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RESEARCH ARTICLE

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The role of inefficiency in a productivity puzzle: Regional evidence for Great Britain

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Abstract

From around the 2008 crisis there has been a marked slowdown in UK productivity. This has been referred to as a productivity puzzle as there is no consensus on the key explanations for this slowdown. Using data for all the 168 International Territorial Level 3 areas in Great Britain (2004–2020), we make two empirical contributions to the literature on this puzzle. First, we are the first to analyze this productivity puzzle using a stochastic frontier model to account for technical inefficiency. Second, to aid policy-makers we uncover the areas that represent spatial total factor productivity (TFP) growth hubs, spokes, leaders and followers. Of the components of TFP growth (growth rates of technical change, returns to scale and efficiency), we find that Britain's productivity slowdown can be more specifically described as a rise in inefficiency.

KEYWORDS

benchmarking, dynamic spatial stochastic frontier analysis, persistent and transient technical efficiencies, total factor productivity, UK productivity puzzle

1 | INTRODUCTION

Productivity growth is a key factor that drives rises and disparities in national and regional living standards. It is well-documented, however, that from around the 2008 crisis labor productivity growth slowed in many Western countries and a number of emerging ones. It is also well-known that this slowdown has been particularly deep and

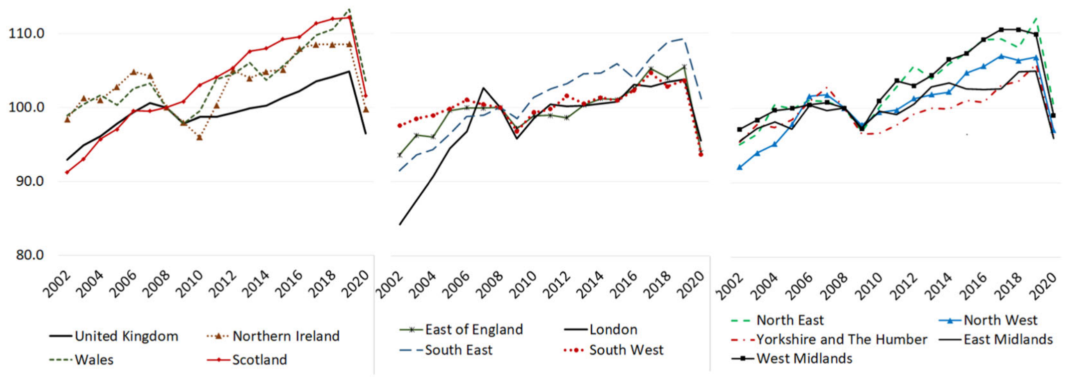

FIGURE 1 Real gross value added per worker indices for the UK and its ITL 1 regions (2008 = 100). ITL, International Territorial Level. [Color figure can be viewed at wileyonlinelibrary.com]

persistent in the UK. To illustrate, Haldane (2018) notes that for much of the period from the start of the crisis, UK labor productivity has been running at almost 20% below what it would have been had it continued along its precrisis trend, and has fallen to as much as a third below that of its major competitors (the United States, France, and Germany).

Van Ark (2021) likens the UK productivity slowdown to a bag full of pieces from a jigsaw puzzle as there are a number of reasons that collectively explain the slowdown. For discussions of the reasons that have been put forward, see the recent discussions of the UK productivity puzzle in Haldane (2018), Mason et al. (2018), Riley et al. (2018), McCann (2020), Van Ark and Venables (2020), Zymek and Jones (2020), and Goldin et al. (2021). Turning now to an overview of the two empirical contributions we make to the literature on this productivity puzzle. The first provides evidence which shows that the productivity growth slowdown in Great Britain can be more specifically described as a rise in technical inefficiency—the increase in the shortfall of output below the maximum attainable level that could be produced using the given levels of inputs.

A headline feature of our empirical analysis is that it accounts for the well-documented intracountry regional economic disparities (McCann, 2016, 2020). To provide some context, in Figure 1 indices with a base year of 2008 are used to present the labor productivity growth for the UK and its International Territorial Level (ITL) 1 areas over the period 2000 – 2020.[1,2] It is clear from this figure that there are marked regional disparities in labor productivity growth rates and to different degrees these regional rates differ from the national picture. However, our starting point for the empirical analysis is the observation that the UK productivity puzzle appears to be primarily a puzzle about the slowdown of total factor productivity (TFP) growth (Bryson & Forth, 2016). For reasons we turn to shortly, we use data for the ITL 3 areas in Great Britain (2004 – 2020).[3] Expanding on the above summary of our first empirical contribution, we find that of the three components of TFP growth—growth rates of technical change, returns to scale (RTS) and technical efficiency—the latter is the key driver. Specifically, we observe that once the effect of the 2008 crisis takes hold, the

[1]The graphs of labor productivity growth for the UK and Great Britain are essentially indistinguishable, so we omitted the latter from Figure 1.

[2]Following the withdrawal of the UK from the EU in 2020, the UK's Office of National Statistics (ONS) replaced its NUTS 1 – 3 labeling of its three tier subnational categorization of its geographical regions with the ITL 1 – 3 terminology. The ITL 1 – 3 regional classification is based on a convention used by OECD member countries and for the UK this classification is very similar to the most recent NUTS 1 – 3 subdivision which has applied since 2018. Comparing the two, the UK comprises the same 12 NUTS and ITL 1 regions, 40 NUTS 2 and 41 ITL 2 regions, and 174 NUTS 3 and 179 ITL 3 regions.

[3]We omit the ITL 3 areas in Northern Ireland because data for a number of variables for these areas are only available from 2009 onwards, which does not cover a key period of interest: namely, the productivity shock in 2008 and the years leading up to it.

sample average efficiency growth falls sharply, going from positive to negative, and although in subsequent years it tends to rise, it remained negative.

We use ITL 3 data because its high geographical disaggregation reflects an important feature for our purposes: namely, the closer proximity of surrounding geographical units. This closer proximity points to higher interunit spatial interaction due to relatively higher commuting and industry interdependence between surrounding areas. In line with the well-documented intracountry regional economic disparities, for some areas in Britain we report relatively low time-invariant own technical efficiencies. This suggests that it may be challenging for these areas to raise their TFP by themselves, or put another way, without assistance from other geographical areas via TFP spill-ins. It is reasonable to think that these spill-ins are more likely to come from nearer geographical areas, which we capture using the granular geographical ITL 3 data. However, using such granular geographical data means that there can be spillovers that come directly from areas outside the surrounding vicinity. As we discuss further in due course, to account for this we use a spatial weights matrix that is specified in such a way that it does not rule out such first-order spillovers from all further afield areas.

Our second empirical contribution is to highlight the nature of the spatial TFP growth hub and spoke networks that exist between the ITL 3 areas in Britain. The motivation for this comes from two sources which point to: (i) the absence of a different, but related, type of hub and spoke network and (ii) a lack of productivity spillovers over longer distances. The first motivation is Haldane's (2018) conclusion that the diffusion of innovation within the UK is like a “hub with no spokes.” The hub comprises a relatively small number of “gazelle-like” firms with high innovation and high technical diffusion within and between firms. The long tail of other “snail-like” firms, many of which are small, have low levels of innovation and diffusion and represent the missing spokes.[4] The second motivation is a general lack of productivity diffusion from firms in cities in the Greater South East to firms in cities elsewhere in Britain (Centre for Cities, 2018; McCann, 2020). Hence, our use of the granular geographical ITL 3 data, as this data allows us to consider TFP growth spillovers over shorter distances. This is motivated by evidence which indicates that when the geographical units are on a smaller spatial scale, the spillovers between neighboring units are greater (Chung & Hewings, 2019). As the idea behind the spatial TFP growth hub and spoke networks we introduce for geographical areas relies on nonnegligible TFP growth spillovers, the granular spatial scale of the ITL 3 areas is appropriate for our analysis. As the spatial TFP growth hub and spoke networks we highlight are already in place, for some geographical areas policymakers may consider exploiting these networks to help tackle Britain's productivity slowdown.

We present and apply a method that uncovers: (a) the areas that represent the biggest contemporaneous spatial TFP growth hubs and spokes and (b) the areas that represent the biggest dynamic spatial TFP growth leaders and followers. Our results can be used to provide a focused steer of further qualitative work as our approach selects a manageable number of areas that represent the biggest hubs, spokes, leaders and followers for case studies and focus groups. The learnings from this additional work about the characteristics of these areas can be used to inform policies designed to grow existing hubs, spokes, leaders and followers and develop new ones. To provide some insights we now turn to a brief outline of some salient features of our study, such as how we determine the areas that represent the hubs, spokes, leaders, and followers.

Stochastic frontier modeling is a common approach to estimate technical efficiency in the regional literature (e.g., Agasisti et al., 2019; Chiariello et al., 2022; Drivas et al., 2018; Kluge, 2018; Männasoo et al., 2018; Tsekeris & Papaioannou, 2018; Mohan et al., 2022, to name a recent selection). To take into account that spillovers can take some time to occur, we build on the static spatial stochastic frontier modeling in the regional literature (Kutlu & Nair-Reichert, 2019; Ramajo & Hewings, 2018; Vidoli et al., 2016) by using a dynamic spatial autoregressive (SAR)

[4]See Henley (2020) on the absorptive capacity challenges of micro-enterprises. This indicates that these firms must develop the capabilities to translate knowledge into innovation.

stochastic frontier model.[5,6] Specifically, our frontier model distinguishes between unobserved heterogeneity and persistent (i.e., time-invariant) and transient (i.e., time-varying) efficiencies. These efficiencies are then used to compute overall time-varying efficiency. Our model is the first to distinguish between unobserved heterogeneity and persistent and transient inefficiencies using the appealing feature of inefficiency measures that are free of a priori assumptions about their statistical distributions. When no such assumption is made, the extant static spatial stochastic frontier literature (Glass et al., 2013, 2014; Kutlu & Nair-Reichert, 2019) estimates only a single (time-invariant or time-varying) efficiency measure. This has involved applying the well-known Schmidt and Sickles (1984) and Cornwell et al. (1990) approaches for the nonspatial setting to estimate time-invariant and time-varying efficiencies, respectively. This does though involve making the strong assumption that unobserved heterogeneity represents inefficiency, whereas our approach is free of this assumption.

From a static spatial stochastic frontier model for US banks, Glass et al. (2020) obtain the contemporaneous asymmetric spill-in and spill-out of TFP growth to and from a bank. To account for a bank where the magnitudes of its TFP growth spill-in and spill-out may be an artifact of one another, they net off the spill-out and spill-in. They classify a bank as one of the largest net spatial TFP growth hubs (spokes) if it is among those with the largest positive net contemporaneous spill-out (spill-in) of TFP growth to (from) the other banks. We adopt this approach here and also extend their work by using absolute TFP growth spill-outs and spill-ins. We classify an area as being one of the largest absolute spatial TFP growth hubs (spokes) if it is among those with the largest positive absolute contemporaneous spill-out (spill-in) of TFP growth. As our spatial model is dynamic, we extend the literature by obtaining the cumulative asymmetric spill-in and spill-out of TFP growth to and from an area over a prespecified number of future in-sample periods. We define an area as being one of the largest net and absolute spatial TFP growth leaders (followers) if it is among those with the largest positive net and absolute cumulated dynamic TFP growth spill-outs (spill-ins).

We are the first to analyze Britain's productivity puzzle using a stochastic frontier model to account for inefficiency. Two of our key empirical findings are as follows. First, mean own overall efficiency for the ITL 3 areas is rather low (48%) and is largely due to a low mean own persistent efficiency (55%). These results are reasonable as they are consistent with Britain's productivity slowdown; the idea that regions can be in a development trap (Diemer et al., 2022); and the persistent regional disparities in economic performance in Britain (McCann, 2016, 2020).[7] Second, we find that Tower Hamlets is the source of some large TFP growth spill-outs and is thus a large spatial TFP growth leader. This is consistent with London's financial center (Canary Wharf) being a district within Tower Hamlets and global financial districts being sources of economic growth in surrounding areas (e.g., Martin & Minns, 1995). In response to the 2008 crisis, the UK Government tightened regulations on financial services. Finding that Tower Hamlets is a large spatial TFP growth leader underlines the big implications of recent Government plans to ease regulations on financial services (BBC, 2022).

[5]There are a number of other studies in the burgeoning literature on spatial stochastic frontier models. See, among others, Glass et al. (2016) and Orea and Álvarez (2019).

[6]The technical efficiency literature almost exclusively involves using either stochastic frontier analysis (SFA), which is regression based, or the linear programming method data envelopment analysis (DEA). There are certain well-known benefits of SFA over DEA and, alternatively, DEA over SFA. A burgeoning group of studies have developed DEA approaches to obtain technical efficiency scores that account for the effect of cross-sectional spatial dependence (e.g., Ramajo et al., 2017, 2021). Whilst both these studies have a number of merits, they are not based on the spatial multiplier matrix, which is a key aspect of spatial econometrics, and therefore account for only local spatial dependence (i.e., spatial interaction between a geographical unit and only its first-order neighbors). Our analysis relies heavily on spatial econometric methods (and hence the spatial multiplier matrix) and, as is preferable, accounts for global spatial dependence (i.e., spatial interaction between a geographical unit and its first, second, etc., order neighbors). Moreover, our analysis requires technical efficiency spillovers and an accompanying spatial TFP growth decomposition. None of the spatial DEA methods though have been used to derive such a decomposition. In contrast, Glass et al. (2013), for example, do so using static spatial SFA. We, therefore, extend the two parts of their spatial approach (i.e., the SFA in the first part and then the decomposition) to the dynamic spatial setting.

[7]To highlight the persistence of these disparities, we note that Beveridge (1944) documents noteworthy inequalities in unemployment rates across the UK's macroregions during the Great Depression. Since over a century of regional policy initiatives have had little success in narrowing spatial inequality in the UK (Fransham et al., 2023), these notable regional inequalities have persisted through to the modern day. We acknowledge an anonymous reviewer for highlighting the extent of this persistence.

The remainder of this paper is organized as follows. Section 2 sets out the research design and has two parts. In the first part we present the spatial production frontier model and the method to estimate the technical efficiencies. In the second part, we show how we obtain the (contemporaneous and dynamic) asymmetric TFP growth spill-ins and spill-outs that we use to uncover the areas that represent the hubs, spokes, leaders and followers. In Section 3 we present the empirical analysis and Section 4 summarizes and concludes.

2 | RESEARCH DESIGN

2.1 | Dynamic spatial stochastic production frontier model and the technical efficiencies

We estimate the dynamic SAR stochastic production frontier model for the ITL 3 areas in two steps. In the first step we estimate the dynamic SAR panel data model in Equation (1), where the variables are logged. An ITL 3 area that lies on the overall best practice frontier has persistent (i.e., time-invariant) and transient (i.e., time-varying) efficiency scores of 100%. In the second step we estimate the distribution-free persistent and transient inefficiencies of an ITL 3 area, PI_i and TI_{it}. These inefficiencies represent the time-invariant and time-varying distances of an area below the overall best practice frontier.

$$y_{it} = \alpha + TL(x_{it}, t) + \gamma' z_{it} + \delta \sum_{j=1}^{N} w_{ij} y_{jt} + \rho \sum_{j=1}^{N} w_{ij} y_{jt-1} + \tau_t + \eta_i + \varepsilon_{it}. \tag{1}$$

The balanced panel data comprises N geographical areas and T periods which are indexed $i, j \in 1, ..., N$ for $i \neq j$ and $t \in 1, ..., T$. y_{it} is an output observation and $TL(x_{it}, t)$ represents the theoretically founded variable RTS translog function.[8] x_{it} is the M dimensional vector of observations of multiple inputs (indexed $m \in 1, ..., M$) and t in $TL(x_{it}, t)$ is a time counter. In contrast to a Cobb–Douglas function, RTS vary over the sample because in addition to $TL(x_{it}, t)$ including x_{it} it also includes its square term, terms that represent interactions between the inputs, and terms that represent interactions between the inputs and t. The latter interactions and also t and t^2 collectively represent a nonlinear time trend which is a proxy that is used to measure technical change that varies over the sample. The remaining variables in Equation (1) are the vector z_{it}, time-period effect τ_t, SAR variable $\sum_{j=1}^{N} w_{ij} y_{jt}$ and its time lag $\sum_{j=1}^{N} w_{ij} y_{jt-1}$. In the efficiency and productivity literature the z's are referred to as environmental variables and we include the time lag of the SAR variable as it may take some time for spillovers to occur.[9]

τ_t accounts for common effects across all the areas in a particular time period. For example, one such effect may be due to the 2016 Brexit referendum result and we would expect that a further such effect would be due to the 2020 COVID pandemic. A time-period effect therefore collectively captures the impacts of the relevant national variables in a particular time period. This resembles multilevel modeling approaches which estimate the effects of indicators of the national economic environment on regional economies (e.g., Chung, 2016; Chung & Hewings, 2015). An appealing feature of this type of multilevel approach is that it estimates the effect of each national economic indicator on a region's economy. Whereas panel data studies usually report a mean parameter over the sample, time-period effects provide further information as the parameters are for individual periods. Also, as the time-period effects collectively capture the impacts of the relevant national determinants, including these

[8] Skuras et al. (2006) and Griffith et al. (2009) also use the translog functional form in their regional analyses of firm efficiency and productivity. The former examines the effects of regional capital subsidies on productivity growth in the Greek food and beverage manufacturing industry, and the latter analyses the relationship between geographical proximity and productivity catch-up in Great Britain.

[9] Note that we do not include y_{it-1}. This is so the nonspatial part of the production frontier in Equation (1) is static and thus consistent with its counterpart in production theory.

time effects can account for the potential bias from the omission of a relevant national variable. From the large literature that highlights the impact of a country's economic performance on the economic activity of its regions, our results are in line with studies which find that omitting national drivers leads to an upwardly biased estimate of the regional interdependence (e.g., Chung, 2016; Chung & Hewings, 2015). Specifically, we find that it is important to include time-period effects to collectively account for a common national impact on the areas, as including these effects substantially reduces the magnitude of the contemporaneous SAR dependence.[10,11]

The pairwise nonnegative spatial weights (w_{ij}'s) are collected in the ($N \times N$) spatial weights matrix W.[12] W is specified before the estimation of the model and, as is standard, all the elements on its main diagonal are set to zero to rule out self-influence. The off-diagonal elements of W represent which areas neighbor one another and the strength of the spatial linkages between neighboring areas. To estimate Equation (1) we follow the vast majority of the spatial econometrics literature by using an estimator that is based on exogenous spatial weights. The SAR variable, however, is endogenous which we account for in the estimation (see footnote 14 for the details). To be sure that the spatial weights in the empirical analysis are exogenous and hence consistent with our estimator, we use a distance-based specification of W. As we expand on in Section 2.2, our definitions of the areas that represent spatial TFP growth hubs, spokes, leaders and followers are in relation to all the other areas, so we use a specification of W that links every pair of areas. Specifically, we use spatial weights that are based on the inverse distance between each pair of areas. This is in contrast to a cut-off based W that assumes each area's neighbors lie within an arbitrary radius. Whilst we use granular geographical ITL 3 data to focus on spillovers over shorter distances (see the discussion of this in the opening section), by not using a cut-off we do not rule out first-order spillovers over longer distances. As a result of not using a cut-off, we avoid some areas being arbitrarily ruled out from being other areas spatial TFP growth hubs, spokes, leaders, or followers.

Even though we use a W that is based on geographical distance to estimate Equation (1), a key feature of our subsequent spatial TFP growth decomposition is that it is clear about the theoretically founded economic phenomena that spill over between the areas. We focus on four measures of spatial TFP growth: namely, contemporaneous and dynamic asymmetric TFP growth spill-ins and spill-outs, where dynamic in this context refers to the cumulation of the spill-ins (spill-outs) over the first three future in-sample time periods in the empirical analysis. As we elaborate on in Section 2.2 (see the below discussion of Equations 4 and 5), we obtain the aforementioned four spatial TFP indices by summing the corresponding contemporaneous and dynamic spill-in and spill-out measures of the growth of three well-known theoretically founded economic phenomena—technical change, RTS and technical efficiency.

A feature of spatial econometrics is the feasible range of the contemporaneous SAR parameter. That is, $\delta \in (1/r_{\min}, 1/r_{\max})$, where $r_{\min}$ and $r_{\max}$ are the most negative and positive real characteristic roots of W, respectively. Following much of the spatial econometrics literature we use a normalized W. As we row-normalize the inverse distance matrix $r_{\max} = 1$. We find this works well, where this normalization means that the inverse distances from an area are relative to the areas location. Given there are big differences in accessibility between a number of the ITL 3 areas in our sample (e.g., there are a small number of areas in our sample that are islands), we suggest that this may well be how people in an area perceive distances to other areas.

[10]We find that when we drop the time-period effects from Equation (1) the estimate of the contemporaneous SAR parameter (δ) increases dramatically from the reported 0.23 (see Table 2) to an implausibly high value of 0.84, where both these estimates are significant at the 1% level. Hence our decision to include time-period effects.

[11]Whilst the focus in this paper is on introducing the first dynamic spatial stochastic frontier model of its type and the first dynamic spatial TFP growth decomposition, extending this spatial literature to account for further hierarchical regional characteristics that go beyond those which we consider here is an interesting area to explore in further work. See Appendix 1 for our thoughts on this.

[12]The spatial weights matrix is a general approach to account for cross-sectional spatial dependence. Our SFA using this matrix and that in other studies (see Section 1) represents one of the many diverse types of applications of this matrix in the regional science literature. A few examples of others include spatial interaction in origin-destination flow models (LeSage & Thomas-Agnan, 2015), investigation of the effect of commuting to cities on rural employment growth (Lavesson, 2017), and analysis of the effects of city-chief turnover on place-based policy changes in China (Shen et al., 2022).

Most studies of peer effects in social networks focus on only exogenous or endogenous peer effects (Lin, 2010). This is to circumvent the well-known "reflection problem" (Manski, 1993). That is, in the standard linear-in-means social interaction model, and without strong exclusion assumptions, it is not possible to separately identify the exogenous and endogenous peer effects. Relating this to the spatial econometrics literature, exogenous and endogenous peer effects in networks correspond to the spatial lag of X model (SLX) and SAR models, respectively (see Halleck Vega & Elhorst, 2015, on the SLX model, where this model includes spatial lags of the exogenous covariates). Bramoullé et al. (2009), however, show that under certain less restrictive conditions the exogenous and endogenous peer effects are separable. In the spatial literature this corresponds to the spatial Durbin model (Elhorst, 2010; LeSage & Pace, 2009), where this model includes the SAR variable and spatial lags of the exogenous covariates. One of these conditions is that there is only a partial overlap between networks, that is, some individuals will not be friends with at least one of her friends' friends. For the reasons we gave above we use a W that is based on the inverse distances between every pair of areas. However, there is no partial overlap between the areas neighborhood sets in our W which rules out the spatial Durbin model as it is not identified.

For the variables in $TL(x_{it}, t)$, we obtain time-varying static (dynamic) asymmetric spill-in and spill-out elasticities for individual areas. These indirect spillover elasticities are key to our approach to uncover whether an area represents a spatial TFP growth hub or spoke (leader or follower) (see Section 2.2 for details). To obtain these elasticities we use a dynamic SAR model. We do not augment this model with a spatially autocorrelated error term and its time lag as we follow a number of peer effects studies that use the SAR model (e.g., Calvó-Armengol et al., 2009; Horrace et al., 2022). This is because of the parallels between the peer effects literature and, first, our peer comparison analysis in the stochastic frontier model in the form of the distances of the areas from the common best practice frontier (i.e., the inefficiencies); and, second, our use of the fitted model postestimation: namely, the areas that represent spatial TFP growth hubs and spokes (leaders and followers) can be viewed as the top performing contemporaneous (dynamic) spatial peers.

The first step of the procedure to estimate the dynamic SAR stochastic frontier model involves fitting Equation (1). From this step we obtain the estimate of the time-invariant area-specific random effect η_i. As we discuss in more detail below, we then use the estimate of this effect in the second step to obtain the distribution-free estimate of the persistent (i.e., time-invariant) inefficiency of an area, $\hat{PI}_i$. We also in the second step decompose the estimate of the error ε_{it} in Equation (1) from the first step. That is, $\varepsilon_{it} = v_i + e_{it} + \theta_{it}$, where v_i is the time-invariant random error, e_{it} is the time-varying random error and θ_{it} represents the time-varying area-specific effect. We then in the second step use the estimate of θ_{it} to obtain the distribution-free estimate of the transient (i.e., time-varying) inefficiency of an area, $\hat{TI}_{it}$. Finally in the second step, we obtain the estimate of overall time-varying inefficiency, $\hat{OI}_{it} = \hat{PI}_i + \hat{TI}_{it}$.

In similar spirit to the estimation of the static spatial stochastic frontiers in Glass et al. (2013, 2014), for the first step estimation we use quasimaximum likelihood (QML).[13,14] This yields estimates of, among other things, the common intercept α, and the coefficients on the variables (e.g., ρ, the vector of parameters γ' and the parameters in the translog function). In similar spirit to our approach, Kutlu and Nair-Reichert (2019) and Glass et al. (2013, 2014) use the unit-specific effects from their static spatial models to obtain a single distribution-free measure of time-invariant or time-varying inefficiency. This involved applying the well-known inefficiency estimators for the nonspatial setting in Schmidt and Sickles (1984) and Cornwell et al. (1990). These approaches though assume that

[13]Using QML to estimate Equation (1) involves drawing on the bias-corrected estimator in Yu et al. (2008). This estimator is for when N and T are not small. This is in line with N in our empirical analysis (168), and although the simulations in Yu *et al*. indicate that increasing T improves the performance of their estimator, their simulations show that the bias-corrected estimator performs reasonably well for a sample where N = 196 and T = 10. This is the closest to our empirical sample, although we note that our T is larger (17 years).

[14]A standard feature of the estimation of Equation (1) is that one of the terms in the log-likelihood function is the scaled logged determinant of the Jacobian of the transformation of ε_{it} to y_{it}. This transformation accounts for the endogeneity of the contemporaneous SAR variable and also the fact that ε_{it} is not observed (Anselin, 1988, p. 63; Elhorst, 2009). Further, and as is also standard in spatial econometrics, we follow LeSage and Pace (2009) and obtain the standard errors for the parameters using the mixed analytical-numerical Hessian matrix.

there is no unobserved heterogeneity. That is, all the heterogeneity is assumed to be observed and captured by the regressors. We extend this type of method by also accounting for unobserved heterogeneity using v_i. Whereas our approach is in the spirit of that in Kutlu and Nair-Reichert (2019) and Glass et al. (2013, 2014), an alternative approach which we leave for further work would be more in line with that of Greene (2005a, 2005b). This would involve switching our approach around by accounting for unobserved heterogeneity using η_i and using v_i to estimate time-invariant inefficiency.

In the second step of the estimation, we extend the method in Glass et al. (2013, 2014) by using the value of the square brackets in Equation (2) as the estimator of an area's distribution-free measure of persistent inefficiency. That is, the time-invariant best practice frontier is set at the point of the largest random effect and the value of the square brackets in Equation (2) represents the estimate of an area's distance below this frontier. Following Battese and Coelli (1988), who demonstrate that moving from the log form of a stochastic frontier model to its multiplicative form transforms a technical inefficiency measure into its corresponding efficiency, we use Equation (2) to obtain the estimate of each area's persistent efficiency ($\hat{PE}_i$).

$$\hat{PE}_i = \exp[\eta_i - \max_i(\eta_i)]. \tag{2}$$

The estimate of the composed error ε_{it} from the first step is decomposed in the second step using $\varepsilon_{it} = \psi_i t + \phi_i t^2 + \kappa t + \xi t^2 + v_i + e_{it}$. That is, we obtain this decomposition by using the random parameters method to regress the estimate of ε_{it} on t and t^2. Hence, across the areas, ψ_i and ϕ_i are heterogeneous coefficients and κ and ξ are fixed homogeneous coefficients. $\theta_{it} = \psi_i t + \phi_i t^2 + \kappa t + \xi t^2$, wherein the estimate of an area's distribution-free measure of transient efficiency ($\hat{TE}_{it}$) in Equation (3), the value of $\kappa t + \xi t^2$ represents the homogeneous time-varying component across the areas, and the value of $\psi_i t + \phi_i t^2$ represents each area's heterogeneous time-varying component. Along the same lines as we obtain $\hat{PE}_i$, for each period we set the time-varying best practice frontier at the point of the largest value of θ_{it} across the N areas.

$$\hat{TE}_{it} = \exp[\theta_{it} - \max_i(\theta_{it})]. \tag{3}$$

The estimate of overall efficiency can then be obtained, $\hat{OE}_{it} = \hat{PE}_i \times \hat{TE}_{it}$.

In summary, we propose a four-component stochastic frontier model (PI_i, TI_{it}, v_i, and e_{it}). The approaches in Kutlu and Nair-Reichert (2019) and Glass et al. (2013, 2014) yield an estimate of a single (time-invariant or time-varying) distribution-free measure of efficiency. We extend these approaches to obtain estimates of three distribution-free efficiency measures, PE_i, TE_{it}, and OE_{it}. Moreover, and as we discuss in the empirical analysis, by using random effects in the first step estimation, cases can easily be made to support the efficiency rankings of many areas.

2.2 | Classifying areas as spatial TFP growth hubs, spokes, leaders, and followers

The coefficients on the z variables in Equation (1) are the mean own elasticities over the sample. The estimate of the translog function, $TL(x_{it}, t)$, also yields mean own elasticities as well as own elasticities for every area for each period, where the latter is due to the inclusion of the interaction and squared terms in the function. The coefficients on the SAR variable and its time lag in Equation (1) represent mean spillovers to an area when there is a marginal change in the spatially weighted dependent variables of the other areas in its first-order neighborhood set. These elasticities do not therefore capture any further higher-order spillovers to an area. To address this we compute further spatial elasticities from the literature, such as the direct (Dir) and indirect (Ind) elasticities. This involves indexing the time horizons in our sample $\lambda \in 0, \ldots, T-1$, where these spatial elasticities measure different types of contemporaneous and dynamic impacts on output (in horizon 0 and each of the remaining future in-sample horizons, respectively) when there is a marginal change in an area's independent variable in the current period. As in Debarsy et al. (2012), calculating these spatial elasticities involves taking partial derivatives of the reduced form of Equation (1).

Contemporaneous and dynamic direct elasticities measure the impacts of a change in an ith area's independent variable in period t on the same area's output in horizon 0 and in each future in-sample horizon ($\lambda \in 1, \ldots, T-1$), respectively. There are two types of contemporaneous indirect-elasticity that measures the asymmetric bidirectional spillover impacts of a change in an ith area's independent variable in period t: (a) the spill-out from the ith area to the outputs in horizon 0 of all, or a subset of, the other areas, where the subset may be just one other area; and (b) the spill-in to the output of the ith area in horizon 0 from all, or a subset of, the other areas. We also compute the two corresponding dynamic indirect elasticities. These indirect elasticities measure the impacts of a change in an ith area's independent variable in period t on the same outputs as those in (a) and (b) above but in each of the future in-sample time horizons.

Turning now to the presentation of how we use the indirect spill-out and spill-in elasticities to uncover the following. (i) The areas with high absolute and net TFP growth spill-outs in the current period and future in-sample horizons. These areas represent the top absolute and net spatial TFP growth hubs, and the top absolute and net spatial TFP growth leaders, respectively. (ii) The areas that are the recipients of the highest absolute and net TFP growth spill-ins in the current period and future in-sample horizons. These areas represent the top absolute and net spatial TFP growth spokes, and the top absolute and net spatial TFP growth followers, respectively.

For horizon λ we use the relevant indirect (spill-in and spill-out) parameters for each variable to specify two translog production functions for the associated outputs: namely, the indirect output spill-out from the ith area to at least one other area ($y^{Ind}_{Out,i,\lambda}$); and the indirect output spill-in to the ith area from at least one other area ($y^{Ind}_{In,i,\lambda}$). In contrast to the observed output variable in Equation (1), $y^{Ind}_{Out,i,\lambda}$, $y^{Ind}_{In,i,\lambda}$, and $y^{Dir}_{i,\lambda}$ are unobserved. This is not an issue as we do not need these variables for our analysis, but if they were of interest they could be computed from their translog functions. The form of the translog equation for $y^{Ind}_{Out,i,\lambda}$ is given in Equation (4). We do not, however, present the equations for $y^{Ind}_{In,i,\lambda}$ and $y^{Dir}_{i,\lambda}$ as they simply involve replacing the ${}^{Ind}_{Out,i,\lambda}$ notation in Equation (4) with ${}^{Ind}_{In,i,\lambda}$ and ${}^{Dir}_{i,\lambda}$, respectively. For the same reason, we only present how we compute the TFP growth spill-out from the ith area to at least one other area for each period that represents time horizon λ and which is denoted $\Delta TFP^{Ind}_{Out,it+1}$.

$$
\begin{aligned}
y^{Ind}_{Out,i,\lambda} = {} & \beta 1^{Ind}_{Out,i,\lambda} t + \tfrac{1}{2}\beta 2^{Ind}_{Out,i,\lambda} t^2 + \beta 3^{Ind'}_{Out,i,\lambda} x_{it} + \tfrac{1}{2} x'_{it} \Omega^{Ind}_{Out,i,\lambda} x_{it} + \beta 4^{Ind'}_{Out,i,\lambda} x_{it} t \\
& + \zeta^{Ind'}_{Out,i,\lambda} z_{it} + \tau^{Ind}_{Out,i,\lambda} + v^{Ind}_{Out,i,\lambda} - OI^{Ind}_{Out,i,\lambda} + e^{Ind}_{Out,i,\lambda}.
\end{aligned} \tag{4}
$$

For each period that represents horizon λ, we compute $\Delta TFP^{Ind}_{Out,it+1}$ by summing its three components in Equation (5). See Appendix 2 for details on how we compute these three components using Equation (4). For each period that represents horizon λ, the approach is the same to compute direct TFP growth for the ith area (ΔTFP^{Dir}_{it+1}) and the TFP growth spill-in to the ith area ($\Delta TFP^{Ind}_{In,it+1}$).

$$
\Delta TFP^{Ind}_{Out,it+1} = \Delta TC^{Ind}_{Out,it+1} + \Delta RTS^{Ind}_{Out,it+1} + \Delta OE^{Ind}_{Out,it+1}, \tag{5}
$$

where $\Delta TC^{Ind}_{Out,it+1}$, $\Delta RTS^{Ind}_{Out,it+1}$, and $\Delta OE^{Ind}_{Out,it+1}$ are the growth rates of technical change, RTS and overall efficiency that spill-out from the ith area, respectively. Importantly, note that, unlike Equation (1), the spatial weights do not feature in the translog functions for $y^{Ind}_{Out,i,\lambda}$ (see Equation 4) and $y^{Ind}_{In,i,\lambda}$. This is because the spatial weights form part of the calculation of, and are thus incorporated within, the indirect spill-in and spill-out coefficients and inefficiencies in these translog functions. As we obtain $\Delta TFP^{Ind}_{Out,it+1}$ and $\Delta TFP^{Ind}_{In,it+1}$ by calculating their three components from these translog functions, it follows that the spatial weights are incorporated within these components and, in turn, within the indirect spill-out and spill-in TFP growth measures. Hence, even though we use a W that is based on geographical distance to estimate Equation (1), the incorporation of the spatial weights within the terms that make up our bidirectional spatial TFP growth decompositions yields asymmetric spillovers of theoretically founded economic phenomena across space. These include the spill-in and spill-out of TFP growth, which are the focus our attention and are obtained by summing their components: namely, the spill-in and spill-out of three further theoretically founded economic phenomena, that is, the growth rates of technical change, RTS and technical efficiency.

For $\lambda = 0$, $\Delta TFP^{Ind}_{Out,it+1} > 0$ and $\Delta TFP^{Ind}_{Out,it+1} - \Delta TFP^{Ind}_{In,it+1} > 0$ indicates that an area has positive absolute and net TFP growth spill-outs, while, on the other hand, $\Delta TFP^{Ind}_{In,it+1} > 0$ and $\Delta TFP^{Ind}_{In,it+1} -$ indicates that an area has positive absolute and net TFP growth spill-ins. We define an area as being one of the top absolute (net) spatial TFP growth hubs if it is among the areas with the highest positive absolute (net) contemporaneous TFP growth spill-outs. We also use the absolute and net contemporaneous TFP growth spill-ins to indicate which areas are the top recipients of these spill-ins and thus represent the top absolute and net spatial TFP growth spokes.

An area that has positive absolute and net dynamic TFP growth spill-outs (or spill-ins) is one with positive absolute and net spill-outs (or spill-ins) across future in-sample time horizons up to and including the prespecified horizon λ^*, where $0 < \lambda^* \leq T - 1$. That is, $\sum_{\lambda=1}^{\lambda^*} \Delta TFP^{Ind}_{Out,it+1,\lambda} > 0$ (or $\sum_{\lambda=1}^{\lambda^*} \Delta TFP^{Ind}_{In,it+1,\lambda} > 0$), and $\sum_{\lambda=1}^{\lambda^*} [\Delta TFP^{Ind}_{Out,it+1,\lambda} - \Delta TFP^{Ind}_{In,it+1,\lambda}] > 0$ (or $\sum_{\lambda=1}^{\lambda^*} [\Delta TFP^{Ind}_{In,it+1,\lambda} - \Delta TFP^{Ind}_{Out,it+1,\lambda} > 0]$), respectively, where in the empirical analysis we use $\lambda^* = 3$. We define an area as being one of the absolute (net) spatial TFP growth leaders if it is among the areas with the highest positive absolute (net) dynamic TFP growth spill-outs in future in-sample horizons. We also use the absolute and net dynamic TFP growth spill-ins to uncover which areas are the top recipients of these spill-ins and thus represent the top absolute and net spatial TFP growth followers.

3 | EMPIRICAL ANALYSIS OF THE ITL 3 AREAS IN GREAT BRITAIN

3.1 | Data

The data set is a balanced panel of annual observations for the 168 ITL 3 areas in Great Britain for the period 2004-2020. The output measure, two inputs and the environmental (z) variables are provided in Table 1, together with the notation for the variables, data sources and summary statistics. Figure 1 presents a heat map of the mean output measure for the ITL 3 areas (gross value added [GVA] at 2019 prices) over the study period. Among other things, this figure highlights the marked geographical divide between the output levels of many ITL 3 areas in different parts of Great Britain, for example, the relatively low output in the most northern parts of Scotland versus the much higher output in a number of areas in the South of England.

We note the following about the data. (i) The estimation of the model was made possible by the release of ITL 3 data on gross fixed capital formation by the ONS in May/June 2022. Using this data we estimate the capital stocks of the areas using the unified approach to the perpetual inventory method in Berlemann and Wesselhöft (2014). To do so we use a depreciation rate of 1.5%, which is within the range considered by Berlemann and Wesselhöft and our results suggest this works well. (ii) Using the GVA deflator the monetary variables are at 2019 prices. (iii) In contrast to the two inputs which are level variables, the two human capital variables (*NVQ4plus* and *NoQualif*, where NVQ level 4 is equivalent to three A-Levels) are shares and so they are included as environmental variables. (iv) We considered four measures of the labor input, L: number employed aged 16+, number of jobs filled, hours worked, and number of economically active people aged 16+. Some regional studies that use the latter labor measure to estimate a production function or a model explaining labor productivity include Filippetti and Peyrache (2015) and Izushi (2008). We have a preference for the results using this labor measure because with the other three measures some of the results for the environmental variables become less plausible.

The continuous variables that are not shared are logged. K, L, t, and their squares and interactions are then mean adjusted. As a result of this mean adjustment, the coefficients on these first-order variables in Equation (1) and their direct and indirect parameters are elasticities at the sample mean. This is because when the data is mean

TABLE 1 Variable descriptions, data sources and summary statistics.

Variable descriptions	Notation	Data source	Mean	SD
Output measure				
Gross value added at 2019 prices (million pounds)	*GVA*	ONS	10, 233.87	9924.57
Input measures				
Capital stock at 2019 prices (million pounds)	*K*	ONS and authors calculation	42, 220.73	31, 776.07
Number of economically active people aged 16+	*L*	ONS-Nomis	185, 652.66	99, 502.99
Environmental (z) variables				
Subsidies on products at 2019 prices (million pounds)	*Subsidies*	ONS	53.59	58.98
Investment in ICT equipment and intangible assets as a share of investment in all assets	*ICT & Int*	ONS	23.15	11.07
Employment rate for people 16 − 64	*Employment*	ONS-Nomis	72.81	5.12
Economic activity rate for people 16 −64	*EconActivity*	ONS-Nomis	77.30	4.03
% Of those in some form of work whose main job is full-time (based on self-assessment)	*FullTime*	ONS-Nomis	73.18	3.64
% Of people 16 − 64 who have the National Vocational Qualification (NVQ) level 4 or above	*NVQ4plus*	ONS-Nomis	32.98	9.77
% Of people 16 − 64 with no academic or professional qualifications	*NoQualif*	ONS-Nomis	10.63	4.45

Note: We use the combined investment in ICT equipment and intangible assets as a share of investment in all assets as the two shares are not significant individually. We revisit this in the discussion of the results.

Abbreviations: GVA, gross value added; ICT, Information and Communication Technology; ONS, Office of National Statistics.

adjusted, the squared and interaction terms in the partial derivatives of a translog function are zero at the sample mean. The specification of W which we use is as previously described in Section 2.1.

3.2 | Spatial production frontier model and the technical efficiencies

The estimated coefficients of the dynamic SAR frontier model are presented in Table 2. We can see from this table that the significant impacts of the nonspatial environmental variables have the expected signs. For example, we find that subsidies have a significant positive impact, which is consistent with an increase in subsidies on products promoting consumption and production. With regard to the role of investment in ICT equipment and intangibles, we find that an increase in this investment as a share of total investment has a significant positive impact on real output. The coefficient on this variable, however, is small, which is consistent with both the omission of intangible assets from our output measure (e.g., Goodridge et al., 2013) and from 2008 the ebbing away of the ICT boom (Crafts & Mills, 2020). We include the combined ICT equipment and intangibles share as the two shares are not significant individually. This points to a complementarity between investment in ICT equipment and investment in

TABLE 2 Estimated dynamic spatial profuction frontier model.

	Model coeff		Model coeff		Model coeff
$WGVA_t$	0.232***	t	−0.067	*EconActivity*	−0.009***
$WGVA_{t-1}$	0.275***	t^2	0.005	*FullTime*	0.002***
L	0.498***	Lt	−0.003***	*NVQ4plus*	−0.0002
K	0.378***	Kt	0.003***	*NoQualif*	0.00001
L^2	−0.017	*Subsidies*	0.037***	2020*Dummy*	−0.110***
K^2	0.025	*ICT & Int*	0.0003*	*Constant*	0.299*
KL	−0.005	*Employment*	0.004***		

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

intangible assets, which has also recently been observed for US firms (Brynjolfsson et al., 2021).[15] The remaining nonspatial environmental variables are the time-period effects, a number of which were automatically dropped in the estimation due to collinearity. The only one that is significant and hence reported relates to 2020. As we would expect, this suggests that, on average, the COVID pandemic led to a negative, nonnegligible fall in an areas output. In Section 3.3 we compare this finding to the result we attribute to Brexit.

Turning to the results for some of the terms in the *TL* function. The estimated coefficients on K and L are elasticities at the sample mean. As expected these elasticities are positive and significant. The sum of these coefficients is below 1, which indicates decreasing RTS at the sample mean. We also suggest that these decreasing returns reflect the lower maximum attainable output levels for the areas due to the productivity slowdown over most of our study period. t is a proxy that is used to measure annual technical change, so typically we would expect its coefficient to be positive and significant. In contrast, we find that the coefficient on t is negative, although not significant. This is consistent with the labor productivity slowdown, slower innovation and technical diffusion (see Section 1), and the ebbing away of the ICT boom from 2008 onwards (Crafts & Mills, 2020).

The coefficients on the two spatial environmental variables ($WGVA_t$ and $WGVA_{t-1}$) indicate that there is positive, nonnegligible and significant contemporaneous and dynamic spatial dependence in the *GVA* data. Moreover, these nonnegligible spillovers are consistent with the ITL 3 data being on a relatively small spatial scale (Chung & Hewings, 2019). The reported coefficient on $WGVA_{t-1}$ is also consistent with our hypothesis that it can take some time for nonnegligible spillovers to occur. In summary, Table 2 points to two categories of variables: specifically, K, L, $WGVA_t$, $WGVA_{t-1}$, and the COVID dummy have nonnegligible impacts, whilst the coefficients on the other variables are relatively small.

Direct, indirect and total elasticities, where the latter is the sum of the direct and indirect impacts, account for higher-order neighbor spillovers and incorporate the effects of the spatial variables ($WGVA_t$ and $WGVA_{t-1}$). When there is a marginal change in an independent variable in a particular period, the contemporaneous and dynamic direct, indirect and total elasticities measure the output impacts in horizon 0 and future-in sample horizons, respectively. For brevity, for the two inputs and horizon 0 and the first 10 future in-sample horizons, Table 3 reports the cumulated direct, indirect and total elasticities at the sample mean. We calculate these elasticities and compute their standard errors by drawing 500 Halton sequences of parameters from the variance-covariance matrix. For reporting ease, for each parameter sequence we calculate mean contemporaneous and dynamic direct, indirect and total elasticities across all the areas and then average across the 500 estimates. In contrast to the asymmetric indirect elasticities we

[15]The impact of the *NVQ4plus* human capital variable has a counterintuitive negative sign, but importantly this impact is not significant. In light of this finding it would have been useful to consider the impacts of the individual qualifications that make up *NVQ4plus*, but such granular data is not available for ITL 3 areas.

TABLE 3 Cumulated direct, indirect, and total labor and capital elasticities for the sample average area.

	Labor (*L*)			Capital (*K*)		
Horizon, λ	Direct	Indirect	Total	Direct	Indirect	Total
	0.498***	0.158**	0.656***	0.379***	0.120**	0.498***
1	0.499***	0.391***	0.891***	0.380***	0.298***	0.678***
2	0.500***	0.483***	0.983***	0.380***	0.368***	0.748***
3	**0. 501*****	0.521***	1.022***	**0. 381*****	0.397***	0.778***
4	0.501***	0.538***	1.039***	0.381***	0.410***	0.790***
5	0.501***	0.546***	1.046***	0.381***	0.416***	0.796***
6	0.501***	0.549***	1.050***	0.381***	0.418***	0.799***
7	0.501***	0.551***	1.052***	0.381***	0.420***	0.801***
8	0.501***	0.552***	1.053***	0.381***	**0. 421*****	0.801***
9	0.501***	0.552***	1.053***	0.381***	0.421***	**0. 802*****
10	0.501***	**0. 553*****	**1. 054*****	0.381***	0.421***	0.802***

Note: The magnitudes of the significant cumulative elasticities (to 3 dp) that persist through to horizon 16 are in bold.
** and *** denote statistical significance at the 5% and 1% levels, respectively.

use in Section 3.3, by averaging across all the areas the mean indirect spill-in and spill-out elasticities are symmetric. On the basis of Table 3, for the sample average area the (cumulated) direct, indirect and total input elasticities for the contemporaneous period (and all 16 future in-sample horizons) are positive and significant. That is, when there is a permanent marginal change in an input in the contemporaneous period, there are (cumulative) direct, indirect and total output effects in the same period (and future in-sample horizons), that is, there is evidence of persistence in the cumulated direct, indirect and total input elasticities over time.

Table 4 provides insights into our technical efficiency results by reporting the persistent efficiencies and average transient and overall efficiencies for the sample and the top 10- and lowest 10-ranked areas. To appreciate whereabouts in Great Britain these ITL 3 areas are, the ITL 1 regions they are located within are in parentheses in Table 4. The complete set of estimates of these three efficiency measures for the 168 areas are available from the corresponding author upon request. By definition the same area lies on the persistent frontier over the study period (City of Edinburgh), whereas we find that the same area does not lie on the annual transient frontiers. The latter is evident as the highest mean transient efficiency is less than 1 (Kensington & Chelsea and Hammersmith & Fulham). Before offering support for our efficiency rankings via explanations of the results for a number of the areas in Table 4, we briefly discuss the efficiency results for the sample.

Consistent with low labor productivity, the sample average time-varying overall efficiency is noticeably low (0.478). A feature of our approach is that the distribution-free overall efficiency is the product of the distribution-free persistent and transient efficiencies. We can see from Table 4 that the aforementioned overall efficiency is being pulled down by the low sample average persistent efficiency (0.545). We can also see from Table 4 that there is a marked gap between the persistent efficiencies of the top- and lowest-ranked areas, which is consistent with the marked persistent regional disparities in economic performance in Britain (McCann, 2016, 2020). Given the time-invariant nature of these results, the areas with low persistent efficiencies are in what can described as an "efficiency trap."[16] Whilst it would be challenging for any of these areas to escape this trap, we shortly describe

[16]This efficiency trap can be interpreted as a specific type of regional economic performance trap that has featured in the recent literature. On this, see Diemer et al. (2022) for the definition and measurement of a European region that is in a development trap.

TABLE 4 Selected efficiencies.

Area	Persistent efficiency	Area	Transient efficiency	Area	Overall efficiency
Top 10-ranked areas					
City of Edinburgh (Scotland)	1.000	Kensington[b] (London)	0.953	City of Edinburgh (Scotland)	0.862
Glasgow City (Scotland)	0.816	Aberdeen City[c] (Scotland)	0.947	Glasgow City (Scotland)	0.705
Leeds (YH, England)	0.783	Central Valleys (Wales)	0.918	Manchester (NW, England)	0.696
Manchester (NW, England)	0.783	Hounslow[a] (London)	0.917	Leeds (YH, England)	0.689
Cheshire East (NW, England)	0.767	Lambeth (London)	0.917	Cheshire East (NW, England)	0.682
Milton Keynes (SE, England)	0.752	Haringey & Islington (London)	0.916	Milton Keynes (SE, England)	0.682
West Surrey (SE, England)	0.741	Wandsworth (London)	0.913	Hounslow[a] (London)	0.662
Mid Lancashire (NW, England)	0.738	West Cumbria (NW England)	0.911	West Surrey (SE, England)	0.655
Hounslow[a] (London)	0.722	Blackburn[d] (NW, England)	0.911	Aberdeen City[cc] (Scotland)	0.645
West Kent (SE, England)	0.707	Berkshire (SE, England)	0.910	Kensington[b] (London)	0.642
Lowest 10-ranked areas					
Hackney & Newham (London)	0.410	Sandwell (WM, England)	0.845	Powys (Wales)	0.358
Powys (Wales)	0.409	Bromley (London)	0.845	Hackney & Newham (London)	0.345
Thurrock (East, England)	0.398	Brent (London)	0.844	East Lothian[e] (Scotland)	0.344
Torbay (SW, England)	0.398	Hackney & Newham (London)	0.842	Torbay (SW, England)	0.337
East Lothian[e] (Scotland)	0.387	Wolverhampton (WM, England)	0.840	Thurrock (East, England)	0.334
Na h-Eileanan Siar (Scotland)	0.368	Harrow & Hillingdon (London)	0.840	Na h-Eileanan Siar (Scotland)	0.333

TABLE 4 (Continued)

Area	Persistent efficiency	Area	Transient efficiency	Area	Overall efficiency
Isle of Anglesey (Wales)	0.366	Thurrock (East, England)	0.839	Wandsworth (London)	0.321
Essex Haven[f] (East, England)	0.359	Croydon (London)	0.837	Essex Haven (East, England)	0.314
Wandsworth (London)	0.352	Isle of Anglesey (Wales)	0.837	Isle of Anglesey (Wales)	0.306
Orkney Islands (Scotland)	0.318	Derby (EM, England)	0.818	Orkney Islands (Scotland)	0.284
Sample average	0.545	Sample average	0.876	Sample average	0.478

Notes: Full names of the areas labeled $a - f$a–f are [a][a]Hounslow & Richmond upon Thames; [b]Kensington & Chelsea and Hammersmith & Fulham; [c]Aberdeen City & Aberdeenshire; [d][d]Blackburn with Darwen; [e][e]East Lothian & Midlothian; [f][f]Essex Haven Gateway.

Abbreviations: EM, East Midlands; NW, North West; SE, South East; WM, West Midlands; YH, Yorkshire & the Humber.

how our results could be used to provide a focused steer of a process to devise more effective policies to raise the persistent efficiencies of the lowest-ranked areas. More encouragingly, and vis-à-vis the persistent efficiency results, the sample average transient efficiency is much higher (0.876) and the gap between the average transient efficiencies of the top and lowest-ranked areas is much smaller.

Although the persistent efficiencies are time-invariant and hence apply to each year in the sample, they are specific to our study period. Hence as the study period changes, the persistent efficiencies can change. Over time, therefore, there is potential to increase the persistent efficiencies of the lowest-ranked areas. We suggest how our results can support this by providing a focused steer of a process to devise more effective policies to raise the persistent efficiencies of these areas. From the areas with comparable but higher transient efficiencies than the lowest-ranked areas, this steering would involve selecting those peer areas with the highest persistent efficiencies. We illustrate this for Thurrock, which is in the bottom 10 of the transient and persistent efficiency rankings.

There are 29 areas with mean transient efficiencies that are no more than one standard deviation higher than Thurrock's (0.839). Of these, 28 have persistent efficiencies higher than Thurrock (0.398). From this pool of 28 we suggest a two-step procedure to select a manageable number of areas for closer analysis. In the quantitative first step a reasonable cut-off is used to select the group of areas with the highest persistent efficiencies, for example, there are nine areas in this pool with persistent efficiencies that are more than one standard deviation higher than Thurrock's. From these areas, the qualitative second step selects a manageable number for closer analysis that shares similar characteristics to Thurrock and can thus be regarded as peers. On the basis of proximity to Thurrock, we suggest that this peer group would consist of just two other areas: namely, West Essex and Kent Thames Gateway, as all three areas border Outer London. This two-step procedure can be useful to policymakers as it can provide an initial focused steer of a process to devise more effective policies to promote regional leveling-up by uncovering a manageable number of better-performing peer areas for case studies. The learnings from the case studies can then be used to settle on specific policies that represent a more effective way of improving the persistent efficiencies of the lowest-ranked areas.

In Section 3.3 we use our fitted model to obtain contemporaneous and dynamic asymmetric TFP growth spill-ins and spill-outs. We then use these spill-ins and spill-outs to uncover the areas that represent the absolute and net spatial TFP growth hubs, spokes, leaders and followers. We first therefore provide support for our fitted model. We do so by giving intuitive explanations of a number of the reported high and low overall efficiency rankings.

Our explanations of the high overall efficiency rankings of a number of areas in Table 4 are as follows. First, finding that the City of Edinburgh and Glasgow City are at the top of the persistent efficiency rankings is consistent with the agglomeration economies in major cities. These rankings are also in line with Scotland's labor productivity growth in the period between the financial crisis and the COVID pandemic being higher than many other ITL 1 regions (see Figure 1). As we may expect, this suggests that major cities can play a key role in more aggregate regional economic performance. Typically, the UK leveling-up literature concludes that key governance and institutional changes in the shape of various further devolution would aid regional leveling-up (e.g., Fransham et al., 2023; McCann, 2023; McCann & Yuan, 2022). On the basis of this, a contributing factor to the high overall efficiency rankings of the City of Edinburgh and Glasgow City may well be the productivity-enhancing effects of Scotland's devolution in 1999. Second, Leeds (Yorkshire & The Humber, England) and Manchester (North West England) have high persistent efficiency rankings, which is in line with the agglomeration economies in both cities. These rankings are also consistent with the key roles of these cities in the Northern Powerhouse initiative to promote wider economic growth across the North of England. Third, in parts of Cheshire East (North West England) living standards are particularly high (e.g., Knutsford and Wilmslow) when compared with the wider corresponding ITL 2 and ITL 1 regions; whilst long-standing features of Milton Keynes (South East England) are its relatively high economic growth and population growth. Fourth, there are a number of particularly affluent parts of West Surrey (South East England) and the two London areas with high overall efficiency rankings (Kensington & Chelsea and Hammersmith & Fulham; and Hounslow & Richmond upon Thames). A further factor that will contribute to the high overall efficiency ranking of Kensington & Chelsea and Hammersmith & Fulham is that many people will commute into this area as it is located within Inner London. Fifth and finally on the overall performance results, eight of the top 10-ranked areas for overall efficiency are in the top 10 of the persistent efficiency rankings, while the other two areas (Kensington & Chelsea and Hammersmith & Fulham; and Aberdeen City & Aberdeenshire [Scotland]) are at the top of the transient efficiency rankings, which we now go on to suggest is due to particular transient economic features of these areas.

On these transient economic features, the origins of the 2008 crisis were in the banking sector and, as a result, there was a marked relative fall in labor productivity measures for London compared to other ITL 1 regions. Additionally, since the crisis there has been a slight decline in the gap between output per hour for London and the rest of the UK, as London has seen a disproportionate rise in working hours in less productive sectors (Van Ark, 2021). Despite these two factors, the labor productivity measures for London in levels (as opposed to the growth rates in Figure 1) have remained well above those of other ITL 1 regions. This is consistent with Kensington & Chelsea and Hammersmith & Fulham and a number of other London areas having high relative transient efficiency rankings (Hounslow & Richmond upon Thames; Lambeth; Haringey & Islington; and Wandsworth). We again suggest that a contributing factor to the high transient efficiency rankings of these areas of London is the large number of people that commute into these areas, as all but one of these areas is in Inner London.

The substantial contribution of North Sea oil to the local economy of Aberdeen City & Aberdeenshire is likely to be a key reason for the area's high transient efficiency. The effect of the industry may be mainly on the area's transient efficiency as the contribution of the industry to the local economy will vary over time as the industry's economic performance is closely linked to the price of crude oil. The high transient efficiency of Aberdeen City & Aberdeenshire is also in line with Scotland's labor productivity growth in the period between the financial crisis and the COVID pandemic being higher than many other ITL 1 regions, which, as we have previously noted, is consistent with the medium-to-longer term productivity-enhancing effects of Scottish devolution in 1999.

Along similar lines to the above role of North Sea oil, we suggest that the high transient efficiency of West Cumbria in Table 4 is due to the economic contributions of the Sellafield nuclear site and the associated Low-Level Waste Repository (Oxford Economics, 2022). In contrast, and consistent with West Cumbria's labor productivity lagging behind that of the ITL 1 region it is located in (North West England) and also national labor productivity (Oxford Economics, 2022), we find that West Cumbria has a relatively low persistent efficiency score (0.474) and ranking (130). Moreover, despite living standards in the Central Valleys (Wales) being lower than many other NUTS 3 areas in Wales (Welsh Government, 2019, p. 11), the high transient efficiency of the Central Valleys is consistent with its relatively high GVA per hour worked (Welsh Government, 2019, p. 8).[17]

We offer the following explanations for the low overall efficiency rankings of a number of areas in Table 4. First, as Anglesey (Wales), Na h-Eileanan Siar (Outer Hebrides, Scotland) and Orkney (Scotland) are islands, to different degrees, this substantially reduces accessibility which is associated with lower economic performance. Second, although Powys (Wales) is on the mainland, it covers a large geographical area that is largely mountainous which reduces accessibility, agglomeration and thus economic performance. Third, for Anglesey, Na h-Eileanan Siar, Orkney, Powys, and Torbay (South West England), tourism is an important income stream, but its seasonality, dependence on the weather and greater competition from other tourist destinations may all contribute to the low overall efficiencies of these areas. Fourth, given the City of Edinburgh is at the top of our overall efficiency ranking, the widely observed inequality between some areas that are relatively near to a major city is a possible explanation for the low overall efficiency ranking of East Lothian & Midlothian. Fifth, compared to other areas in the East of England, for Essex Haven Gateway and Thurrock labor productivity (and/or its growth) is relatively high (Productivity Institute, 2021). This is consistent with these areas benefiting from regeneration to raise observed

[17]The economic context of the Welsh Valleys provided by the Welsh Government (2019) notes that the high GVA per hour worked in the Central Valleys "probably partly reflects industrial composition" (p. 8). In particular, GVA is not adjusted for capital consumption or the return on capital, which tends to be higher in the production sector which is disproportionately represented in the Welsh Valleys. This may also be a factor that contributes to the high transient efficiency of the industrialized Blackburn with Darwen area (in East Lancashire, North West England).

output and labor productivity. Labor productivity, however, does not account for the difference between observed output and unobserved maximum potential output, that is, unobserved inefficiency. Our findings for these two areas highlight the difference between using labor productivity and efficiency as measures of economic performance. This is because, whilst there has been the regeneration of these areas to boost labor productivity, our overall efficiency results suggest that both areas could use their inputs to produce substantially more output.[18]

The persistent disparities in regional economic performance in the UK have created a considerable policy challenge known as the "regional innovation paradox." This paradox refers to the inability of underperforming regions to effectively utilize government innovation and entrepreneurship programmes as the regions lack the capabilities to absorb the investments (Van Ark, 2021). With regard to the regeneration projects in Essex Haven Gateway and Thurrock, the labor productivity (and/or its growth) for these areas suggests that these projects are not an example of this paradox. In contrast, our persistent and overall efficiencies for these areas suggest that these projects are consistent with the paradox.

3.3 | Areas that represent spatial TFP growth hubs, spokes, leaders and followers

Before turning to the results for the hubs, spokes, leaders and followers, we first consider the decomposition in Figure 2 of average contemporaneous direct TFP growth across all the areas. As the own coefficient on each nonspatial variable in Table 2 is essentially the same as the contemporaneous direct parameter, there is very little spatial feedback in the latter. Figure 2 is therefore essentially its own TFP growth decomposition. Of the three components of own TFP growth (growth rates of own technical change, RTS and overall efficiency), it is clear from Figure 2 that changes in overall efficiency are driving TFP growth. We can also see from Figure 2 that the evolution of the annual change in own overall efficiency is consistent with the headline characteristics of Britain's productivity slowdown. That is, we find that once the effect of the 2008 crisis took hold, the annual change in own overall efficiency falls sharply, going from positive to negative. Although in subsequent years we find that the changes in this efficiency measure tended to rise, these changes remained negative. We, therefore, suggest that the slowdown of Britain's TFP growth can be more specifically described as a slowdown in the growth of technical efficiency. Additionally, whereas we found that the COVID pandemic led to a nonnegligible fall on average output, Figure 2 suggests that once the impact of the Brexit referendum started to take effect, the negative impact on output was in the form of a downward shift on average overall efficiency (Figure 3).

Figure 4 presents bivariate heat maps of the averages over the study period of each area's absolute TFP growth spill-ins and spill-outs from and to all the other areas. These heat maps group the areas of TFP growth spill-ins and spill-outs into the top, middle, and bottom thirds of the sample. Further in this subsection for the areas with TFP growth spill-ins and spill-outs that are among the largest in the sample, we report the actual magnitudes of these asymmetric bidirectional flows. Parallels can be drawn between our analysis of the flows of TFP growth spill-ins and spill-outs and the analysis by Carrascal-Incera and Hewings (2023) of income formation flows and flows of goods and services between regions in the UK. Given we use ITL 3 data due to the case we made earlier in the paper for data at this smaller spatial scale, this effectively rules our following Carrascal-Incera and Hewings (2023) or the analysis of the shares and positions of regions in global value chains in Bolea et al. (2022). This is because their analyses rely on specific data from a bespoke calibrated model or specialist database, both of which are not at the ITL 3 level. In the latter study, the shares measure the different levels of participation of regions in global value

[18]Whilst it is clear that one of the likely reasons why Hackney & Newham has low rankings for the three efficiency measures is the inequality across areas of London, the findings for Wandsworth (London) are very different, that is, whilst its rankings for the persistent and overall efficiencies are low, it has a high transient efficiency ranking. We cautiously suggest that Wandworth's high transient efficiency ranking may be because a large number of young professionals choose to live there; while this area's low persistent and overall efficiency rankings may be associated with its high population mobility, as many of these young professionals pay high rent and in the next stage of their careers move out of the area to become homeowners.

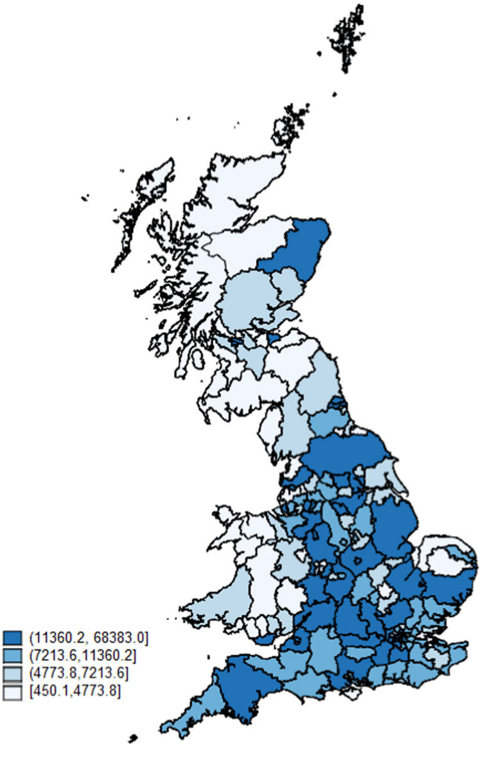

FIGURE 2 Mean annual real gross value added of the ITL 3 areas in Great Britain (2004–2020). ITL, International Territorial Level. [Color figure can be viewed at wileyonlinelibrary.com]

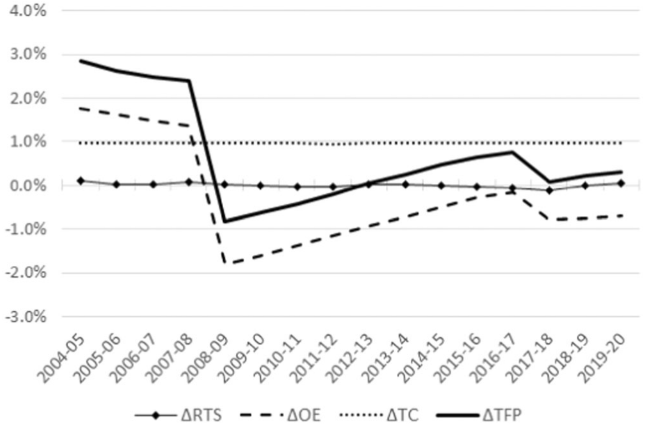

FIGURE 3 Decomposition of contemporaneous direct-own TFP growth. ITL, International Territorial Level; OE, overall efficiency; TC, technical change; TFP, total factor productivity.

chains and position refers to how far upstream a region's production is in these chains. That is, if a region's production is primarily upstream in these chains, its production will be more focused on intermediate inputs and less on final goods. To illustrate the difference between their datasets and our ITL 3 data for 2004 – 2020, the data which Carrascal-Incera and Hewings (2023) use are from the social-economic impact model of the UK developed at City-REDI, University of Birmingham. This model is a multiregional input–output model and the data is for a single

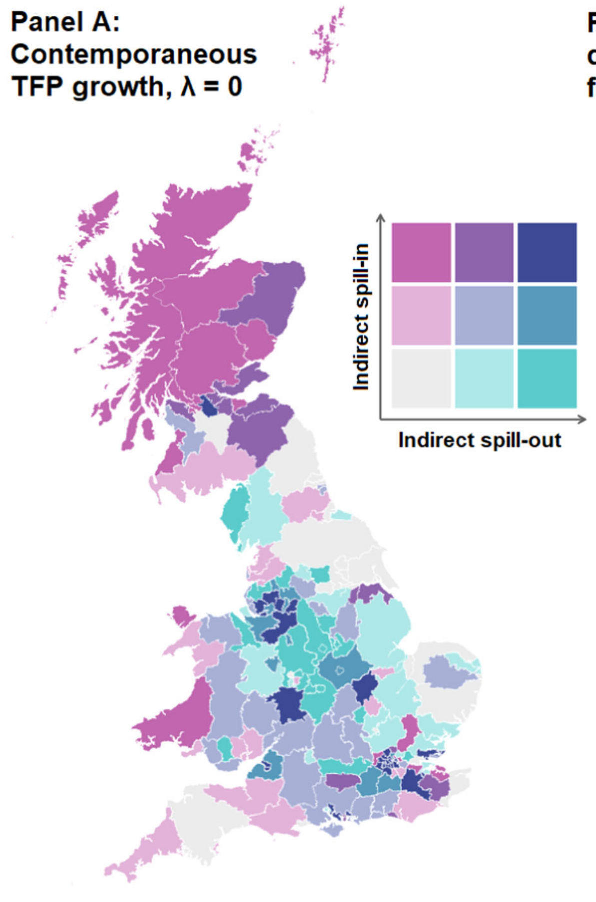

FIGURE 4 Contemporaneous and dynamic absolute TFP growth spill-ins and spill-outs. TFP, total factor productivity. [Color figure can be viewed at wileyonlinelibrary.com]

year as the model is calibrated for 2016. In Bolea et al. (2022) their data are for the most recent year (2010) of the EUREGIO input–output database for the EU NUTS 2 regions. Nevertheless, and whilst our analysis of economic spillovers is based on the well-established use of TFP as a single all-encompassing measure of economic performance, we draw inspiration from the interest of both above studies in a number of other spatial economic relationships. Further in this subsection, therefore, we use correlations to provide a tentative descriptive look at the associations between the flows of TFP growth spill-ins and spill-outs and the real GVA of the areas (see also Figure 2), real GVA of 10 sectors in the areas, and distance traveled to work.

We make three remarks about Figure 4, where to appreciate in which parts of Britain the ITL 3 areas we refer to are located, their ITL 1 regions are again provided in parentheses. First, as we may expect, a number of the dark blue areas with absolute TFP growth spill-ins and spill-outs in the top thirds of the sample are located within (or border) major cities. Examples include a number of areas in Inner and Outer London, the City of Bristol (South West England), West Kent (South East England), and three areas that border Manchester (North West England). Second, we find that there are some dark blue areas that are not especially near major cities, for example, North Northamptonshire (East Midlands, England), West Northamptonshire (East Midlands, England), Telford & Wrekin (West Midlands, England), and Blackburn with Darwen (North West England). Given these areas are not especially near major cities, this demonstrates that our approach can uncover some less obvious and interesting cases for further qualitative work on the characteristics of areas with relatively large TFP growth spill-ins and spill-outs.

A better understanding of these characteristics can be used to help increase the TFP growth spill-ins to areas with relatively low direct-own TFP growth (see Section 3.4 for more on this). Third, although there are many areas in panels A and B where the contemporaneous absolute TFP growth spill-ins and spill-outs correspond with the cumulated dynamic results (i.e., the color of an area in panels A and B is the same), there are no shortage of exceptions. Notable exceptions include many areas in Scotland with contemporaneous absolute TFP growth spill-ins that are among the top third of the sample, while the same areas have cumulated dynamic absolute TFP growth spill-ins that are in the bottom third of the distribution.

Next, we summarize the correlations between the annual (net and absolute) contemporaneous and dynamic TFP growth spill-outs and spill-ins for an area (from and to all the other areas) and (i) annual real ITL 3 GVA; (ii) annual real GVA for 10 ITL 3 sectors, as per ONS and Nomis; and (iii) number of people that reside in an ITL 3 area that commute up to 10 km to work, more than 10 km, or who mainly work from home or offshore.[19] For the full set of correlations see Table A1 in Appendix 3.[20] We highlight three salient features of these correlations. First, there are some nonnegligible positive correlations between ITL 3 GVA and the contemporaneous and dynamic absolute and net TFP growth spill-outs. As we would expect, this suggests there is some evidence that areas with higher output are associated with higher TFP growth spill-outs. These correlations (33.8% – 37.1%), however, are low enough to suggest that there may be some areas with relatively low output that are associated with relatively high TFP growth spill-outs. This may point to some generality in the use of TFP growth spill-outs to try and improve the UK's productivity situation, as some ITL 3 areas in different parts of the GVA distribution could be sources of relatively high spill-outs. Second, we report some nonnegligible positive correlations between the GVA of some ITL 3 sectors (transport and communication; banking, finance & insurance; other services; total services) and the contemporaneous and dynamic absolute and net TFP growth spill-outs. This is intuitive as there is high human capital within services (e.g., Bolea et al., 2022). Third, the positive correlation between the contemporaneous (dynamic) net TFP growth spill-out and the number of people who worked from home in 2011 is notably lower than the corresponding correlation with home working in 2021. Again this is intuitive because, as a consequence of COVID, more people who are sources of positive net TFP growth spill-outs will have spent more time working from home in 2021.

Table 5 presents the 10 areas with the highest mean values of various measures of the TFP growth spill-ins and spill-outs from and to all the other areas. These spill-ins and spill-outs differ according to whether they are contemporaneous or cumulated dynamic measures, and absolute or net measures. We define an area as a spatial TFP growth hub (leader) if its net and/or absolute contemporaneous (cumulated dynamic) TFP growth spill-out is one of the highest in the sample. If an areas net and/or absolute contemporaneous (cumulated dynamic) TFP growth spill-in is one of the highest in the sample, we conclude that the area is a spatial TFP growth spoke (follower). To add some context to the reported TFP growth spill-ins and spill-outs, in parentheses in Table 5 we report the ITL 1 region where an area is located, the mean real GVA of the area over the sample, and the rank of this mean value.[21]

For the various measures of the TFP growth spill-ins and spill-outs in Table 5, a number of the top 10 areas are intuitive. To illustrate, many of the top spatial TFP growth hubs and leaders are areas in Inner London. Of these areas, we report some particularly large TFP growth spill-outs from Tower Hamlets. To put these spill-outs in context, we note that the mean contemporaneous annual direct-own TFP growth for the sample is 0.69%. Such

[19]For (iii) we report two sets of correlations, as we use ONS data on the people counts for the commuting distances from the two most recent Census surveys (2011 and 2021). We use the latter because, even though its for the year that follows the end of our sample, to some degree, the correlations appear to pick up the increase in working from home due to the COVID pandemic (see below for further discussion). As the data on the people counts for the commuting distances is at a smaller spatial scale than we need (i.e., local authority districts), we aggregated up to ITL 3 counts.

[20]Note that we only report the correlations with the net TFP growth spill-outs as they are the same as those with the corresponding net spill-ins.

[21]Due to space constraints in Table 5 some area names were shortened. The full names of these areas are Kensington & Chelsea and Hammersmith & Fulham; North & North East Lincolnshire (Yorkshire & The Humber); Inverclyde, East Renfrewshire & Renfrewshire; Cornwall & Isles of Scilly; Hounslow & Richmond upon Thames; and Blackburn with Darwen.

TABLE 5 Top spatial TFP growth hubs, spokes, leaders, and followers.

Mean absolute spatial TFP growthhubs: Top 10	Mean absolute contemporaneous (λ = 0) annual TFP growth spill-out (%)	Mean absolute spatial TFP growth spokes: Top 10	Mean absolute contemporaneous (λ = 0) annual TFP growth spill-in (%)
Tower Hamlets (London −£24670.7m,[6])	0.85	Tower Hamlets (London −£24670.7m,[6])	0.39
Kensington & Chelsea (London −£13334.6m,[30])	0.77	North Lanarkshire (Scotland −£5964.7m,[107])	0.36
Lambeth (London −£9067.0m,[59])	0.55	Inverclyde (Scotland −5669.1m,[111])	0.36
Wandsworth (London −£6002.7m,[106])	0.52	Brent (London −£7206.9m,[85])	0.35
Haringey & Islington (London −£14071.1m,[26])	0.51	Worcestershire (West Midlands, England −£11646.5m,[40])	0.35
Lewisham & Southwark (London −£16061.7m,[17])	0.42	Essex Thames Gateway (East, England −£7111.9m,[88])	0.34
Hounslow (London −£15906.6m,[19])	0.40	Barnet (London −£7758.3m,[81])	0.32
Westminster (London −£48148.1m,[2])	0.39	N & NE Lincolnshire (Yorkshire, England −£7053.9 m,[89])	0.32
Camden & City of London (London −£68383.0m,[1])	0.35	Derby (East Midlands, England −£7757.3 m,[82])	0.31
Blackburn (North West, England −£2517.6m,[155])	0.28	West Essex (East, England −£8042.6 m,[74])	0.30
Mean absolute spatial TFP growth leaders: Top 10	Mean absolute cumulated dynamic (λ = 1-3) annual TFP growth spill-out (%)	Mean absolute spatial TFP growth followers: Top 10	Mean absolute cumulated dynamic (λ = 1-3) annual TFP growth spill-in (%)
Tower Hamlets (London −£24670.7m,[6])	6.14	Tower Hamlets (London −£24670.7m,[6])	2.31
Kensington & Chelsea (London −£13334.6m,[30])	2.81	North Lanarkshire (Scotland −£5964.7m,[107])	1.91
Brent (London −£7206.9m,[85])	2.01	Worcestershire (West Midlands, England −£11646.5m,[40])	1.87
Lambeth (London −£9067.0m,[59])	1.96	Inverclyde (Scotland −5669.1m,[111])	1.85

TABLE 5 (Continued)

Mean absolute spatial TFP growthhubs: Top 10	Mean absolute contemporaneous (λ = 0) annual TFP growth spill-out (%)	Mean absolute spatial TFP growth spokes: Top 10	Mean absolute contemporaneous (λ = 0) annual TFP growth spill-in (%)
Haringey & Islington (London −£14071.1m,[26])	1.87	Essex Thames Gateway (East, England −£7111.9m,[88])	1.77
Wandsworth (London −£6002.7m,[106])	1.83	Brent (London −£7206.9m,[85])	1.73
Lewisham & Southwark (London −£16061.7m,[17])	1.53	N & NE Lincolnshire (Yorkshire, England −£7053.9m,[89])	1.45
Essex Thames Gateway (East, England −£7111.9m,[88])	1.49	Barnet (London −£7758.3m,[81])	1.41
Westminster (London −£48148.1m,[2])	1.46	West Essex (East, England −£8042.6m,[74])	1.32
Hounslow (London −£15906.6m,[19])	1.45	Derby (East Midlands, England −£7757.3m,[82])	1.27
Mean net spatial TFP growth hubs: Top 10	Mean net contemporaneous (λ = 0) annual TFP growth spill-out (%)	Mean net spatial TFP growth spokes: Top 10	Mean net contemporaneous (λ = 0) annual TFP growth spill-in (%)
Kensington & Chelsea (London −£13334.6m,[30])	0.48	Isle of Anglesey (Wales −£1129.7m,[165])	0.44
Tower Hamlets (London −£24670.7m,[6])	0.46	Derby (East Midlands, England −£7757.3m,[82])	0.43
Lambeth (London −£9067.0m,[59])	0.26	Shetland Islands (Scotland −£679.7m,[166])	0.40
Haringey & Islington (London −£14071.1m,[26])	0.23	Orkney Islands (Scotland −£611.9m,[167])	0.38
Wandsworth (London −£6002.7m,[106])	0.22	Na h-Eileanan Siar (Scotland −£450.1m,[168])	0.37
Lewisham & Southwark (London −£16061.7m,[17])	0.13	Croydon (London −£9016.2m,[61])	0.37
Hounslow (London −£15906.6m,[19])	0.12	Torbay (South West, England −£2315.9m,[160])	0.37
Westminster (London −£48148.1m,[2])	0.09	Thurrock (East, England −£3758.0m,[145])	0.37
Camden & City of London (London −£68383.0m,[1])	0.05	Cornwall (South West, England −£9356.0m,[55])	0.37

(Continues)

TABLE 5 (Continued)

Mean absolute spatial TFP growthhubs: Top 10	**Mean absolute contemporaneous (λ = 0) annual TFP growth spill-out (%)**	**Mean absolute spatial TFP growth spokes: Top 10**	**Mean absolute contemporaneous (λ = 0) annual TFP growth spill-in (%)**
Blackburn (North West, England −£2517.6m,[155])	0.01	Plymouth (South West, England −£5070.5m,[121])	0.37
Mean net spatial TFP growth leaders: Top 10	Mean net cumulated dynamic (λ = 1-3) annual TFP growth spill-out (%)	Mean net spatial TFP growth followers: Top 10	Mean net cumulated dynamic (λ = 1-3) annual TFP growth spill-in (%)
Tower Hamlets (London −£24670.7m,[6])	3.83	Isle of Anglesey (Wales −£1129.7m,[165])	1.59
Kensington & Chelsea (London −£13334.6m,[30])	1.79	Shetland Islands (Scotland −£679.7 m,[166])	1.49
Lambeth (London −£9067.0m,[59])	0.97	Orkney Islands (Scotland −£611.9m,[167])	1.46
Haringey & Islington (London −£14071.1m,[26])	0.88	Derby (East Midlands, England −£7757.3m,[82])	1.45
Wandsworth (London −£6002.7m,[106])	0.83	Na h-Eileanan Siar (Scotland −£450.1m,[168])	1.44
Lewisham & Southwark (London −£16061.7m,[17])	0.52	South West Wales (Wales −£6499.3m,[94])	1.40
Hounslow (London −£15906.6m,[19])	0.44	Torbay (South West, England −£2315.9m,[160])	1.37
Westminster (London −£48148.1m,[2])	0.42	Cornwall (South West, England −£9356.0m,[55])	1.37
Brent (London −£7206.9m,[85])	0.28	Inverclyde (Scotland −£5669.1m,[111])	1.32
Camden & City of London (London −£68383.0m,[1])	0.28	Croydon (London −£9016.2m,[61])	1.32

Abbreviation: TFP, total factor productivity.

large spill-outs are consistent with London's financial center (Canary Wharf) being a district within Tower Hamlets and global financial districts being sources of economic growth in surrounding areas (e.g., Martin & Minns, 1995).

Whilst this role of Tower Hamlets is somewhat obvious, a feature of the richness of our method is its capability to uncover areas that act as spatial TFP growth hubs or leaders when the intuition is less clear. This is the case for Blackburn with Darwen, which we find is the tenth largest absolute spatial TFP growth hub, with a mean annual absolute contemporaneous TFP growth spill-out of 0.28%. This is nonnegligible particularly in the context of Blackburn with Darwen not being especially near a major city and being located in the North West of England ITL 1 region. Whilst it is not immediately obvious why Blackburn with Darwen makes it into our top 10 spatial TFP growth hubs, one possibility is due to it being a long-established industrial area.

For some time the economic inequalities between a number of UK regions have been growing, so in recent years the government's response has been to place much greater emphasis on regional leveling-up. Fransham et al. (2023) appraise the government's recent leveling-up policy and conclude that it is lacking in a number of respects. We consider one further plausible shortcoming of this policy that has thus far been overlooked and which is closely related to our empirical analysis. In the simplest terms, a key feature of this policy is that allocating leveling-up funding to laggard areas will support their growth and reduce regional economic inequalities. This overlooks, however, an important question: namely, can low-productivity areas that receive the funding help themselves to narrow the gap? Given the long-standing regional economic inequalities in the UK, we suggest that there are low-productivity areas that cannot be expected to help themselves. On the basis of this, rather than focusing on allocating leveling-up funding to these low-productivity areas, we suggest some redirecting of this funding to areas that represent large spatial TFP growth hubs (and/or leaders) and which are outside London and its hinterland. This because we suggest these hubs (and/or leaders) are better equipped to pull up the low-productivity areas that find it challenging to help themselves.

Our results suggest that there would be merits in channeling some further leveling-up funding to Blackburn with Darwen to help it become a larger spatial TFP growth hub. Whilst we suggest channeling funding to spatial TFP growth hubs and leaders would be an innovative development of the UK's leveling-up policies, as we may expect for big issues like the UK's productivity slowdown and its persistent regional economic inequalities, this would be challenging. This is because there must be large hubs and leaders outside London and its hinterland to channel funds to. Blackburn with Darwen, however, is the only area in our top 10 spatial TFP growth hubs that is outside of London and its hinterland.[22] It is clear, therefore, that the funding channeling we favor should also focus on trying to help other areas outside London and its hinterland become large spatial TFP growth hubs and leaders. The values of the measures in Table 5 for the other 158 areas are available from the corresponding author and could be used to shed some light on which of these areas may be viable candidates for further funding to help address the shortage of large hubs and leaders outside London and its hinterland.

Turning to the results in Table 5 for the spatial TFP growth spokes and followers. In line with major cities playing a key role in wider economic growth, we find that a few of the areas that are in the top 10 spatial spokes and followers border Outer London (West Essex, Thurrock, and Essex Thames Gateway). A further area that is one of the top spokes and followers in this table is Inverclyde, East Renfrewshire & Renfrewshire, which borders Glasgow City. Also, finding, for example, that Torbay, Cornwall & the Isles of Scilly, and Anglesey are among the top spokes and followers is consistent with these areas being heavily reliant on tourism. More generally, it is important to note that a number of the top spatial TFP growth spokes and followers in Table 5 are located outside London and its hinterland. It is also important to observe that a number of these top spokes and followers (e.g., Derby in the East Midlands, and North and North East Lincolnshire in Yorkshire & The Humber) are located in ITL 1 regions whose labor productivity growth lags behind that of a number of other regions (see Figure 1). Taken together this suggests our method may be a specific tool that could be used to inform the development of policies to help tackle the

[22]Essex Thames Gateway is in our top 10 absolute spatial TFP growth leaders and is located in the East of England ITL 1 region. It is classified as part of the London hinterland in this discussion as it borders Outer London.

productivity slowdown and regional inequalities in the UK by steering place-based policies to certain geographical areas.[23] This steering would involve directing place-based policies to certain geographical areas that our method suggests are top spokes and followers and which are located in laggard ITL 1 regions, as leveling-up rests on these regions narrowing the gap to their better-performing counterparts. These place-based policies would be geared to making these areas larger spokes and followers by increasing the TFP growth that spills in to these areas.

There was a big shift in the EU's regional development policy in 2014 when it switched its attention to smart specialization strategies. There are some parallels between these strategies and our above policy recommendation. This is because both are place-based and focus on enhancing the parts of a region's economy where there is relatively high growth potential. Di Cataldo et al. (2022) note that the EU's smart specialization policy is designed to support regions (and countries) by helping them identify and harness their comparative and competitive advantages. Our recommendation is related in the sense that it suggests that policymakers should place greater emphasis on where an area is doing comparatively better by seeking to further raise its TFP growth spill-ins, and focus less on trying to raise the area's relatively low own TFP growth. Our recommendation, however, raises an important issue. That is, as Table 5 reports the total TFP growth spill-in to an area from all the other areas, to help steer policymakers efforts to further raise such spill-ins, a key issue that we turn to next is which areas are the sources of the biggest spill-ins to a particular area.

3.4 | Areas with low own TFP growth

Thus far in our contemporaneous and dynamic spatial TFP growth decompositions, the TFP growth spill-ins to an area are from all the other areas. To uncover the areas that are the sources of the biggest TFP growth spill-ins to a particular area, we first obtain own TFP growth by summing its three components—growth rates of technical change, RTS and overall efficiency. These own components come from a standard own TFP growth decomposition. This involves making the relevant simple adjustments to the notation in Equations (A1)–(A3) in Appendix 2. From the adjusted equations and using the own coefficients in Table 2, the corresponding variables and the own overall efficiencies, we obtain the three components. Next, we obtain the contemporaneous and cumulated dynamic TFP growth spill-ins to an area from each of the other areas, that is, for horizon 0 and the sum across horizons 1 − 3, respectively. To obtain these spill-ins, for each horizon we decompose the product of the spatial multiplier matrix and the own TFP growth vector. The decompositions of these products correspond to that in Equation (A4) in Appendix 2, where the form of the spatial multiplier matrix changes with the time horizon.

Given declines in higher-performing regions is not, of course, how leveling-up should be achieved, as it would lead to a reduction in living standards, there has been a lot of focus on improving lower-performing areas. In Table 6, therefore, we present the areas that represent the top three sources of TFP growth spill-ins to the 10 areas with the lowest own contemporaneous TFP growth. The corresponding results for the other 158 areas are available from the corresponding author upon request. To add some context to the TFP growth spill-ins reported in Table 6, in parentheses in this table we also report the ITL 1 region where an area is located and the distance between each low TFP growth area and the three areas from which it obtains its largest TFP growth spill-ins. We make five observations about Table 6.

First, the results for some areas in Table 6 support the idea of switching attention away from improving the areas relatively low own TFP growth, in favor of focusing on where the area is performing relatively better by seeking to raise its TFP growth spill-ins from other areas. For other areas the results do not support this idea. Consistent with the productivity slowdown and persistent regional inequalities in the UK being complex issues to

[23]The general case in favor of place-based policies is well-documented for regions experiencing development challenges when regional policy is place-neutral. For a general discussion of this for EU regions, see Barca et al. (2012).

TABLE 6 Absolute TFP growth spill-ins to areas with low own TFP growth.

Mean contemporaneous (λ = 0) annualown TFP growth: Bottom 10	Top 3 mean contemporaneous annual TFP growth spill-ins to the low own TFP growth area	Top 3 mean cumulated dynamic (λ = 1-3) annual TFP growth spill-ins to the low own TFP growth area
Wakefield(−0.982%) (Yorkshire[a], England)	0.008% from Leeds (Yorkshire[a], England – 19 km) 0.006% from Barnsley[b] (Yorkshire[a], England – 24 km) 0.005% from East Derbyshire (EM, England – 50 km)	0.019% from Leeds (Yorkshire[a], England – 19 km) 0.014% from Barnsley[b] (Yorkshire[a], England – 24 km) 0.014% from East Derbyshire (EM, England – 50 km)
Hartlepool & Stockton-on-Tees (−0.199%) (NE, England)	0.009% from Darlington (NE, England – 18 km) 0.009% from South Teesside (NE, England – 17 km) 0.007% from Sunderland (NE, England – 31 km)	0.021% from Darlington (NE, England – 18 km) 0.020% from South Teesside (NE, England – 17 km) 0.017% from Sunderland (NE, England – 31 km)
Croydon (−0.034%) (London)	0.018% from Tower Hamlets (London – 17 km) 0.014% from Lambeth (London – 11 km) 0.013% from Kensington[c] (London – 16 km)	0.055% from Tower Hamlets (London – 17 km) 0.040% from Lambeth (London – 11 km) 0. 039%fromKensington[c] (London – 16 km)
Isle of Anglesey (0.013%) (Wales)	0.004% from Conwy[d] (Wales – 52 km) 0.004% from Flintshire[e] (Wales – 87 km) 0.004% from Cheshire West[f] (NW, England – 109 km)	0.015% from Tower Hamlets (London – 351 km) 0.011% from E. Merseyside[g] (NW, England – 106 km) 0.011% from Flintshire[e] (Wales – 87 km)
Thurrock (0.046%) (East, England)	0.015% from Tower Hamlets (London – 26 km) 0.012% from Essex Th.[d] (East, England – 19 km) 0.008% from Kensington[b] (London – 37 km)	0.047% from Tower Hamlets (London – 26 km) 0.030% from Essex Th.[d] (East, England – 19 km) 0.027% from Kensington[b] (London – 37 km)
Bournemouth, Christchurch & Poole (0.070%) (SouthWest, England)	0.006% from Tower Hamlets (London – 153 km) 0.006% from South Hampshire (SE, England – 44 km) 0.006% from Isle of Wight (SE, England – 37 km)	0.055% from Tower Hamlets (London – 153 km) 0.039% from Kensington[b] (London – 142 km) 0.005% from South Hampshire (SE, England – 44 km)
Hackney & Newham (0.110%) (London)	0.065% from Tower Hamlets (London – 5 km) 0.014% from Haringey & Islington (London – 10 km) 0.012% from Kensington[b] (London – 16 km)	0.157% from Tower Hamlets (London – 5 km) 0.039% from Haringey & Islington (London – 10 km) 0.038% from Kensington[c] (London – 16 km)
Derby (0.123%) (East Midlands, England)	0.006% from S.&W. Derbyshire (EM, England – 22 km) 0.006% from South Nottinghamshire (EM, England – 27 km) 0.006% from E. Derbyshire (EM, England – 34 km)	0.016% from S. &W. Derbyshire (EM, England – 22 km) 0.016% from E. Derbyshire (EM, England – 34 km) 0.016% from Tower Hamlets (London – 184 km)

(Continues)

TABLE 6 (Continued)

Mean contemporaneous (λ = 0) annualown TFP growth: Bottom 10	Top 3 mean contemporaneous annual TFP growth spill-ins to the low own TFP growth area	Top 3 mean cumulated dynamic (λ = 1-3) annual TFP growth spill-ins to the low own TFP growth area
East Riding of Yorkshire (0.145%) (Yorkshire[a], England)	0.008% from City of Hull (Yorkshire[a], England – 27 km) 0.007% from N. &NE Lincs[h] (Yorkshire[a], England – 35 km) 0.004% from Tower Hamlets (London – 266 km)	0.019% from City of Hull (Yorkshire[a], England – 27 km) 0.017% from N. &NE Lincs[h] (Yorkshire[a], England – 35 km) 0.015% from Tower Hamlets (London – 266 km)
Luton (0.148%) (East, England)	0.010% from Tower Hamlets (London – 50 km) 0.007% from Kensington[c] (London – 47 km) 0.006% from Haringey & Islington (London – 42 km)	0.033% from Tower Hamlets (London – 50 km) 0.024% from Kensington[c] (London – 47 km) 0.018% from Haringey & Islington (London – 42 km)

Notes: Full names of the areas labeled *a* – *h*a–h are [a]aYorkshire and The Humber; [b]Barnsley, Doncaster & Rotherham; [c]Kensington & Chelsea and Hammersmith & Fulham; [d]Conwy & Denbighshire; [e]Flintshire & Wrexham; [f]Cheshire West & Chester; [g]Essex Thames Gateway; [h]North & North East Lincolnshire.

Abbreviations: E, East; EM, East Midlands; N, North; NE, North East; NW, North West; S.&W., South & West; SE, South East; TFP, total factor productivity.

tackle, we conclude that this idea can assist in tackling these issues for some areas with low TFP growth, but certainly not all. Accordingly, our further three observations about Table 6 focus on particular areas.

Second, the flows of positive TFP growth spill-ins to Wakefield, Hartlepool & Stockton-on-Tees, and Croydon are relatively large as these areas have negative average annual own TFP growth. As these spill-ins are a domain where these areas are performing relatively well, we suggest that it is worthwhile considering policies that focus on further increasing the spill-ins on these flows. Third and relatedly, an appealing feature of our method is that it uncovers some sources of the largest TFP growth spill-ins that are not well-known and are thus worthy of closer attention from policymakers. To demonstrate this consider the case of Wakefield. It is not surprising that one of the sources of the largest TFP growth spill-ins to Wakefield is Leeds, as the latter is a major city and the two areas share a border. Anecdotally one can see how better links between Wakefield and Leeds may promote Wakefield's economic growth. Things are often not quite as they seem and the gap between the TFP growth spill-ins to Wakefield from Leeds and East Derbyshire (and possibly also Barnsley, Doncaster & Rotherham) is smaller than we would have expected. We suggest this is because there is more similarities between Wakefield, East Derbyshire and Barnsley, Doncaster & Rotherham. Links between Wakefield and its second-order contiguous neighbor East Derbyshire (and possibly also Barnsley, Doncaster & Rotherham) are not as prominent as links with Leeds and may therefore have received less attention from policymakers. On the basis of this and the comparatively large TFP growth spill-ins to Wakefield from East Derbyshire and Barnsley, Doncaster & Rotherham, we suggest that it is worthwhile considering policies to increase these spill-ins.

Fourth, the largest flows of TFP growth spill-ins to Derby, East Riding of Yorkshire and Luton are rather small in comparison to their own TFP growth rates. Since these flows are not a domain where these areas are performing relatively well, we do not recommend policies that try to increase the spill-ins on these flows. We suggest that East Riding of Yorkshire and Luton are two areas that face the challenging inward-looking task of raising their own productivity performance, as opposed to relying on individual flows of TFP growth spill-ins. Derby is a different and interesting case which we turn to next. Fifth, whilst Derby is one of the areas in Table 5 with the largest TFP growth spill-ins from all the other areas, Table 6 suggests that there is no relatively large TFP growth spill-in to Derby from any one particular area. This may be because Derby is part of the country's "golden logistics triangle" (BBC, 2018; Logistics Manager, 2024), and as a result of its logistics activity has links with a large number of other areas (rather than just certain ones). On the basis of this, rather than policies to increase particular flows of TFP growth spill-ins to Derby, we suggest more broader policies that seek to increase its total TFP growth spill-ins, for example, initiatives to grow and diversify its established logistics activity.

4 | SUMMARY AND CONCLUDING REMARKS

This paper seeks to gain a better understanding of the puzzling slowdown in Britain's productivity from around 2008 onwards. Using data for the 168 ITL 3 areas in Great Britain for 2004 − 2020 we make two empirical contributions. First, our paper is the first empirical analysis of the productivity slowdown using a stochastic frontier model. This involves accounting for unobserved heterogeneity and distinguishing between persistent and transient technical efficiencies, which are then used to compute overall efficiency. To the best of our knowledge, our model is the first to distinguish between persistent and transient efficiencies using an appealing relaxation of restrictions in the form of efficiency measures that are free of a priori assumptions about their statistical distributions. Of the three components of TFP growth—growth rates of technical change, RTS and overall efficiency—our first empirical contribution shows that the productivity slowdown in Great Britain can be more specifically described as a rise in inefficiency.

Our second empirical contribution involves using our dynamic spatial stochastic frontier model to uncover the areas that represent spatial TFP growth hubs, spokes, leaders and followers. We define areas as hubs and leaders using the magnitudes of the contemporaneous and dynamic TFP growth spill-outs from an area to all the other areas. In a similar way we define areas as spokes and followers using the corresponding TFP growth spill-ins to an area. Our second contribution also involves estimating the flows of TFP growth spill-ins and spill-outs to and from individual areas. As the overriding aim of UK leveling-up policy is for the areas with low productivity to narrow the gap to the better-performing areas, we focus on the biggest flows of TFP growth spill-ins to the laggard areas. For some of these areas our results support the idea of diversifying away from trying to improve an area's relatively low own TFP growth, in favor of focusing on where the area is performing relatively better by seeking to raise its TFP growth spill-ins from other areas. For other areas with low own TFP growth, our results do not support this idea. In summary, and consistent with the productivity slowdown and persistent regional inequalities in the UK being complex issues to tackle, we conclude that this idea can assist in tackling these issues for some areas with low own TFP growth, but certainly not all.

Finally, we suggest how the findings from this paper can aid policymaker's efforts to raise productivity in Britain. By uncovering peer areas that are more efficient and represent larger spatial TFP growth hubs, spokes, leaders or followers, we can pinpoint which areas should be the focus of further qualitative work (case studies and focus groups) to improve productivity. The information gathered from this further work can inform policies designed to increase productivity in a particular area. Since our study finds that a rise in inefficiency is the key driver of the productivity slowdown, conducting an industry-level efficiency analysis of Britain's ITL 3 areas would provide more specific guidance for this further work.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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APPENDIX 1

Some thoughts on multilevel spatial analysis of technical efficiency and TFP growth

When using more disaggregated regional data (ITL 2 or 3), developing a multilevel spatial stochastic frontier model to introduce hierarchical characteristics that go beyond those which feature here would not pose any substantive technical challenges. This is because it would involve, among other things, including national-level regressors and regressors for the less disaggregated (i.e., higher-level) regions. As our translog model includes a number of squared and interaction terms this would mean that accounting for these further hierarchical characteristics by including squared and interaction terms at the national level and for the higher-level regions would substantially increase the number of regressors, that is, the model would no longer be relatively parsimonious like the one we report here. While a lack of parsimony is not appealing this does not preclude the estimation of such a model. The form of a TFP growth decomposition, however, must match the form of the stochastic frontier model. This is the case in this paper because two key contributions are the presentation of the first dynamic spatial stochastic frontier model of its type and the development of the first dynamic spatial TFP growth decomposition. As the literature lacks a multilevel spatial TFP growth decomposition, this is an area for further work. This would, however, involve addressing the following two methodological issues. These two issues are the reason why we do not seek to develop a multilevel spatial stochastic frontier model and a multilevel spatial TFP growth decomposition to account for further hierarchical characteristics beyond those which feature in our analysis.

First, any multilevel TFP growth decomposition should include components that measure the growth in technical change at the national level and each of the higher regional levels. Whereas in our empirical analysis we compute the growth in technical change using the fitted coefficients on the time counter t, t^2 and interactions with t, we cannot apply this approach to a multilevel specification. This is because there would be perfect collinearity between t (and hence also t^2) at the national level and each of the higher regional levels.

Assuming the first issue can be resolved this leaves the following second issue. In line with the standard single-level nonspatial generalized Malmquist TFP growth decomposition, in the corresponding static and dynamic spatial decompositions, the nonspatial (i.e., direct) and spatial (i.e., indirect) growth in technical change and RTS components for regions in the lowest level of the hierarchy all relate to observations for these regions. A multilevel spatial TFP growth decomposition would also include direct and indirect growth in technical change and RTS for the higher-level units, where these components would relate to observations for the higher-level environmental variables. For context the single-level environmental variables in Equation (1) are the z's. A generalized Malmquist TFP growth decomposition would not include terms that relate solely to the environmental variables (although it could include terms that relate to interactions between these variables and, e.g., x_{it} in Equation 1). We therefore maintain that it would not be advisable to adopt a generalized Malmquist-type approach to derive a multilevel spatial TFP growth decomposition. The nonspatial TFP growth decomposition that O'Donnell (2018, 8.5.2.1 beginning on p. 353, 2022) proposes, on the other hand, has components which solely relate to the environmental variables. Whereas the derivation of a static spatial generalized Malmquist TFP growth decomposition is set out in, for example, Glass et al. (2013) and its extension to the dynamic spatial setting is presented here, there is no spatial version of O'Donnell's method. Accordingly, an area for further work would be to explore using an O'Donnell-type approach to derive a multilevel spatial TFP growth decomposition.

APPENDIX 2

Components of contemporaneous and dynamic spatial TFP growth

For each time period that corresponds to horizon λ, the approach to compute the three components of the $\Delta TFP^{Ind}_{Out,it+1}$ index in Equation (5) (see Section 2.2) is as follows. The same approach is used to compute the three components of the corresponding ΔTFP^{Dir}_{it+1} and $\Delta TFP^{Ind}_{In,it+1}$ indices. This simply involves replacing the ${}^{Ind}_{Out}$ notation in Equations (A1)–1 −(A3) (see below) with ^{Dir} and ${}^{Ind}_{In}$. For each period in the sample that corresponds to $\lambda = 0$, we calculate the contemporaneous $\Delta TC^{Ind}_{Out,it+1}$, $\Delta RTS^{Ind}_{Out,it+1}$, and $\Delta OE^{Ind}_{Out,it+1}$ and sum these components to obtain the contemporaneous $\Delta TFP^{Ind}_{Out,it+1}$. For each period in the sample that corresponds to $\lambda \geq 1$ we calculate and sum the same three components for each λ. For each period and each $\lambda \geq 1$ this gives dynamic $\Delta TFP^{Ind}_{Out,it+1}$, which we then cumulate across a prespecified number of λ's≥1. In the empirical analysis we consider the first three future in-sample time horizons and so cumulate the dynamic $\Delta TFP^{Ind}_{Out,it+1}$ across $1 \leq \lambda \leq 3$.

1.

$$\Delta TC^{Ind}_{Out,it+1} = TC^{Ind}_{Out,it+1} - TC^{Ind}_{Out,it} = \frac{\partial y^{Ind}_{Out,it+1}}{\partial t} - \frac{\partial y^{Ind}_{Out,it}}{\partial t}, \tag{A1}$$

which involves obtaining the relevant first-order derivatives of Equation (4) for successive time periods.

2.

$$\Delta RTS^{Ind}_{Out,it+1} = \frac{1}{2}\left[\sum_{m=1}^{M}\left(e^{Ind}_{m,Out,it+1}SF^{Ind}_{Out,it+1} + e^{Ind}_{m,Out,it}SF^{Ind}_{Out,it}\right)\ln\left(\frac{x_{m,it+1}}{x_{m,it}}\right)\right], \tag{A2}$$

$e^{Ind}_{m,Out}$ is the spill-out elasticity with respect to the mth input, where these M elasticities are obtained from Equation (4); and SF^{Ind}_{Out} is the indirect spill-out scale factor, where $SF^{Ind}_{Out,it} = \left(-\sum_{m=1}^{M} e^{Ind}_{Out,m,it} + 1\right)/\sum_{m=1}^{M} e^{Ind}_{Out,m,it}$.

3.

$$\Delta OE^{Ind}_{Out,it+1} = OE^{Ind}_{Out,it+1} - OE^{Ind}_{Out,it}. \tag{A3}$$

To obtain for $\lambda = 0$ the estimate of the contemporaneous $OE^{Ind}_{Out,it}$ we first substitute $\varepsilon_{it} = v_i + e_{it} + \theta_{it}$ for ε_{it} in Equation (1). We then obtain the reduced form of the resulting dynamic equation, that is, the dynamic spatial data generating process (DGP). Next, we apply to the dynamic spatial DGP the approach in Glass et al. (2014) for their static spatial DGP. This process begins with Equation (A4).

$$\lambda = 0 : (I - \delta W)^{-1} \begin{pmatrix} \theta_1 \\ \vdots \\ \theta_N \end{pmatrix}_t = \begin{pmatrix} \theta_{11}^{Dir} & + & \cdots & +\theta_{1N}^{Ind} \\ \vdots & & \ddots & \vdots \\ \theta_{N1}^{Ind} & + & \cdots & +\theta_{NN}^{Dir} \end{pmatrix}_t , \tag{A4}$$

where I is the $(N \times N)$ identity matrix, $(I - \delta W)^{-1}$ is the spatial multiplier matrix for $\lambda = 0$, and θ_{iit}^{Dir} and θ_{ijt}^{Ind} represent direct and indirect time-varying effects. We also obtain the corresponding equation for $(I - \delta W)^{-1}(\eta_1, ..., \eta_N)'$ which yields the direct and indirect random effects η_{ii}^{Dir} and η_{ij}^{Ind}. The estimates for $\lambda = 0$ of the contemporaneous direct and asymmetric indirect spill-in and spill-out transient efficiencies ($\hat{TE}_{it}^{Dir}$, $\hat{TE}_{it,In}^{Ind}$, and $\hat{TE}_{jt,Out}^{Ind}$) are then obtained as follows.

$$\begin{aligned} \hat{TE}_{it}^{Dir} &= \exp\left[\theta_{ii}^{Dir} - \max_i\left(\theta_{ii}^{Dir}\right)\right]_t, \\ \hat{TE}_{it,In}^{Ind} &= \exp\left[\textstyle\sum_{j=1}^{N}\theta_{ij}^{Ind} - \max_i\left(\sum_{j=1}^{N}\theta_{ij}^{Ind}\right)\right]_t, \\ \hat{TE}_{jt,Out}^{Ind} &= \exp\left[\textstyle\sum_{i=1}^{N}\theta_{ij}^{Ind} - \max_j\left(\sum_{i=1}^{N}\theta_{ij}^{Ind}\right)\right]_t. \end{aligned} \tag{A5}$$

In the same way, we use the equation for $(I - \delta W)^{-1}(\eta_1, ..., \eta_N)'$ to obtain the estimates for $\lambda = 0$ of the contemporaneous direct and asymmetric indirect spill-in and spill-out persistent efficiencies ($\hat{PE}_i^{Dir}$, $\hat{PE}_{i,In}^{Ind}$, and $\hat{PE}_{i,Out}^{Ind}$). We then obtain the estimates for $\lambda = 0$ of the contemporaneous direct and asymmetric indirect spill-in and spill-out overall efficiencies by multiplying the corresponding persistent and transient estimates.

Next, we apply the approach in Glass et al. (2014) for their static spatial DGP to our dynamic spatial DGP to obtain Equation (A6) for each future in-sample time horizon $\lambda \in 1, ..., T - 1$.

$$\lambda \in 1, ..., T - 1 : (-1)^\lambda[(I - \delta W)^{-1}(-\rho W)]^\lambda \begin{pmatrix} \theta_1 \\ \vdots \\ \theta_N \end{pmatrix}_{t-\lambda} , \tag{A6}$$

where the expression in Equation (A6) is the premultiplication of $(\theta_1, ..., \theta_N)'_{t-\lambda}$ by the spatial multiplier matrix for horizon λ. It is therefore evident that the spatial multiplier matrix changes with the time horizon λ. In the empirical analysis we consider up to the third future in-sample time horizon. In the same way as we do in Equation (A4), we decompose the multiplicative product in Equation (A6) for each $\lambda \in 1, ..., 3$. We could then use the relevant elements from these decompositions in Equation (A5) to obtain dynamic $\hat{TE}_{it}^{Dir}$, $\hat{TE}_{it,In}^{Ind}$, and $\hat{TE}_{jt,Out}^{Ind}$ for each $\lambda \in 1, ..., 3$. Instead we cumulate the corresponding elements from these decompositions across the the first three future in-sample time horizons and use these cumulated elements in Equation (A5) to obtain estimates of the three cumulated dynamic transient efficiencies. Using the same approach but with the vector of θ's in Equation (A6) replaced with the vector of η's, we obtain the cumulated dynamic $\hat{PE}_i^{Dir}$, $\hat{PE}_{i,In}^{Ind}$, and $\hat{PE}_{i,Out}^{Ind}$. Finally, in the same way as we do for $\lambda = 0$ above, we obtain the cumulated dynamic $\hat{OE}_{it}^{Dir}$, $\hat{OE}_{it,In}^{Ind}$, and $\hat{OE}_{jt,Out}^{Ind}$.

APPENDIX 3

TABLE A3 Correlations with the TFP growth spillovers 0.70.

	Contemporaneous (λ = 0)			Cumulateddynamic (λ = 1-3)		
	TFP growth spill-in (%)	TFP growth spill-out (%)	Net spill-out (%)	TFP growth spill-in (%)	TFP growth spill-out (%)	Net spill-out (%)
Real GVA	11.9	37.1	36.7	6.8	33.8	36.9
Agriculture, forestry & fishing, and mining & quarrying	−4.8	−14.4	−14.2	−4.5	−14.6	−15.3
Manufacturing	−6.1	−1.1	−0.1	−0.4	20.8	24.6
Electricity, gas & water, and sewerage & waste management	−10.4	−3.2	−1.6	−10.3	−5.6	−2.3
Construction	−1.6	11.0	11.7	−0.3	9.4	11.2
Distribution, hotels, & restaurants	3.2	27.5	28.1	−0.4	20.8	24.6
Transport & communication	14.7	45.8	45.3	7.7	40.6	44.6
Banking finance & insurance	16.6	37.6	36.3	10.7	37.3	39.4
Public admin education & health	2.9	23.6	24.2	−0.8	18.0	21.5
Other services	10.8	39.5	39.4	3.8	32.8	37.1
Total services	14.1	39.9	39.2	8.0	36.8	40.1
2011—Travel to work						
Distance⁻—up to 10 km	−2.1	20.5	21.2	−4.3	16.5	20.8
Distance—more than 10 km	−0.9	−4.4	−4.3	−0.5	−4.6	−4.8
Distance⁻—works mainly from home	3.0	6.1	5.6	0.6	5.2	5.5
2020—Travel to work						
Distance—up to 10 km	−2.6	3.4	5.9	−3.4	−0.1	6.8
Distance⁻—more than 10 km	5.6	−6.3	−11.5	5.1	−0.7	−11.7
Distance⁻—works mainly from home	−5.7	14.4	20.7	−4.1	7.3	21.0
Distance⁻—works mainly offshore	−1.1	−1.5	−0.8	−0.5	0.1	1.2

Abbreviations: GVA, gross value added; TFP, total factor productivity.