MANCHESTER INDEPENDENT ECONOMIC REVIEW

Productivity and agglomeration economies in the Manchester City Region

A working paper for the MIER, produced by IPEG

Professor Michael Artis, Dr Stephen Greasley and Ernest Miguélez

1. Introduction

In this report we attempt to analyse the productivity performance of the Manchester City Region with special reference to the phenomenon of agglomeration economies. The aim of the study is to locate the MCR in relation to the nation as a whole and to selected comparator regions in respect of its productivity performance and the factors that determine that performance.

By examining the determinants of productivity within a comparative framework, we are taking a first step in the necessary process of isolating areas in which policy initiatives could be most useful. The way in which we have chosen to go about this is as follows: we begin with agglomeration economies and show how Manchester is placed with respect to them.

It emerges that whilst Manchester has an employment density higher than the national average, it does not display a corresponding productivity premium – rather the contrary. From this observation we move on to considering other factors that influence productivity –considered technically as controls – which should enable us to pinpoint why Manchester does not perform as well as it should.
The basic structure of the report follows from the logic set out above. Section 2 discusses some basic issues pertaining to the data that we use and to the spatial dimensions involved. Then (in section 3) we present some graphical evidence on the basic relationship between density and productivity, a simple representation of "agglomeration economies".

We accompany this by an explication of what the term is supposed to mean and then present a brief review of the literature. This is intended to give the reader some idea of the normal methods of estimation used and results achieved, with particular reference to the fact that different investigators have used different measures both of agglomeration itself and of productivity - as well as deploying a diverse range of alternative controls.

In section 4 we turn to a discussion of what controls should be used in the present study – i.e. what other factors should be allowed for in the explanation of productivity so as not to mistakenly attribute to agglomeration effects which are due to other factors. Here we refer, *inter alia*, to HM Treasury's influential treatment of the subject (HM Treasury 2001). We show Manchester's relative position in respect of the factors identified.

Section 5 then discusses what estimation methods should be used in an econometric treatment of the subject. A principal preoccupation here is with the issue of possible "two-way causation". Are cities big because they are highly productive, or are cities highly productive because they are big? A summary of the main results is introduced. More detailed results are presented in an appendix. Section 6 concludes the report.

2. Basic definitions

The basic spatial definition that we use is that of the NUTS2 region corresponding to "Greater Manchester". Comparator NUTS2 regions are taken to include Inner London, Outer London, Bristol (represented as Gloucestershire, Wiltshire and North Somerset), Birmingham (represented as West Midlands), Glasgow (South West Scotland) and Leeds (West Yorkshire); these are all identified in Figure 1 below. Like Greater Manchester these comparator regions themselves comprise of smaller NUTS3 sub-regions. The Greater Manchester region comprises two NUTS3 regions, namely Greater Manchester North and Greater Manchester South; as we shall see (Table 1 below), the performance of these two sub-regions differs greatly from one to the other.

The basic data on productivity comes from a comparatively new release by the ONS (see Wosnitza and Walker 2008) and refer to GVA per job filled. This may be contrasted with the much-used "prosperity index", GVA per capita. The relationship between the two measures is explored in detail by Wosnitza and Walker and need not concern us further here (except to note that because of its familiarity we have included GVA per capita in some of our displays).

The data are in nominal terms, uncorrected for price change, though they are provided for several years (2001-2005) and exist for NUTS3 regions as well as for the less localized NUTS2 and NUTS1 regions. The definition of "job filled" does not distinguish between part-time and full-time work. Relative to a paradigm definition of productivity for which a descriptor would be "number of widgets produced per person hour worked" the ONS data leave something to be desired. Though provided for several years they are not adjusted for inflation or for hours worked.

Some previous investigators (e.g. for the UK, Fingleton (2003)) have used wages and salaries per person employed (or equivalent) as the basis for a measure of productivity rather than GVA and whilst profits should be included in principle, practice cautions that the attribution of profit or operating surplus between regions at a high level of localisation conveys an element of arbitrariness. Local data are also prone to exhibit lumpiness from year to year which is compensated for here by using the average of the five years' productivity figures and the corresponding explanatory variables.

3. Agglomeration economies

Since the inception of what is often called the "New Economic Geography"[1], agglomeration economies have featured prominently in the discussion of regional economic development. Broadly speaking investigators have had in mind three broad types of efficiency-raising effects stemming from the concentration of economic activity. These appear as productivity "externalities"- exogenous to the actions of individuals in the agglomeration but a product of the creation of the concentration as a whole.

One of these is the notion that concentration allows for "thicker" labour markets in which the chances of good matches, between the skills that workers can offer and employers want, is increased. Then there is the notion that the concentration of activity and the saving of transport costs implied creates bigger markets within the limits of the agglomeration – holding constant firms' input endowments and technology, firms' outputs will increase – in the felicitous phrase of Ciccone and Hall (1996) "the ratio of output to input will rise with density".

A third main source of agglomeration economies arises from the facilitation of knowledge transmission between individuals and firms in close physical proximity with the added value of face-to-face communication and interactive exploration. It is not difficult to think of other ways in which agglomeration can bring production

[1] Seminal papers in this literature include Krugman (1991a) and Fujita, Krugman and Venables (1999).

benefits – for example, by creating a critical mass for the provision of cultural benefits agglomeration may help attract the presence of highly skilled personnel.

At the same time, it is well-recognized that agglomeration has limits. There are centripetal and centrifugal forces at work. Most obviously, agglomerations lead to congestion, long commuting times and pollution. It is well-recognized also that the accretion of agglomeration benefits varies with the kind of economic activity in question: Overman and Rice (2008) argue that the activities that drive the "knowledge economy" are particularly prone to benefit from agglomeration.

Empirical verification of agglomeration economies has been an industry that has seen considerable growth in recent years and some useful surveys (e.g. Rosenthal and Strange, 2004; and Graham, 2007a,b) already exist. An obvious focal point is the estimate of the effect of agglomeration economies that the various studies come up with; usually expressed in the form of an elasticity. There is quite a wide range in the estimates retrieved – as these pertain to different countries, different periods of time, different sectors of economic activity and different estimation methods Such variation is no surprise. We comment on some examples below.

In our own work, our estimates pertain to the total of all activities and will thus be biased down compared to measures based on service activities alone where agglomeration returns (as discussed below) appear to be higher than in, say, traditional manufacturing.

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 the agglomeration effects for the NUTS3 regions of France, Germany, Italy, Spain, and the UK within a model where the concentration of production is the main source of agglomeration economies. This study suggested substantial agglomeration effects in Europe, with estimated elasticities of around 4.5%. These do not differ significantly across countries.
Subsequent empirical studies for the US, using alternative definitions of agglomeration and productivity and conducted at both aggregate and plant level have generally reported somewhat higher agglomeration coefficients than appeared in the

Ciccone and Hall study, but with a wide range from 0.01 to 0.20 (that is, in elasticity terms, from 1 to 20%). A preponderance of the estimates lies below 0.10 so a doubling of city or region size leads to an increase in productivity of between 1% and 10% (Graham, 2007a)[2].

Using wage data as the productivity proxy, Combes et al. (2004), find that in the French economy both local endowments and individual skills matter in an agglomeration economies empirical framework. Their results suggest that density of local employment plays an important role, and endowments a secondary one, although controlling for skilled individuals, the estimated coefficient for agglomeration falls dramatically from 6% to 3.7% (then down to only 2% when controlling for endogeneity and reverse causality). According to their research, then, a small but significant effect of agglomeration on productivity is found; but it should be noted that using wage data as the proxy for productivity tends to bias the agglomeration coefficient down according to Rosenthal and Strange (2004).

Moving to the Italian case, Cingano and Schivardi (2004), drawing on a panel of plant-level data across Italian cities, estimate a long-run elasticity of plant productivity to city employment of 0.067. Broersma and van Dijk (2008) embark on a growth accounting exercise for the regions of the Netherlands, between 1995 and 2002. Using this approach it turns out that the slow productivity advances of those regions can be explained by the fact that positive agglomeration advantages (between 0.341 and 0.357) are overruled by negative congestion effects caused by traffic jams (between -0.285 and -0.455). Brülhart and Mathys (2007) carry out an empirical analysis by estimating the effects of density on labour productivity within a large set of 245 European NUTS2 regions. Their results suggest high long-run positive net productivity effects of employment density, with estimated elasticities for the European case around 13%.

More recently, Nakamura (2008) has published a comparative analysis of Japanese and British regions over the period 1995-2003, in order to estimate industrial agglomeration effects on the observed disparities of per capita value-added. The results suggest, at first sight, estimated elasticities around 0.15 for the Japanese case,

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

and 0.095 for the UK case, although some larger differences appear when the analysis is repeated sector by sector.

For the British case, Baptista (2003) develops an empirical model of local productivity where the spatial density of economy activity is the source of economic increasing returns, in a similar way to Ciccone and Hall (1996). His analysis leads him to the result that doubling employment density in a county would increase average labour productivity by almost 7%.

Fingleton (2003) estimates the consequences of agglomeration for productivity and wages among NUTS4 British regions. Assuming equal technology among areas, his model brings to the fore the importance both of spillovers across regions – so including spatial effects in his estimations - and the role played by differential access of each area to knowledge and human capital. His results show one of the smallest values of the agglomeration effect among the studies reviewed up to this point, estimated at around 0.015 in several specifications[3].

A recent study by Rice et al. (2006) decomposes the spatial variation of earnings into a productivity effect and an occupational composition effect. In this way, these authors are able in effect to take filtered earnings as their productivity proxy as the filter takes into account the occupational composition of each area, which could shape local earnings as well. Their results suggest a best estimate of 3.5% for the effect of agglomeration on productivity, even controlling for endogeneity problems.

The work by Graham (2007a,b) is an interesting reference point for the British case as well, due its explicit introduction of some elements related to transport infrastructure. His work is an attempt to investigate, within a trans-log production function framework, the link between urban density, productivity and road traffic congestion. His results range from elasticities of around 0.04 for manufacturing sectors up to 0.18 for certain service sectors, although all the sectors analysed show some degree of diminishing returns to urban density. That being said, as the author argues, the policy implications are that positive agglomeration effects rely on investment in transport infrastructure. This underlies the conclusion in the Eddington Report (Eddington

[3] As mentioned earlier, estimates tend to be somewhat lower when wages are used as the dependent variable.

2006) that transport improvements in the UK that could bring about a reduction of 5% in travel times for business and commuting journeys, would generate an increase in GDP of around 0.2%.

No review of the costs and benefits of agglomeration would be complete without reference to the recent work of Brülhart and Sbergami (2008) who stress the importance of diseconomies when dealing with agglomeration effects on economic outcomes.

While estimating growth regressions with OLS and dynamic GMM techniques for the European regions, these authors find evidence that supports the "Williamson hypothesis" (Williamson, 1965; cited in Brülhart and Sbergami, 2008), i.e., agglomeration boosts GDP growth only up to a certain level of development, which the authors empirically estimate around 10,000 US dollars of 2006 per capita –Brazil or Bulgaria are current examples.

With this review of previous empirical studies as a backdrop we can now move on to discuss our own findings, which are presented here with specific reference to the position of the Manchester region[4]. We show in Figure 1 the simple bilateral relationship between productivity on our measure and agglomeration, measured as employment density (i.e. employment per hectare). In the top part of the Figure we show the scatter for the NUTS2 areas that are the main focus of our analysis and in the lower part the scatter for the NUTS3 regional definition.

We show the two to emphasize the difference between Greater Manchester North and Greater Manchester South. A line of best-fit slopes up from left to right suggesting the presence of agglomeration economies. As can be seen, the Greater Manchester economy is further to the right in the diagram than most of the comparator regions outside London. By British standards it is highly agglomerated. Nevertheless the observation corresponding to Greater Manchester as a whole lies below the line, suggesting that the economy is not doing as well out of its potential agglomeration benefits as could be expected.

[4] A larger and more technical treatment of the subject (Artis, Moreno and Miguelez, 2008), directed at an analysis of UK NUTS3 regions, is available in mimeo.

The lower diagram in the Figure shows that, when Greater Manchester North and Greater Manchester South are shown separately, whilst the density of employment in each is similar, it is in Greater Manchester North that the short-fall can be observed. Greater Manchester South is "on the line". The comparator economies could also conceal a similar disparity of achievement between their constituent parts and we measured a "dissimilarity index" (Krugman 1991b) over each of the NUTS2 comparator regions to test whether this is so. It seems that, aside from the two London NUTS2 regions, Manchester has an outstandingly uneven productivity performance in its constituent NUTS3 components[5].

A higher score on this index indicates greater divergence of productivity within a given NUTS2 region. The average diversity on this measure is 1393, with a maximum of 4458, the minimum was 0 where the NUTS 2 and NUTS3 regions coincided. The Greater Manchester NUTS2 region, made up of two NUTS3 regions, ranked 9th highest out of all 37 in terms of the diversity of productivity scores. Looking at the comparator regions (Table 1), only the London NUTS2 regions are more diverse than Greater Manchester in terms of productivity performance.

Table 1. Diversity of Productivity Performance within NUTS2 Regions [6]

Comparator	Productivity diversity	Greater Manchester=100
Outer London	3360	165.35
Inner London	2502	123.13
Greater Manchester	2032	100
Bristol (Gloucestershire etc)	1774	87.30
Birmingham (West Midlands)	1418	69.78
Leeds (West Yorkshire)	935	46.01
Glasgow (SW Scotland)	795	39.12

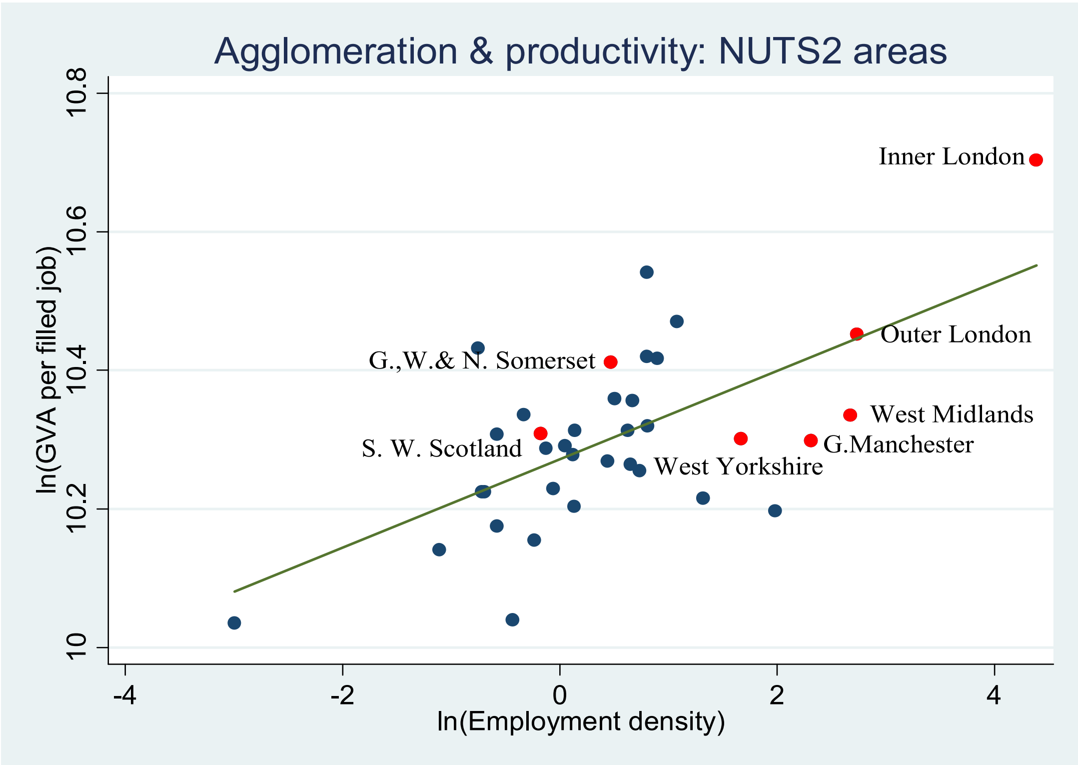
[5] The formula for the Krugman dissimilarity index can be given as

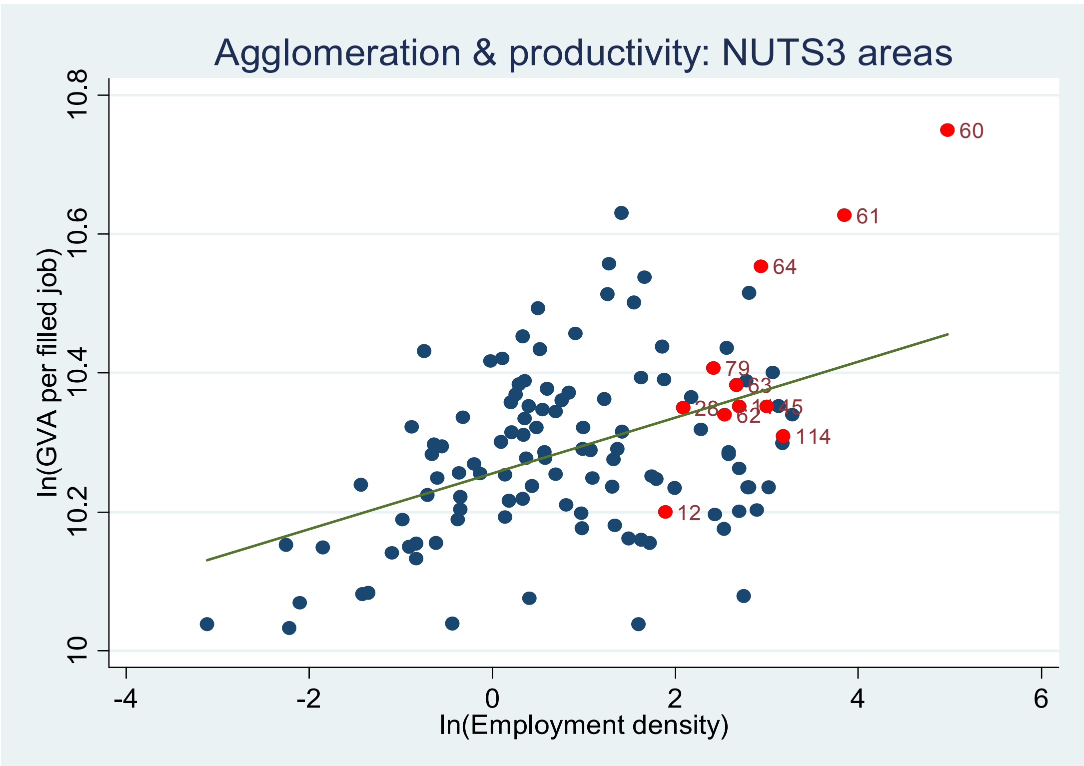
$$DI_i = \sum \left\{ \left(GVA_{ji} / GVA_i \right) \left| prod_{ji} - prod_i \right| \right\}$$

where i is the NUTS2 region and j are every NUTS3 region within each NUTS2 comparator region *prod* stands for productivity and the weights are relative GVAs.

[6] Calculation of this index is based on averaged productivity over the period 2001-2005.

Figure 1. Bilateral relationships between productivity and density





Note: 11 is Greater Manchester South; 12 is Greater Manchester North; 28 Leeds; 45 Birmingham; 60 Inner London-West; 61 Inner London-East; 62 Outer London-East & North East; 63 Outer London-South; 64 Outer London West and North-West; 79 Bristol; and 114 Glasgow. Employment density is the number of jobs filled for each hectare of land.

4. Other factors that influence productivity

As our review of previous work has made clear, the location of individuals *per se* cannot be the unique source of increasing returns and, therefore, higher economic outcomes and productivity. Actually, the observed differences in terms of labour productivity among British regions are strongly correlated with the endowments of certain inputs in each region, aside from employment density.

In this sense, therefore, several qualitative aspects have been identified, and correctly recognized in several reports -e.g. HM Treasury (2001, 2003) which focuses on the regional and local dimension of productivity. Where these sources of productivity are not controlled for, the estimation of the agglomeration effect could be biased upward. Thus, the agglomeration economies literature has widely stressed the role played by human skills and abilities in determining regional economic outcomes within an agglomeration economies framework (Ciccone and Hall, 1996; Ciccone, 2002; Moretti, 2003; Ciccone and Cingano, 2003; Rice et al. 2006; Anastassova, 2005; Fingleton, 2003; Combes et al., 2004; Duranton and Monastiriotis, 2002; and so on), and, although the first results available were rather negative (Ciccone and Cingano, 2003), some others are not.

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 productive (Fingleton, 2003). On the other hand, human capital spillovers increase aggregate productivity beyond the effect of human capital on an individual's productivity. A An increase of the overall level of human capital of each region leads to higher levels of productivity (Moretti, 2003)[7].

Given all the arguments above, we hypothesize that the level of education of each region should enter the production function as an externality. Specifically, we use two alternative indicators to proxy it, that is, the proportion of highly educated workers in each region and the total number of economically active individuals without qualifications. However, human capital could be acquired both in the educational

[7] See Moretti (2003) for a detailed review of theories and empirical studies on human capital, human capital externalities, and economic outcomes, where the effects of human capital on crime activity and political participation are also considered.

system and whilst working, as skills that are accumulated in certain occupations beyond the formal level of education of each worker, in a learning-by-doing style (Lucas, 1988). Thus, the occupational composition of the region is important too (Ciccone and Cingano, 2003) and may bias the density parameter upward if not controlled for appropriately.

In a similar way to human capital endowments, the different access of each region to knowledge could explain productivity differentials across regions as well (Fingleton, 2003). 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 (Lucas, 1988; Romer, 1986, 1990; Jones, 1995) and its influence has been widely tested. We hypothesize that private returns of knowledge and knowledge externalities arise both from knowledge inputs – that is, R&D effort, and from knowledge outputs, that is to say, existing ideas, since codified knowledge is easily transmitted between individuals, even over long distances. Our estimations will test the importance of proxies for R&D efforts and applied patents.

As has been pointed out (Overman and Rice, 2008), certain high-technological sectors of the knowledge based economy stand to benefit the most from agglomeration. Thus, we have included indicators for high technology manufacturing sectors and for financial intermediation, in order to control for the number of employees working in knowledge intensive economic branches.

In addition, as Audretsch (1998, 2002) and Rosenthal and Strange (2004) suggest, the entrepreneurial or business culture of a country or region could be expected to boost economic performance. As has been widely suggested (HM Treasury, 2001), entrepreneurial activity is a key driver of productivity growth in the economy, since the creation of new firms and the enlargement of existing ones is associated with the introduction of new technologies, innovative production processes, and, furthermore, increased competitive pressure on the other firms in a given market, providing them with strong incentives to innovate and adopt new technologies (Porter, 1990; Glaeser et al., 1992). We will include as an important part of our estimations indictors of new entrepreneurial projects set up in a given region[8].

As a first exploration, we can see in table 2 below the relative position of Greater Manchester in relation to the averages for Great Britain (which are standardized at the value of 100) for the control variables we have discussed above. As can be seen, the level of GVA per filled job (the first column) in this region is somewhat lower than the national mean (first column), whilst the same is true for the other variables considered with the exception of our entrepreneurship measure – and the human capital lack measure, which is of course a bad sign. Strikingly, this lack of endowments is dramatically strong for the case of the variables related to knowledge, both from an input perspective and from an output perspective –employment in RD and IT and applied patents according to inventor residence. Where a confirmatory analysis confers explanatory power on these variables as boosting productivity, we have located part of the reason why Greater Manchester is lagging behind the average in terms of productivity.

Figure 2. Endowments of Greater Manchester compared to the national mean. Great Britain=100

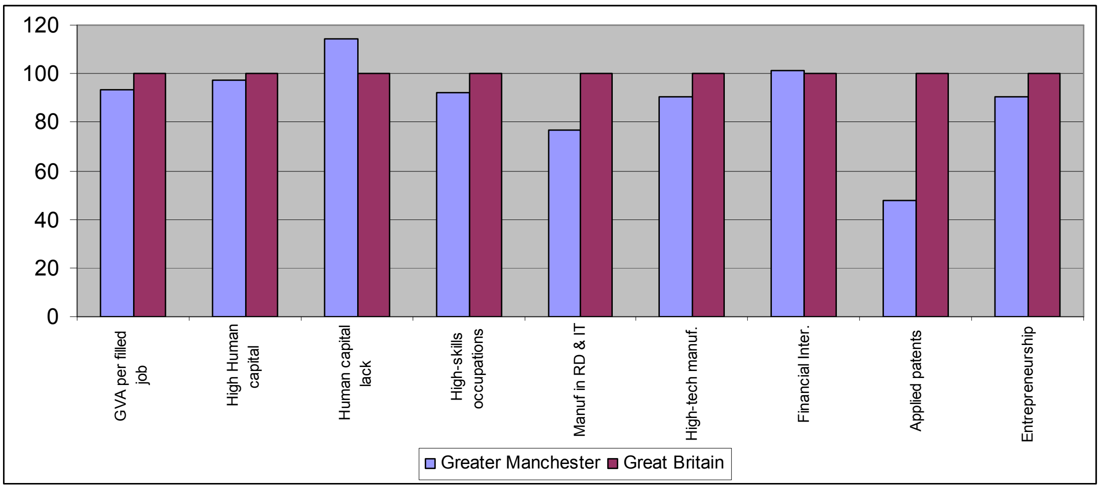
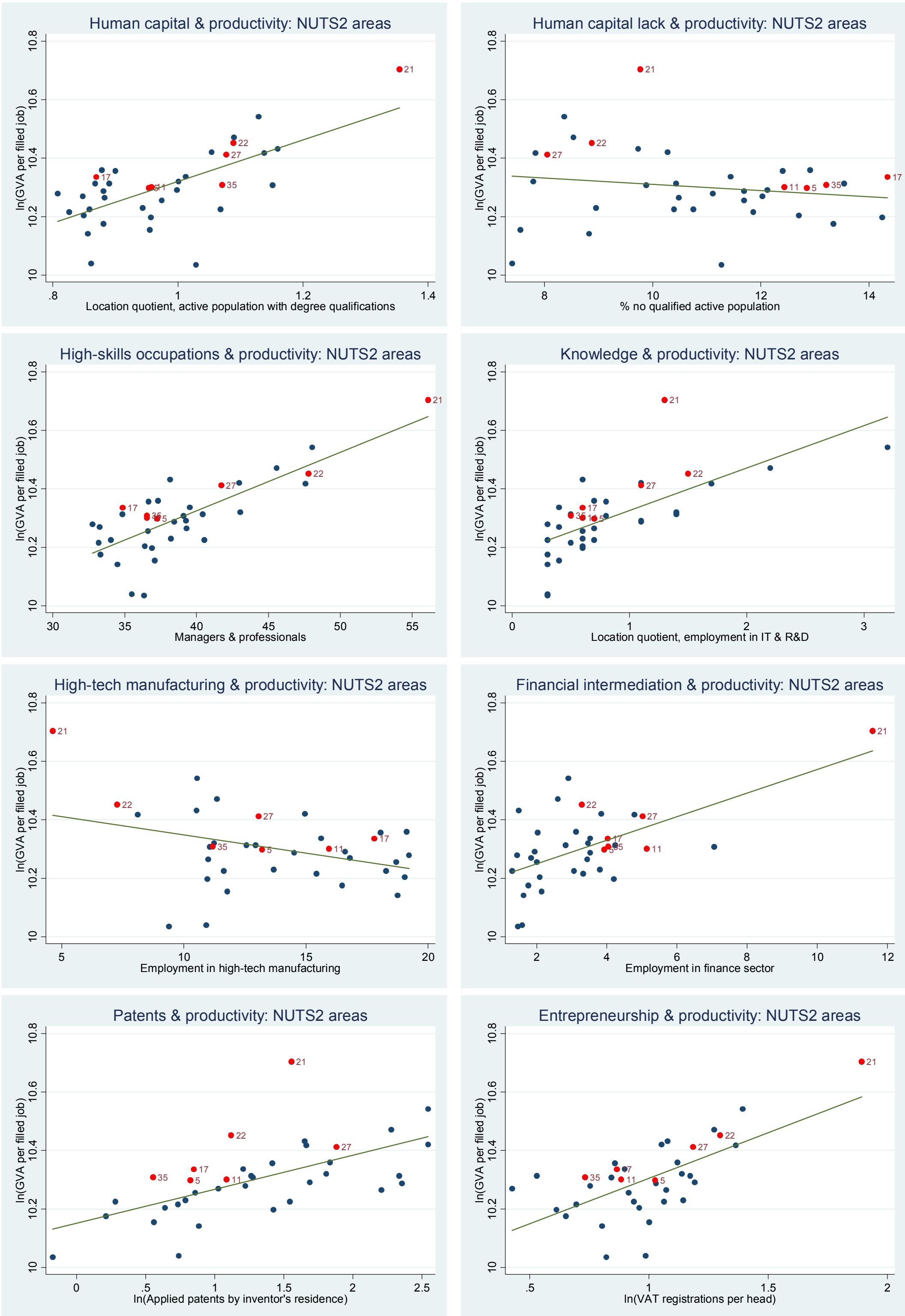


Figure 3 in fact shows the bilateral relationships between each of the potential explanatory variables and productivity in all the NUTS2 regions. The slope of the line of best fit in each case supports our hypothesis of the effect of the variable under

[8] A detailed explanation of the variables chosen and how they have been calculated can be found in the appendix. Values of these (other) explanatory variables have been taken from a period (generally the year 2000) which predates that of the productivity variables we are using in the sample. This allows us to assume that they are completely exogenous.

consideration on productivity. Being “off the line” in a noticeable way might suggest a special “Manchester effect”, but we do not in fact see this.

Figure 3. Bilateral relationships



Note: 5 is Greater Manchester; 11 is West Yorkshire; 17 West Midlands; 21 Inner London; 22 Outer London; 27 is Gloucestershire, Wiltshire and North Somerset; and 35 is South Western Scotland Glasgow.

5. Econometric issues

The principal econometric issues that confront this study are two: how to integrate additional determining variables controls into the analysis of agglomeration effects; and how to deal with the issue of two-way causation or endogeneity.[9]

We have discussed the first of these issues in the previous section and will report below on the effect of including additional determining variables into a productivity-agglomeration relationship. A likely consequence of including the additional variables will be to diminish the effect that would otherwise be attributed to agglomeration. We shall see that this expectation is borne out.

The second issue can be dealt with by employing a suitable form of estimation that takes account of the possible two-way causation that seems likely to be present. Once again, starting with the simplest form of estimation, which does not take account of these effects and comparing the result with those that do, could be expected to disclose a reduction in the effect attributed to agglomeration.

Table 2 – the tables of estimates are shown in Appendix 2 - illustrates the results of an initial estimation, using the technique of ordinary least squares and starting (i) with an estimate that includes only agglomeration (measured in this study as employment density) as an explanatory factor. Equation (ii) adds to this a NUTS1 dummy to take account of the rental price of capital (see Ciccone 2002).

In equations (iii) to (xiii) we have repeated the estimations but included a set of controls in each regression –between 3 and 6 controls in each one, in order to minimise collinearity problems. By doing so, we are able to explore the robustness of the agglomeration proxies (in terms of value and significance) and we are able to draw several conclusions about the importance of a set of alternative variables which have the potential to influence productivity. The omission of these would lead to a biased estimate of the effect of agglomeration *per se*.

[9] In principle we might need to deal with a further problem, related to the overspill from one region to another. Where this is significant inference drawn from considering the regions as constituting independent observations would be impaired. In fact, this does not appear to be an issue for our estimations.

The first thing we should notice is that when control variables are included, adjusted R-squared rises from values of 39% and 43% up to values between 78% and 92%. Further, the elasticity of the agglomeration effect is around 7.8% in models (i) and (ii), but lower in the subsequent models where additional variables are allowed for. The reduction is in the order of 1 to 2.3 percentage points.

Next, we should bear in mind that almost every control variable is significant when introduced, perhaps surprising considering the likelihood of collinearity amongst them. This is particularly true for educational and occupational human capital variables, and for the number of applied patents according to the inventor's residence per million inhabitants.

Once the robustness of the agglomeration effect is verified, model (xii) is our preferred one, for several reasons. It shows the highest adjusted R-squared and meets the Akaike and Schwartz criterions, whilst all the five control variables are significant and with the expected sign. Thus, we could conclude that, aside from agglomeration *per se*, educational human capital, knowledge efforts (employment in R&D), high-tech manufacturing employment share, innovation outputs (applied patents), and entrepreneurship culture (VAT registrations) matter in explaining labour productivity as well. Hence, the value of the agglomeration effect is around 1.4 points lower relative to the estimation without control variables.

In the lower panel of table 2, we show normality tests for the residuals, where the null hypothesis of normality is, broadly speaking, not rejected – so maximum likelihood estimations given a spatial lag will be consistent.

Despite these initial results, the literature on agglomeration economies has insistently stressed the possibility that reverse causation will be present. Indeed it is not *a priori* clear whether agglomeration and density lead to higher levels of productivity, or on the contrary, whether it is the better economic outcomes which attract people and employees to work and live in a given region.

To deal with such an endogeneity problem, which makes OLS estimates inconsistent and biases upward the coefficient of the agglomeration effect, previous studies have used basically two-stages least squares (2SLS) estimation procedures (table 3). 2SLS estimates are presented in Table 3.

We follow Anastassova (2006) in employing two instruments, used widely before, since they are clearly correlated with the agglomeration of employment, but not productivity. By doing so, we will be able to perform over-identification tests (Sargan test), so we will be able to test the instruments' validity and assess whether some of them are not needed. Our best instruments will be total land area of each region (like Ciccone (2002)), and population density according to the 1801 census (cf Anastassova, 2006 and Rice et al., 2006).

Moreover, we should consider the possibility of estimating our model by the Generalized Methods of Moments (GMM). GMM estimators, by using all the orthogonality conditions, lead us to an efficient estimator in the presence of heteroscedasticity of unknown form, where IV estimations would lead us to consistent but inefficient estimations –so inference would be affected. However, if heteroscedasticity is not present, the GMM estimator is worse than IV in small samples. Thus, we have included a test for the presence of heteroscedasticity (Pagan and Hall, 1983), and the null hypothesis of homoscedasticity in the instrumental variables estimations cannot be rejected, so GMM estimations are not needed. See table 4 for the results by GMM estimates.

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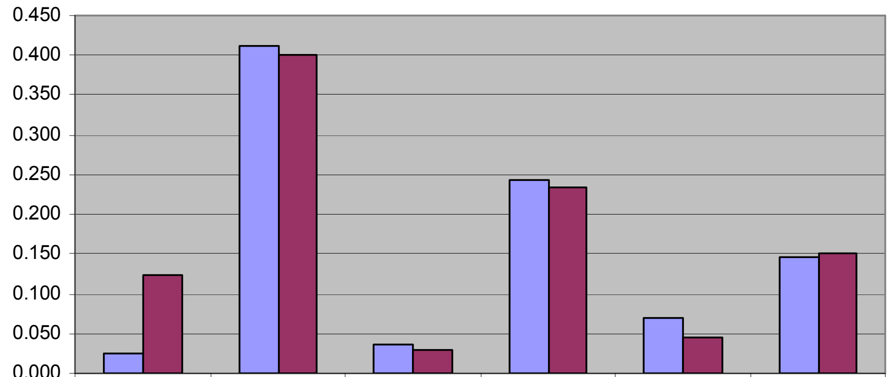
Tables 3 and 4 present the results of the 2SLS and GMM estimations. The basic results, when we have performed these estimations, remain, although several points should be noticed. First, the estimated elasticity of agglomeration economies when instrumented is somewhat lower for the majority of the regression –between 0.001 and 0.005 points lower, indicating that some degree of reverse causation existed and the instrumental variables procedures were needed. Second, in order to examine whether our instruments are weak, we have provided at the bottom of the table partial R-squared and F-statistics of the first stage.

Since the R-squared are high and the F-statistics are well above 10, we can conclude that our instruments are not weak, but are jointly highly relevant (Baum et al., 2003, 2007). Next, since two instruments are available, the Sargan-Hansen test for their mutual consistency could be performed. Thus, as can be seen in tables 3 and 4, the null hypothesis that the excluded instruments are valid instruments and uncorrelated with the error term is not rejected for the majority of our estimations. Other results concerning the robustness of the agglomeration effect, the importance of other up to the moment omitted variables in explaining productivity and our preferred specification, remains as in OLS estimations.

In the Figures below we present the contribution of each variable to the dependent one for the case of specification (xii) – our preferred one. The calculation underlying the graphs is simply the product of the mean value of the variable listed and the estimated coefficient, and exercise that we carry out for the sample as a whole and for Greater Manchester. Thus, as we can see, agglomeration economies for Manchester are more important than for other NUTS2 regions, but offset to a degree by weaknesses in the other factors isolated there. Recalling Figure 1 we may remember that Manchester is a highly agglomerated region relative to the rest of Great Britain – but its advantage in this respect is offset by relative weaknesses in respect of the other variables.

Figure 4. Contributions of each variable according to OLS estimations of specification (xii)



	Employment density	Human capital	RD and IT	Manufacturing	Applied patents	Entrepreneurship
Great Britain	0.026	0.411	0.035	0.244	0.070	0.146
Greater Manchester	0.123	0.402	0.029	0.235	0.044	0.151

Figure 5. Contributions of each variable according to 2SLS estimations of specification (xii)

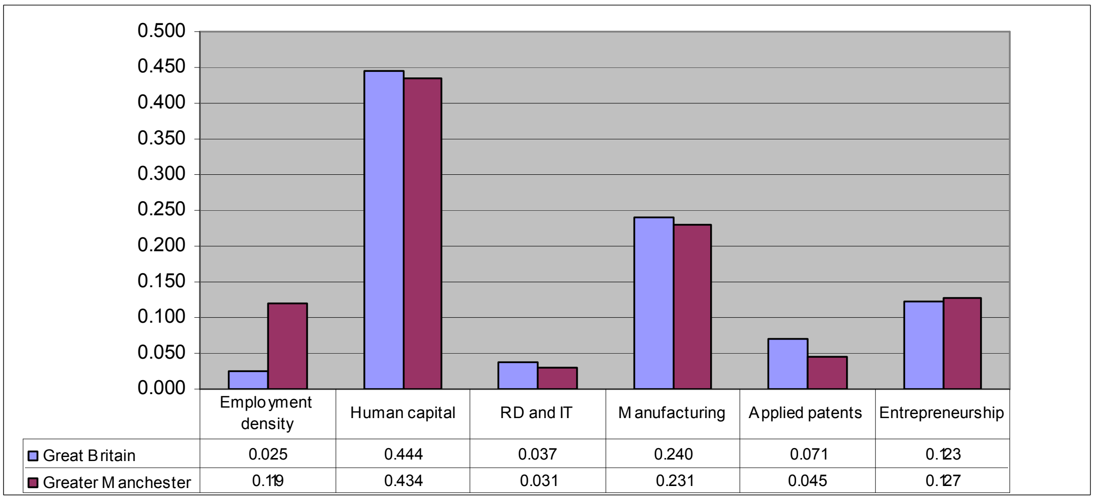
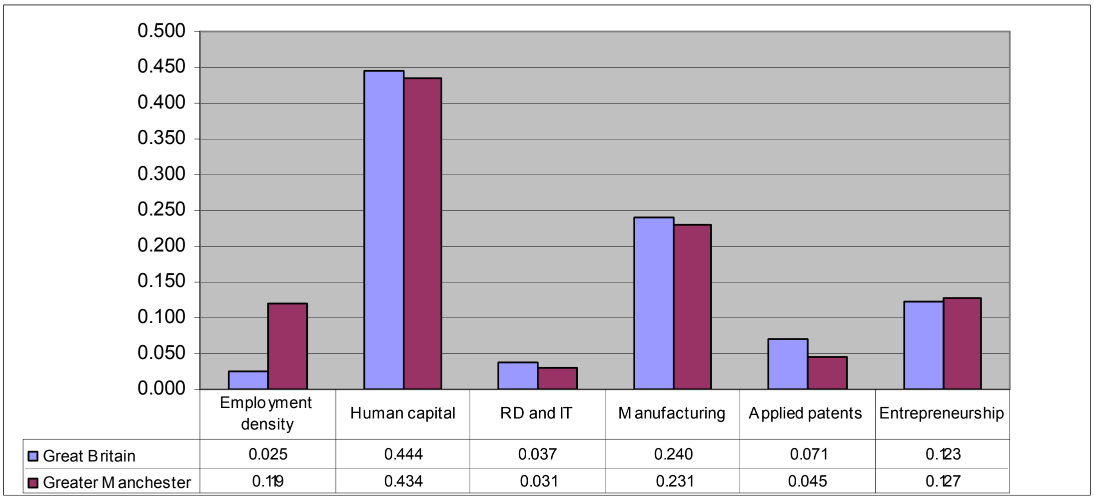


Figure 6. Contributions of each variable according to GMM estimations of specification (xii)



6. Concluding remarks

Throughout previous pages, the aim of this report was to analyse the productivity performance of the MCR region, with special emphasis on the phenomenon of agglomeration economies. Moreover, we wanted to locate MCR in relation to the nation as a whole and to selected comparator regions. To do so, we have used a new dataset by ONS (Wosnitza and Walker, 2008) which refers to GVA per job filled, and take account of several particularities, compared to previous GVA datasets –e.g., it takes account of the commuting phenomena, the regional activity rate, and the regional employment rate, thus adding consistency to our subsequent findings.

The descriptive analysis shows that Manchester is lagging behind the leaders in terms of productivity, which more is striking when we consider that the region is in the queue among the selected comparators. Further, by plotting density against productivity, the main conclusion is that, even though Manchester has an employment density higher than the national average, it does not display a corresponding productivity premium – rather the contrary.

From these facts, we have moved on to consider other factors that boost productivity, which could reveal, to some extent, why Manchester is not performing as well as it should. Thus, following previous relevant literature (Ciccone, 2002; Audretsch, 2002; HM Treasury, 2001, 2003; Fingleton, 2003; Moretti, 2003; Rice et al., 2006; Artis et al., 2008), we have considered a set of variables that could foster productivity as well: human capital, the occupational composition of the workforce, R&D efforts, employment in high-technology manufacturing sectors and in finance and banking, applied patents according to the inventor's residence, and entrepreneurship. Strikingly enough we have observed that Manchester is endowed with lower levels of such inputs comparing to the national mean, which gave us some clues as to why it is lagging behind in terms of productivity.

In a second stage of our report, we have performed regression analysis with a twofold aim. On the one hand, we liked to assess the quantitative impact of agglomeration economies among NUTS2 British regions using our new dataset, even when a set of controls are introduced to check the robustness of the mentioned relationship. On the other hand, we liked to know to what extent the previously mentioned control variables are statistically significant in fostering productivity.

Our results suggest that the majority of the variables are significant in explaining productivity, whilst the explained variation of the model is higher when those variables are introduced. Furthermore, the agglomeration effect remains highly significant and only somewhat lower when other variables are introduced –suggesting that the parameter was only slightly biased upward. This result is consistent even when treating explicitly endogeneity problems, and using GMM techniques to assess the influence of agglomeration on productivity when those problems arise (using as instruments total land area and population density in 1801).

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Appendix 1. Data

Human capital

To proxy educational human capital we have constructed the location quotient -that is, the regional share over the national share- 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), doing the average for the years 1999 to 2001. Next, to proxy the lack of human capital, we have used the share of economically active people with no qualifications or with trade apprenticeships qualifications only. Finally, to proxy the occupational human capital, we have performed the 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, doing the average for the years 1999 to 2001. Data on human capital is available on the NOMIS database, and is collected by Office of National Statistics (ONS).

Knowledge capital

To proxy knowledge efforts, we have performed the location quotient for each area giving the workforce specialisation in computing and related activities and in research and development, calculated from data available through NOMIS, doing the average for the years 1996 to 2000. To proxy high-technology manufacturing sectors, and financial intermediation we have calculated the share of the workforce in chemicals and man-made fibres; machinery and equipment; optical and electrical equipment; and transport equipment for the former, and employment in banking and finance for the latter, calculated from data available through NOMIS, doing the average for the years 1996 to 2000. To proxy knowledge outputs, that is, existing ideas, we have included the number of 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 (OECD REGPAT database, May 2008), averaged out over the years 1996 to 2000. Colleting data on applied patents in that way, we try to avoid the bias introduced by the accumulation of patents in regions where the headquarters of several firms are located.

Entrepreneurship capital

To proxy the entrepreneurial culture of a region, we have collected data on VAT registrations per head, doing the average for the years 1996 to 2000, from the NOMIS database.

Appendix 2. Tables

Table 2. Ordinary Least Squares. Dependent variable: GVA per filled job. White-robust standard errors

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)
Constant	10.272***	10.346***	9.371***	9.804***	9.819***	9.098***	10.513***	10.485***	9.305***	9.371***	9.344***	9.483***	9.444***
	(0.017)	*(0.053)*	*(0.216)*	*(0.174)*	*(0.176)*	*(0.120)*	*(0.138)*	*(0.136)*	*(0.337)*	*(0.216)*	*(0.248)*	*(0.167)*	*(0.189)*
ln(Employment density)	0.064***	0.067***	0.057***	0.044***	0.047***	0.059***	0.078***	0.072***	0.070***	0.057***	0.061***	0.053***	0.059***
	(0.015)	*(0.018)*	*(0.008)*	*(0.013)*	*(0.013)*	*(0.009)*	*(0.011)*	*(0.011)*	*(0.013)*	*(0.008)*	*(0.014)*	*(0.006)*	*(0.009)*
Educational human capital			0.511**	0.390**						0.511**	0.549**	0.421**	0.479**
			(0.185)	*(0.162)*						*(0.185)*	*(0.214)*	*(0.167)*	*(0.175)*
Occupational human capital					0.011**	0.026***			0.022***				
					(0.005)	*(0.002)*			*(0.008)*				
Human capital lack							-0.028***	-0.029**	-0.009				
							(0.009)	*(0.010)*	*(0.009)*				
Employment in RD and computers			0.054***	0.051***	0.052***	0.032**				0.054***	0.048*	0.042***	0.031*
			(0.017)	*(0.017)*	*(0.016)*	*(0.014)*				*(0.017)*	*(0.027)*	*(0.009)*	*(0.015)*
Manufacturing employment			0.020***			0.022***	0.007	0.007	0.021***	0.020***	0.020**	0.018***	0.018***
			(0.007)			*(0.005)*	*(0.005)*	*(0.006)*	*(0.006)*	*(0.007)*	*(0.007)*	*(0.005)*	*(0.005)*
Financial Intermediation								0.006			-0.004		-0.006
								(0.011)			*(0.009)*		*(0.006)*
ln(Applied patents by inventor)				0.070***	0.067**		0.105***	0.101***				0.054***	0.056***
				(0.018)	*(0.024)*		*(0.019)*	*(0.020)*				*(0.015)*	*(0.015)*
ln(VAT registrations)			0.187**						0.123	0.187**	0.191**	0.148**	0.155**
			(0.077)						*(0.118)*	*(0.077)*	*(0.081)*	*(0.061)*	*(0.055)*
NUTS1 dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.387	0.429	0.879	0.834	0.822	0.868	0.783	0.779	0.872	0.879	0.874	0.923	0.923
Sample size	36	36	36	36	36	36	36	36	36	36	36	36	36
Normality													
Skewness-Kurtosis test	0.18	1.19	0.40	4.08	1.91	8.29	2.47	3.45	0.81	0.40	0.10	1.37	1.95
p-value	*0.915*	*0.550*	*0.817*	*0.130*	*0.386*	*0.016*	*0.291*	*0.178*	*0.669*	*0.817*	*0.953*	*0.505*	*0.377*
Akaike criteria	-60.55954	-55.65909	-110.0249	-98.82291	-96.44834	-107.2348	-89.33046	-88.28989	-107.979	-110.0249	-108.4882	-126.2725	-126.27
Schwartz criteria	-57.3925	-36.65687	-84.68859	-75.07013	-72.69556	-83.48204	-65.57768	-62.95358	-82.64271	-84.68859	-81.56838	-99.35264	-97.76665

Note: OLS parameter estimates are reported with robust White standard errors in italics and parenthesis below every estimated coefficient. The values of the diagnostic test are presented with their p-value below each one, in italics and parenthesis.

Table 3. Two Stages Least Squares. Dependent variable: GVA per filled job. White-robust standard errors

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)
Constant	10.277***	10.336***	9.362***	9.795***	9.814***	9.098***	10.489***	10.442***	9.249***	9.362***	9.345***	9.479***	9.444***
	(0.016)	*(0.049)*	*(0.163)*	*(0.141)*	*(0.140)*	*(0.091)*	*(0.115)*	*(0.121)*	*(0.266)*	*(0.163)*	*(0.178)*	*(0.123)*	*(0.132)*
ln(Employment density)	0.053***	0.058***	0.055***	0.041***	0.044***	0.060***	0.072***	0.062***	0.065***	0.055***	0.059***	0.052***	0.058***
	(0.020)	*(0.016)*	*(0.006)*	*(0.011)*	*(0.011)*	*(0.007)*	*(0.011)*	*(0.013)*	*(0.010)*	*(0.006)*	*(0.011)*	*(0.005)*	*(0.007)*
Educational human capital			0.521***	0.395***						0.521***	0.546***	0.043***	0.477***
			(0.139)	*(0.129)*						*(0.139)*	*(0.152)*	*(0.123)*	*(0.123)*
Occupational human capital					0.011***	0.026***			0.023***				
					(0.004)	*(0.002)*			*(0.006)*				
Human capital lack							-0.026***	-0.026***	-0.007				
							(0.007)	*(0.008)*	*(0.007)*				
Employment in RD and computers			0.054***	0.051***	0.053***	0.032***				0.054***	0.050**	0.042***	0.032***
			(0.013)	*(0.014)*	*(0.013)*	*(0.011)*				*(0.013)*	*(0.020)*	*(0.006)*	*(0.011)*
Manufacturing employment			0.020***			0.022***	0.006	0.007*	0.021***	0.020***	0.020***	0.018***	0.018***
			(0.005)			*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*	*(0.005)*	*(0.005)*	*(0.004)*	*(0.004)*
Financial Intermediation								0.009			-0.003		-0.006
								(0.010)			*(0.007)*		*(0.005)*
ln(Applied patents by inventor)				0.071***	0.067***		0.107***	0.103***				0.054***	0.056***
				(0.014)	*(0.019)*		*(0.015)*	*(0.015)*				*(0.011)*	*(0.011)*
ln(VAT registrations)			0.182***						0.118	0.182***	0.187***	0.145***	0.152***
			(0.057)						*(0.091)*	*(0.057)*	*(0.061)*	*(0.044)*	*(0.041)*
NUTS1 dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.376	0.425	0.879	0.833	0.822	0.868	0.782	0.775	0.871	0.879	0.874	0.923	0.923
Sample size	36	36	36	36	36	36	36	36	36	36	36	36	36
Sargan statistic	1.235	0.638	1.438	0.000	0.037	0.424	3.024	2.297	0.885	1.438	2.62	1.126	0.348
p-value	*0.26643*	*0.42451*	*0.230*	*0.99471*	*0.84756*	*0.51507*	*0.08206*	*0.1296*	*0.34672*	*0.23042*	*0.10553*	*0.28856*	*0.5552*
Pagan-Hall test	4.714	29.043	25.260	21.919	22.232	29.422	26.610	25.653	18.554	25.260	25.629	27.462	26.393
p-value	*0.4517*	*0.617*	*0.8873*	*0.9585*	*0.9538*	*0.734*	*0.8449*	*0.8757*	*0.9898*	*0.8873*	*0.8765*	*0.8143*	*0.85*
ln(Employment density)													
Partial R2	0.9014	0.838	0.8931	0.8584	0.8662	0.8679	0.7915	0.7363	0.8446	0.8931	0.8324	0.893	0.8334
First stage F-statistic	150.790	59.48	79.38	60.62	64.73	65.68	37.96	26.520	51.620	79.380	44.700	75.130	42.530

Note: 2SLS parameter estimates are reported with robust White standard errors in italics and parenthesis below every estimated coefficient. The values of the diagnostic test are presented with their p-value below each one, in italics and parenthesis, and include the Sargan statistic of overidentifying restrictions where the null hypothesis is that the excluded instruments are valid instruments and uncorrelated with the error term; and the Pagan-Hall test for heteroscedasticity, where the null is that the disturbance is homoscedastic. Partial R-squared and F-statistics of the first stage are provided too in order to check the strength and validity of the instruments. The instrumented variable is the employment density of each NUTS2 region, whilst the excluded instruments are population density in 1801 and total land area.

Table 4. GMM estimations. Dependent variable: GVA per filled job.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)
Constant	10.281***	10.352***	9.359***	9.795***	9.829***	9.094***	10.469***	10.455***	9.119***	9.359***	9.348***	9.465***	9.448***
	(0.016)	*(0.045)*	*(0.163)*	*(0.134)*	*(0.117)*	*(0.091)*	*(0.115)*	*(0.121)*	*(0.227)*	*(0.163)*	*(0.178)*	*(0.123)*	*(0.132)*
ln(Employment density)	0.044**	0.061***	0.053***	0.041***	0.045***	0.057***	0.065***	0.058***	0.061***	0.053***	0.057***	0.052***	0.058***
	(0.018)	*(0.016)*	*(0.006)*	*(0.010)*	*(0.010)*	*(0.006)*	*(0.010)*	*(0.013)*	*(0.010)*	*(0.006)*	*(0.011)*	*(0.005)*	*(0.007)*
Educational human capital			0.550***	0.395***						0.550***	0.551***	0.456***	0.473***
			(0.136)	*(0.124)*						*(0.136)*	*(0.152)*	*(0.120)*	*(0.122)*
Occupational human capital					0.011***	0.026***			0.026***				
					(0.003)	*(0.002)*			*(0.005)*				
Human capital lack							-0.024***	-0.027***	-0.005				
							(0.007)	*(0.008)*	*(0.006)*				
Employment in RD and computers			0.056***	0.051***	0.053***	0.033***				0.056***	0.046**	0.044***	0.033***
			(0.013)	*(0.013)*	*(0.013)*	*(0.011)*				*(0.013)*	*(0.020)*	*(0.006)*	*(0.011)*
Manufacturing employment			0.019***			0.022***	0.004	0.006	0.022***	0.019***	0.020***	0.018***	0.018***
			(0.005)			*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*	*(0.005)*	*(0.005)*	*(0.003)*	*(0.004)*
Financial Intermediation								0.013			-0.002		-0.006
								(0.009)			*(0.007)*		*(0.005)*
ln(Applied patents by inventor)				0.071***	0.069***		0.098***	0.094***				0.055***	0.056***
				(0.013)	*(0.017)*		*(0.014)*	*(0.014)*				*(0.011)*	*(0.011)*
ln(VAT registrations)			0.145***						0.062	0.145***	0.171***	0.124***	0.153***
			(0.048)						*(0.069)*	*(0.048)*	*(0.060)*	*(0.040)*	*(0.041)*
NUTS1 dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.348	0.424	0.875	0.833	0.822	0.866	0.765	0.762	0.865	0.875	0.872	0.922	0.923
Sample size	36	36	36	36	36	36	36	36	36	36	36	36	36
Sargan statistic	1.235	0.638	1.438	0.000	0.037	0.424	3.024	2.297	0.885	1.438	2.620	1.126	0.348
p-value	*0.26643*	*0.42451*	*0.230*	*0.99471*	*0.84756*	*0.51507*	*0.08206*	*0.1296*	*0.34672*	*0.23042*	*0.10553*	*0.28856*	*0.5552*
ln(Employment density)													
Partial R2	0.9014	0.838	0.8931	0.8584	0.8662	0.8679	0.7915	0.7363	0.8446	0.8931	0.8324	0.893	0.8334
First stage F-statistic	150.790	59.48	79.38	60.62	64.73	65.68	37.96	26.520	51.620	79.380	44.700	75.130	42.530

Note: 2SLS parameter estimates are reported with standard errors in italics and parenthesis below every estimated coefficient. The values of the diagnostic test are presented with their p-value below each one, in italics and parenthesis, and include the Sargan statistic of overidentifying restrictions where the null hypothesis is that the excluded instruments are valid instruments and uncorrelated with the error term. Partial R-squared and F-statistics of the first stage are provided too in order to check the strength and validity of the instruments. The instrumented variable is the employment density of each NUTS2 region, whilst the excluded instruments are population density in 1801 and total land area.