PIN - Productivity Projects Fund

Small Project Report

UK regional capital shocks and productivity, an updated analysis

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About PIN

The Productivity Insights Network was established in January 2018 and is funded by the Economic and Social Research Council. As a multi-disciplinary network of social science researchers engaged with public, private, and third sector partners, our aim is to change the tone of the productivity debate in theory and practice. It is led by the University of Sheffield, with co-investigators at Cambridge Econometrics, Cardiff University, Durham University, University of Sunderland, SQW, University of Cambridge, University of Essex, University of Glasgow, University of Leeds and University of Stirling. The support of the funder is acknowledged. The views expressed in this report are those of the authors and do not necessarily represent those of the funders.

Table of Contents

1. Introduction

Background

In 2019 Cambridge Econometrics (CE) produced a regional (NUTS2) capital stock series for the European Union, as part of a wider database project for the European Commission (JRC-ISPRA). These data were used in a paper (Gardiner et al, 2020) to shed light on regional labour productivity disparities in the United Kingdom, and through this helped to fill in some of the missing pieces of the "productivity puzzle". However, the data used in that paper suffered from a number of limitations. In particular:

- They were somewhat dated, ending in 2016.
- They were based on an old/outdated NUTS2 classification.
- Due to the European nature of the project, certain compromises were made (e.g. limited sector disaggregation) in order to achieve a full coverage dataset.

In December 2019 the ONS released a regional (NUTS2) investment (GFCF) dataset covering the period 2000-18[1]. These data are more up-to-date, based on the latest NUTS classification, and have a greater sectoral disaggregation than the European dataset previously produced by CE.

Objectives

With this context in mind, the objectives of the research are twofold:

(i) To construct an updated regional (NUTS2) capital stock (gross fixed capital formation,GFCF) series for the UK regions from the new ONS investment series.

(ii) To use these revised data to improve the understanding on the role played by capital stock in the productivity slowdown across different UK regions, and to provide a more robust relationship between capital intensity and labour productivity.

Remaining sections

The remaining sections of this report are based around the two objectives. Firstly, the construction of the updated and revised capital stock dataset is established. Secondly, the estimates from Gardiner et al (op cit) are updated and compared.

2. An updated capital stock dataset

New vs old investment data

The regional capital stock series produced for the JRC were based on CE's European regional database. CE implemented a rigorous procedure to ensure comparability across countries in the context of the ARDECO database project for JRC-ISPRA. These series ended in 2016, featured a six sectors breakdown and were based on an outdated NUTS classification. In comparison, the new ONS investment series published in December 2019 feature eleven sectors, corresponding to individual one-digit SIC2007 codes or groupings thereof[2]. The 11 sectors

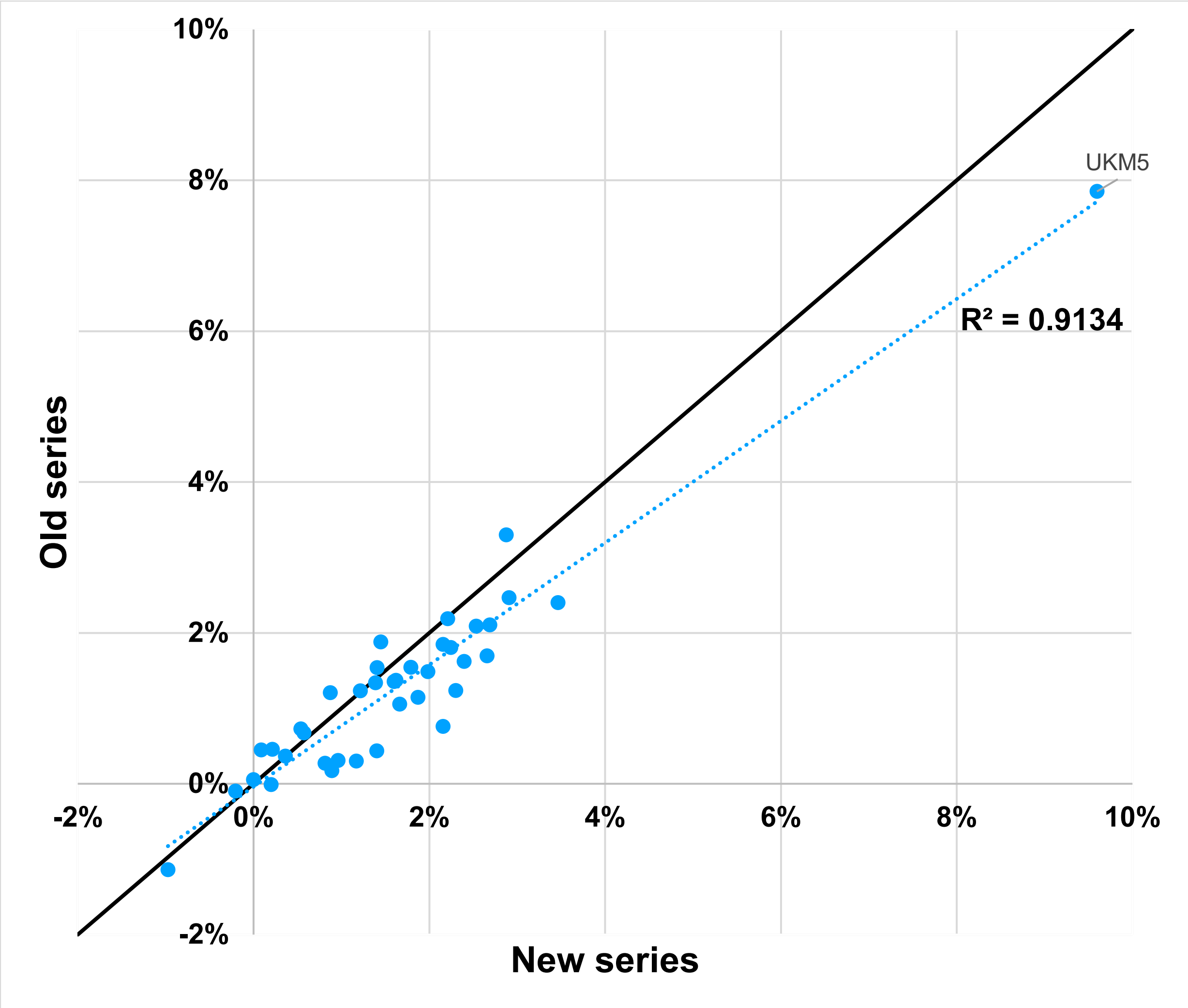
[1] See https://www.ons.gov.uk/economy/regionalaccounts/grossdisposablehouseholdincome/adhocs/10949regionalgrossfixedcapitalformationnuts1andnuts22000to2018

[2] The regional ONS investment data featured a sudden spike in manufacturing investment in 2005, which was corrected using other investment data sources from the ONS.

were eventually grouped into four[3] broad categories for the purpose of the productivity-capital stock estimation: manufacturing, business services, mining and utilities, and others. The NUTS2016 classification used in the new series differs from the previous one by modifying boundaries within Scottish regions. Regional estimates for 2019 were obtained by sharing the 2019 sectoral investment figures for the whole UK (from the national accounts) with the regional shares in 2018.

Figure 1 shows the growth rates of total investment (GFCF) for the new and old series for the period 2000-16 in order to verify whether comparable figures are produced. Despite some differences, the growth rates are largely aligned. Therefore, the new series allow us to extend the estimation period to 2019 without significantly modifying the picture highlighted by the old series for the 2000-16 period. The high-growth region in the top right corner of the chart is North East Scotland (UKM5), which experienced a massive growth in mining and utilities during this period due to continued extraction of North Sea Oil.

Figure 1 Regional GFCF growth old series vs new series, 2000-16



Note: NUTS2013 regions UKM2 and UKM3 changed boundaries in NUTS2016 and therefore are not included in the graph.
Source: Cambridge Econometrics

[3] Manufacturing includes SIC2007 code C; financial and business services includes codes J (ICT), K (financial and insurance activities), M (professional services) and N (administrative and support services); mining and utilities includes codes B (mining), D (electricity) and E (gas); others includes all the remaining sectors.

Revisions to the methodology

As in Gardiner et al (2020), the capital stock series are computed with the Perpetual Inventory Method (PIM), whereby in each period investment is added to the capital stock in the previous period while accounting for depreciation. A starting value for capital stock is needed to initialise the PIM equation. In the exercise for the JRC-ISPRA, total (national) capital stock was taken from AMECO and shared first across sectors and then across regions using investment data. In this update, a sectoral value for initial capital stock is taken from ONS data, and successively shared across regions using investment figures.
The main differences between the new and previous approaches are the data sources for investment and initial capital stock (ONS for the update vs ARDECO for the old series, the different sectoral breakdown, the different starting year (2000 for the update vs 1995 for the old series), different deflators used (sectoral deflators derived from ONS investment series for the new series vs a single deflator for all sectors for the old series) and the computation of depreciation rates, which for the old series were derived from the EU-KLEMS database and for the update were derived from consumption of fixed capital provided by the ONS. Table 1 shows the comparison between the two sets of sectoral depreciation rates. The discrepancy between depreciation rates is attributable to the difference in data sources used and in the sectoral breakdown. For example, the significant discrepancy observed for the 'Business Services' depreciation rates is mainly due to the exclusion of the real estate sector (moved into 'Other') and in the inclusion of ICT in the new series, while 'Industry' in the old series is a combination of 'Manufacturing' and 'Mining and Utilities', which are kept separate in the new series.

Table 1 Depreciation rates comparison

Old series		New series	
Business services	3%	Business services	16%
Agriculture	8%	Manufacturing	13%
Industry	8%	Mining & utilities	6%
Construction	4%	Other	6%
WRTAFIC[4]	8%		
Non-Market Services	10%		

Source: Cambridge Econometrics

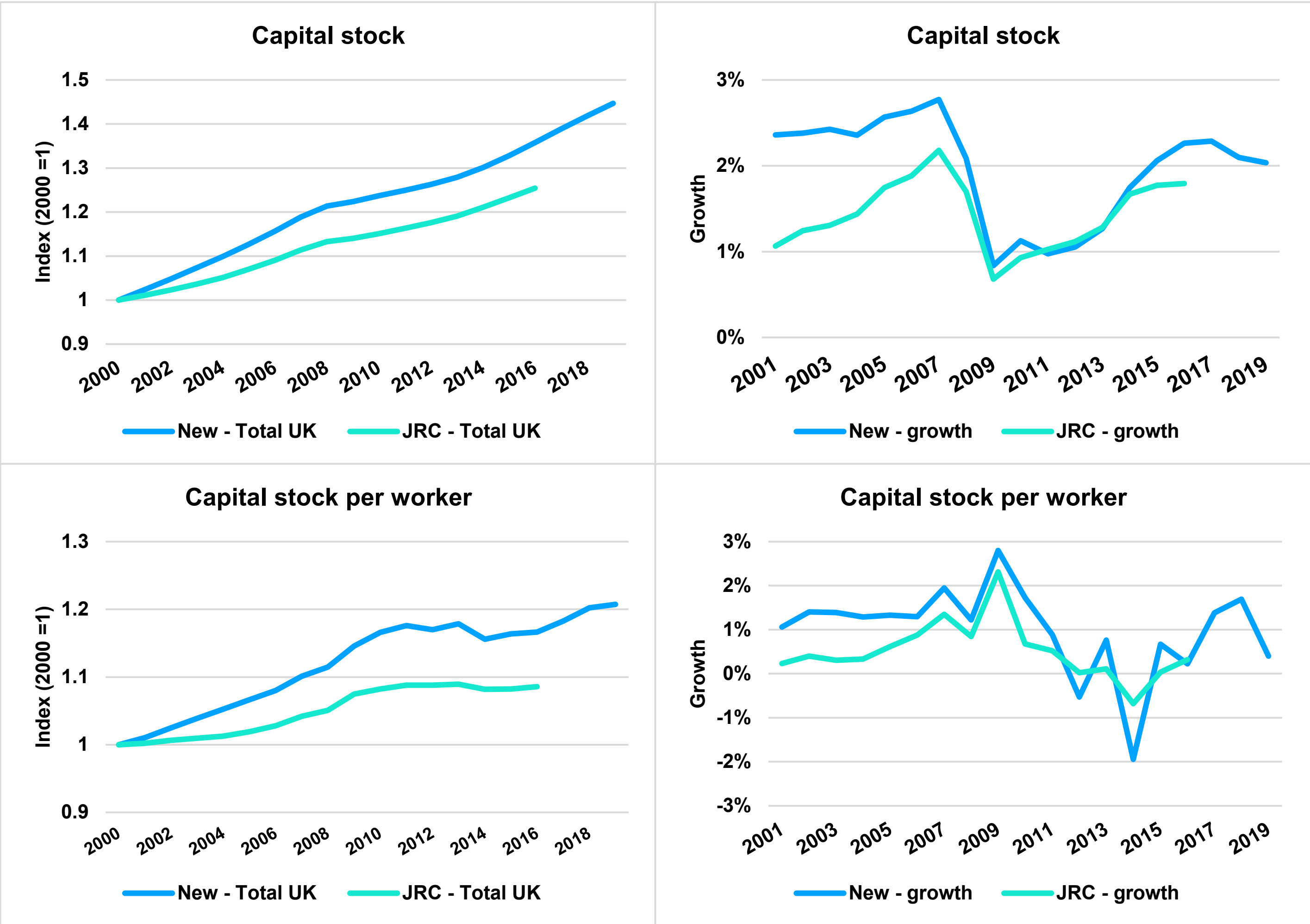
A comparison of capital stock estimates

Figure 2 compares the new capital stock and capital stock per worker series to those produced previously. The series follow the same broad dynamic but the new series grows faster until 2008. These results are explained by the methodological differences outlined above, i.e. more up-to-date data, different starting years, deflators, and different depreciation rates. Despite

[4] WRTAFIC stands for Wholesale, Retail, Transport, Accommodation & Food Services, Information and Communication (SIC2007 codes G to J).

these differences the series follow the same trend and are broadly comparable. Therefore, it is possible to conclude that the new series represent a sensible update of the previous series.

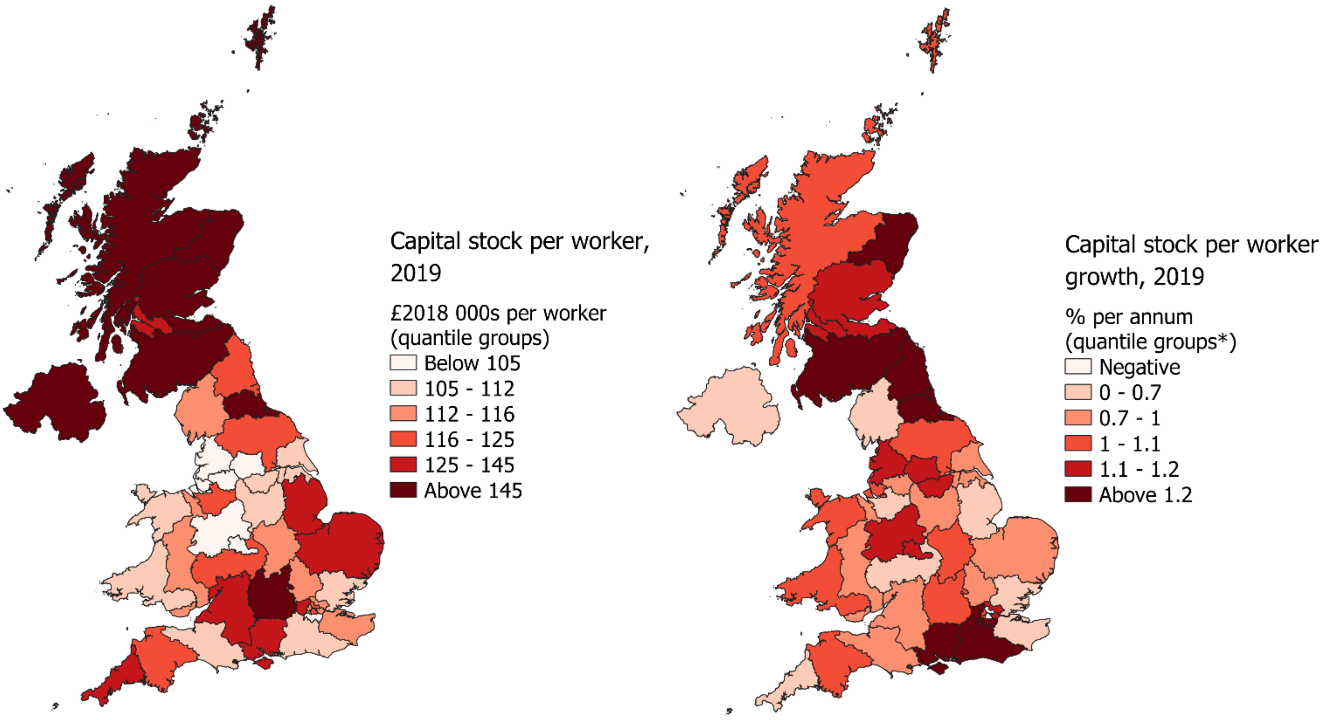
Figure 2 Capital stock and capital stock per worker comparison



Source: Cambridge Econometrics

Figure 3 shows a NUTS2 regional map of the updated level of capital stock per worker in 2019 alongside with the associated growth per annum over 2000-19. The left-hand map shows that the highest levels of capital stock per worker are concentrated in some eastern and southern regions, and in the north. The Midlands and many regions in the south have lower levels of capital stock per worker. The right-hand map shows that the strongest growth in capital per worker over 2000-19 was achieved mainly in the north of the country, Outer London, Hampshire and Sussex. Nevertheless, capital stock per worker grew at around 1% per annum in most regions over the period. The high levels and growth of capital stock per worker in the north, particularly in Scotland, are due to the high levels of capital stock in the mining and utilities sector compared to the size of the workforce.

Figure 3 Capital per worker levels and growth



* The "Negative" band contains a single region, the other bands contain eight regions each.
Source: Cambridge Econometrics

3. An updated capital stock – productivity relationship

The basic model

Our basic model follows that of Gardiner et al (2020) and relates the level of labour productivity to the level of capital stock per worker and the level of technology. To show this we commence with the Cobb-Douglas production function:

$$Q_t = A_t K_t^{\alpha} L_t^{1-\alpha} \tag{1}$$

in which Q_t is the level of output (GVA) in n regions at time t, A_t is the technology level, K_t is capital stock and L_t is employment. From this it is easy to show that

$$\ln P_t = \ln A_t + \alpha \ln\left(\frac{K_t}{L_t}\right) \tag{2}$$

In which $\ln P_t$ is the natural log of labour productivity. Assume that

$$A_t = A_0 e^{t\lambda_t} \tag{3}$$

where A_0 is technology at time $t=0$ and λ_t is the rate of technical progress. As in Gardiner et al(2020), we assume that the rate of technical progress in region $j=1,...,n$ depends on j's human capital, the level of output in j and the level of productivity in regions that are spatially and temporally proximate to j, thus

$$\lambda_t = g_1 \ln H_t + g_2 \ln Q_t + g_3 \ln P_{t-1} + g_4 W \ln P_t + g_5 W \ln P_{t-1} + r_t \quad (4)$$

in which W is an n by n matrix quantifying the spatial proximity of pairs of regions, and $W \ln P_t$ and $W \ln P_{t-1}$ are n by 1 vectors of productivity levels weighted by proximity. Combining capital stock per worker levels and technology levels, and taking averages across regions to create region-invariant common factors $\bar{P}_t, \bar{H}_t, \bar{Q}_t$ and $\left(\bar{K}_t/\bar{L}_t\right)$ controlling for macro-economic variation, gives

$$\begin{aligned} \ln P_t &= k + \beta_1 \ln H_t + \beta_2 \ln Q_t + \beta_3 (\ln H_t \ln\left(K_t/L_t\right)) + \beta_4 \ln \bar{P}_t + \beta_5 \ln \bar{H}_t + ... \\ &\beta_6 \ln \bar{Q}_t + \beta_7 \ln\left(\bar{K}_t/\bar{L}_t\right) + \gamma \ln P_{t-1} + \rho W \ln P_t + \theta W \ln P_{t-1} + \alpha \ln\left(K_t/L_t\right) + \varepsilon_t \end{aligned} \quad (5)$$

Note also the presence of the interaction term $(\ln H_t \ln\left(K_t/L_t\right))$ which was also a feature of the specification in Gardiner et al (2020). One aspect of our approach is that we assume causal reciprocity so that for example $\ln P_t$ both depends on variation in $\ln\left(K_t/L_t\right)$ and is a cause of it. An additional feature is the inclusion of compound errors such that

$$\varepsilon_t = \mu + v_t \quad (6)$$

where μ is an n by 1 vector of individual effects controlling for time-invariant heterogeneity across regions, v_t are idiosyncratic random effects, with $\mu_i \sim iid(0,\sigma_\mu^2)$ and $v_{it} \sim iid(0,\sigma_v^2)$. For simplicity we abstract from modelling spatial error dependence.

Updated results and findings

A variant of the method used in Baltagi et al (2019) is applied to estimate the equation (5) parameters, thus allowing for endogeneity in the right-hand side variables but eliminating error spatial dependence. This parallels Gardiner et al (2020) but now we have newly available data, including the updated capital stock variable K_t, which allows estimation based on the period from 2001 to 2019 rather than 2001 to 2015 as previously. In addition, all variables are treated as endogenous, whereas previously some were only considered to be predetermined. We therefore relax the assumption that some variables were contemporaneously independent of the errors. This provides a tougher test of the causal relationship between capital stock per worker and productivity. Additionally, estimation is based on a different matrix *W*, based on updated NUTS regions, equal to the reciprocals of inter-regional distances scaled by its maximum eigenvalue. Unlike the previously adopted row-standardized contiguity matrix, this preserves the symmetry of the matrix *W*, so that matrix $W_{ij} = W_{ji}$ which is arguably more appropriate for economic interactions, since 'distances' are 'true' rather than relative. To support this, our analysis shows that applying the distance-based *W* matrix rather than the contiguity *W* matrix significantly reduces the Root Mean Square Error and Mean Absolute Error for both model residuals and out-of-sample predictions (using estimates to 2015 and 2018). Moreover, data are also now available for some sectors in addition to the total economy, so Table 2 also contains estimates for the labour productivity in the manufacturing sector (GVA in manufacturing divided by manufacturing employment) and for Business Services. All models pass standard diagnostic tests of stationarity and dynamic stability and lack of serial correlation in the residuals (see Table 3), as described in Gardiner et al (2020).

The estimates in Table 4 indicate, for the whole economy, the significant causal impact of capital per worker on productivity growth. The total long-run elasticity of capital per worker is 0.593 (see Table 4), so a persistent increase of 1% in the level of capital per worker will, taking account of spillovers, lead to an increase of about 0.6% in the level of labour productivity. This is much lower than the elasticity of 1.2856 reported in Gardiner et al (2020). The estimated human capital parameter is also smaller and not significantly different from zero, with correspondingly smaller total long-run elasticity equal to 0.313. In contrast, Gardiner et al (2020) give a higher elasticity (0.8099) and significant effect. The negative interaction effect involving human capital and capital stock per worker again appears as reported in Gardiner et al (2020) but is relatively minor. Focusing on the manufacturing sector, total long-run elasticity of capital per worker is higher than for the economy as a whole, equal to 0.676. In the case of Business Services, evidently neither physical nor human capital levels have a significant impact on productivity, suggesting that Business Services productivity is mainly driven by the significant effects of output, common factors and spillovers.

Table 2 2001-2019 Estimates of the parameters in GM-TS-RE models

Variable		Total		Manufact.		Bus. Servs.	
	Param.	Est.	Est/s.e.	Est.	Est/s.e.	Est.	Est/s.e.
$\ln P_{t-1}$	γ	0.237	4.80	0.093	2.32	0.123	2.09
$W \ln P_t$	ρ_1	0.343	9.08	0.219	5.18	0.332	7.27
$W \ln P_{t-1}$	θ	-0.419	-6.75	-0.215	-6.03	-0.356	-4.60
$\ln(K_t/L_t)$	α	0.461	2.73	0.612	2.79	0.397	1.43
$\ln H_t$	β_1	0.243	1.41	0.249	1.10	-0.060	-0.22
$\ln Q_t$	β_2	0.407	7.81	0.514	9.42	0.437	7.41
$\ln H_t \ln(K_t/L_t)$	β_3	-0.059	-1.70	-0.066	-1.22	-0.023	-0.32
$\ln \bar{P}_t$	β_4	0.663	12.38	0.857	20.79	0.743	13.63
$\ln \bar{H}_t$	β_5	0.083	3.75	0.065	1.33	0.209	3.06
$\ln \bar{Q}_t$	β_6	-0.342	-6.64	-0.450	-7.18	-0.404	-6.27
$\ln(\bar{K}_t/\bar{L}_t)$	β_7	-0.334	-6.02	-0.406	-8.29	-0.201	-2.91
Error process							
	σ_μ^2	0.0345		0.1041		0.0687	
	σ_v^2	0.0002		0.0009		0.0007	

Table 3 Diagnostics for GM-TS-RE models

test	diagnostic	requirement	Total	Manufact.	Bus. Servs.

First-order serial residual correlation	Arellano and Bond m_1, ref N(0,1)	Should be significantly negative	-4.563	-3.060	-4.444
Second-order serial residual correlation	Arellano and Bond m_2, ref N(0,1)	Should not differ significantly from zero	0.328	0.954	-0.700
Independence of instruments from errors	Sargan-Hansen test	p-value >0.05	31.153 p-value >>0.05	33.285 p-value >>0.05	28.146 p-value >>0.05
Dynamic stability and stationarity	$(\rho_1+\theta)$		-0.076	0.005	-0.023
	$(\rho_1-\theta)$		0.762	0.43425	0.688
	$\gamma+(\rho_1+\theta)e_W^{max}$	stationary if < 1 given $(\rho_1+\theta)$ >=0	-------	0.098	-------
	$\gamma+(\rho_1+\theta)e_W^{min}$	stationary if < 1 given $(\rho_1+\theta)$ <0	0.291	-------	0.139
	$\gamma-(\rho_1-\theta)e_W^{max}$	stationary if >-1 given $(\rho_1-\theta)$ >=0	-0.525	-0.341	-0.566
RMSE	residuals		0.020	0.043	0.040
MABE	residuals		0.015	0.032	0.031

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.

Table 4 Estimates of total long-run elasticities in GM-TS-RE models

Variable		Total	Manufact.	Bus. Servs.
	Param.			
$\ln(K_t/L_t)$	α	0.593	0.676	0.450
$\ln H_t$	β_1	0.313	0.274	-0.068

4. Conclusions

The work set out two objectives, firstly to update the capital stock data and secondly to update the capital stock – productivity relationship.

The data work has established an updated capital stock series for the UK NUTS2 regions and an expanded sectoral disaggregation compared to the previous work in this area. Although some underlying assumptions are different and reflect alternative data sources, the resulting series are comparable and lead to the conclusion that the updating process is robust.

The outcome of our current modeling effort is a set of estimates that reaffirm the previous work reported in Gardiner et. al. (2020) regarding the significant effect of capital. Although the current estimator is different, avoiding possible endogeneity bias, and allowing for more extensive direct spatial interaction between regions, with the new capital stock data extending to 2019, we have produced new and more robust evidence that, for the total economy, capital intensity does have a significant causal impact on labour productivity. However, taking account of temporal and spatial spillovers, the long-run elasticity of capital intensity with respect to productivity is lower than previously estimated. Also, our new estimates for human capital, and the interaction involving human capital and capital intensity are now weak and insignificant. However, the previously observed significance of human capital and the interaction term is reasserted given estimation over the period 2008-2019 (details omitted due to space consideration), again supporting the thesis that human capital has increased in importance in recent years. Given that the new data allows exploration of sectoral diversity, we can show that the long-run elasticity of capital intensity is much greater for manufacturing than for Business Services, though this could be partly explained by intangible capital assets not being captured by our measure of capital intensity. On the other hand, it does reflect the inexorable rise in automation across much of manufacturing. However, unlike for the total economy, estimation over the period 2008-2019 evidently does not point to the rising significance for human capital, nor of the interaction term in these specific sectors, though these account for 42.75% (based on GVA in 2019) of the total economy.

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