REGIONAL DISPARITIES IN LABOUR PRODUCTIVITY AND THE ROLE OF CAPITAL STOCK

Ben Gardiner,* Bernard Fingleton** and Ron Martin***

This paper reports on the availability of regional capital stock data,[1] in the form of new/updated regional (NUTS2 level) capital stock estimates,[2] building on an approach (Perpetual Inventory Method) which had been previously developed for the European Commission. The particular focus here is on the UK and how these data are used to shed light on regional labour productivity disparities. Using a NUTS2 level dataset constructed for the period 2000–16, we use a dynamic spatial panel approach from Baltagi *et al.* (2019) to estimate a model relating productivity to output (growth or levels) and augmented by explicit incorporation of capital stock plus various other covariates such as human capital. We find that regional variations in capital stocks per worker make a significant contribution to regional variations in labour productivity, but the geography of human capital is also highly relevant. Moreover, we give evidence to show that as human capital rises, notably as we move from the regions to London, the impact of capital stock per worker is less. The effect of capital stock depends on the level of human capital.

Keywords: Regional Disparities, Labour Productivity, Capital Stock, Dynamic Spatial Panel Model.

JEL codes: C23; C33; D24; O47; R12.

1. Introduction

Since emerging from the Great Recession of 2008–9, two of the key policy concerns that have pre-occupied the UK Government have been the flat-lining of national productivity (the so-called 'productivity puzzle') and marked spatial imbalances in economic prosperity and recovery across the country (the problem of 'left behind places', and more latterly the 'levelling up' agenda). The two issues are interrelated, in as much as productivity differences across the regions and cities of the UK are substantial (Martin *et al.*, 2018; Office for National Statistics, 2019; Zymek and Jones, 2020), with levels in London between 35 and 70 per cent higher than in major northern cities (Martin *et al.*, 2018). From a policy perspective, raising national productivity growth is thus in large part a problem of raising productivity in much of Britain outside London and the South East region, and particularly in those places that have been left behind economically over recent decades. Solving the 'spatial productivity problem' would go some way to resolving the national productivity puzzle.

Explaining productivity disparities across different cities and regions is not straightforward, and various causal factors have been suggested, including geographical differences in sectoral structures, in skill levels of local workforces, in innovation, entrepreneurship, firm size and ownership patterns, local infrastructure, connectivity, and degree of agglomeration of activity, to name but some. While such factors appear to play a part, one potential determinant that has largely eluded detailed analysis is that of capital stocks, despite this being a core component of most theories of economic and productivity growth. This has been primarily because reliable data on regional and subregional capital stocks are few and far between. In many ways, the influence of capital stocks is a missing piece in the regional productivity puzzle (Zymek and Jones, 2020). In this paper, we seek to begin to remedy this situation by utilising a novel data set of estimates of physical capital stocks for the British sub-regions (NUTS2 level areas) over the past two decades, to examine the contribution of such stocks to explaining geographical disparities in labour productivity across the economy. In so doing we are conscious that most theories of macroeconomic and regional growth also emphasise the importance of human capital (and especially skilled and highly

*Director, Cambridge Econometrics, Cambridge UK, e-mail: bg@camecon.com. **Department of Land Economy, University of Cambridge, e-mail: bf100@cam.ac.uk Department of Geography, University of Cambridge, e-mail: rlm1@cam.ac.uk.

DOI: 10.1017/nie.2020.28

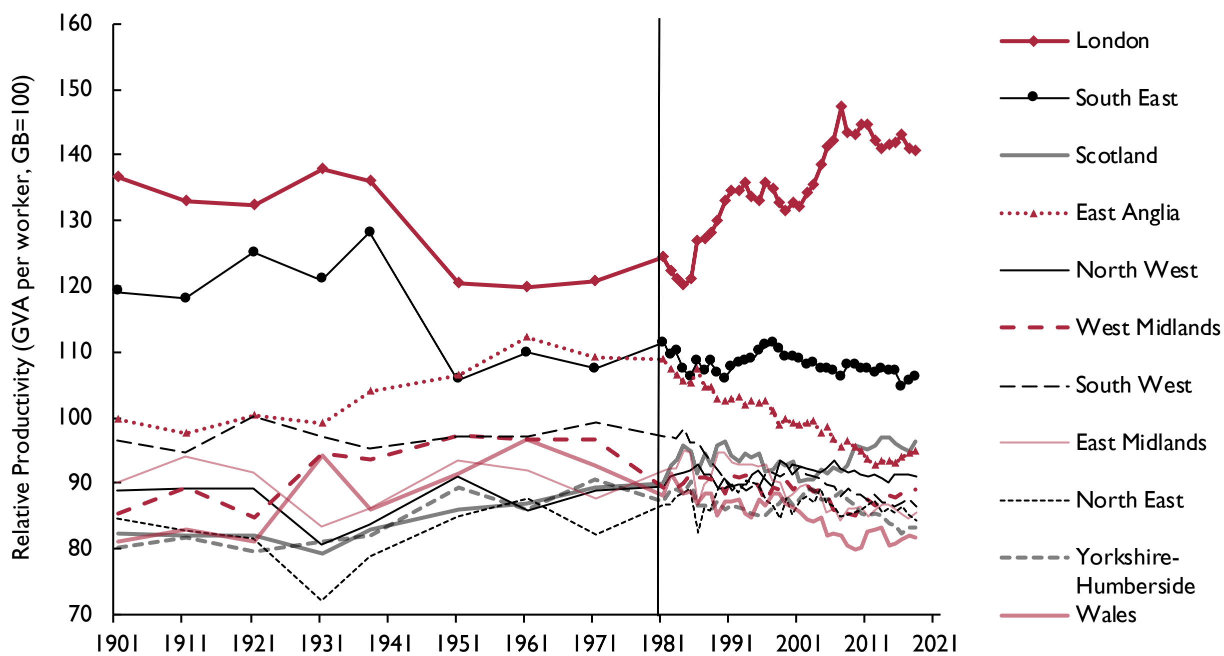
educated labour) for productivity. Indeed, some authors have argued that, as the advanced economies have shifted from a mode of growth driven by manufacturing to one based increasingly on information technology, digital activities and intangible services – to a form of 'capitalism without capital' (Haskel and Westlake, 2018) – so the importance of physical capital is declining whilst that of human capital is increasing. We therefore also explore, within the temporal limits of our data set, whether the contribution of capital stocks to subregional labour productivity has been indeed declining over time.

We begin by briefly reviewing trends in regional and subregional productivity disparities in historical perspective, since such disparities are in fact hardly new, and predate the Great Recession. We then set out the model of subregional productivity growth, with capital stocks per worker, that is the focus of our econometric analysis, having first introduced our novel data set and some of its basic empirics. From the econometric analysis we find that regional variations in capital stocks per worker make a significant contribution to regional variations in labour productivity, but the geography of human capital is also highly relevant. Moreover, we give evidence to show that as human capital rises, notably as we move from the regions to London, the impact of capital stock per worker is less. The effect of capital stock depends on the level of human capital. So, from a policy perspective, if we wish to increase labour productivity, the effect of increasing capital stock per worker will depend on the level of human capital. In high human capital regions such as Inner London West, increasing capital stock per worker will have a smaller effect than in a lower human capital region such as Tees Valley and Durham region.

2. Regional labour productivity disparities in historical perspective

Regional disparities in labour productivity, as measured by GDP or GVA per worker, have characterised Britain for at least the past 150 years. To be sure, in the nineteenth century some parts of northern and peripheral Britain – the textile towns of the North West, the shipbuilding centres of Newcastle-Tyneside and Glasgow-Clydeside, and the coal mining areas of South Wales, the East Midlands,

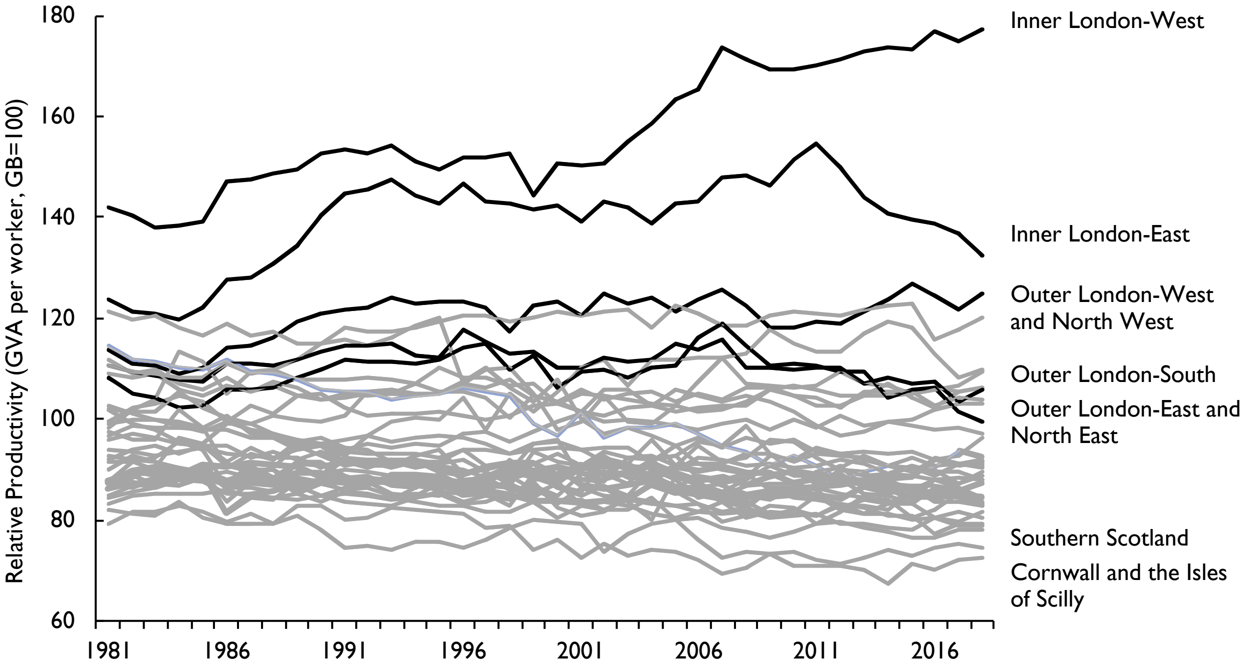
Figure 1. Long-run trends in labour productivity (NUTS1 regions, GB=100)



Note: The data series from 1901–81 are taken from the estimates compiled by Geary and Stark (2016) and refer to (estimated) GDP per worker. Estimates of regional GDP in Great Britain for 1938 (the nearest available year to 1941) are from Geary and Stark's ESCoE Technical Report, 6 March, 2020. The series from 1981–2018 are derived from chained estimates of GVA per job filled compiled by Cambridge Econometrics, based on the most recent estimates by the Office for National Statistics. There are also some changes in regional boundaries and definitions as between the Geary and Stark series and the ONS series, adding to the discontinuity between the two data sets, but the data have been spliced together to provide the best match possible.

https://doi.org/10.1017/nie.2020.28 Published online by Cambridge University Press

Figure 2. Recent trends in labour productivity (NUTS2 regions, London regions highlighted), GB = 100



Source: Cambridge Econometrics local area database, based on ONS data.

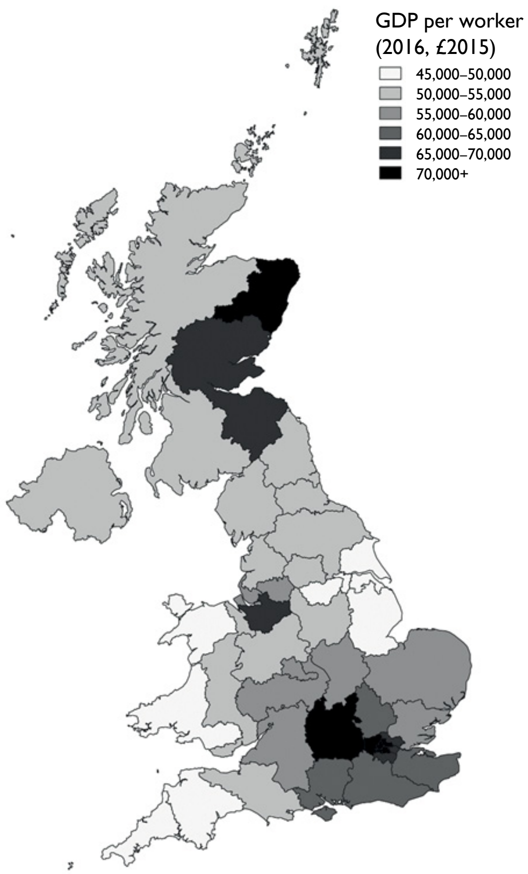
Durham, and Lancashire – helped forge the industrial revolution and fuelled the expansion of Empire abroad. But even in the middle of the nineteenth century, London and the South East had the highest worker productivity in the nation (Crafts, 2005; Geary and Stark, 2015; 2016; Martin and Gardiner, 2017). In the interwar years of the early twentieth century, this divide became more pronounced, as northern industrial regions and cities bore the brunt of structural decline and the impact of the Great Depression, while London and the South East attracted the bulk of the new mass consumer goods industries of the period (Scott, 2007; see figure 1).

For almost three decades after the Second World War, from 1945 to around the beginning of the 1970s, some slight reduction occurred in the scale of disparity between London-South East and the northern regions (figure 1). However, from the late-1970s through the 1980s, convergence gave way to renewed spatial economic divergence: by the mid-1980s London's and the South East's lead over the rest of the UK had come to exceed even that of a hundred years earlier. This prompted a debate over what became labelled the 'North-South Divide', a moniker that may have been oversimplified in its geographical claims, but which nevertheless highlighted an undeniable broad spatial cleavage in socio-economic life (Martin, 1988, 2004).

Yet, a decade later, by the mid-1990s, the 'North-South Divide' narrative had largely evaporated: indeed, some economists even claimed that the divide no longer existed. In actuality, the divide continued to widen still further into the 2000s, as shown by figure 2.

The financial crisis of 2008–9 and the Great Recession it triggered sharply revealed just how spatially unbalanced the national economy had become (see figure 3). Various policy initiatives have been introduced intended to rebalance the economy, including the idea of a 'northern powerhouse' of cities which together would rival the London powerhouse, a limited devolution of powers to certain urban local authorities in the regions, the proposal for a High Speed rail (HS2) between London and Birmingham-Manchester-Leeds, and moves towards a new 'place-based' Industrial Strategy, involving, amongst other things, local industrial strategies (see, for example, H.M. Government, 2010, 2017). The Brexit vote in 2016 then added a whole new urgency to the rebalancing issue. How far local economic conditions played a part in shaping this vote is open to debate (see for example, Alaimo and Solivetti, 2019). But the fact of the matter is that many of those same northern towns and cities that voted to leave the European Union are also among the least productive and economically dynamic in the UK.

Figure 3. UK regional GDP per worker (NUTS2 regions)



Source: Cambridge Econometrics local area database, based on ONS data.

And now, at the time of writing, as the UK, along with many other nations, faces deep recession associated with the global Covid-19 pandemic, the fear is that the main impact will again be on those parts of the country with the lowest productivity. While the focus of government policy has rightly been on trying to contain and control the scale of the pandemic, the recession will reinforce the need to address the spatial productivity problem across regional Britain.

3. Explaining regional labour productivity: the role of capital stock

This begs the question, of course, of what determines local labour productivity. Different economic theories postulate different determinants. Taking more of a firm-level perspective, the ONS (2019) identifies a number of features (exposure to international trade, management efficiency, and structural effects such as age, size and ownership) as important in explaining within-sector firm differences, which are generally seen to be more significant than between-sector differences in explaining geographical disparities. Meanwhile, a dominant theme in the spatial economics literature is that agglomeration – as measured for example by city size or local density of economic activity – is a crucial factor. It has been estimated, for example, that a doubling of city size increases a city's productivity level by between 4 per cent and 8 per cent (see Rosenthal and Strange, 2003). However, the evidence for the importance of agglomeration externalities in raising the productivity of cities and regions is far from unequivocal (see Beaudry and Schiffauerova, 2009).[3] In the UK, certainly, the spatial proximity or local agglomeration of firms does not appear to have a significant influence on their productivity (Harris *et al*., 2019). Clearly, as we show below, agglomeration may play a part, but consideration is needed of other possible determinants of regional disparities in productivity.

In fact, most theories of economic growth assign importance to physical capital as a source of increasing productivity (both labour productivity and total factor productivity). Investment in new machinery and other physical capital typically involves innovation and technological advance and, other things being equal, an increase in capital per worker ('capital deepening') raises output per worker (productivity) (Owyang, 2018). Increases in productivity and output may in turn stimulate further capital investment, so complex recursive causal relationships tend to exist between output, capital and productivity. Empirical studies tend to find stable relationships between productivity and capital over time (for example, Funk and Strauss, 2000). Likewise, most models of regional economic growth, being derived from macroeconomic counterparts, also stress the importance of capital and investment. Regional disparities in productivity can be hypothesised, therefore, to be influenced by differences in capital per worker, and differences in productivity growth across regions by differences in capital accumulation. The simple, stylised, model below shows why this is the case.

Starting from a basic Cobb-Douglas production function, where Q is output, L is labour, K is capital, and A represents technological progress (and thus incorporates aspects of innovation and human capital and, more generally, new ways in which existing quantities of labour and capital can be combined and enhanced to increase production), we have:

$$Q_t = A_t K_t^{\alpha} L_t^{1-\alpha} \quad (1)$$

https://doi.org/10.1017/nie.2020.28 Published online by Cambridge University Press

Changing the equation to represent labour productivity gives:

$$\frac{Q_t}{L_t} = \frac{A_t K_t^\alpha}{L_t^\alpha} = A_t \left(\frac{K_t}{L_t}\right)^\alpha \tag{2}$$

Thus, from a basic structure, which can be enhanced and extended, we have a basic relationship between productivity, technological progress, and capital intensity (capital stock per unit of labour).

Taking logs of the labour productivity function (2) gives

$$\ln P_t = \ln A_t + \alpha \ln(K_t/L_t) \tag{3}$$

in which the level of labour productivity at time t, equal to total real output (GVA) divided by total employment across all sectors, is denote by P_t. Consider A_t to be the level of technology at time t, which determines the extent to which existing quantities of capital and labour at time t can be used efficiently. Assume that the technology level at t is given by the initial level in each region A_0 which then grows exponentially at the rate λ_t so that

$$A_t = A_0 e^{\lambda_t t} \tag{4}$$

Assume also that the rate of technical progress λ_t depends on the level of human capital H_t, given, for example, by the tertiary education indicator (see table 1) which affects the rate of innovation and the efficiency with which capital can be utilised. λ_t also depends on the size of the economy Q_t with commensurate externalities due to knowledge generation, diffusion and accumulation, or learning effects, which when combined with the wider set of agglomeration economies produces a strong empirical association between productivity and economic mass.[4] Additionally, technical progress is assumed to depend on the weighted average of the level of productivity in nearby regions, denoted by $W \ln P_t$. This represents the spillover of the effects of P_t in neighbouring regions, reflecting innovation due to high rates of productivity in nearby competitors, commuting, local input-output linkages and various other linkages across administrative and arbitrary rather than functional regional boundaries. The term $W \ln P_t$ is the outcome of the matrix product of the N by N matrix W and the N by 1 vector $\ln P_t$. The matrix W describes the connectivity of the N regions, with zeros on the main diagonal. Typically, the off-diagonal elements would be measured by some function of geographical, time or cost distance between regions, but this raises quite profound questions when regions are large in area, and relating to the function of distance to be adopted. A common solution is to use a very simple contiguity indicator of distance, where $W_{ij} = 1$, regions i and j share a common boundary. Standardising by dividing each cell of W by its row total makes each region's element of the vector $W \ln P_t$ equal to the weighted average of P_t in its contiguous regions.[5] Also we assume that productivity in the past determines the rate of technical progress by the inclusion of P_{t-1} and $W \ln P_{t-1}$. In this we are allowing for the possibility that changes in productivity locally and in nearby regions take time to influence technical progress. This cannot be a complete set of determinants of technical progress, but we have limited data and so unobservable effects are represented by r_t.

We capture all of these effects in a technical progress rate function

$$\begin{aligned}\lambda_t &= g_1 \ln H_t + g_2 \ln Q_t + g_3 \ln P_{t-1} \\ &\quad + g_4 W \ln P_t + g_5 W \ln P_{t-1} + r_t\end{aligned} \tag{5}$$

Combining (5) with capital stock per worker and introducing ε_t to represent combined unobservable or omitted effects gives

$$\begin{aligned}\ln P_t &= \ln A_0 + \beta_1 \ln H_t + \beta_2 \ln Q_t + \gamma \ln P_{t-1} \\ &\quad + \rho W \ln P_t + \theta W \ln P_{t-1} + \alpha \ln(K_t / L_t) + \varepsilon_t\end{aligned} \tag{6}$$

In the productivity function given by equation (6), we have two types of capital, physical capital per worker and human capital. Additionally, we hypothesise that there will be interaction between physical and human capital, so that their combined effect on productivity will be given not solely by individual effects, but also by an additional contribution determined by the product of the individual levels. Thus we expand the productivity function (6) to give

$$\begin{aligned}\ln P_t &= \ln A_0 + \beta_1 \ln H_t + \beta_2 \ln Q_t \\ &\quad + \beta_3 (\ln H_t \ln(K_t / L_t)) \\ &\quad + \gamma \ln P_{t-1} + \rho W \ln P_t + \theta W \ln P_{t-1} \\ &\quad + \alpha \ln(K_t / L_t) + \varepsilon_t\end{aligned} \tag{7}$$

An extra consideration is the role of common factors. These are general or system-wide effects, typically associated with macroeconomic factors affecting all regions. We assume that they have the same impact in each region and we adopt the approach favoured in the literature (Bailey *et al.*, 2016) by using cross-unit

https://doi.org/10.1017/nie.2020.28 Published online by Cambridge University Press

averages to represent common factors and so each common factor variable is invariant across regions but varies by time. Thus

$$\bar{P}_t = \frac{\sum_{i=1}^{N} P_{it}}{N}; \bar{H}_t = \frac{\sum_{i=1}^{N} H_{it}}{N}; \bar{Q}_t = \frac{\sum_{i=1}^{N} Q_{it}}{N};$$
$$(\bar{K}_t / \bar{L}_t) = \frac{\sum_{i=1}^{N} (K_{it} / L_{it})}{N} \quad (8)$$

We assume that the effect of each common factor is the same for each region, rather than attempting to capture region-specific common factor effects. Accordingly, each is included in the model with a single, specific common factor parameter, to give

$$\begin{aligned} \ln P_t &= k + \beta_1 \ln H_t + \beta_2 \ln Q_t + \beta_3 (\ln H_t \ln(K_t / L_t)) \\ &+ \beta_4 \ln \bar{P}_t + \beta_5 \ln \bar{H}_t + \beta_6 \ln \bar{Q}_t \\ &+ \beta_7 \ln(\bar{K}_t / \bar{L}_t) + \gamma \ln P_{t-1} + \rho W \ln P_t \\ &+ \theta W \ln P_{t-1} + \alpha \ln(K_t / L_t) + \varepsilon_t \end{aligned} \quad (9)$$

A final issue relates to the unobservables represented by ε_t. Within ε_t there are two error components: μ captures time-invariant heterogeneity across regions, with $\mu_i \sim iid(0, \sigma_\mu^2)$ and v_t is a remainder effect with $v_{it} \sim iid(0, \sigma_v^2)$ and μ_i and v_{it} are assumed to be independent of each other and among themselves, so that in the absence of spatial dependence, $\varepsilon_t = u_t = \mu + v_t$. Among the unobservables, we have the (presumably non-zero) initial level of technology in each region, $\ln A_0$. Accordingly, in equation (9), $\ln A_0$ and non-zero means of unobservables are represented by the vector of constants k, which takes account of the fact that we are assuming a mean of zero for the μ_i.

To date, testing this relationship at the regional scale has not proved straightforward, however, because reliable data on regional and subregional capital stocks are scant (Zymek and Jones, 2020). This has resulted in some research (see, for example, PWC 2019) using the investment-output ratio (which is more readily available at regional levels) as a proxy for the capital stock, although Alexander (1994) demonstrates why this may not be appropriate. In this paper, we utilise a novel data set of estimates of physical capital stocks for the British sub-regions (NUTS2 level) over the past two decades, and examine the contribution of such stocks to explaining geographical disparities in labour productivity across the economy. We begin, in the next section, however, by first charting recent trends in labour productivity and capital stocks across the British subregions, using our novel estimates, before testing the impact of capital stocks on local productivity more formally in Section 4.

4. Recent empirical trends in subregional labour productivity and capital stocks

Background to the database

The capital stock data used in this paper are essentially an update, building and improving upon a feasibility study conducted for the European Commission (DG Regio) back in 2011, with the objective to see whether it was possible to construct regional capital stocks for Europe's NUTS2 regions[6] (Derbyshire *et al.*, 2011). As part of work transferring its European regional database to the recently-established ARDECO data platform,[7] Cambridge Econometrics revisited its earlier methodology and updated the capital stocks data using more recent data on Gross Fixed Capital Formation (GFCF). The same methodology (Perpetual Inventory Method, PIM) was used, as recommended by the OECD (2009). This involved taking on board constructive criticism of the earlier feasibility dataset (see Pérez and Garcia, 2014), expanding the Member State coverage, but also making some sacrifice in terms of not including the asset dimension as this is no longer available from the Eurostat regional data. The resulting database of real net capital stocks sits alongside other data extracted from the ARDECO database which establishes a regional information set from which to undertake the empirical analysis. Table 1 below summarises the available data and sources. Ultimately, the database permits two methods of labour productivity (GVA per worker or per hour worked), and measures of both human capital and innovation to be investigated for their inter-relationships.

Preliminary analysis

As one of the primary purposes is to explore the evolution of regional capital stocks in the UK, we examine here some of the developments. Figure 4 shows both the (relative) level and growth of capital stocks per worker across the UK regions over the 2000–16 period. As a precursor to the econometric modelling, some bivariate correlation analysis was undertaken to get a preliminary feel both for the data (and look for any anomalies) and its association with productivity across space and time.

The following charts (collected together in figure 5) show the cross-section relationship between labour productivity and other variables for the last year of available data,

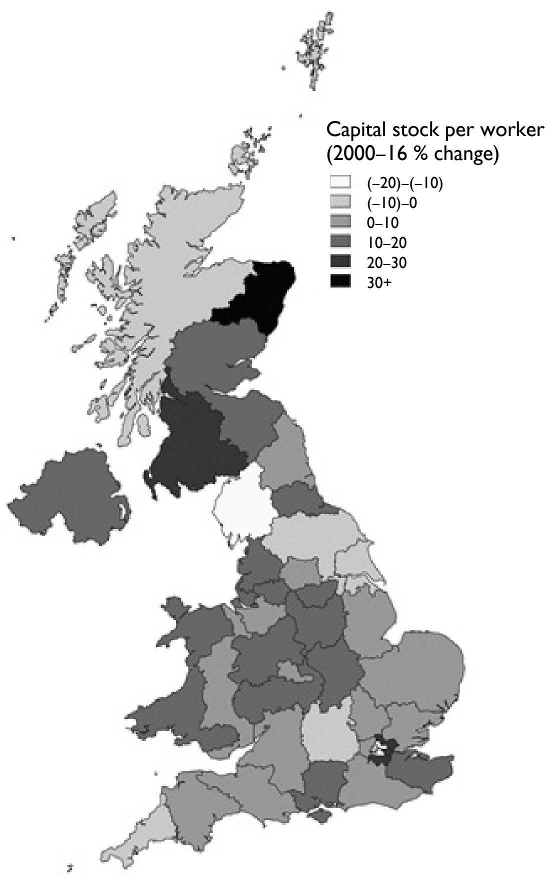
https://doi.org/10.1017/nie.2020.28 Published online by Cambridge University Press

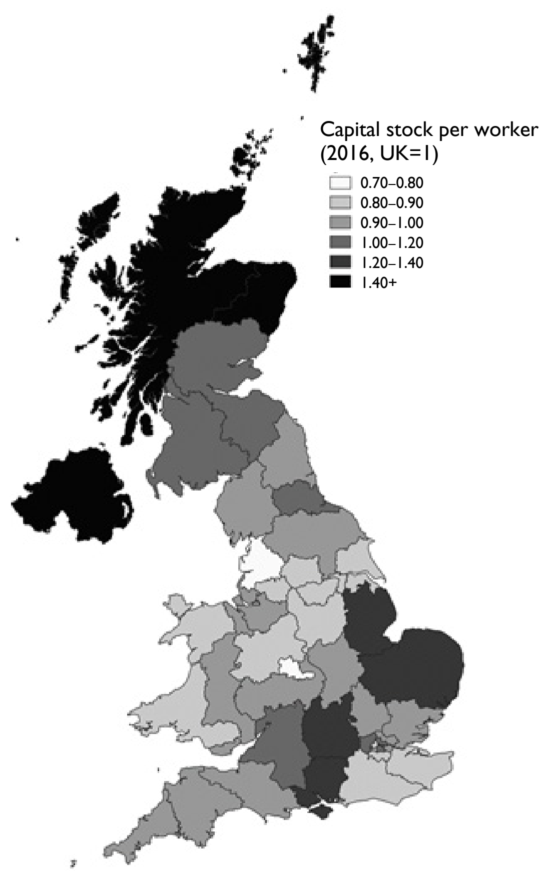
Table 1. Available data[a] for empirical analysis

Indicator	Units	Period[b]	Source
Real net capital stock	£2010m, 6 sectors	1995–2016	ARDECO data platform
Real investment (GFCF)	£2015m, 6 sectors	1995–2016	ARDECO data platform
Real output (GVA)	£2015m, 6 sectors	1995–2016	ARDECO data platform
Employment	000s of people, 6 sectors	1995–2016	ARDECO data platform
Hours worked	Actual, 6 sectors	1995–2016	ARDECO data platform
Population (total and active)	000s of people	1995–2016	ARDECO data platform
R&D expenditure	% of GDP	2006–2016	Eurostat database
Total patents	Patents per million workers	2000–2013	Eurostat database
Tertiary education	% of working population achieving ISCED levels 5-8	2000–2016	Eurostat database
Professional occupations	% of total employment in ISCO professional occupations	1995–2015	Working Futures database
Regional distance	km, centroid-based.	na	Internally generated.
Regional area	km2	na	Eurostat database.

Notes: (a) Other data could have been collected, for example on quality of regional governance, identified as important by work such as Rodriguez-Pose and Garcilazo (2015), but the focus on the UK, where governance quality is relatively uniform, means this would not be of much use in explaining productivity differentials. Similarly sectoral mix, which is often suggested as a source of regional productivity differentials, is not included as it has been shown previously that "industry mix appears to only play a relatively small role in explaining average productivity differences between different areas" (ONS, 2019). (b) Most data on the ARDECO platform are available for earlier periods (1981-) but due to the capital stock data not starting until 1995 (for consistency purposes across all the EU regions) a common period was selected for data wherever possible.

Figure 4. UK regional capital stock (NUTS2)





Source: Cambridge Econometrics local area database, based on ONS data.

https://doi.org/10.1017/nie.2020.28 Published online by Cambridge University Press

and also how the correlation coefficient from the period cross-sections has changed over time. Interestingly, the story is not all about London, but of high levels of capital intensity outside of the capital in more peripheral regions, particularly Scotland and Northern Ireland. The increase in capital intensity over the period since 2000 has also been widely spread with no obvious north-south divide – North East Scotland stands out as having both a high level and growth by virtue of the North Sea oil industry around Aberdeen.

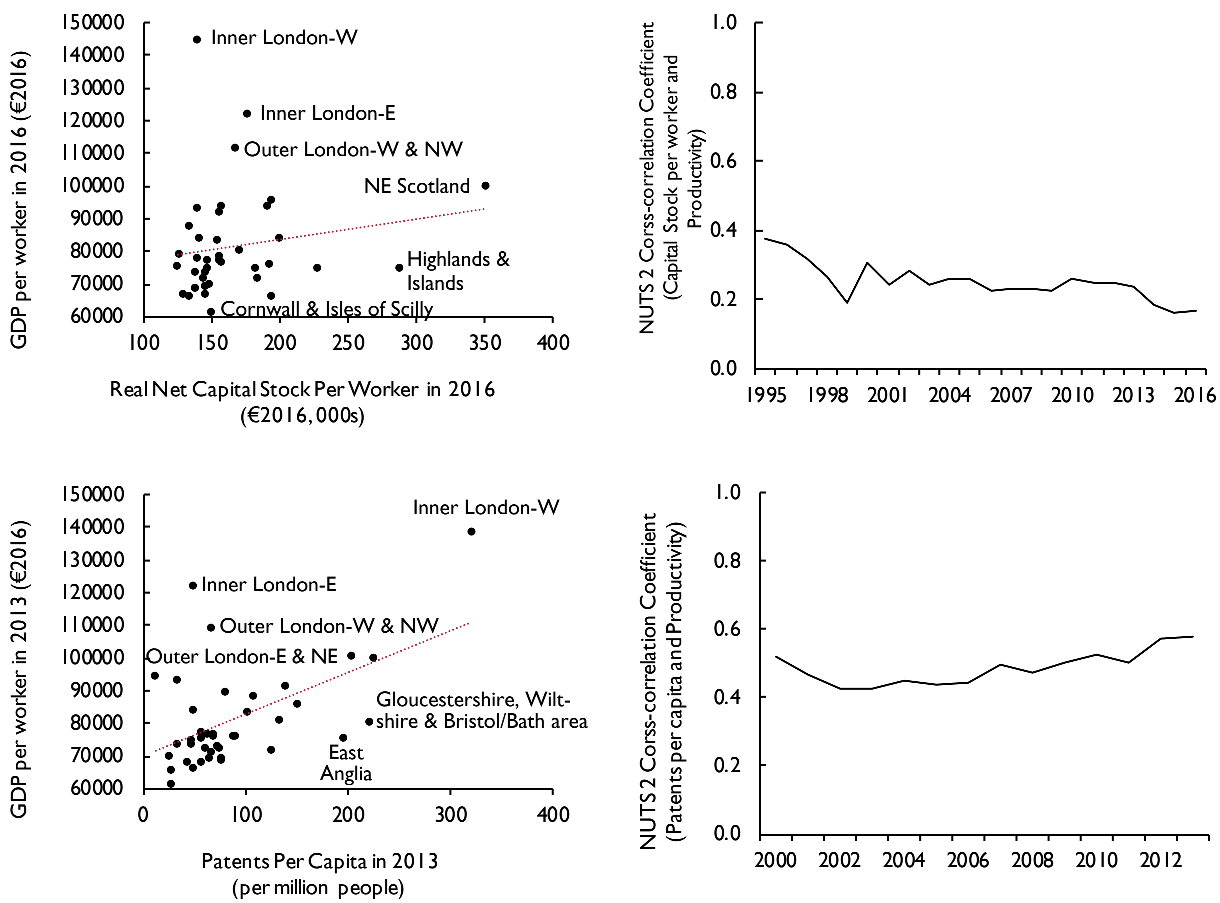
Some interesting findings emerge from the correlation analysis:

- For capital stocks, the correlation with productivity is positive (as would be expected) but not particularly strong. It is also trended down over time, suggesting a reduction in the link between the regional productivity spread and that of capital intensity. There are reasons why this might be expected, such as the rising important of Knowledge-Intensive Business Services (KIBS) which put more emphasis on human rather than physical capital, and the increasing importance of the intangible economy[8] (e.g. intellectual property) as mentioned previously.

- For the innovation proxies, patents per capita has a stronger association with productivity, which might be expected as patents are also an outcome indicator. The association with R&D also drops off markedly after the Great Recession.

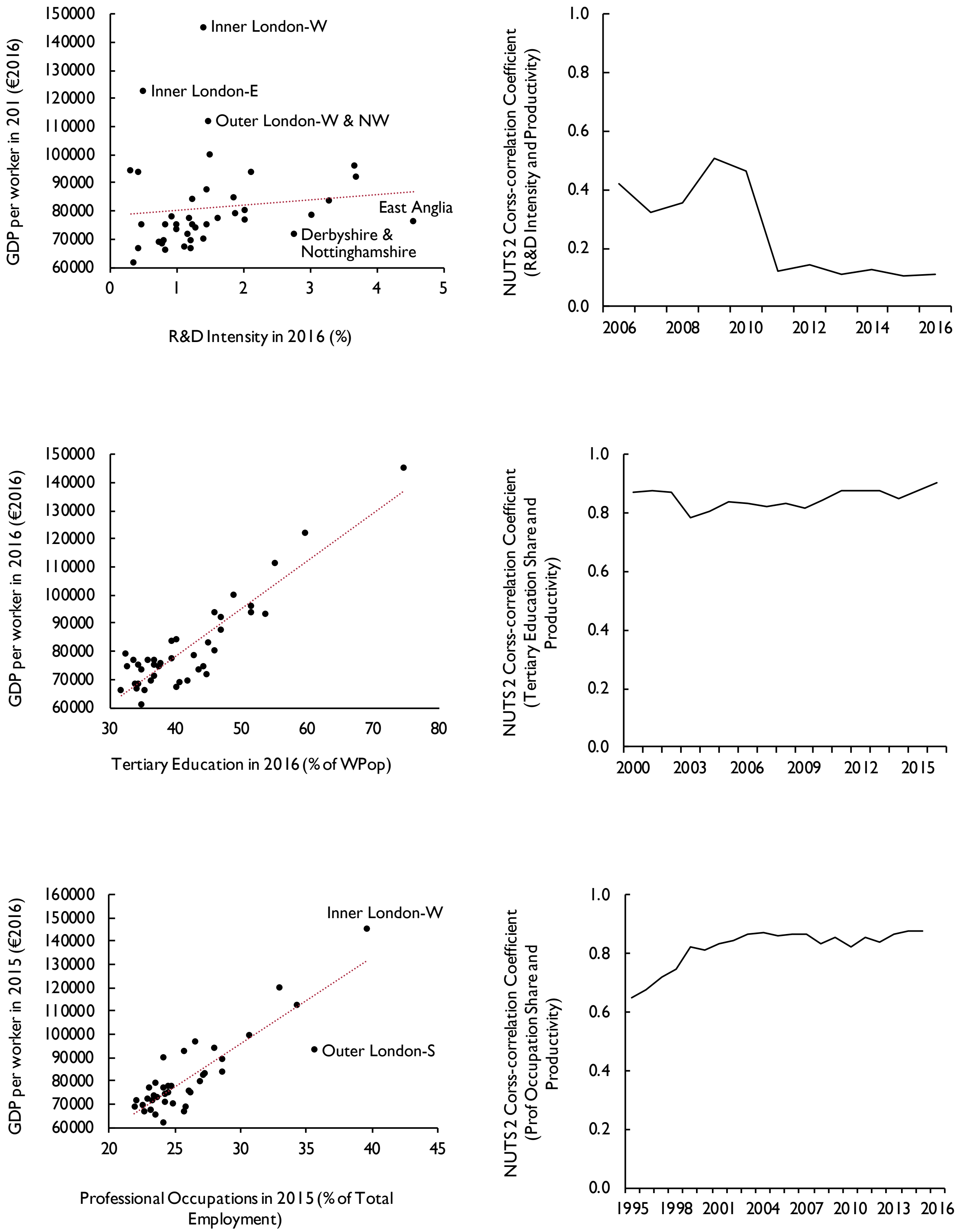
- The association with human capital is remarkably strong, whether measured in terms of educational attainment or as professional occupations. There is also some evidence of an increasing trend over time, suggesting human capital disparities are becoming more closely interlinked with that of productive performance.

Figure 5. Productivity correlation analysis



https://doi.org/10.1017/nie.2020.28 Published online by Cambridge University Press

Figure 5. Productivity correlation analysis (continued)



While correlation analysis provides a useful basis for understanding productivity, it cannot solve the main issue of endogeneity which plagues the majority of 'production function' type approaches. The econometric approach described and estimated below seeks to resolve this problem.

5. Econometric analysis

Estimation

Estimation of the model given in equation (9) is now well-documented in the literature so here we simply give an outline of the approach. The starting point for the estimator is Arellano and Bond (1991) (see also Bond, 2002), which implicitly incorporates the restriction $\rho = \theta = 0$ and has a relatively simple set of instrumental variables. This was extended by Baltagi *et al.* (2014, 2019) by relaxing this restriction to take account of the spatial dimension of the specification. With the presence of spatially lagged variables (for example $W \ln P_t$) and other endogenous or predetermined regressors, the estimator controls for lack of exogeneity using lagged values of the regressors as instruments, with the proviso that they pass the test of the orthogonality conditions required for the instruments, that they are independent of the differenced errors. Following Baltagi *et al.* (2019), we refer to this as the GM-TS-RE estimator.

Estimation commences by first differencing the data, which removes μ from the model. The errors embody the time-invariant individual effects μ capturing unobservables but differencing eliminates these to give

$$\begin{aligned}\Delta \ln P_t = {} & \beta_1 \Delta \ln H_t + \beta_2 \Delta \ln Q_t + \beta_3 \Delta(\ln H_t \ln(K_t / L_t)) \\ & + \beta_4 \Delta \ln \bar{P}_t + \beta_5 \Delta \ln \bar{H}_t + \beta_6 \Delta \ln \bar{Q}_t \\ & + \beta_7 \Delta \ln(\bar{K}_t / \bar{L}_t) + \gamma \Delta \ln P_{t-1} + \rho \Delta W \ln P_t \\ & + \theta \Delta W \ln P_{t-1} + \alpha \Delta \ln(K_t / L_t) + \Delta \varepsilon_t\end{aligned} \tag{11}$$

Apart from the endogenous spatial lag, the time lag and the time-space lag of the dependent variable, we are assuming that the other right-hand side variables in equation (9) are predetermined, which means that they are contemporaneously independent of the errors, but do depend on previous errors. The idea is that it takes time for a shock to affect regressors, so it is non-instantaneous. In contrast, endogenous variables are contemporaneously related to the errors. These assumptions require a judicious choice of instruments so that the moments equations will be satisfied. Observe that as in the Arellano and Bond (1991) estimator the regressors in the model are used to form the instruments, but are lagged by two periods in the case of endogenous variables, and by one period in the case of predetermined variables, so as to satisfy the orthogonality conditions relating to instruments and differenced errors. The orthogonality assumption is tested subsequently.

Stating this in a bit more detail, consistent estimation of equation (11) requires satisfaction of the moments equations. The first set involves lagged levels of the dependent variable, for example

$$\begin{aligned}& E(\ln P_{il} \Delta \upsilon_{it}) = 0 \\ & \forall i, l = 1,2,\ldots,T-2, t = 3,4,\ldots,T \\ & E\left(\sum_{i \neq j} W_{ij} \ln P_{il} \Delta \upsilon_{it}\right) = 0 \\ & \forall i, l = 1,2,\ldots,T-2, t = 3,4,\ldots,T\end{aligned} \tag{12}$$

The second of these equations illustrates the use of spatially lagged variables as additional instruments, as introduced by Baltagi *et al.* (2019). Note in this case, we are using the dependent variable, the log of productivity, as an instrument. It is endogenous, and as a consequence lagged by two periods.

Expressions similar to equations (12) but involving levels of the regressors give additional moments equations, although under the assumption of predeterminedness we have l = 1, 2, ..., T–1, t = 2, 3, ..., T. For example, for predetermined regressor ln H_t an appropriate set of instruments is

$$[\ln H_1, \ldots, \ln H_{t-1}; W \ln H_1, \ldots, W \ln H_{t-1}] \tag{13}$$

and similar sets are used relating to other predetermined regressors on the right hand side of equation (9). The complete set of instruments is used to obtain initial estimates of the model parameters and, given satisfaction of the diagnostics checking the validity of the moments equations, the instruments give consistent estimates of the errors leading to estimates of σ_μ^2 and σ_ν^2. These lead to preliminary one-stage consistent spatial GM estimates, then two-stage Spatial GM parameter estimates, as detailed in table 2, based on a robust version of the variance-covariance matrix.

Results

Table 2 gives parameter estimates using the aspatial Arellano and Bond (1991) estimator, and using the GM-TS-RE estimator of Baltagi *et al.* (2019) which includes spatial interaction effects and with additional

https://doi.org/10.1017/nie.2020.28 Published online by Cambridge University Press

Table 2. Estimates of the parameters in model (11)

Capital stock definition		Arellano and Bond (1991) $\ln(K_t/L_t)$		GM-TS-RE $\ln(GFCF_t/GVA_t)$		GM-TS-RE $\ln(K_t/L_t)$	
Variable	Param.	Est.	Est/s.e.	Est.	Est/s.e.	Est.	Est/s.e.
$\ln P_{t-1}$	γ	0.1054	4.671	0.0287	0.1707	0.1813	1.97
$W\ln P_t$	ρ	--------	--------	0.4003	2.646	0.2524	2.186
$W\ln P_{t-1}$	θ	--------	--------	0.0065	0.0410	–0.163	–1.897
Capital stock	α	0.6699	2.88	0.0637	0.3759	0.9375	5.124
$\ln H_t$	β_1	0.8438	5.074	0.0094	0.0938	0.5906	2.506
$\ln Q_t$	β_2	0.5976	13.77	0.3428	2.007	0.5999	7.799
$\ln H_t \ln(K_t/L_t)$	β_3	–0.1479	–3.262	–0.0186	–0.3974	–0.1237	–2.683
$\ln \bar{P}_t$	β_4	0.8799	18.91	0.4907	3.584	0.5005	3.819
$\ln \bar{H}_t$	β_5	0.1796	5.94	–0.0119	–0.2618	0.09791	3.409
$\ln \bar{Q}_t$	β_6	–0.6059	–13.58	–0.3093	–1.808	–0.4801	–6.341
$\ln(\bar{K}_t / \bar{L}_t)$	β_7	–0.6498	–8.294	0.01135	0.4838	–0.7303	–7.506
	σ_μ^2	0.0080		0.0303		0.0820	
	σ_ν^2	0.0001		0.0002		0.0002	

instruments involving the connectivity matrix W. Both sets of estimates are based on data over the period 2001–15 and assume that variables involving P are endogenous, otherwise it is assumed that variables are predetermined. A feature of these estimates is that physical and human capital interact, so that the net effect of given levels of human and physical capital is not simply the sum of their individual contributions as given by $\beta_1 \ln H_t + \alpha \ln(K_t / L_t)$ but also depends on $\beta_3(\ln H_t \ln(K_t / L_t))$. Note that the significant estimates given in table 2 contrast markedly with those obtained estimating the same model specification but with capital stock per worker approximated by the ratio of GFCF to GVA, which is typically applied to estimating the growth of productivity in the absence of capital stock. Unlike our new capital stock variable, the approximation provided by the ratio of GFCF to GVA is clearly unrelated to the level of labour productivity. Note that the GM-TS-RE estimator gives a larger error variance estimate than produced by the Arellano and Bond (1991) estimator. The larger σ_μ^2 estimate points to larger unobserved time-invariant region-specific effects. In our view the existence of omitted unobserved effects attributable to regional heterogeneity is a reasonable assumption. In the case of the Arellano and Bond (1991) estimator these are mainly captured by the regressors, leaving relatively little for the error term, and this could be a source of estimation bias.

The validity of the predictions and estimates depends on passing several diagnostic tests, summarised by table 3. The first relates to the assumed consistency of the estimates. For this we adopt the Arellano-Bond(1991) m_1 and m_2 test statistics. These test for serially dependent errors, which would invalidate the moments equations. The hypothesis tested is that there is no second-order serial correlation in the first differenced residuals, which implies that the levels of the residuals are not serially correlated. Under an assumption of no serial correlation in residuals, differenced residuals will exhibit negative first order (m_1) correlation, but show insignificant second order (m_2) correlation.

The table 3 diagnostics show that we fail to reject the null hypothesis, indicating valid moments equations and consistent estimates for both estimators. The test relies on independent errors across regions, which is affirmed by re-estimating the model including a spatial moving average process error dependence process, which is called the GM-TS-SMA-RE estimator in Baltagi *et al.* (2019), and which shows insignificant error dependence. In addition we find a lack of residual correlation using a more general test, namely the CD test due to Pesaran (2015). The basis of the CD test is the set of $N(N–1)$ correlations between the time series of residuals for each pair of regions, so there is no *a priori* reliance on a proximity matrix or error process model. The resulting test statistic for the GM-TS-RE residuals is –1.3387, which is insignificant when referred to the $N(0,1)$ distribution. A second test, of the null hypothesis of independence of the instruments from the errors, is the Sargan-Hansen test of over-identifying restrictions

https://doi.org/10.1017/nie.2020.28 Published online by Cambridge University Press

Table 3. Diagnostics for models in table 2

diagnostic		Arellano and Bond(1991)		GM-TS-RE	
	Param.	Est.	Est/s.e.	Est.	Est/s.e.
Arellano and Bond	m_1	–0.0180	–2.6999	–0.0182	–2.8921
Arellano and Bond	m_2	–0.0026	–0.6732	0.0066	1.7099
Sargan-Hansen	SH	26.66	p>>0.05	26.83	p>>0.05
	$\gamma+(\rho+\theta)e_w^{\max}$	--------	--------	0.27073	--------
	$\gamma+(\rho+\theta)e_w^{\min}$	--------	--------	0.1062	--------
	$\gamma-(\rho-\theta)e_w^{\max}$	--------	--------	–0.23401	--------
	$\gamma-(\rho-\theta)e_w^{\min}$	---------	---------	0.53055	---------

Note: p>>0.05 indicates that the statistic has a p-value very much in excess of 0.05 when referred to the relevant χ^2 distribution.

which is the standard test for the validity of instruments. We fail to reject the null hypothesis adding further support to the consistency assumption.

Stationarity and dynamic stability is required in order to be able to give valid elasticities, as discussed below. In table 3, $e_w^{\max}=1, e_w^{\min}=-0.8407$ are the largest and smallest real eigenvalues of W. Rules governing dynamic stability are given in the standard literature (Baltagi *et al.*, 2019 give sources). It turns out that the model parameters are consistent with a dynamically stable, stationary model, since, given $(\hat{\rho}+\hat{\theta})\geq 0$, $\hat{\gamma}+(\hat{\rho}+\hat{\theta})e_w^{\max}$ = 0.27073 < 1, and given $(\hat{\rho}-\hat{\theta})\geq 0$, $\gamma-(\rho-\theta)e_w^{\max}$ = –0.23401 > –1, as required.

The parameter estimates relating to the Baltagi *et al.* (2019) estimator given in table 2 are not the true elasticities, or partial derivatives, because they do not take into account spillover effects. Also, in a dynamic context, there are short-run and long-run elasticities. The short run elasticity is the effect on y of an instantaneous change of 1 per cent in x, where the change in x does not persist through time, but occurs at just one point in time, so that the impact of the change in x dies out over time. The long-run elasticity is the effect of a persistent increase of 1 per cent in x in each region which is maintained over time, the outcome being that y goes to a long-run equilibrium level. The elasticity of productivity with respect to capital stock per worker is given by matrices of partial derivatives. These are N by N, where N is the number of regions, and it is conventional to use means as summary measures. For the short-run elasticities resulting from a temporary 1 per cent change in (K_t/L_t) at time t, the matrix of partial derivatives is given by $\hat{\alpha}\hat{B}^{-1}$ where $\hat{B}=(I-\hat{p}W)$, in which I is an N by N identity matrix. The total short-run elasticity is the mean row total of $\hat{\alpha}\hat{B}^{-1}$. Likewise, the total short-run elasticity of productivity with respect to human capital is given by the mean row total of $\hat{\beta}_1\hat{B}^{-1}$.

The long-run effects of a 1 per cent change in (K_t/L_t) are given by the mean row total of $\hat{\alpha}(-\hat{C}+\hat{B})^{-1}$ in which $\hat{C}=(\hat{\gamma}I+\hat{\theta}W)$. Similarly, for H_t the long-run elasticity is the mean row total of $\hat{\beta}_1(-\hat{C}+\hat{B})^{-1}$. These give the total short and total long-run elasticities in table 4.

It is useful to note that an alternative but mathematically equivalent way to calculate the short-run total elasticity of, for example, capital stock per worker is the difference between the prediction based on equation (9) and the prediction with $\alpha\ln((K_t/L_t)+1)$ in place of $\alpha\ln(K_t/L_t)$. Fingleton and Szumilo (2019) provide technical details. With respect to the interaction term, this is the product of logs, and therefore to achieve the same effect of a 1 per cent increase, the prediction equation with $\beta_3(\ln H_t\ln(K_t/L_t))$ is compared with the prediction given by substituting this by $\beta_3(\ln H_t\ 1.01\ln(K_t/L_t))$. Table 4 gives the combined outcomes that result from a 1 per cent increase across all regions in capital stock per worker and human capital including the interaction effect. The long-run elasticities are obtained in a similar way, but involve iteration until the outcomes achieve equilibrium. This depends on the model being stationary and dynamically stable, which we have shown to be the case. Table 4 shows that for the period 2001–15, both the long and short-run elasticities for capital stock per worker exceed those relating to human capital.

With regard to the spatial and temporal effects, it is appropriate to consider their net effect. Based on the 2001–15 parameter estimates, the total net effect of a simultaneous 1 per cent increase in the endogenous variables P_t and P_{t-1}, thus giving the time lag, the spatial lag and the space-time lag variables, is 0.3621 in the short run, and 0.3713 in the long run. While these are

https://doi.org/10.1017/nie.2020.28 Published online by Cambridge University Press

Table 4. Elasticities

	2001–2015		2008–2015	
	Capital stock per worker	Human capital (tertiary education)	Capital stock per worker	Human capital (tertiary education)
Total short run	1.2540	0.7900	1.1760	1.2916
Total short run(b)	1.2205	0.7588	1.1261	1.2422
Total long run	1.2856	0.8099	1.2370	1.3585
Total long run(b)	1.2513	0.7779	1.1845	1.3066

Note: (b) denotes including the interaction effect.

comparatively small compared with the table 4 estimates, they are not negligible.

Since, rather than the UK regions being functional, self-contained economic entities, they are essentially arbitrary, administrative, areas presenting zero hindrance to localised economic interaction across regional boundaries, so one would expect interventions due to policy in any one region to spill over and affect nearby regions. The full spatial impact of intervention in a region's economy can be demonstrated by simulation. As an example, consider the implications of a permanent 1 per cent increase in capital stock per worker confined to Greater Manchester. The elasticity, defined as the difference in predicted log productivity levels for the region both with and without intervention (or equivalently as the log of the ratio of predicted productivity levels) is 1.1483. However, the notable feature of the model is that, because of the presence of spillovers, the region-specific impact extends to other regions, in this case to Merseyside (0.0437), Cheshire (0.0264), Lancashire (0.0266) and even non-contiguous Cumbria (0.0005).

Table 4 also shows the elasticities as a result of fitting the same model to the post-shock period 2008–15. To save space, details of the estimates and the diagnostics are not given here, but the diagnostic tests are all passed and the estimates are therefore consistent and dynamically stable. It is evident that over the shorter, more recent period, a significant change occurs in the relative elasticities of capital stock per worker and human capital. Human capital elasticities are higher than they are for the 2001–15 estimates, and physical capital stocks have lower elasticities than previously. It is apparent that over the more recent period human capital has become the more important driver of variations in productivity than physical capital. Consequently, the fact that London's human capital exceeds other regions combined with an increased sensitivity of productivity levels to human capital stocks goes a long way to explaining the increasing disparity between the regions and London's productivity level.

6. Conclusions

Regional disparities in economic performance, for example as measured by labour productivity, have long been a feature of the British economy. The evidence suggests that the scale of these disparities has widened in recent decades (figures 1 and 2), at a time when national productivity advance has slowed and become a major policy concern. Understanding why regions differ in productivity is thus of both local and national importance. Various factors have been suggested for why productivity might differ from locality to locality (see, for example, OECD, 2020), including human capital (skill or education levels) and the stock of physical capital per worker. Data on the latter have typically been difficult to obtain, so that the role of this factor has been something of a missing piece in the puzzle. In this paper, new estimates of physical capital stock for the subregions of Britain over the past decade and a half enable at least part of this puzzle to be completed.

We have applied a state-of-the-art modelling approach to these new physical capital stock data in which full account is taken of both the spatial and temporal dimension in productivity analysis, and the estimates are adjusted for the presence of common factors, such as macroeconomic conditions. The estimator enables us to infer causal effects, and dismiss the possibility that what is being observed is merely correlation. Moreover, we have illustrated how our approach enables the calculation of true elasticities and simulation of outcomes due to possible policy interventions. More specifically, estimation based on data for 2001 to 2015, shows, as one might anticipate, that increasing capital stock per worker causes labour productivity to increase, and increasing human capital also increases labour productivity. However, our estimator enables us to quantify the magnitudes of the respective true elasticities given the presence of spatio-temporal spillovers and, most notably, an additional new finding is that there exists a significant interaction effect involving physical and human capital. As we move from low to high levels of human capital, the effect of capital stock per worker becomes less. Interestingly, we find that estimating over the post-2007 recession period magnifies the sensitivity of productivity to human capital and diminishes the effect of capital stock per worker variation across regions. Also, the interaction effect becomes stronger, with the effect of capital stock becoming smaller as we move to higher levels of human capital. It is evident that the regional stock of human capital is increasingly becoming a more dominant force affecting productivity variations across regions. This implies that regions like London, which already has the highest levels of human capital, could pull away still further from other regions in the future.

Clearly there is scope for further research. A key issue is how we define capital stock. To the extent that intangible assets (including IT assets) are becoming increasingly important in shaping worker productivity, then our definition of 'capital' needs to be widened accordingly. Relatedly, exploring the role of capital by sector (at the very least as between manufacturing and services) could provide additional insight into how the scale and nature of capital per worker influences geographical disparities in labour productivity. What does seem clear is that policies that aim to 'level up' productivity across regional Britain will need to include measures that promote and support local investment in capital, both tangible and intangible.

NOTES

1 See https://industrialstrategycouncil.org/uk-regional-productivity-differences-evidence-review.

2 Produced by Cambridge Econometrics, see https://ec.europa.eu/regional_policy/sources/docgener/work/2011_01_capital_stock.pdf for the original European Commission report.

3 Empirical findings vary according to how agglomeration itself is measured or proxied, what other (conditioning) variables are included in regression models testing for the impact of agglomeration, and the type and scale of geographical units used. Such is the variation in findings that it is somewhat puzzling that the claims made for agglomeration have assumed the prominence they have: it might be argued that it is often a case of theory over evidence, or 'confirmation bias' (a tendency to exaggerate the support for the agglomeration theory and to discount evidence that contradicts it).

4 Our estimates reflect wider agglomeration economies due to technological spillovers, labour pooling and intermediate input linkages (Marshall, 1890) or equivalently sharing, matching and learning effects (Duranton and Puga, 2004), which cannot be separated from learning effects per se.

5 Normalising the contiguity matrix is the preferred solution adopted in this paper, although we also find that similar viable and consistent estimates and conclusions are produced using normalised reciprocal of inter-regional centroid distances squared.

6 https://ec.europa.eu/regional_policy/sources/docgener/work/2011_01_capital_stock.pdf

7 https://ec.europa.eu/knowledge4policy/territorial/ardeco-database_en. ARDECO is essentially a regional counterpart to the AMECO database of DG EcFIN.

8 The gross fixed capital formation on which the capital stock data are based do contain elements of intangible investment, such as computer software and the value of original literary or artistic work, but important gaps remain.

9 To retain stationarity, as ρ increases typically γ falls, so that there is a negative covariance. The presence of θ control for this covariance and thus allows a greater range of values of ρ and γ that is consistent with stationarity. Otherwise restricting $\theta=0$ introduces the possibility of bias by the need to restrict the range of feasible values of parameters ρ and γ so as to ensure stationarity.

REFERENCES

Alaimo, L.S. and Solivetti, L.M. (2019), 'Territorial determinants of the Brexit vote', *Social Indicators Research*, Springer, 144(2), pp. 647–67, July.

Alexander, W.R. (1994), 'The investment–output ratio in growth regressions', *Applied Economic Letters*, 1, pp 74–6.

Arellano, M. and Bond, S.R. (1991), 'Some tests of specification for panel data: Monte Carlo evidence and an application to employment', *Review of Economic Studies*, 58, pp. 277–97.

Bailey, N., Holly, S. and Pesaran, M.H. (2016), 'A two-stage approach to spatio-temporal analysis with strong and weak cross-sectional dependence', *Journal of Applied Econometrics* 31, pp. 249–80.

Baltagi, B.H., Fingleton, B. and Pirotte, A. (2014), 'Estimating and forecasting with a dynamic spatial panel model', *Oxford Bulletin of Economics and Statistics*, 76, pp. 112–38.

—(2019), 'A time-space dynamic panel data model with spatial moving average errors', *Regional Science and Urban Economics*, 76, pp. 13–31.

Beaudry, C. and Schiffauerova, A. (2009), 'Who's right, Marshall or Jacobs? The localization versus urbanisation debate', *Research Policy*, 38, pp. 318–37.

Bond, S.R. (2002), 'Dynamic panel data models: a guide to micro data methods and practice', *Portuguese Economic Journal*, 1, pp. 141–62.

Crafts, N. (2005), 'Regional GDP in Britain, 1971–1911: some estimates', *Scottish Journal of Political Economy*, 52, pp. 54–64.

Derbyshire, J., Gardiner, B. and Waights, S. (2011), 'Estimating the capital stock for the NUTS2 regions of the EU27', *Applied Economics*, 45:9, pp. 1133–49.

Duranton, G. and Puga, D. (2004), 'Micro-foundations of urban agglomeration economies', in Henderson, J.V. and Thisse, J-F. (Eds), *Handbook of Regional and Urban Economics*, *Volume 4*, Amsterdam: North-Holland, pp 2063–117.

Fingleton, B. and Szumilo, N. (2019), 'Simulating the impact of transport infrastructure investment on wages: a dynamic spatial panel model approach', *Regional Science and Urban Economics*, 75, pp. 148–64.

Funk, M. and Strauss, J. (2000), 'The long run relationship between productivity and capital', *Economic Letters*, 69, pp. 213–7.

Geary, F. and Stark, T. (2015), 'Regional GDP in the UK, 1861–1911: new estimates', *Economic History Review*, 68, pp. 123–44.

—(2016), 'What happened to regional inequality in Britain in the twentieth century', *Economic History Review*, 69, pp. 216–28.

Harris R., Moffat, J., Evenhuis, E., Martin, R., Pike, A. and Sunley, P. (2019), 'Does spatial proximity raise firm productivity? Evidence from British manufacturing', *Cambridge Journal of Regions, Economy and Society*, 12, 3, November, pp. 467–87.
Haskel, J. and Westlake, S. (2018), *Capitalism without Capital: The Rise of the Intangible Economy*, Princeton University Press.
H.M. Government (2010), *Local Growth: Realising Every Place's Potential*, *Cmnd 7961*, London: H.M. Government.
—(2017), *Industrial Strategy: Building a Britain Fit for the Future*, London: H.M. Government.
Marshall, A. (1890), *Principles of Economics*, London: Macmillan.
Martin, R.L. (1988), T*he Political Economy of Britain's North-South Divide, Transactions of the Institute of British Geographers*.
—(2004), 'The contemporary debate over the North-South Divide: images and realities of regional inequality in late-twentieth century Britain', in Baker, A.R.H. and Billinge, M. (Eds) *Geographies of England: The North South Divide, Imagined and Material*, Cambridge: Cambridge University Press, pp. 15–43.
Martin, R.L. and Gardiner, B. (2017), 'Reviving the Northern 'Powerhouse' and spatially rebalancing the British economy', Chapter 2 in Berry, C. and Giovannini, A. (Eds), *Developing England's North: The Political Economy of the Northern Powerhouse*, London: Palgrave-Macmillan, pp. 23–58.
Martin, R.L., Sunley, P., Gardiner, B. Evenhuis, E. and Tyler, P. (2018), 'The city dimension to the productivity growth puzzle: the relative role of structural change and within-sector slowdown', *Journal of Economic Geography*, 18, pp. 539–70.
OECD Manual (2009), *Measuring Capital*, Paris: OECD, available at http://www.oecd.org/dataoecd/16/16/43734711.pdf.
OECD (2020), *The Spatial Dimension of Productivity: Connecting the Dots Across Firms, Industries and Places*, Regional Development Report 2020/1, Paris: OECD.
Office for National Statistics (2019), *Understanding spatial productivity in the UK*, https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/labourproductivity/articles/understandingspatiallabourproductivityintheuk/2019-05-03.
Owyang, M. (2018), *How Capital Deepening Affects Labour Productivity*, Federal Reserve Bank of St Louis, https://www.stlouisfed.org/on-the-economy/2018/april/capital-deepening-affects-labor-productivity.
Pérez, J.E., and García, J.M. (2014), 'New estimates of capital stocks for European regions (1995–2007)', *Revista de Economía Aplicada*, 66, vol. XXII, pp. 113–37.
Pesaran, M.H. (2015), 'Testing weak cross-sectional dependence in large panels', *Econometric Reviews*, 34 (6–10), pp. 1088–116.
Price Waterhouse Coopers (2019), 'What drives regional productivity gaps across the UK and how can these be closed?', https://www.pwc.co.uk/economic-services/ukeo/ukeo-november-2019-regional-productivity.pdf.
Rosenthal. S. and Strange, W. (2003), 'Geography, industrial organization, and agglomeration', *Review of Economics and Statistics*, 85, pp. 377–93.
Scott, P. (2007), *The Triumph of the South: A Regional Economic History of Early Twentieth Century Britain*, Farnham: Ashgate.
Zymek, R. and Jones, B. (2020), *UK Regional Productivity Differences: An Evidence Review*, Industrial Strategy Council.