inventor region of residence, are not significant either. Strikingly, when the interaction between educational human capital and knowledge outputs are included (columns (iv) and (v)), as we hypothesized in the former section, their total elasticities are increased, especially that of applied patents, which goes from a non-significant 1.5% up to a strongly significant 2.2%, at least at a 5% level of significance. However, the interaction between educational human capital and knowledge inputs seems to be less clear –there exists a slight complementarity with high-tech manufacturing employment, but there is not with R&D efforts.

In short, although the estimated agglomeration effect, θ, and the implied production density parameter are somewhat smaller when intangible assets are included in the model, agglomeration economies still matter, although their impact – in quantitative terms- and their scope –in terms of distances- are estimated to be lower and shorter respectively.

[Insert table 3 about here]

At this point we should be aware of several sources of endogeneity and omitted variables in our model which could bias our estimates and make them inconsistent. On the one hand, the concentration of economic activity and employment could suffer from reverse causality with productivity, since workers could tend to concentrate where economic outcomes, and consequently wages, are higher. Moreover, other sources of externalities aside from those related to the concentration of employment may arise not only within a given region, but also across neighbouring regions. Their omission could lead us to make biased and inconsistent estimates. In the next section, we will take all these considerations into account.

5. Endogeneity and spatial dependence

5.1. Endogeneity

A principal concern when assessing the robustness of the relationship between the concentration of economic activity and productivity is with the issue of possible "two-way causation" -are cities highly productive because they are big and dense, or are cities big because they are highly productive? To deal with such an endogeneity problem, the literature has used instrumental variables and two-stage least squares procedures (2SLS). However, we are aware that GMM estimators, by using all the orthogonality conditions, can lead us to an efficient estimator in the presence of heteroskedasticity of unknown form, whilst IV-2SLS estimations would lead us to consistent but inefficient estimates - so inference would be affected. However, if heteroskedasticity is not present, the GMM estimator can have less desirable small sample properties than IV-2SLS because the weighting matrix of the efficient GMM estimator is a function of fourth moments, which could be difficult to estimate without large samples (BAUM et al., 2003)[8]. Consequently, for our purpose 2SLS estimators are preferred. Concretely, we will use two instruments, so we will be able to perform overidentification tests as well. Thus, just as in RICE et al. (2006), we will use as instrument the population in 1801 in regions whose centre is within two travel time bands. As the authors noted, the validity of this instrument lies in the assumption that the patterns that determined the settlement at the beginning of the XIXth century are not correlated with current levels of productivity, aside from its influence through current population and employment concentration. Further, following CICCONE´s (2002) suggestions, we will use total land area of the regions the centre of which is located within each of our two isochrones as a second instrument, since, as stressed by the author, current administrative boundaries were drawn in order to make equal the level of population of each region, so it can be used as an instrument if the original sources of population concentration (mainly geographical explanations) affect productivity only through agglomeration.

In table 4 we have repeated the procedure of table 3, but instrumenting our main explanatory variables – i.e., employment within each isochrone - using the aforementioned instruments. The first stage F-statistics for the joint significance of the instruments are larger than 10, which is usually considered a good threshold not to judge the instruments as weak ones, whilst partial R-squares of the first regression are high – both statistics are provided at the bottom of the table. Moreover, Shea partial R-squares (which take account of the collinearity among instruments –see SHEA, 1997) are shown as well, since in models with multiple endogenous variables the first stage F-statistic and usual partial R-squares of the first stage are not sufficiently informative. In the case that the partial R-squared were large values and the Shea R-squared small ones, the instruments would lack sufficient relevance to explain all the endogenous regressors (BAUM et al., 2003). As can be seen, the differences between the two measures are almost negligible.

The results and conclusions arising from table 4 are similar to those of table 3: there is a reduction (both in quantitative and distance terms) of the agglomeration effect when controlling for intangible capital assets; these assets are important in fostering productivity, and there is a complementarity between educational human capital and

[8] Pagan-Hall test statistics are provided at the bottom of each table to check for heteroskedasticity when one or more regressors are endogenous and the null of homoskedasticity cannot be rejected. However, we have repeated the estimation of table 4 using GMM techniques and the results (which are available upon request from the authors) do not change to any large extent.

technological outputs. It is worth noting that the estimated coefficient of the agglomeration effect is somewhat lower for all the specifications when instrumented, suggesting that the parameter was somewhat upward biased in the OLS estimation and that the 2SLS estimation was necessary.

[Insert table 4 about here]

5.2. Spatial structure of productivity: Feasible GS2SLS

A second problem with our OLS estimates is the existence of spatial autocorrelation. Moran's I and Geary's C pointed to the need for checking for spatial autocorrelation after OLS estimates – see section 3. Here, as can be seen from Table 3, Moran's I test for spatially autocorrelated residuals after the OLS estimates seems to indicate that spatial autocorrelation remains. However, Robust Lagrange multiplier tests do not clearly discriminate where the spatial process is allocated, either as a spatial lag of the endogenous variable or in the error term. The first one is known as substantive spatial autocorrelation; its omission would imply an error term being spatially correlated, and its solution comes from the inclusion of the spatial lag of the dependent variable. On the other hand, when the spatial autocorrelation is not caused by the omission of a spatial lag of the dependent variable, we are confronted with residual or nuisance spatial autocorrelation, which may arise from the omission of relevant variables or from measurement errors (ANSELIN, 1988). The first type of spatial dependence can be interpreted as arising from economically meaningful spillovers, whilst the second one is merely due to noise (BODE, 2004). In such a setting, we theoretically hypothesize that when the sender and the receiver of social returns are not in the same region, spatial autocorrelation arises and summarizes a wide range of externalities across regions which could be taken into account with the inclusion of a spatial lag of the dependent variable. However, even when a spatial lag is included, residual spatial autocorrelation may remain, and in this case we should also include a spatially autoregressive error term (AR). Indeed, if there are significant spatially autocorrelated explanatory variables, aside from the spatial lag and not accounted for by means of its inclusion, their absence would tend to induce a spatially non-random pattern of residuals. To the best of our knowledge no other paper has hitherto sought to estimate agglomeration economies whilst at the same time dealing with reverse causality and spatial autocorrelation both in the dependent variable and in the error term. Equation (11) shows the mixture model, where both types of spatial autocorrelation are included[9]:

$$\begin{aligned} y &= \rho W y + X\beta + \varepsilon \\ \varepsilon &= \lambda W \varepsilon + u \\ u &- N(0, \sigma^2 I) \end{aligned} \tag{11}$$

At this point is necessary to choose the appropriate estimation method. Most of the literature has used Maximum Likelihood (ML) procedures, the work by RICE et al. (2006) being an example. However, its reliability and feasibility requires specific distributional assumptions (KELEJIAN and PRUCHA, 1998). Moreover, such procedures are not available for models with substantive and residual autocorrelation at the same time, and this procedure when other endogenous variables in the right hand side of the model exist would be difficult to implement, if not impossible (FINGLETON and LE GALLO, 2008).

Thus, we adopt the feasible generalized spatial two-stages least squares estimator proposed by KELEJIAN and PRUCHA (1998), which will be somewhat modified in order to control for endogeneity problems arising from reverse causality of the agglomeration variable. Hence, in a first step the model in (10) is estimated by 2SLS, but including a spatial lag of the dependent variable. In this first step, we will instrument the spatial lag and the other two endogenous variables (total employment in each isochrone) with the historical instruments described in previous sections and with the spatial lag of the remaining exogenous variables and the spatial lag of these historical instruments. This is the procedure implemented in FINGLETON (2003) when estimating agglomeration economies for Great Britain. In the case that spatial autocorrelation remains in the residuals, the second step would consist in estimating the

[9]Even when we need to account for only one type of spatial dependence, ordinary least squares would not be an appropriate technique, leading to unsatisfactory consequences if used, dependent upon the kind of spatial autocorrelation in question. In the case of nuisance spatial autocorrelation, OLS estimations would not be biased, but would be inefficient since the variance-covariance matrix would not be spherical. Furthermore, residual variance will be biased, and consequently, inference will be biased as well (MORENO and VAYÁ, 2000). When a spatial lag of the dependent variable should be included, OLS leads to biased and inconsistent estimates, even when the error term is not spatially correlated. Although the consequences of ignoring spatial autocorrelation in the estimation of a model are important, to our knowledge, very few papers dealing with agglomeration economies have controlled for spatial processes, either in the dependent variable or in the error term. RICE et al. (2006) – using maximum likelihood- and FINGLETON (2003) – using 2SLS- are exceptions for Great Britain.

autoregressive parameter λ in equation (11) using the residuals from the first step and the generalized moments procedure proposed in KELEJIAN and PRUCHA (1999). In the final step, our model with the spatial lag will be reestimated by 2SLS, in the same manner as in the first step, but having transformed it through a Cochrane-Orcutt type transformation to account for the spatial autocorrelation of the error term.

The results for the estimation of model (10) with a spatial lag of the endogenous variable – not reported here to save space - indicate that this spatial lag matters, although its value is small. Moreover, Moran's I test for 2SLS[10] indicates that some residual spatial autocorrelation remains - results reported at the bottom of table 5. So, in table 5 we show the results with the inclusion of a spatial lag both in the dependent variable and in the error term. As before, Sargan statistics and Pagan-Hall tests are reported.

Next, the most striking aspects of table 5 are, basically, that the parameters accompanying proxies for intangible capital assets remain significant – the majority of them - and with similar values as in table 3. Additionally, the spatial lag is significant at 5% and with values around 0.001. Likewise, the elasticity of the agglomeration effect falls to 0.023, from values around 0.042 and 0.039 in table 3 – with and without interactions - when spatial autocorrelation is taken into account.

To sum up, from table 5 we should conclude that externalities arising from neighbouring regions –summarized through a spatial lag of the dependent variable- matter, although their values are very small (0.1%). Besides, increasing returns arising from agglomeration economies are markedly reduced when spatial autocorrelation is allowed for and are significant only for distances below 60 minutes' travelling by car. However, the small value of the coefficient of the spatial lag and the residual spatial autocorrelation that remains after the first step of the FGS2SLS lead us to think that the spatial lag does not account for all the externalities across regions. Indeed, the value of λ (the spatial parameter in the residuals) is high, so the inclusion of this spatial lag does not account for the entire spatial picture. Thus, several externalities across regions, not summarized in the spatial lag, matter as well in explaining productivity levels, though the particular sources behind them are left for future research.

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[10] A Moran's I test for 2SLS residuals (distributed as a standard normal) proposed by ANSELIN and KELEJIAN (1997) is performed, since the usual Moran's I based on OLS residuals, where all the explanatory variables are exogenous, is not appropriate. The test has been performed using a row-standardized binary matrix where w=1 if a centre of a region is within a 0-60 minutes travel time band, and w=0 otherwise.

[Insert table 5 about here]

6. Conclusions

Throughout previous pages, the aim of this paper was to analyse whether agglomeration economies, understood as the concentration of production, and therefore employment, in a given region still matter once several qualitative features of each region aside from merely the typical inputs of the production process – land, capital, and labour - are taken into account. Specifically, departing from CICCONE's (2002) model, we entertained the hypothesis that regions are endowed with certain kinds of intangible asset which characterize the knowledge-based economy, beyond purely the location of individuals, and which are sources of private and social returns at the same time. Unlike previous works, we have taken account of these qualitative features when estimating the aggregate effect of agglomeration economies on economic performances of regions in order not to bias upward our parameter estimations. Further, we have hypothesised that strong social returns arising from several sources – tangible and intangible, will affect regions from one to another and can be summarised in a process of spatial dependence of our dependent variable, *i.e.* labour productivity.

The main conclusions arising from our methodological approach and datasets available are as follows: agglomeration economies – as we have measured them - matter in explaining differences in economic performance across regions although their importance in quantitative terms and, especially, their extension, are somewhat constrained when several variables proxying intangible assets – knowledge, human capital, and entrepreneurial culture - are included in our estimations. Specifically, the majority of the variables proxying intangible assets are significant and with the expected sign. The results are consistent even when treating explicitly "two-way causation" problems between productivity and agglomeration.

What is more, the explanatory power of intangible assets in our framework is mostly not reduced when externalities across regions – proxied by a spatial lag of our dependent variable and a spatially autocorrelated error term- are taken into account in the model. However, the coefficients for agglomeration economies are somewhat reduced, though significant. We can conclude, therefore, that inter-regional externalities arising from physical and intangible endowments do, indeed, exist.

Regarding some policy implications, our results suggests that, to some extent, local/regional transportation system improvements – especially public ones - which reduce the length of business and commuting journeys might boost labour productivity by means of increasing returns derived from transportation costs reductions, sharing inputs, and knowledge spillovers, so investments in this kind of infrastructure should be carried out, as has been stressed before (GRAHAM, 2007). However, the accumulation of certain kinds of intangible endowments in a given region is extremely important as well, so low-dense, non-metropolitan areas could also profit from the concentration of these intangible assets. Policies concerned with this issue are correspondingly relevant.

Tables

Table 1. Statistics

	Observations	Mean	Coefficient of variation	Min	Max
GVA filled job	119	29785	0.136	22761	46594
Employment within 60 mn	119	1251878	0.965	51342	6120282
Employment within 60-120 mn	119	4827812	0.704	0	1.26e+07
Educational human capital	119	0.96	0.162	0.66	1.48
Occupational human capital	119	24.24	0.184	11.53	39.63
Employment in RD and computers	119	0.79	0.846	0.2	4.3
High tech manufacturing employment	119	1.17	0.501	0.08	2.84
Applied patents	119	407	1.107	25	3247
VAT registrations	119	2.73	0.430	1.23	12.37
CAGR VAT registrations	119	1.64	0.623	-0.34	4.92

Table 2. Global spatial autocorrelation tests

	W1	W2	W3	W4	W5	W6
Moran's I						
ln(GVA filled job)	12.994	6.598	5.800	6.858	7.318	11.117
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Geary's c						
ln(GVA filled job)	-3.337	-5.721	-4.598	-5.933	-6.191	-3.020
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*

Notes: W1: main matrix ($w_{ij}=\exp(-0.01d_{ij})$, d_{ij} being the travel time by car between the centres of region i and region j); W2: row-standardized contiguity binary matrix; W3: row-standardized binary matrix where w=1 if a centre of a region is within a 0-60 minutes travel time band, and w=0 otherwise; W4: row-standardized binary matrix where w=1 if a centre of a region is within a 0-90 minutes travel time band, and w=0 otherwise; W5: row-standardized binary matrix where w=1 if a centre of a region is within a 0-120 minutes travel time band, and w=0 otherwise; W6: w=1/m, where m=miles between each regional centre.

Table 3. Ordinary Least Squares estimates. Dep. Var.: lnGVA per job filled

	(i)	(ii)	(iii)	(iv)	(v)
ln(employment within 0-60 minutes)	0.059***	0.042***	0.041***	0.039***	0.039***
	(0.009)	*(0.008)*	(0.008)	(0.008)	(0.008)
ln(employment within 60-120 minutes)	0.015**	0.009*	0.009*	0.008	0.008
	(0.006)	*(0.005)*	(0.005)	(0.005)	(0.005)
Educational HK	0.333***	0.167**	-0.008	-0.759***	-0.667**
	(0.059)	*(0.073)*	(0.111)	(0.279)	(0.321)
Occupational HK		-0.002	-0.004	-0.003	-0.004
		(0.003)	(0.003)	(0.003)	(0.003)
Empl. RD&IT		0.048***	-0.257***	0.037**	-0.148
		(0.015)	(0.097)	(0.014)	(0.108)
High tech manuf. employment		0.056***	0.031	0.055***	0.002
		(0.013)	(0.074)	(0.013)	(0.074)
ln(Applied patents by inventor)		0.015	0.018*	-0.141***	-0.101*
		(0.010)	(0.010)	(0.047)	(0.055)
ln(VAT registrations)		0.079**	0.084**	0.060	0.069*
		(0.040)	(0.038)	(0.038)	(0.038)
CAGR VAT registrations		0.020*	0.025**	0.024**	0.027***
		(0.010)	(0.010)	(0.010)	(0.010)
Empl. RD&IT*educ.HK			0.280***		0.171*
			(0.088)		(0.100)
High-tech man.*educ.HK			0.031		0.059
			(0.077)		(0.077)
Ln(Patents)*educ.HK				0.169***	0.127**
				(0.049)	(0.058)
Constant	8.950***	9.203***	9.414***	10.157***	10.082***
	(0.121)	*(0.120)*	(0.151)	(0.301)	(0.340)
NUTS1 dummies	Yes	Yes	Yes	Yes	Yes
Educational HK		0.167**	0.250***	0.191**	0.247***
		(0.073)	*(0.078)*	*(0.069)*	*(0.077)*
Empl. RD&IT		0.048***	0.012	0.036**	0.017
		(0.015)	*(0.018)*	*(0.014)*	*(0.018)*
High tech manuf. employment		0.056***	0.061***	0.054***	0.059***
		(0.013)	*(0.013)*	*(0.013)*	*(0.013)*
ln(Applied patents by inventor)		0.015	0.018*	0.022**	0.021**
		(0.010)	*(0.010)*	*(0.010)*	*(0.010)*
Sample size	119	119	119	119	119
Adj. R-squared	0.616	0.739	0.759	0.765	0.768
Breusch-Pagan test	2.41	0.36	0.00	0.18	0.02
p-value	*0.121*	*0.548*	*0.951*	*0.674*	*0.892*
Moran's I	3.801	3.550	3.559	3.482	3.487
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Robust LM (error)	0.316	0.859	0.601	1.142	0.949
p-value	*0.574*	*0.354*	*0.438*	*0.285*	*0.330*
Robust LM (lag)	8.997	2.068	2.090	2.063	1.871
p-value	*0.003*	*0.150*	*0.148*	*0.151*	*0.171*

Notes: OLS estimates with several levels of significance: 1%***, 5%**, 10%*. Standard errors are presented in italics and parenthesis below each associated parameter. Breusch-Pagan test for heteroskedasticity indicates that the null hypothesis of equality between variances cannot be rejected, so heteroskedasticity problems do not arise from our estimations. Moran's I test for the residuals of the OLS estimations is provided, indicating that they remain spatially autocorrelated. Robust Lagrange multiplier tests are provided as well, in order to choose which kind of spatial dependence arises. However, the results are not conclusive. Each test presents its p-value in italics below. The variables expressed in percentages and location quotients are not log-transformed in order to facilitate the interpretation of their coefficient. The average values to calculate the semi-elasticities are: H=0.96; RD&IT=0.79; High-tech man.=1.17; lnPAT=5.61

Table 4. Two-Stages Least Squares estimations. Dep. Var.: lnGVA per job filled

	(i)	(ii)	(iii)	(iv)	(v)
ln(employment within 0-60 minutes)	0.056***	0.039***	0.039***	0.037***	0.038***
	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)
ln(employment within 60-120 minutes)	0.016***	0.009**	0.009**	0.008*	0.008*
	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
Educational HK	0.335***	0.171**	-0.007	-0.765***	-0.670**
	(0.056)	(0.066)	(0.100)	(0.254)	(0.289)
Occupational HK		-0.002	-0.004	-0.003	-0.004
		(0.003)	(0.003)	(0.002)	(0.002)
Empl. RD&IT		0.049***	-0.258***	0.037***	-0.148
		(0.013)	(0.088)	(0.013)	(0.097)
High tech manuf. employment		0.057***	0.032	0.055***	0.003
		(0.012)	(0.067)	(0.012)	(0.067)
ln(Applied patents by inventor)		0.015	0.018**	-0.142***	-0.102**
		(0.009)	(0.009)	(0.042)	(0.050)
ln(VAT registrations)		0.077**	0.083**	0.059*	0.069**
		(0.036)	(0.035)	(0.035)	(0.034)
CAGR VAT registrations		0.021**	0.026***	0.024***	0.027***
		(0.009)	(0.009)	(0.009)	(0.009)
Empl. RD&IT*educ.HK			0.281***		0.171*
			(0.079)		(0.090)
High-tech man.*educ.HK			0.031		0.058
			(0.070)		(0.069)
ln(Patents)*educ.HK				0.171***	0.128**
				(0.045)	(0.052)
Constant	8.966***	9.234***	9.428***	10.180***	10.097***
	(0.122)	(0.118)	(0.142)	(0.280)	(0.311)
NUTS1 dummies	Yes	Yes	Yes	Yes	Yes
Educational HK		0.171**	0.251***	0.193***	0.249***
		(0.066)	*(0.071)*	*(0.063)*	*(0.069)*
Empl. RD&IT		0.049***	0.013	0.037***	0.017
		(0.013)	*(0.016)*	(0.013)	*(0.016)*
High tech manuf. Employment		0.057***	0.062***	0.055***	0.059***
		(0.012)	*(0.012)*	(0.012)	*(0.012)*
ln(Applied patents by inventor)		0.015	0.018**	0.023**	0.021**
		(0.009)	(0.009)	*(0.009)*	*(0.009)*
Sample size	119	119	119	119	119
Adjusted R-squared	0.616	0.739	0.759	0.765	0.768
Sargan statistic	0.838	0.712	0.443	0.956	0.793
p-value	*0.658*	*0.700*	*0.801*	*0.620*	*0.673*
Pagan-Hall test	15.271	18.930	23.456	17.762	23.710
p-value	*0.432*	*0.590*	*0.434*	*0.720*	*0.478*
ln(Empl. 60 mn) - *Partial R2*	*0.778*	*0.751*	*0.756*	*0.751*	*0.753*
ln(Empl. 60 mn) - *Shea R2*	*0.734*	*0.732*	*0.738*	*0.734*	*0.737*
ln(Empl. 60 mn) - *First stage F-stat*	*90.37*	*72.98*	*73.76*	*72.30*	*71.80*
ln(Empl. 60-120 mn) - *Partial R2*	*0.973*	*0.968*	*0.968*	*0.968*	*0.967*
ln(Empl. 60-120 mn) - *Shea R2*	*0.917*	*0.944*	*0.944*	*0.946*	*0.946*
ln(Empl. 60-120 mn) - *First stage F-stat*	*913.84*	*724.95*	*713.50*	*714.20*	*694.37*

Notes: 2SLS estimates with several levels of significance: 1%***, 5%**, 10%*. Standard errors are presented in italics and parentheses below each associated parameter. Sargan statistics for mutual consistency of the available instruments are provided and we cannot reject the null hypothesis that the excluded instruments are valid and uncorrelated with the error term, so there are no overidentification problems. Pagan-Hall tests are provided as well and the null hypothesis of homoskedasticity in the instrumental variables estimations cannot be rejected, so GMM estimations are not needed.. Each test presents its p-value in italics below. The average values to calculate the semi-elasticities are: H=0.96; RD&IT=0.79; High-tech man.=1.17; lnPAT=5.61

Table 5. Two-Stages Least Squares estimations. Dep. Var.: lnGVA j.f. (error and lag)

	(i)	(ii)	(iii)	(iv)	(v)
W·lnGVA filled job	0.001***	0.001**	0.001**	0.001**	0.001**
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
ln(employment within 0-60 minutes)	0.023	0.023*	0.023*	0.023*	0.022*
	(0.014)	*(0.013)*	*(0.012)*	*(0.012)*	*(0.012)*
ln(employment within 60-120 minutes)	0.009	0.003	0.005	0.003	0.005
	(0.006)	*(0.006)*	*(0.005)*	*(0.005)*	*(0.005)*
Educational human capital	0.291***	0.147**	0.150	-0.597***	-0.422
	(0.052)	*(0.067)*	*(0.100)*	*(0.227)*	*(0.265)*
Occupational human capital		0.003	0.000	0.002	0.000
		(0.003)	*(0.003)*	*(0.003)*	*(0.003)*
Employment in RD and computers		0.042***	-0.233***	0.032**	-0.163*
		(0.013)	*(0.077)*	*(0.013)*	*(0.085)*
High tech manufacturing employment		0.038***	0.052	0.038***	0.030
		(0.012)	*(0.063)*	*(0.011)*	*(0.063)*
ln(Applied patents by inventor)		0.010	0.013	-0.114***	-0.064
		(0.009)	*(0.008)*	*(0.037)*	*(0.044)*
ln(VAT registrations)		0.034	0.046	0.020	0.035
		(0.035)	*(0.034)*	*(0.034)*	*(0.034)*
CAGR VAT registrations		0.021**	0.025***	0.025***	0.027***
		(0.009)	*(0.008)*	*(0.008)*	*(0.008)*
Empl. RD&IT*educ.HK			0.253***		0.183**
			(0.070)		*(0.079)*
High-tech man.*educ.HK			-0.007		0.014
			(0.066)		*(0.065)*
ln(Patents)*educ.HK				0.134***	0.083*
				(0.040)	*(0.047)*
Constant	9.468***	9.482***	9.612***	10.212***	10.045***
	(0.203)	*(0.179)*	*(0.186)*	*(0.282)*	*(0.307)*
NUTS1 dummies	Yes	Yes	Yes	Yes	Yes
Sample size	119	119	119	119	119
Sargan statistic	8.342	12.055	13.681	10.562	12.968
	0.214	*0.441*	*0.322*	*0.567*	*0.371*
Hall-Pagan test	11.783	17.118	23.962	23.185	26.403
	0.945	*0.990*	*0.921*	*0.919*	*0.879*
| Moran's I z statistic |	0.19	1.68	1.62	1.56	1.63
Lambda	0.375	0.582	0.502	0.586	0.533
Sigma	0.007	0.007	0.006	0.006	0.006

Notes: 2SLS estimates with several levels of significance: 1%***, 5%**, 10%*. Standard errors are presented in italics and parenthesis below each associated parameter. Sargan statistics for mutual consistence of the available instruments are provided and we cannot reject the null hypothesis that the excluded instruments are valid and uncorrelated with the error term, so there are not overidentification problems. Pagan-Hall tests are provided as well and the null hypothesis of homoskedasticity in the instrumental variables estimations cannot be rejected, so GMM estimations are not needed. Each test presents its p-value in italics below. Instruments validity and total semi-elasticities are not reported to save space, although can be provided upon request from the authors.

Appendix

A1. Variables and data construction

Variable	Proxy	Dates	Source
Educational human capital	Location quotient(1) of the percentage of economically active population with first and higher degree; nursing and teaching qualifications (NVQ4) or with A-level; GNVQ Higher level, or Advanced certificate of Vocational Education (NVQ3)	Average 1999-2001	NOMIS database, collected by the Office of National Statistics (ONS)
Occupational human capital	Percentage of economically active population who are enrolled in occupations like corporate managers, managers/proprietors in agriculture/services, science and technology professionals, health professionals, teaching and research professionals, and business and public service professionals	Average 1999-2001	NOMIS database, collected by the Office of National Statistics (ONS)
Employment in RD and IT	Location quotient for each area giving the workforce specialisation in computing and related activities and in research and development	Average 1996-2000	NOMIS database
High tech manuf. employment	Location quotient for each area giving the workforce specialisation in chemicals and man-made fibres; machinery and equipment; optical and electrical equipment; and transport equipment	Average 1996-2000	NOMIS database
Applied patents by inventor	Patents applied in a given region, regionalising them according to the household of the inventor who has registered the patent to the European Patent Office, using the OECD database(2)	Average 1996-2000	OECD REGPAT database, May 2008
Entrepreneurship culture	VAT registrations per head	Average 1996-2000	NOMIS database
Entrepreneurship success	Cumulative Annual Growth Rate (CAGR) of VAT registrations	Average 1996-2000	NOMIS database

(1) The regional share over the national share
(2) Collecting data on applied patents in this way we try to avoid the bias introduced by the accumulation of patents in regions where the headquarters of several firms are located.
(3) These data are only available for the British case at NUTS1 level.

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