Does Spatial Proximity Raise Firm Productivity? Evidence from British Manufacturing

Richard Harris[a], John Moffat[a], Emil Evenhuis[b], Ron Martin[c], Andy Pike[d], Peter Sunley[b]

The United Kingdom's economy is one of the most regionally imbalanced in Europe. The government's recent industrial strategy discusses various means of addressing this, one of which is the strengthening of existing clusters. Using plant-level indices of spatial proximity derived from postcode district data, this article investigates the extent of spatial concentration and its impact on total factor productivity in advanced manufacturing sectors in Great Britain. The results from estimation of production functions indicate that, in most advanced manufacturing sectors, spatial concentration has a negative impact on productivity in small plants and a positive effect in larger plants. Large plants likely benefit more from knowledge spillovers due to their higher levels of absorptive capacity.

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[a] Durham University [b] University of Southampton [c] University of Cambridge [d] Newcastle University

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Introduction

Ever since Michael Porter's influential work advanced the claim that the geographical clustering of similar and related interconnected businesses raises their competitive advantage (for example Porter, 1990, 1998a,b), the general assumption has been that firms inside such clusters will have higher productivity than those outside. As Porter himself puts it:

> Clusters affect competition in three broad ways: first, by increasing the productivity of companies based in the area; second, by driving the direction and pace of innovation, which underpins future productivity growth; and third, by stimulating the formation of new businesses, which expands and strengthens the cluster itself (Porter, 1998, p.)

Four main advantages are alleged to be associated with the spatial proximity of similar and related firms: access to a pool of specialised labour, expertise and suppliers; access to and transfer of specialised information and knowledge; the attraction and emergence of various complementarities (from products to marketing to dependent businesses and activities); and access to specialised institutions and public goods (such as universities and transport infrastructure).[1]

The UK is among several countries that have adopted or pursued some form of cluster policy over recent decades. In the UK, it was an explicit element of the New Labour governments' approach to national and regional industrial policy between 1997 and 2010 (DTI, 1998; DETR, 2000). Indeed, Michael Porter was an advisor to the then Department of Trade and Industry, and the Regional Development Agencies that were established under New Labour also drew heavily on Porter's cluster theory. Around 2004, however, the scale at which regional industrial development policy was focused shifted from regions to city regions, and cluster policies became much less visible (Swords, 2013). With the abolition of the Regional Development Agencies under the Conservative-LibDem coalition government in 2010, this de-emphasis on cluster based industrial policy continued. More recently, clusters have resurfaced as part of the Conservative Government's recent embrace of industrial policy as a means of achieving its stated goal of spatially rebalancing the national economy and addressing the UK's poor productivity performance (DBEIS, 2017). Thus, according to the UK Government "Clustering is viewed as beneficial to firms (particularly to small firms) because they can access a shared pool of expertise and labour, suppliers, and information or contacts." (HC, 2018).

Apart from the issues of identifying clusters and how, exactly, cluster policies can best be operationalised (what, precisely, should such policies do?), there is the question of how much empirical support there actually is that firms that co-locate benefit. The belief that spatial proximity produces advantages for firms that raise their productivity is fundamental to most cluster strategies, as it is typically assumed that spatial proximity and co-location support firms' learning and the development of beneficial inter-linkages. However, the empirical evidence is by no means unequivocal (see Duranton, 2011). In the innovation literature, it has been argued that spatial proximity *per se* does not always raise interactive learning and innovation (Boschma, 2005). In some cases, spatial

[1] This list, of course, bears some similarity to the triad of localisation externalities invoked by Alfred Marshall (1890) in his much earlier discussion of industrial districts. Porter's cluster concept is derived from Marshall's industrial district notion, updated and extended to embrace ideas from businesses economics on the nature of firm competition and competitive advantage.

proximity does not lead to the formation of inter-linked and collaborative clusters of firms, and in other cases it may actually restrict and constrain firm learning. There is hence an analytical need to distinguish the effects of spatial proximity on productivity and to examine how spatial or geographical proximity interacts with other dimensions of firm proximity such as cognitive, organisational and social proximities.

Set against this background, our aim in this paper is to test how far spatial proximity raises firm productivity in the case of knowledge-intensive British manufacturing. We analyse plant-level total factor productivity using data from the Annual Business Survey for office machinery and data processing equipment, electrical and electronic engineering, motor vehicles and motor vehicle parts, instrumental engineering, pharmaceuticals and aerospace equipment and repairing, over the period 1984-2016. To examine the effects of different degrees of spatial co-location we construct a spatial proximity index that measures the proximity of each plant to every other plant within the same industry, and then use this to test if plants with high values of the index (a high degree of spatial concentration) have higher total factor productivity (TFP). Since intra-industry externalities are only one element of what is understood to be the potential localisation economies that can come from the co-location of plants, inter-industry externalities that take account of potential effects from the co-location of plants in related industries are also modelled. We find that the productivity benefits from spatial proximity are by no means universal, and in many cases only exist for larger plants (with sufficient absorptive capacity). This runs counter to the claim, referenced above, that spatial co-location and clustering are particularly beneficial for small firms and therefore raises some important caveats concerning the benefits that might be expected from the pursuit of cluster policies as a component of the Government's new Industrial Strategy.

We would argue this paper makes three major contributions to the literature. First, we measure intra-industry effects and effects arising across related industries using plant-level distance indices, rather than the aggregate measures commonly used in other studies that require *a priori* specification of the spatial area in which spillovers and interactions occur. Second, plant-level data are used and therefore we are able to directly test the extent to which each plant's TFP is determined by the degree to which it is co-located with other plants in the same and/or related industries. And third, we recognize the need to treat location as endogenous, and thus each distance index used is instrumented when undertaking econometric modelling.

In the next section we review the literature on the possible externalities associated with different types of spatial proximity, and their effects on firm performance. We then discuss the data and model specification used to examine the effect of spatial proximity on total factor productivity of plants in six advanced manufacturing sectors in Britain. In the subsequent section, the baseline findings are presented; followed by a discussion of results obtained from different specifications with regard to the 'distance decay' of the possible externalities, as well as whether clusters are narrowly defined, or more broadly (i.e., when also including related industries). Based on these results, we consider the potential implications for place-based policies targeting clusters, specifically in light of the UK's Industrial Strategy and concomitant local industrial strategies.

Identifying and measuring the externalities from spatial proximity[2]

As we have noted, the contention that the spatial proximity of similar firms acts to raise their productivity was basic to Michael Porter's formulation of the cluster concept and has been central to most accounts of the benefits of clusters.[3] According to Porter (1996), clusters raise the productivity of firms primarily through dynamic externalities related to learning, rather than by static cost-reducing externalities. This contention has been supported and reinforced by theoretical work on agglomeration economies more generally, in relation to the benefits that accrue to firms and plants from being located in the vicinity of large concentrations of other firms and plants. These benefits can be summarised as being processes of 'sharing', 'matching' and 'learning' (Duranton and Puga, 2004; Overman *et al.,* 2009). Agglomeration benefits arise through sharing when firms benefit from drawing on a common pool of resources, such as indivisible goods or facilities, a wide variety of input suppliers, a larger pool of labour, as well as the sharing of risk across plants. The probability, and the speed, of matching is also improved in areas with many firms and workers. Finally, the diffusion and accumulation of knowledge is expected to be better in areas with a high density of both firms and workers. By facilitating face-to-face contact, the concentration of both workers and entrepreneurs in a cluster can facilitate spillovers and the transfer of knowledge. In addition, workers will find it easier to move from one firm to another. This process will assist in the transfer of knowledge (i.e., 'learning') across firms (see e.g. Acs *et al.*, 2002; Anselin *et al.*, 1997; Audretsch and Feldman, 1996). It is possible that industry clusters – specialised localised concentrations of firms in the same or closely related sectors - benefit from all three of these processes.

Providing empirical assessment of this possibility is much more challenging. There has, of course, been considerable ambiguity about the definition of clusters and their spatial extent (Martin and Sunley, 2003), and it is difficult to disentangle the effects of spatial proximity from other forms of firm proximity. While Porter's approach suggests that clusters are sets of related industries, many others have assumed that clusters are essentially based on localisations of single industries and thus have assumed that clusters benefit primarily from Marshallian (intra industry) localisation economies (Marshall, 1890; Arrow, 1962; Romer, 1986). Such MAR-spillovers, it is argued, lead to specialization (Audretsch *et al.*, 2007), since they suggest that firms within a specific industry locate near other firms along the supply chain (be they customers or suppliers); locate near other firms that use similar specialised labour; and/or locate near other firms that might share knowledge (Ellison *et al.*, 2010).[4] However, if clusters consist of wider

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[2] For a more comprehensive survey of the literature, see De Groot *et al.* (2016), Harris (2017) and Harris and Moffat (2012).

[3] At the outset, it is important to note that in the empirical work we are treating 'clusters' as co-located plants in the same or related industries, where 'related' refers to mostly technical inter dependencies such as 'supply-chain' linkages. The notion of a cluster as co-located plants belonging to diverse industries is not the central focus of this study, although we discuss the distinctions in more detail below.

[4]In more detail, MAR-spillovers are based on different types of externalities, according to how they are mediated. Scitovsky (1954) and then Griliches (1979, 1992) distinguished between pecuniary (also called vertical, welfare or rent) spillovers which are based on market transactions, and non-pecuniary (also called horizontal, knowledge and technological) spillovers which are based on non-market interactions usually involving the sharing of knowledge and expertise. As explained by Koo (2005), such pecuniary externalities are associated with: intermediate inputs and labour pools and are emphasized in new economic geography models (Neary, 2001; Fujita and Thisse, 2002, p. 9). In contrast, technological spillovers when firms in proximity share a general pool of knowledge, and are emphasized in the new industrial geography (see

groups of interrelated industries they may also benefit from some inter-industry spillovers across linked or related industries, which might be conventionally subsumed under Jacobsian or urbanization spillovers[5]. The distinction between intra- and inter-industry spillovers is somewhat blurred if related industries (that are linked technologically or by close upstream and downstream dependencies, or which share labour or knowledge) are classified as part of a 'cluster' (see Delgado *et al.*, 2014). We return to this type of 'related spillover' later in our discussion.

However, the empirical evidence on whether spatial proximity does act to raise firm productivity is not as strong as either cluster theory or agglomeration theory would lead us to expect. Robust empirical studies are relatively scarce (Duranton, 2011). While there has been extensive empirical research on agglomeration, most of this has been framed in terms of localisation and urbanisation economies and their combinations. Many studies have sought to estimate the impact of agglomeration externalities on productivity without clearly distinguishing between localisation, cluster-based, or urban externalities. Examinations of the relations between employment and population density and productivity across local areas (usually cities) typically estimate that doubling of employment density increases labour productivity by between 3 and 6 percent (see Åberg, 1973; Sveikaukus, 1975 and Segal, 1976; Ciccone and Hall, 1996; Ciccone, 2002; Rice *et al.*, 2006). Using French area-level data, for example, Combes *et al.* (2008) estimate the impact of population density and market potential on TFP and obtain elasticities of 3.5% and 2.5% for population density and market potential respectively (also Andersson and Lööf, 2009; Wixe, 2015). While these studies provide some evidence in favour of the benefits of co-location externalities, the magnitude of the effects is generally small.

A further literature has sought to distinguish the relative importance of localisation and urbanisation externalities, but has also used area-level data. These analyses have been rather mixed and inconclusive, and also suffer from the problem that they do not specifically measure the distance between firms in the same or related industries. Some studies suggest that both types of externality have significant effects on productivity (for example, Rigby and Essletzbichler, 2002; Moomaw, 1983; Graham *et al.*, 2010). In contrast, other studies report stronger localisation economies (Henderson, 1986; Drennan, 2002; Acs *et al.*, 2002). However, other studies conclude that urbanisation externalities are more important than localisation externalities, and, indeed, report evidence of localisation *dis*economies (Brülhart and Mathys, 2008; Glaeser *et al.*, 1992; Quigley, 1998; van Stel and Nieuwenhuijsen, 2004; van Oort, 2007). While the evidence from studies using aggregate data suggests that both types of externality operate in some cases, in general most findings are too inconsistent, and too indirectly linked to spatial proximity to be compelling.[6] Some studies try to explain this variation by focusing on differences between types of industry or different stages of the industry or product lifecycle (Nakamura, 1985; Faggio *et al.*, 2017). Others suggest that clustering and co-

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Barnes and Gertler, 1999) and new growth theory literatures (for example Romer, 1990; Black and Henderson, 1999).

[5] Urbanization externalities are due to the size and heterogeneity (or diversity) of an (urban) agglomeration and result when different industries benefit from economies of scope (rather than scale). A greater range of activities (for example, R&D, business services, cultural and lifestyle amenities, and the overall quality of the public infrastructure – see Florida, 2002; Glaeser *et al.*, 2001) leads to inter-industry spillovers. Urbanisation externalities often stem from the co-location in cities of firms that are weakly linked.

[6] De Groot *et al.* (2016) have analysed 73 journal articles which build on the seminal work of Glaeser *et al.* (1992) and find a very mixed set of results (although perhaps more weight in favour of Jacobsian spillovers, particularly for papers related to city growth, which may not be surprising).

location only yield positive externalities up to a threshold, and above this begin to have a negative effect on productivity (Antonelli, *et al.*, 2011).

A substantial number of studies that use firm and micro-data evidence have found that localisation externalities and spatial proximity to firms in the same industry have a positive effect on firm productivity, although other studies show mixed results (more details are provided in the Supplementary Appendix). These inconsistent results may partly reflect the fact that micro-level studies have measured MAR or localisation externalities in different ways. For example, Harris and Moffat (2012) proxied MAR spillovers using the percentage of industry output (at 5-digit industry SIC level) located in the local authority district in which the plant was located. Such empirical studies typically use relatively small administrative areas, such as local authority districts since spatial productivity spillovers are assumed to have a strong distance decay; but the extent to which they are limited is likely to be an empirical issue (e.g., Gertler, 2003; Venables, 2011). Moreover, whether these small areal units correspond with the spatial dimensions of clusters is unknown. There is much uncertainty concerning the 'correct' geographic area needed to capture cluster externalities, and different papers use different statistics, while some experiment with different industrial agglomeration and diversification indices (see, for example, Devereux *et al.,* 2007; Baldwin *et al.*, 2010).

Attempts to estimate the productivity benefits of spatial proximity also encounter significant endogeneity problems. Clusters of co-located firms may, of course, be created by local spin-off processes, and it is not credible to simply demonstrate that a cluster exists and then deduce that proximity spillovers are benefiting firms. Higher productivity firms may also choose to locate in clusters. This issue of reverse causality is thus especially relevant when considering whether spatial proximity and colocation are a source of productivity spillovers. Greenstone *et al.* (2010) use a novel approach to overcome the problem by looking at TFP outcomes in areas that attract new large plants (e.g., multinationals) versus areas that were the second-choice location for these plants (and thus share common advantages). They conclude that there are significant productivity spillovers from the opening of new plants that are larger for firms that share labour pools and similar technologies. Therefore, in this paper we treat co-location and productivity as endogenous and instrument both sets of variables (as explained below).

Finally, a key response to the mixed and varied results of research on cluster and localisation spillovers has been to pay much more attention to firm heterogeneity (Wixe, 2015). There is mounting evidence that differences in firm characteristics mean that while some benefit from spatial proximity, other firms may gain no advantage, or even be disadvantaged by such a location (Knoben *et al.*, 2016). For example, Rigby and Brown (2015) report that smaller and younger firm benefit most from knowledge spillovers within a radius of 5km, but that older firms benefit from having upstream suppliers nearby. Others suggest that multilevel models are needed to control for firm-specific effects and their interactions (Raspe *et al.*, 2011). Some authors argue that smaller firms tend to benefit more from co-location as such firms are more dependent on local sources for inputs, knowledge and collective capabilities (Cainelli *et al.*, 2016; Raspe *et al.*, 2011). However, size may be less important than whether firms possess local connectedness and can access local resources, whether they can absorb and internalize those resources, and whether they can also utilize these resources in their production practices (Knoben *et al.*, 2016). Absorptive capacity plays a key role in these processes.

The absorptive capacity of a firm or plant especially in terms of its ability to internalise potential external knowledge spillovers (which for TFP may be more important in the long run than other sources of spillovers) is a key component of this heterogeneity. Harris and Yan (2019) conclude that firms will not fully benefit from external knowledge unless they have sufficient absorptive capacity. As Harris and Le (2018, p.1) explain "… like the ability of an individual to learn, absorptive capacity is not just about firms being able to benefit from spillovers but rather using knowledge from the external environment to improve their productivity; if firms are not able to learn, then new strategies or technology that are designed to help firms become more productive are likely to have only limited impact." Harris and Yan, *op. cit.*, show that in the UK context, absorptive capacity levels are strongly and positively associated with firm size, especially in manufacturing (Harris and Li, 2018, show the same for New Zealand). Others have also demonstrated the importance of absorptive capacity: for example, Lööf and Nabavi (2015, p. 251) report that in their study of Swedish manufacturing firms, the productivity effect from agglomeration spillovers was restricted to large, high-technology firms and foreign-owned multinational enterprises in non-high-technology sectors. They conclude that "… spillovers can also be neutral or very limited if firms lack sufficient absorptive capacity or operate in technological niches where few other firms operate in their field" (pp. 260-261). Moreover, Papalia and Bertarelli (2009, p. 163) noted in their review of the subject – confirmed by their own results – that: "The main result emerging from these papers is that absorptive capacity is one of the most important prerequisites for transfer of firm specific advantages to domestic firms and effective linkages". Lychagin (2016) concurs, stating that "… spillovers affect firms differently… if firms are heterogeneous in *absorptive capacity*" (emphasis in original text). Lastly, Wang and Zhao (2010) examined whether firms increase their 'technological distance' from competitors, especially when it is not feasible to increase their geographical distance, as a way of reducing knowledge spillovers to their competitors. They note that this is more likely to be successful when competitors lack absorptive capacity and complementary assets, which is more likely to be the case for smaller (rather than larger) plants. In this paper we therefore examine the relationships between co-location (with other firms in the same industry and in related industries), productivity, and plant size in some detail.

Finally, in order to avoid ambiguity, in this paper the emphasis is on the potential spillover benefits from localisation externalities of the MAR-type, arising from the co-location of plants within the same industry or 'related' industries (e.g., making up the supply-chain). The impact of both intra-industry and inter-industry spatial proximity effects are included, where inter-industry refers to 'related' industries[7] (although we do also include a variable in the models estimated that seeks to measure such Jacobsian urbanization economies).

Analysis of British advanced manufacturing - data and model specification

In this study, we use plant-level panel data covering 1984-2016 from the Annual Business Survey (ABS, prior to 2008, the ABS was called the Annual Respondents' Database)[8] for six sectors of manufacturing (using the 1980 Standard Industrial Classification): office

[7] The distinction between intra- and inter-industry spillovers is often blurred if related industries (that are linked technologically, share labour, or share knowledge) are classified as part of a 'cluster' (see Delgado *et al.*, 2014) while colocation of industries (e.g., in cities) with weaker links lead to urbanisation externalities.
[8] For a detailed description of the ARD and discussion of several issues concerning its appropriate use, see Oulton (1997), Griffith (1999), and Harris (2002, 2005a).

machinery and data processing equipment (SIC33) (henceforth referred to as 'computers'), electrical and electronic engineering (SIC34) (henceforth abbreviated to 'electronic engineering'), motor vehicles and motor vehicle parts (SIC35) (henceforth abbreviated to 'motor vehicles'), instrumental engineering (SIC37), pharmaceuticals (SIC257) and aerospace equipment and repairing (SIC364) (henceforth abbreviated to 'aerospace'). This data is collected by the UK's Official for National Statistics (ONS) each year for calculating the national income accounts. In our econometric analysis we weight the data using sample weights to ensure that the distribution of plants for which there is financial data are representative of the population of plants operating in each year in Great Britain. Weighting is necessary both to ensure that population parameters are estimated and because of the fact that one of the endogenous variables in the model (employment) is used by the ONS as part of the stratified sampling approach to collect the ABS data; thus leading to the problem of endogenous sampling or stratification (see the appendix in Harris, 2002). Harris and Moffat (2015) describe in detail the rationale for inclusion of the variables in the model, the data (and especially the use of plants rather than firms as the unit of analysis) and the econometric methodology, and the reader is referred to the earlier article for detailed information. Below, only the core elements of the approach are set out.

The first step was estimation of Cobb-Douglas log-linear production functions (including fixed-effects, α_i) for each of the six advanced manufacturing sectors identified above. Both sides of the productivity relationship (the demand-side, covering firm market power and thus competitive influences; and supply-side factors such as firm efficiency and technological progress) are incorporated.[9] The model is estimated using system-GMM to address the issues of endogeneity inherent to revenue production function estimation:[10]

$$\tilde{r}_{it} \equiv y_{it} + p_{it} - p_{It} = \left(\frac{\sigma-1}{\sigma}\right)(\alpha_i + \alpha_E e_{it} + \alpha_M m_{it} + \alpha_K k_{it} + \alpha_X X_{it} + \alpha_T t) + \frac{1}{\sigma}(r_{It} - p_{It}) + u_{it} \qquad (1)$$

where $\tilde{r}_{it}$ is the natural logarithm of plant *i*'s revenue deflated by an *industry* price index, p_{It}, since firm-level prices, p_{it}, are unobserved; y_{it}, e_{it}, m_{it} and k_{it} refer to the

[9] Ehrl (2013) sets out the approach and underlying assumptions. Since individual firm level prices are not observed, and thus by necessity firm's nominal gross output is deflated by *industry* price to obtain output in constant prices, then if firm prices depart systematically from the average industry price level, estimating the production function results in biased parameter estimates because of the omitted firm price variable. Using a Dixit and Stiglitz (1977) CES firm-level demand function:

$$y_{it}^d = -\sigma(p_{it} - p_{It}) + q_{It} + u_{it}^d$$

where y_{it}^d is the (logged) demand for output from firm *i*; σ is the constant elasticity of demand; q_{It} is an aggregate demand shifter; and u_{it}^d represents demand shocks faced by the firm. Combining the demand function with the production function and noting that $y_{It}^d = r_{It} - p_{It}$ (where r_{It} is industry total revenue) results in equation (1).

[10] Estimators (such as Olley and Pakes, 1996; Levinsohn and Petrin, 2003) that purport to overcome these endogeneity issues are based on assumptions we believe are more restrictive than those implied by system-GMM (Ackerberg *et al.*, 2015). In particular, these estimators do not allow for fixed effects, which previous work has shown to be important because the distribution of productivity is persistent over time (see, for instance, Bartelsman and Dhrymes, 1998; Martin, 2008). Note, like the Olley-Pakes approach, system-GMM is used to overcome the bias that would arise from OLS estimation if firms make decisions on factor inputs based on the value of the TFP shock (error term), which is unobservable to the researcher. Del Gatto *et al.* (2011) and Van Beveren (2011) provide useful surveys on these different approaches to measuring TFP.

natural logarithms of real gross output, employment, intermediate inputs[11] and capital stock in plant i in time t (i = 1,..., N; t=1,...T) respectively; X_{it} is a vector of observed variables determining TFP (as set out in Table 1) which includes the (logged) distance index (described in detail below) and an interaction between this variable and (logged) employment while t represents technical progress; the extent to which the industry experiences a mark-up (or mark-down – see Caselli *et al.*, 2018), is measured by $\sigma/(\sigma - 1)$; and u_{it} is the residual term capturing all other effects on revenue TFP. Note, we treat y_{it} (and its lagged value), e_{it}, m_{it}, k_{it} and the natural log of the spatial proximity/distance index as endogenous (and thus instrument these variables).

The source of the data used to estimate equation (1) is described in Table 1; in particular, estimates of plant level capital stock are obtained using the perpetual inventory approach and plant level estimates of real investment – the methods used are set out in Harris and Drinkwater (2000) and Harris (2005b).

[11] Intermediate inputs cover materials, fuels, semi- and finished-goods and (especially business) services used in the production of new goods and services. We are not estimating a gross valued-added function because we do not want to impose weak separability (capital and labour are separable from intermediate inputs in production) and thus homogeneity with respect to α_M - see Gandhi *et al.* (2012) for a discussion.

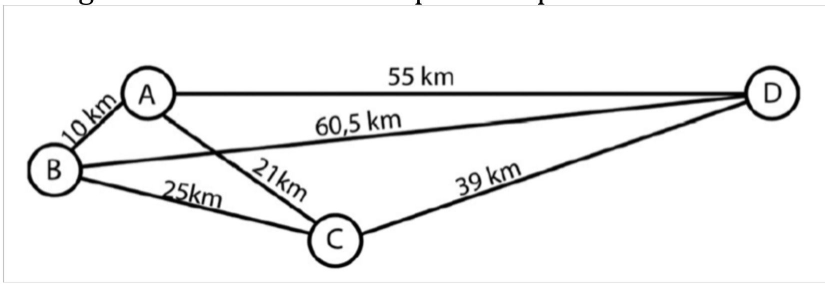
Table 1: Definitions of variables used – 6 advanced manufacturing sectors, 1984-2016

Variable	Definition	Mean	Std. Dev.	Source[a]
ln Gross Output	*ln* real gross output (£m 2000 prices)	-0.160	1.989	ABS
ln Intermediate Inputs	*ln* intermediate inputs (gross output - GVA) (£m 2000 prices)	-0.951	2.204	ABS
ln Employment	*ln* numbers employed in plant	2.516	1.741	ABS
ln Capital	*ln* plant and machinery capital stock (£m 1995 prices) plus real value hires. Source: Harris and Drinkwater (2000, updated)	4.815	2.560	ABS
ln Distance (intra-low)	*ln* distance index based on 4-digit industries (low decay, $e^{-0.01(d_{i,j})}$)	-1.592	0.638	BSD
ln Distance (intra-medium)	*ln* distance index based on 4-digit industries (medium decay, $e^{-0.05(d_{i,j})}$)	-3.910	1.285	BSD
ln Distance (intra-high)	*ln* distance index based on 4-digit industries (high decay, $e^{-0.10(d_{i,j})}$)	-5.097	1.696	BSD
ln Distance (inter-low)	*ln* distance index based on related industry groupings (low decay, $e^{-0.01(d_{i,j})}$)	-1.622	0.538	BSD
ln Distance (inter-medium)	*ln* distance index based on related industry groupings (medium decay, $e^{-0.05(d_{i,j})}$)	-3.881	0.896	BSD
ln Distance (inter-high)	*ln* distance index based on related industry groupings (high decay, $e^{-0.10(d_{i,j})}$)	-4.957	1.045	BSD
ln Age	*ln* number of years since year of opening	1.721	1.035	ABS
Single-Plant Enterprise	Dummy coded 1 if plant comprises a single-plant enterprise	0.353	0.478	ABS
Multi-Region Enterprise	Dummy coded 1 if plant belongs to an enterprise operating plants in more than one UK region	0.523	0.499	ABS
Multi-SIC Enterprise	Dummy coded 1 if enterprise has more than one 4-digit SIC80 across plants it owns	0.360	0.480	ABS
USA	Dummy coded 1 if plant is US-owned	0.083	0.276	ABS
EU	Dummy coded 1 if plant is EU-owned	0.092	0.289	ABS
OFO	Dummy coded 1 if plant is other foreign-owned	0.024	0.153	ABS
Urbanisation	*ln* proportion of the 206 4-digit SIC80 industries in each LA in which plant is located - Jacobsian spillovers	-0.708	0.257	ABS
ln Herfindahl Index	*ln* Herfindahl index of industry concentration (3-digit level)	-2.605	0.786	ABS
Cities	Dummy coded 1 if plant is located in 'core' city (defined by NUTS3 code)[b]	0.148	0.355	ABS
Industry gross output	Real gross output (£m 2000 prices) at 3-digit SIC level	9.945	0.773	ABS
Region	Dummies coded 1 if plant is located in particular Government Office Region			ABS
Unweighted N		98,086		

[a] Source: ONS (2012, 2017, 2018)

[b] These are London, Manchester, Birmingham, Glasgow, Edinburgh, Cardiff, Tyneside, Liverpool, Bristol, Nottingham, Leicester and Coventry; i.e., either capitals (i.e., Cardiff and Edinburgh) or they met the criteria of (in 2001) employing over 250,000 with a population density of 20+ persons per hectare; or they had employment of over 100,000 and densities of 30+ persons per hectare. They closely accord with the definition of 'core' cities used in Great Britain (see http://www.corecities.com/). Thus 'urban areas' that incorporate large hinterlands (e.g., Leeds) are excluded on the population density criterion.

Figure 1: Calculating the distance index: simple example



Source: Scholl and Brenner (2016)

As discussed in section 2, MAR localisation economies are usually proxied by some aggregate measure at a predefined spatial level (e.g. the percentage of industry output located in the local authority district in which the plant was located). The approach taken in this study is to use a more direct measure of the extent to which a plant is 'co-located' with other plants in the same 4-digit industry or plants in related 4-digit industries.[12] This is based on mapping the location of every plant and calculating the distance in kilometres between all pairs of plants in each industry/related industry grouping, using the plant's postcode district (first 4-digits of the UK postcode) and the following formula:

$$Distance_i = \frac{1}{J-1}\sum_{j=1,j\neq i}^{J} e^{-x(d_{i,j})} \times \frac{E_j}{\sum_{k=1,k\neq i} E_k} \quad (4)$$

where J is the number of observations; x is the rate of decay of the function; and $d_{i,j}$ is the distance between plant i and j;[13] E_j is the number of employees in plant j; and $\sum_{k=1,k\neq i} E_k$ is the total employment in all other plants, except plant i, in the industry/related industry grouping.

From Figure 1, for plant A, using Equation (3) (and assuming a decay function of -0.05 and all plants are of equal size) gives $\frac{1}{3}\left(e^{-0.05(10)} + e^{-0.05(21)} + e^{-0.05(55)}\right) = 0.34$. The values for plants B, C, D are: 0.31, 0.26 and 0.08, respectively, and the higher is the $Distance_i$ value, the more a plant is located in spatial proximity to other plants in the same industry.

We use $e^{-0.05(d_{i,j})}$, labelling this the 'medium' function, but in what follows results are also presented based on $e^{-0.01(d_{i,j})}$ (low decay) and $e^{-0.10(d_{i,j})}$ (high decay). Based along the lines of the simple example above, Figure 2 illustrates how adopting different decay functions impact on a plant's contribution to spatial proximity as captured by the distance index ($Distance_i$); when the decay is low, a plant located a long distance from another plant (e.g., $d_{i,j}$ = 200 km) still contributes a fairly large potential spillover ($e^{-0.01(200)}$ = 0.135), but with low or medium decay the impact of such a distant plant on the function is effectively 0. In contrast, a plant located 20 km distant contributes the same to the overall distance index using a high rate of decay ($e^{-0.1(20)}$ = 0.135), while with medium decay the plant would need to be 40 km distance to produce this same contribution.

[12] The appendix provides information on the groupings of related industries.
[13] If plants i and j are located in the same postcode district $d_{i,j}$ is assumed to be half of the distance between that postcode district and the closest (distinct) postcode district.

Figure 2: Impact of different decay functions on distance index

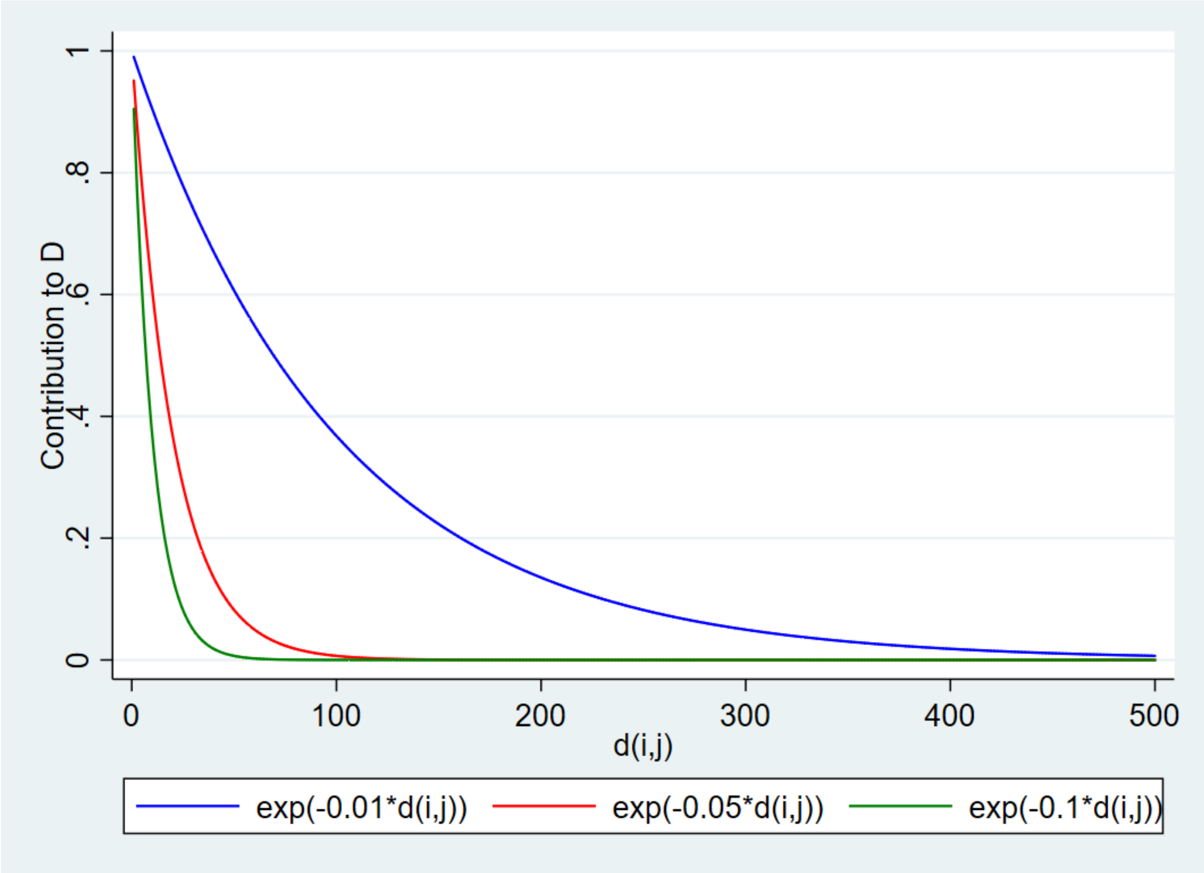


Table 2 Means of $Distance_i$, 2014-16

	Intra			Inter		
	Low, $e^{-0.01(d_{i,j})}$	Medium, $e^{-0.05(d_{i,j})}$	High, $e^{-0.10(d_{i,j})}$	Low, $e^{-0.01(d_{i,j})}$	Medium, $e^{-0.05(d_{i,j})}$	High, $e^{-0.10(d_{i,j})}$
Motor Vehicles (SIC35)	0.275	0.046	0.021	0.247	0.033	0.013
Electronic Engineering (SIC34)	0.236	0.037	0.017	0.219	0.028	0.010
Computers (SIC33)	0.228	0.037	0.016	0.221	0.029	0.011
Instrumental Engineering (SIC37)	0.227	0.032	0.014	0.221	0.028	0.010
Aerospace (SIC364)	0.226	0.029	0.012	0.221	0.028	0.011
Pharmaceuticals (SIC257)	0.221	0.031	0.012	0.216	0.031	0.013

Source: see Table 1 and text

Figure 3: Average *ln* Distance by local authority, 2016: 6 sectors in manufacturing

(a) Low decay $e^{-0.01(d_{i,j})}$ 4-digit SIC (b) Medium decay $e^{-0.05(d_{i,j})}$ 4-digit SIC (c) High decay $e^{-0.10(d_{i,j})}$ 4-digit SIC

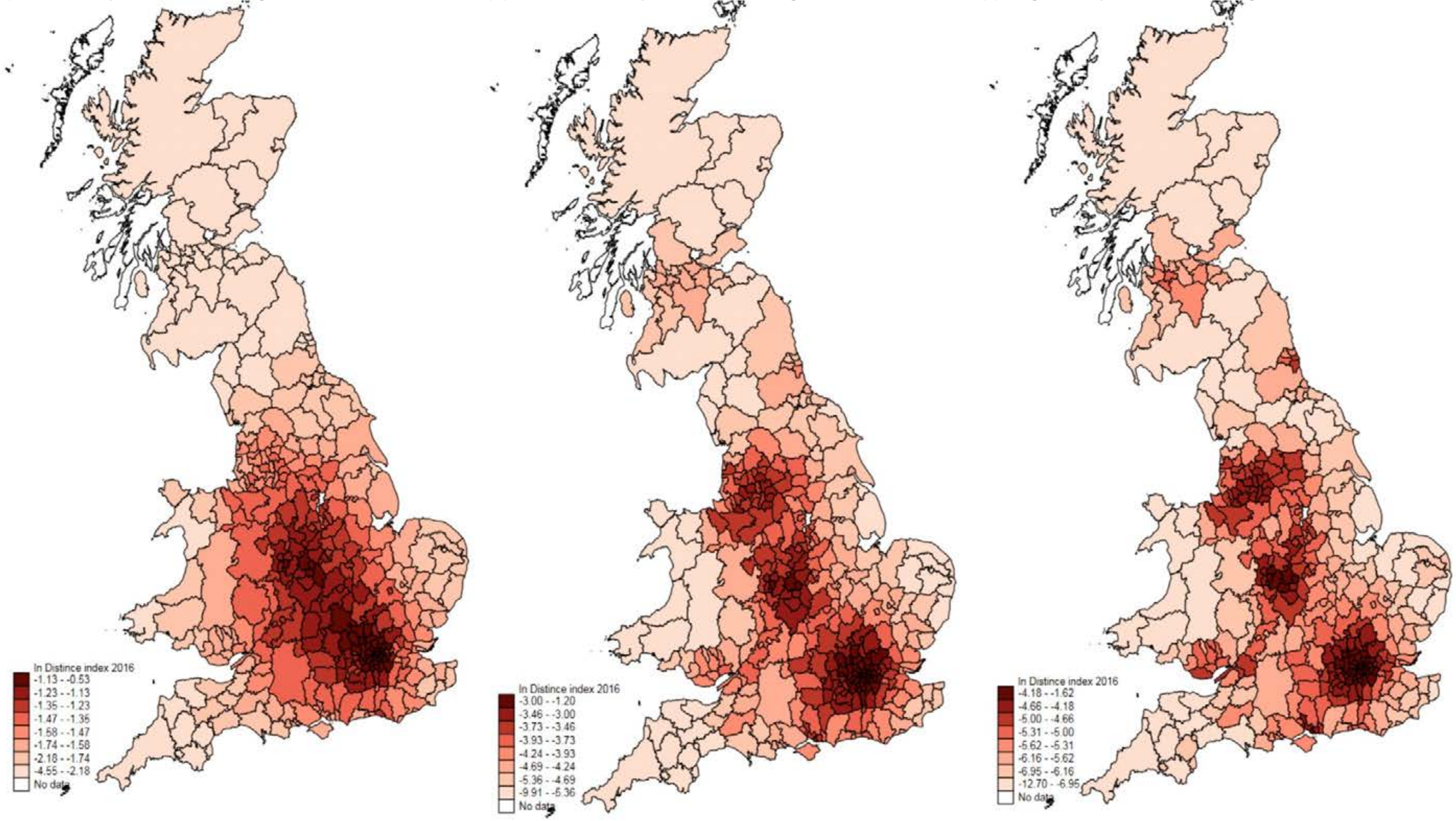


Table 2 shows which industries had the highest proximity levels (ranked on the data in column 1), with motor vehicles having the highest mean value, and pharmaceuticals being the least co-located in this period. However, there are differences in the ranking depending on which index is used (pharmaceuticals comes joint top on the basis of the inter-high index), and there are significant differences in the value of distance indices with values declining as the measure moves from a low rate of decay to a high rate of decay (measures that incorporate both the sector of interest and related sectors, see Supplementary Appendix, are also lower than intra-industry based indices).

To illustrate how the distance indices vary across space, Figure 3 shows the average (logged) values, obtained from the industry-level distance specification, across local authority areas in 2016, based on plants from all six sectors. Spatial proximity is strongest in areas such as London and its hinterland, the industrial heartlands of the West Midlands, and Manchester and Liverpool; but the latter is only particularly apparent with a high rate of decay, which confines spatial proximity to those (larger number of) plants that are close by.[14]

Baseline findings for the six advanced manufacturing sectors

Supplementary Figure U.3 shows the co-location of each of the six case-study advanced manufacturing sectors, using the 'intra-medium' distance index. Each of the sectors has both a different geography and a different degree of spatial clustering. The main results from estimating Equation (1) for the six advanced manufacturing industries are provided in Supplementary Table U.1. There are six sets of results for each industry, reflecting the different measures of the distance index used (Table 1). In this section, we concentrate on the results based on using a medium decay function, $e^{-0.05(d_{i,j})}$, and 4-digit industry co-location; however, all estimated models using various distance indices are deemed sufficient in terms of tests for over-identification (i.e., the Hansen test of validity of the instrument set used – where instruments for the endogenous variables comprised lagged values in first differences and levels; the former being used in the levels equation and the latter the first differenced equation of the system GMM model), and for autocorrelation (*cf*. the AR(1) and AR(2) test statistics).[15] To reduce the likelihood that our estimates are biased due to the problem of over-instrumentation (see Roodman, 2009), the instrument set was 'collapsed'.[16] This had the expected effect of reducing dramatically the p-value of the Hansen test (although not to the extent that the null of valid instruments was rejected).

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[14] Note, the maps are based on different percentile cut-off points in Figure 3 (using one set of points would hide the differences obtained when using different decay functions). A set of maps based on wider 'clusters' is available in the appendix (Figure U.1); these show patterns very similar to the ones based on intra-industry indices (Figure 3).

[15] Stata reports tests for the first-differenced residuals, thus there should be evidence of significant negative first order serial correlation in differenced residuals and no evidence of second order serial correlation in the differenced residuals, which is the case here.

[16] That is, we use Roodman's suggested approach of typically using only the lagged values of the particular variable being instrumented, rather than instruments based on the lagged values of all endogenous variables (which often leads to over-instrumentation).

There is only a brief discussion of the results relating to those determinants of TFP which are not the main focus of this paper: e.g., the age of the plant, foreign-ownership and various economies-of-scale.[17] With respect to the latter, we note that most sectors benefited from increasing internal returns-to-scale; only in electronic engineering is there any systematic evidence to suggest the coefficients on the factor inputs sum to less than one. Technical change was strong in computers (some 4-5% p.a.); around 1-2% p.a. in electronic engineering, motor vehicles and instrumental engineering; 0.5% in pharmaceuticals; and not statistically significant in aerospace. Older plants, *cet. par.*, generally had lower TFP (the exceptions were in computing where age was positively associated with TFP, and aerospace where it was not significant). Single-plant enterprises had higher productivity in computing, instrumental engineering and pharmaceuticals, and lower productivity in the other sectors. The effect of external economies-of-scale linked to being part of a multi-regional or multi-SIC enterprise were a mix of positive and negative (the latter was confined to multi-product firms and computing and electronic engineering, with some evidence that this extends to motor vehicles). Generally, US-owned plants had, *cet. par.*, higher TFP, as did EU-owned (but to a lesser extent); the results for 'other' foreign-owned are weaker but if anything suggest little or no productivity advantage (suggesting their external owners are technologically sourcing rather than exploiting – Driffield and Love, 2007). Being located in a city had mixed effects (positive for electronic engineering and instrumental engineering, negative for aerospace and insignificant otherwise), while urbanization economies were not evident in four sectors (and had a positive effect for computing, but a negative effect for aerospace). Belonging to a concentrated industry increased (decreased) TFP in three (two) sectors, while only in computing and motor vehicles was there strong evidence of any sizeable mark-ups of price over marginal costs (indicating lower product market competition); in other sectors there was no positive mark-up although there was some evidence of a mark-down for electronic engineering.

It is also important to note that the impact on TFP of being located in a particular administrative region – relative to the benchmark region, the South East – was important for almost all industries, with effects that were sometimes significant and large.[18] For example, computing plants in the North West, the East Midlands and to a lesser extent Wales had (*cet. par.*) higher TFP; while computing plants in Scotland did less well. In electronic engineering, plants located in all regions except the North West did worse than the South East. For motor vehicles, there was no evidence of (*cet. par.*) regional effects on TFP. In instrumental engineering, plants in the Midlands, Eastern England, London and Wales, did worse; while in pharmaceuticals only the Yorkshire-Humberside, the North West and the South West had higher TFP vis-à-vis the South East. Lastly, plants located in the West Midlands and South West in aerospace had significantly higher TFP compared to the South East and other regions.

[17] Note, our results are consistent with *a priori* expectations and previous work (cf. Harris and Moffat, 2012, 2015).

[18] The results for 'regional' effects are more mixed across the different models estimated for each sector depending on which distance index was used. Thus here, comments are confined to those obtained using the intra-medium distance measure.

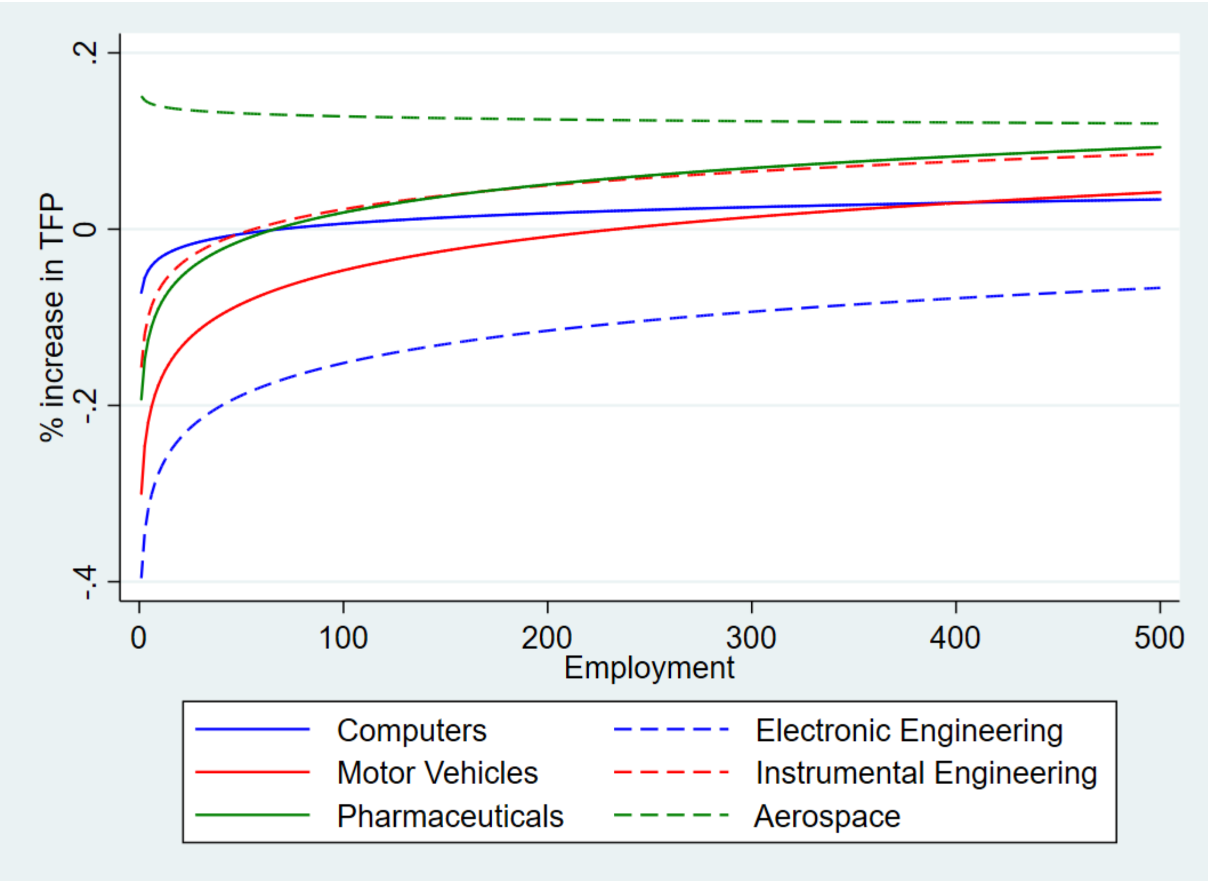
Table 3: Long-run (weighted) impact of *ln* Distance based on 4-digit industry (medium decay, $e^{-0.05(d_{i,j})}$) on TFP by size of plant, 1984-2016 (Great Britain)

	Computers SIC33	Electronic Engineering SIC34	Motor Vehicles SIC35	Instrumental Engineering SIC37	Pharmaceuticals SIC257	Aerospace SIC364
ln Distance	-0.072**	-0.396***	-0.300*	-0.157***	-0.193	0.151***
ln Distance × *ln* employment	0.017*	0.053***	0.055**	0.039***	0.046*	-0.005
Distance × 5 employees	-0.044**	-0.310***	-0.211*	-0.094***	-0.119	0.143***
Distance × 50 employees	-0.005	-0.188***	-0.085	-0.004	-0.013	0.131***
Distance × 500 employees	0.035	-0.065	0.042	0.087***	0.094	0.119***

Source: based on model estimates in Table U.1

Table 3 produces the main results showing the (*cet. par.*) impact of the distance index (measuring MAR spillovers at the industry-level) for plants of different sizes in the six advanced manufacturing industries; Figure 4 (below) produces a graphical version. Generally, there is evidence that the effect of greater co-location on smaller (larger) plants was generally negative (positive), with the exception of aerospace where a 1% increase in the distance index resulted in higher TFP of around 0.12-0.14% (slightly decreasing with size). For example, in the computers sector (SIC33), the effect of a 1% increase in the distance index on plants employing 5 workers was to reduce TFP by 0.04% but the effect was not significant for larger plants (Table 3, first data column). For electronic engineering (SIC34), the negative impact on TFP of co-locating is large for small plants (–0.31% for plants employing 5 workers), decreasing to no statistically significant impact for very large plants. There is a similar pattern for motor vehicles and instrumental engineering, although the negative effect of co-location on smaller plants is larger in motor vehicles and the positive effect on larger plants is bigger in instruments. Pharmaceuticals has a similar profile, but the negative impacts of being smaller are not statistically significant. Figure 5 shows more clearly the steepness of the elasticities for each industry, and the overall average impact of the distance index on TFP[19] (highest overall for aerospace, and lowest for electronic engineering where no plants of any size benefit from agglomeration).

Figure 4: Effect of a 1% increase in distance index on TFP for different sized plants, 1984-2016



Source: based on model estimates in Table 3

[19] Note, the (weighted) means in Figure 5 are heavily influenced by the fact that most industries are dominated by small plants (usually experiencing negative spillover effects).

Alternative models for the six advanced manufacturing sectors

The results presented in the last section were based on the index using distances between plants belonging to the same 4-digit industry with a rate of decay of –0.05. To test the sensitivity of the results to alternative specifications of the distance index, Table 4 extends the results presented in Table 3 to include those obtained using different rates of decay and also plants belonging to wider sets of related industries rather than just their own industry. Supplementary Table U.2 presents these extended results (along with a discussion), showing that the general conclusion reached in the previous section –which were based on just the intra-medium distance index – is in large part supported (indeed strengthened). Only in two sectors (aerospace and to some extent computing) is there evidence that spillovers are generally beneficial to plants of all sizes; for the others, small plants do not generally experience a positive TFP spillover if they co-locate. There is variability (see especially Figure U.3) depending on which distance index is used; but there is also some evidence that the results based on related industries generate higher estimates of spillovers than those based on within- industry specifications. This is possibly in line with prior expectations (spillovers are likely higher in larger related industry groupings with low rates of decay and lowest in specific industries with high rates of decay), but the evidence presented in the Supplementary Appendix is more tentative in nature, and clearly would benefit from extending the methodology to other (including non-advanced) manufacturing sectors, and indeed services.

Potential implications for place-based policies and local industrial strategies

As noted in the review of the literature, there are, essentially, two different accounts or interpretations of the beneficial roles that spatial proximity is assumed to confer on firms, by improving their growth and productivity. The first is Porter's cluster theory. The spatial proximity or geographical concentration of firms in the same and closely related (both upstream and downstream) sectors of activity is assumed to be a key attribute, indeed, prerequisite, for the formation and functioning of specialised business clusters. Spatial proximity (the close co-location of firms) of itself does not equate to a functioning cluster, but it is assumed to play a fundamental role by facilitating and fostering a range of Marshallian localisation externalities, such as the attraction of a local pool of specialised and skilled labour, the local development of specialist intermediary firms and services, transfers and exchange of knowledge and information among local firms (spatial proximity is assumed to confer cognitive proximity), and local supportive institutions, that all contribute to the operation and development of a cluster as a functioning local industrial ecosystem. As such, the spatial proximity of similar and related firms, as the basis of clusters, is assumed to foster higher growth, innovation and productivity among the firms concerned.

The second account is the agglomeration argument. Strictly speaking agglomeration refers to the geographical concentration, usually in a city or an urban region, of a diverse range of firms, spanning several economic activities, both related and unrelated. Agglomeration, like clustering, is also assumed to produce various external economies and untraded interdependencies on which firms can draw – usually referred to as Jacobsian externalities – including a large and diverse labour pool, a large 'home' market of both suppliers and customers, extensive opportunities for new firm entrants, the promotion of innovation through competition and the availability of market niches, a dense infrastructure network that facilitates connectivity, and the like. Again, these positive agglomeration externalities are alleged to boost the economic performance of the local firms in the agglomeration. Studies have shown, for example, that doubling the size of a city is typically associated with an increase in the city's productivity of between 4-8 percent (see Li and Gibson, 2015). As in clusters, the spatial proximity of firms in an agglomeration is viewed as a key driver of firm growth and performance.

Both the clusters concept and the notion of agglomeration have attracted considerable attention from policymakers. Indeed, from the very start, Porter gave his 'cluster theory' an explicit policy dimension, arguing that clusters should be a central component of a policymaker's tool kit for boosting both local economic development and, in turn, national competitive advantage.

> ... governments should promote cluster formation and upgrading and the build-up of public or quasi-public goods that have a significant impact on many linked businesses. ... the aim of cluster policy is to reinforce the development of all clusters... Governments should not choose among clusters, because each one offers opportunities to improve productivity and support rising wages. Every cluster not only contributes directly to national productivity but also affects the productivity of other clusters (Porter, 1998, p.89).

Porter argues that cluster policy is quite distinct from 'traditional' industrial policy in that it is not concerned with targeting 'desirable' or 'strategic' industries ('picking winners') that are then supported by selective subsidies or other financial inducements. Rather, cluster policy is about promoting and upgrading clusters of all sorts, regardless of their specialisms, in an effort to improve their productive performance. Government, working with the private sector, should reinforce and build on existing and emerging clusters rather than attempt to create entirely new ones.

Over the past 30 years or so, many countries and regions have pursued some sort of cluster-based industrial policy, not just in advanced economies but also in developing countries (see Wolman and Hincapie, 2014). The UK has been no exception to this appeal of the cluster concept to policy-makers. Similarly, much has been written in recent years, mainly by spatial economists, on the arguments in favour of agglomeration and encouraging bigger cities as a means of increasing productivity (Cheshire *et al.*, 2014). Whether the policy discussion is on clusters or agglomeration – and often the two are confusingly elided - the spatial proximity of firms is assumed to be of crucial beneficial importance.

The claims made for both clusters and agglomeration have of course been challenged, both on theoretical and policy grounds (on clusters, see, for example, Martin and Sunley, 2003; Duranton, 2011; on agglomeration, see Moomaw, 1983). As various commentators have observed, even some of those who have championed the cluster concept (for example, Delgado, Porter and Stern, 2012), have since questioned its policy usefulness:

"So far there is little empirical evidence of the overall effectiveness of … different cluster programs" (op cit p. 4). Moreover, according to Duranton (2011), not only are most empirical estimates of the impact of clustering on firm productivity modest at best, they are probably exaggerated. Our study in this paper of the impact of spatial proximity on firm productivity in some key UK manufacturing sectors does not offer much comfort to those national or local policy-makers who consider clusters an essential weapon in their industrial policy armoury. Several key issues remain unresolved. For example, just how spatially proximate do firms have to be to both produce and benefit from Marshallian-type localisation externalities? In a globalised world, with instant telecommunications and considerably enhanced mobility of capital, supply chains and knowledge networks have become ever more geographically dispersed, and with improvements in transport, workers now commute further to work than they once did. Thus, the importance of simple close physical spatial proximity may have become much less crucial for firm performance than it once was. Similarly, the geographical agglomeration of firms may itself generate diseconomies, such as higher land, wage and housing costs, congestion problems, pollution, pressure on infrastructure, and so forth, which may dent the advantages of a dense spatial proximity of firms.

Our main finding in this paper, namely that once various other factors are taken into account spatial proximity does not consistently emerge as a key determinant of total factor productivity in British advanced manufacturing firms, raises a caveat in relation to local industrial strategies or place-based policies aimed at promoting clusters or city-region agglomerations in order to increase local and national productivity. This is not to argue that the spatial proximity of firms is unimportant, nor that place-based policies are misconceived. Our results suggest that cluster policies may achieve impact in the case of larger firms, but not necessarily for small firms, which are often viewed as the primary targets and beneficiaries of such policies. 'Spatial proximity' per se would not appear to be a key driver of small firm performance, and encouraging spatial proximity on its own will most likely prove an inadequate strategy. Further research is needed to explore why this may be so.

One of the intriguing aspects of the UK's productivity puzzle is the existence and persistence of a long tail and lagging middle of low productivity firms, a problem that appears to be more pronounced in the older industrial regions. It is a problem that has been attributed in part to a lack of technological diffusion from high productivity firms to low productivity firms (Haldane, 2018). It could well be, therefore, that smaller firms lack absorptive capacity, that is the ability to internalise Marshallian-type externalities and agglomeration spillovers arising from their spatial proximity to other firms. This would mean that even when firms are spatially proximate they do not form effective clusters with interactive learning and collaborative linkages. If this is the case, then an obvious implication for industrial policy – in the UK case: the new national Industrial Strategy and associated Local Industrial Strategies – is to recognise the need to boost absorptive capacity in order to maximise the benefits of co-location (see also Harris and Yan, 2019). More research on this aspect of (small) firm performance in clusters and city-regions across the UK would help inform such policies.

At the same time, of course, the fact that the UK's overall productivity performance in manufacturing is inferior to that of its main competitors may point to wider systemic problems and national policy failures (for example relating to education, skills, infrastructure, support for R&D and so on), though such 'national' problems are almost certain to have their own specific internal geographies. What does seem clear is that the positive influence of spatial proximity *per se* on the economic performance and productivity of firms is by no means a universal or 'natural' outcome, and hence not in itself a robust presumption on which to proclaim a case for a 'place-based' industrial policy.

Conclusions

It is generally assumed that clustering – the spatial proximity and geographical concentration of sectorally similar and related firms – increases both the productivity of the plants concerned, and, by implication, the overall productivity and performance of the wider geographical area, the region, in which the 'cluster' is situated. This assumption has become something of a 'conventional wisdom' in the academic literature. Such has been its academic visibility that the notion of clusters has also proved highly influential in policy circles, the belief being that measures and incentives to boost or even promote clusters is a valid instrument of both national and local industrial policy.

The UK has been no exception to this appeal of the cluster concept to policy-makers. As the manufacturing sector as a whole has declined in importance, as measured by its share of national employment, output and exports, and economic growth has become heavily dependent on financial and related service activities, especially those concentrated in London, so policy attention has focused on the performance and potential of 'advanced' manufacturing activities as a means of achieving a more sectorally and spatially balanced economy. At the same time, there is considerable concern over what has become labelled as the 'productivity puzzle', the slowdown in productivity growth that has taken place not just since the financial crisis of 2007-8, as is often argued, but actually since the 1990s, if not earlier. Under these circumstances, the role of business clusters assumes particular salience. Is the decline in productivity growth due to the break-up of pre-existing clusters of manufacturing activity, perhaps because of the off-shoring of activity or the delocalisation of supply chains, and the consequential atrophy of the local industrial ecosystems that clusters are presumed to foster? Or is it the case that manufacturing clusters in the UK lack the critical mass to generate the positive externalities and spillovers that are assumed to accompany well-developed clusters? Is there scope for policy intervention to help strengthen and deepen clusters of advanced manufacturing, so as to boost local and national productivity? These are all pertinent issues.

The novelty of our approach in this paper is that we have tested for the impact of varying degrees of spatial proximity in six advanced manufacturing sectors (at 4-digit SIC level) and in wider sets of related industries, allowing different rates of decay in the impact of distance on co-located plants. We find that positive impacts of spatial proximity on firm productivity are by no means universal, and in all but two sectors the benefits appear to be significant only for larger plants (which presumably have sufficient absorptive capacity to take advantage of inter-firm spillovers and other such externalities). We also find other 'place' factors influence TFP, especially the impact of being located in particular regions, which are often larger geographically than narrowly defined spatial clusters. However, there is little evidence, after controlling for other firm and place effects, that being located in a major city leads to a positive TFP impact, while urbanization economies were not evident in four sectors. The overall finding is that the spatial proximity of similar and related firms in 'clusters' neither necessarily nor consistently leads to firms having higher levels of total factor productivity. This is particularly the case for small firms. In this respect, our findings provide no support for claims that small firms in particular benefit from geographical clustering.

Of course, this is not to argue that spatial proximity and co-location, bring no benefits to firms. Clustering and agglomeration are about more than spatial proximity per se, even though close proximity is supposed to encourage various traded and untraded spillovers and interdependencies among co-located firms. At the same firm productivity is determined by a host of factors other than spatial proximity to other similar, related or connected firms. The main message of this paper, however, is that spatial proximity is not a certain means of raising productivity growth, and clustering policies will need to do much more than just increasing co-location if they are to boost local, and national, productivity.

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Does spatial proximity raise firm productivity? Evidence from British manufacturing

Richard Harris, John Moffat, Emil Evenhuis, Ron Martin, Andy Pike, Peter Sunley

Online Appendix

Identifying and measuring the externalities from spatial proximity[1]

As we have noted, the contention that the spatial proximity of similar firms acts to raise their productivity was basic to Michael Porter's formulation of the cluster concept and has been central to most accounts of the benefits of clusters.[2] According to Porter (1996), clusters raise the productivity of firms primarily through dynamic externalities related to learning, rather than by static cost-reducing externalities. This contention has been supported and reinforced by theoretical work on agglomeration economies more generally, in relation to the benefits that accrue to firms and plants from being located in the vicinity of large concentrations of other firms and plants. These benefits can be summarised as being processes of 'sharing', 'matching' and 'learning' (Duranton and Puga, 2004; Overman *et al.,* 2009). Agglomeration benefits arise through sharing when firms benefit from drawing on a common pool of resources, such as indivisible goods or facilities, a wide variety of input suppliers, a larger pool of labour, as well as the sharing of risk across plants. The probability, and the speed, of matching is also improved in areas with many firms and workers. Finally, the diffusion and accumulation of knowledge is expected to be better in areas with a high density of both firms and workers. By facilitating face-to-face contact, the concentration of both workers and entrepreneurs in a cluster can facilitate spillovers and the transfer of knowledge. In addition, workers will find it easier to move from one firm to another. This process will assist in the transfer of knowledge (i.e., 'learning') across firms (see e.g. Acs *et al.*, 2002; Anselin *et al.*, 1997; Audretsch and Feldman, 1996). It is possible that industry clusters – specialised localised concentrations of firms in the same or closely related sectors - benefit from all three of these processes.

Providing empirical assessment of this possibility is much more challenging. There has, of course, been considerable ambiguity about the definition of clusters and their spatial extent (Martin and Sunley, 2003), and it is difficult to disentangle the effects of spatial proximity from other forms of firm proximity. While Porter's approach suggests that clusters are sets of related industries, many others have assumed that clusters are essentially based on localisations of single industries and thus have assumed that clusters benefit primarily from Marshallian (intra industry) localisation economies (Marshall, 1890; Arrow, 1962; Romer, 1986). Such MAR-spillovers, it is argued, lead to specialization (Audretsch *et al.*, 2007), since they suggest that firms within a specific industry locate near other firms along the supply chain (be they customers or suppliers); locate near other firms that use similar specialised labour; and/or locate near other firms that might share knowledge (Ellison *et al.*, 2010).[3] However, if clusters

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[1] This an extended version of the material presented in the main text.

[2] At the outset, it is important to note that in the empirical work we are treating 'clusters' as co-located plants in the same or related industries, where 'related' refers to mostly technical inter dependencies such as 'supply-chain' linkages. The notion of a cluster as co-located plants belonging to diverse industries is not the central focus of this study, although we discuss the distinctions in more detail below.

[3]In more detail, MAR-spillovers are based on different types of externalities, according to how they are mediated. Scitovsky (1954) and then Griliches (1979, 1992) distinguished between pecuniary (also called vertical, welfare or rent) spillovers which are based on market transactions, and non-pecuniary (also called horizontal, knowledge and technological) spillovers which are based on non-market interactions usually involving the sharing of knowledge and expertise. As explained by Koo (2005), such pecuniary externalities are associated with: intermediate inputs and labour pools and are emphasized in new economic geography models (Neary, 2001; Fujita and Thisse, 2002, p. 9). In contrast, technological spillovers when firms in proximity share a general pool of knowledge, and are emphasized in the new

consist of wider groups of interrelated industries they may also benefit from some inter-industry spillovers across linked or related industries, which might be conventionally subsumed under Jacobsian or urbanization spillovers[4]. The distinction between intra- and inter-industry spillovers is somewhat blurred if related industries (that are linked technologically or by close upstream and downstream dependencies, or which share labour or knowledge) are classified as part of a 'cluster' (see Delgado *et al.*, 2014). We return to this type of 'related spillover' later in our discussion.

However, the empirical evidence on whether spatial proximity does act to raise firm productivity is not as strong as either cluster theory or agglomeration theory would lead us to expect. Robust empirical studies are relatively scarce (Duranton, 2011). While there has been extensive empirical research on agglomeration, most of this has been framed in terms of localisation and urbanisation economies and their combinations. Many studies have sought to estimate the impact of agglomeration externalities on productivity without clearly distinguishing between localisation, cluster-based, or urban externalities. Examinations of the relations between employment and population density and productivity across local areas (usually cities) typically estimate that doubling of employment density increases labour productivity by between 3 and 6 percent (see Åberg, 1973; Sveikaukus, 1975 and Segal, 1976; Ciccone and Hall, 1996; Ciccone, 2002; Rice *et al.*, 2006). Using French area-level data, for example, Combes *et al.* (2008) estimate the impact of population density and market potential on TFP and obtain elasticities of 3.5% and 2.5% for population density and market potential respectively (also Andersson and Lööf, 2009; Wixe, 2015). While these studies provide some evidence in favour of the benefits of co-location externalities, the magnitude of the effects is generally small.

A further literature has sought to distinguish the relative importance of localisation and urbanisation externalities, but has also used area-level data. These analyses have been rather mixed and inconclusive, and also suffer from the problem that they do not specifically measure the distance between firms in the same or related industries. Some studies suggest that both types of externality have significant effects on productivity (for example, Rigby and Essletzbichler, 2002; Moomaw, 1983; Graham *et al.*, 2010). In contrast, other studies report stronger localisation economies (Henderson, 1986; Drennan, 2002; Acs *et al.*, 2002). However, other studies conclude that urbanisation externalities are more important than localisation externalities, and, indeed, report evidence of localisation *dis*economies (Brülhart and Mathys, 2008; Glaeser *et al.*, 1992; Quigley, 1998; van Stel and Nieuwenhuijsen, 2004; van Oort, 2007). While the evidence from studies using aggregate data suggests that both types of externality operate in some cases, in general most findings are too inconsistent, and too indirectly linked to

industrial geography (see Barnes and Gertler, 1999) and new growth theory literatures (for example Romer, 1990; Black and Henderson, 1999).

[4] Urbanization externalities are due to the size and heterogeneity (or diversity) of an (urban) agglomeration and result when different industries benefit from economies of scope (rather than scale). A greater range of activities (for example, R&D, business services, cultural and lifestyle amenities, and the overall quality of the public infrastructure – see Florida, 2002; Glaeser *et al.*, 2001) leads to inter-industry spillovers. Urbanisation externalities often stem from the co-location in cities of firms that are weakly linked.

spatial proximity to be compelling.[5] Some studies try to explain this variation by focusing on differences between types of industry or different stages of the industry or product lifecycle (Nakamura, 1985; Faggio *et al.*, 2017). Others suggest that clustering and co-location only yield positive externalities up to a threshold, and above this begin to have a negative effect on productivity (Antonelli, *et al.*, 2011).

A substantial number of studies that use firm and micro-data evidence have found that localisation externalities and spatial proximity to firms in the same industry have a positive effect on firm productivity. Henderson (2003), using plant-level data from the US, finds evidence that the average localisation elasticity of productivity across industries is 0.03. Capello (2002) also finds evidence that localisation externalities have a positive impact on TFP using data on high-tech firms in Milan. Similarly, López and Südekum (2009) found strong evidence of intra-industry spillovers in Chilean plants but generally not inter-industry spillovers (with some upstream exceptions). Baldwin *et al.* (2010), using Canadian plant-level data, find that productivity growth is positively associated with indicators of Marshallian externalities (see also Martin *et al.*, 2011). Van Der Panne (2004) finds that localisation has a positive impact on innovativeness in Dutch firms. Assuming a link between innovation and productivity (see, for example, Crepon *et al.*, 1998), this also supports the idea that Marshallian externalities have a positive impact on productivity.

However, we should note that other micro-data based analyses show mixed results. Graham (2009), for instance, uses the UK's FAME dataset on 27 industries and finds evidence of positive and statistically significant impact of localisation externalities for only around half of the industries included. Overman *et al.* (2009), using establishment level data, provide evidence for urbanisation externalities, but find that being situated near other establishments in the same industry has a negative impact on TFP. Their coefficients also indicate that, with the exception of London, firms in regions and cities outwith the South East have lower TFP than firms inside the South East region. In general, regional and urban effects appear to be stronger than co-location and localisation. Similar conclusions are reached by Harris and Moffat (2012) using plant level data from the ARD.

These inconsistent results may partly reflect the fact that micro-level studies have measured MAR or localisation externalities in different ways. For example, Harris and Moffat (2012) proxied MAR spillovers using the percentage of industry output (at 5-digit industry SIC level) located in the local authority district in which the plant was located. Such empirical studies typically use relatively small administrative areas, such as local authority districts since spatial productivity spillovers are assumed to have a strong distance decay; but the extent to which they are limited is likely to be an empirical issue (e.g., Gertler, 2003; Venables, 2011). Moreover, whether these small areal units correspond with the spatial dimensions of clusters is unknown. There is much uncertainty concerning the 'correct' geographic area needed to capture cluster externalities, and different papers use different statistics, while some experiment with different industrial agglomeration and diversification indices (see, for example, Devereux *et al.,* 2007; Baldwin *et al.*, 2010).

[5] De Groot *et al.* (2016) have analysed 73 journal articles which build on the seminal work of Glaeser *et al.* (1992) and find a very mixed set of results (although perhaps more weight in favour of Jacobsian spillovers, particularly for papers related to city growth, which may not be surprising).

Another set of spillover studies uses spatial econometric models which involve the use of pre-defined spatial 'weighting' or 'W' matrices to define spillovers between areas. Such models can be criticised on the grounds that ex-ante, researchers have little information on the nature of spatial spillovers (they may be a mix of global, national and local effects) and, despite recent developments in tests of the specification of spatial econometric models (see, e.g., Kelegian, 2008), it is not possible to empirically test the validity of what could be a very large number of potentially relevant 'W' matrices (see Harris *et al.*, 2011). Once again, the role of spatial proximity is not distinct. However, as we have noted, the other methods usually employed also suffer from a similar weakness as the area is predefined, for example, an administrative unit such as a local authority district. Other variables which would allow measurement of particular sources of agglomeration externalities (such as 'labour-mix' and the location of upstream suppliers – cf. Baldwin *et al.*, 2010 – or the extent to which clustered firms trade with each other and/or employ similar workers – cf. Ellison *et al.*, 2010) are often not available.

Another possible reason, why spatial proximity may lead to higher productivity relates to firm selection and higher competition (as recognised in Porter's cluster model). Melitz and Ottaviano (2008) argue that larger markets attract more firms and this increases competition, causing less productive firms to exit. This implies that firms and plants operating in spatial clusters and cities will have higher levels of productivity. Combes *et al.* (2012) attempt to distinguish between agglomeration and firm selection effects by exploiting their different implications for the distribution of firm productivity. However, using French firm level data, they find strong evidence for agglomeration effects in large cities but no systematic evidence of selection effects.

Attempts to estimate the productivity benefits of spatial proximity also encounter significant endogeneity problems. Clusters of co-located firms may, of course, be created by local spin-off processes, and it is not credible to simply demonstrate that a cluster exists and then deduce that proximity spillovers are benefiting firms. Higher productivity firms may also choose to locate in clusters. This issue of reverse causality is thus especially relevant when considering whether spatial proximity and colocation are a source of productivity spillovers. Greenstone *et al.* (2010) use a novel approach to overcome the problem by looking at TFP outcomes in areas that attract new large plants (e.g., multinationals) versus areas that were the second-choice location for these plants (and thus share common advantages). They conclude that there are significant productivity spillovers from the opening of new plants that are larger for firms that share labour pools and similar technologies. Therefore, in this paper we treat co-location and productivity as endogenous and instrument both sets of variables (as explained below).

Recent research has also proposed a third class of spatial spillover that is in one sense intermediate; lying between Marshallian localisation and Jacobsian urbanization effects. These are spillovers that occur between related industries that have a degree of cognitive proximity that allows employees to share and understand knowledge. When there is a diversity of such related industries in a particular locality, it is argued that spillovers will be particularly strong and effective and that these will increase innovation and firm productivity growth (Boschma and Iammarino, 2009; Eriksson, 2011; Aarstad *et al.*, 2016; Cainelli *et al.*, 2016). This type of 'related variety' externality accords quite closely with Porter's vision of how relatedness between firms in clusters raises productivity and has sparked interest in 'cluster diversity' (see Slaper *et al.*, 2018). While related variety has rapidly become a popular and influential concept, knowledge relatedness is difficult to measure and empirical studies have therefore been forced to rely on a range of different indicative proxies (such as entropy measures of industry classifications, patent co-citations and labour flows) (Content and Frenken, 2016). Partly as a result, the empirical results on whether related variety does boost firm growth and productivity have been inconclusive, with some studies finding a negative effect on firm productivity growth (compare Frenken *et al.*, 2007; Eriksen and Lindgren, 2009; Wixe, 2015, with Falcioglu, 2011). Wixe and Andersson (2017) find contrasting effects on productivity growth depending on whether relatedness is measured by occupation or by industry variety. Cainelli *et al.* (2016) use a large panel of Italian manufacturing firms and find that localisation effects on TFP are in fact stronger than related variety effects as measured by input-output relations. To date, there have been very few studies that provide strong evidence that the combination of spatial proximity and related variety significantly raises plant productivity.

Finally, a key response to the mixed and varied results of research on cluster and localisation spillovers has been to pay much more attention to firm heterogeneity (Wixe, 2015). There is mounting evidence that differences in firm characteristics mean that while some benefit from spatial proximity, other firms may gain no advantage, or even be disadvantaged by such a location (Knoben *et al.*, 2016). For example, Rigby and Brown (2015) report that smaller and younger firm benefit most from knowledge spillovers within a radius of 5km, but that older firms benefit from having upstream suppliers nearby. Others suggest that multilevel models are needed to control for firm-specific effects and their interactions (Raspe *et al.*, 2011). Some authors argue that smaller firms tend to benefit more from co-location as such firms are more dependent on local sources for inputs, knowledge and collective capabilities (Cainelli *et al.*, 2016; Raspe *et al.*, 2011). However, size may be less important than whether firms possess local connectedness and can access local resources, whether they can absorb and internalize those resources, and whether they can also utilize these resources in their production practices (Knoben *et al.*, 2016). Absorptive capacity plays a key role in these processes.

The absorptive capacity of a firm or plant especially in terms of its ability to internalise potential external knowledge spillovers (which for TFP may be more important in the long run than other sources of spillovers) is a key component of this heterogeneity. Harris and Yan (2019) conclude that firms will not fully benefit from external knowledge unless they have sufficient absorptive capacity. As Harris and Le (2018, p.1) explain "… like the ability of an individual to learn, absorptive capacity is not just about firms being able to benefit from spillovers but rather using knowledge from the external environment to improve their productivity; if firms are not able to learn, then new strategies or technology that are designed to help firms become more productive are likely to have only limited impact." Harris and Yan, *op. cit.*, show that in the UK context, absorptive capacity levels are strongly and positively associated with firm size, especially in manufacturing (Harris and Li, 2018, show the same for New Zealand). Others have also demonstrated the importance of absorptive capacity: for example, Lööf and Nabavi (2015, p. 251) report that in their study of Swedish manufacturing firms, the productivity effect from agglomeration spillovers was restricted to large, high-technology firms and foreign-owned multinational enterprises in non-high-technology sectors. They conclude that "… spillovers can also be neutral or very limited if firms lack sufficient absorptive capacity or operate in technological niches where few other firms operate in their field" (pp. 260-261). Moreover, Papalia and Bertarelli (2009, p. 163) noted in their review of the subject – confirmed by their own results – that: "The main result emerging from these papers is that absorptive capacity is one of the most important prerequisites for transfer of firm specific advantages to domestic firms and effective linkages". Lychagin (2016) concurs, stating that "… spillovers affect firms differently… if firms are heterogeneous in *absorptive capacity*" (emphasis in original text). Lastly, Wang and Zhao (2010) examined whether firms increase their 'technological distance' from competitors, especially when it is not feasible to increase their geographical distance, as a way of reducing knowledge spillovers to their competitors. They note that this is more likely to be successful when competitors lack absorptive capacity and complementary assets, which is more likely to be the case for smaller (rather than larger) plants. In this article we therefore examine the relationships between co-location (with other firms in the same industry and in related industries), productivity, and plant size in some detail.

Figure U.1 Related industries groupings (SIC1980) [a]

<u>Computers:</u>
Office machinery (3301)
Electronic data processing equipment (3302)
Telephone equipment (3441)
Electrical instruments a& control systems (3442)
Radio & electronic capital goods (3443)
Active components & electronic sub-assemblies (3453)
Electronic consumer goods (3454)
Measuring, checking &precision instruments (3710)
Medical & surgical equipment (3720)

<u>Aerospace:</u>
Compressors & fluid power equipment (3283)
Pumps (3287)
Electronic data processing equipment (3302)
Electrical instruments & control systems (3442)
Active components & electronic sub-assemblies (3453)
Aerospace equipment manufacturing (3640)
Measuring, checking &precision instruments (3710)
Clocks, watches & other timing devices (3740)

<u>Instrumental engineering:</u>
Pharmaceutical products (2570)
Compressors & fluid power equipment (3283)
Pumps (3287)
Electrical instruments & control systems (3442)
Measuring, checking &precision instruments (3710)
Medical & surgical equipment (3720)
Optical precision instruments (3732)
Photographic & cinematographic equipment (3733)
Clocks, watches & other timing devices (3740)
Other manufacturing n.e.s. (4959)

<u>Motor vehicles:</u>
Asbestos goods (2440)
Packaging products of metal (3164)
Precision chains &power transmission equipment (3261)
Internal combustion engines (3281)
Compressors & fluid power equipment (3283)
Pumps (3287)
Electrical equipment for vehicles (3434)
Electrical instruments & control systems (3442)
Electrical lighting equipment (3470)
Motor vehicles (3510)
Motor vehicle bodies (3521)
Trailers & semi-trailers (3522)
Caravans (3523)
Motor vehicle parts (3530)
Measuring, checking &precision instruments (3710)
Soft furnishings (4555)
Canvas goods, sacks & other made-up textiles (4556)
Plastics semi-manufactures (4832)
Plastics building products (4834)
Plastics packaging products (4835)
Plastics products n.e.s. (4836)

<u>Pharmaceutical</u>:
Basic organic chemicals (2512)
Misc. chemical products for industrial use (2567)
Pharmaceutical products (2570)

<u>Electronic engineering:</u>
Finished metal products n.e.s. (3169)
Insulated wires & cables (3410)
Basic electric equipment (3420)
Batteries &accumulators (3432)
Alarms & signalling equipment (3433)
Domestic electrical appliances (3460)
Electrical lighting equipment (3470)

[a] Industries denoted in italics feature in more than one group. Membership of each group is based on information from the U.S. cluster mapping project (2014), augmented by UK input-output data for various years.

Table U.1(a): Long-run (weighted) parameter estimates of production function: Computers (SIC33) using System-GMM, 1984-2016[a]

Variables	Intra-medium	Intra-low	Intra-high	Inter-medium	Inter-low	Inter-high
ln Intermediate Inputs	1.042***	0.733***	0.703***	0.694***	0.720***	0.678***
ln Employment	0.103***	0.261***	0.298***	0.163***	0.443***	0.123**
ln Capital	0.080**	0.056***	0.169***	0.094***	0.055***	0.106***
Time trend	0.029***	0.049***	0.049***	0.049***	0.056***	0.050***
ln Age	-0.030	-0.023	-0.186***	-0.083***	-0.021	-0.112***
Single-Plant Enterprise	0.076	0.058***	0.028*	0.033	0.070***	0.019
Multi-Region Enterprise	0.027	0.030**	0.008	0.013	0.047***	-0.005
Multi-SIC Enterprise	-0.097***	-0.029**	-0.018	-0.036**	-0.032**	-0.041**
USA	0.108*	0.123***	0.067**	0.089***	0.127***	0.098***
EU	0.114***	0.001	0.004	0.010	0.023	0.007
OFO	-0.201***	-0.062	-0.160***	-0.044	0.025	-0.096**
ln Distance	-0.072**	0.035	0.029***	-0.009	0.297***	0.158***
ln Distance × *ln* employment	0.017*	-0.040***	0.002	-0.049***	0.050**	-0.051***
Urbanisation	0.123*	0.104***	0.060*	0.115***	0.046*	0.010
Cities	-0.075	-0.102**	-0.073	-0.081	-0.029	-0.079
ln Herfindahl Index	-0.068**	-0.096***	-0.105***	-0.103***	-0.082***	-0.091***
$1/\sigma$	0.132***	0.146***	0.129***	0.142***	0.131***	0.133***
Mark up $(\frac{\sigma}{\sigma-1})$	1.152***	1.171***	1.149***	1.166***	1.150***	1.153***
North-East	-0.098	-0.061	0.132**	-0.091	0.023	0.026
Yorkshire-Humberside	0.057	0.095**	0.068	0.097**	0.074	0.103**
North-West	0.213***	0.017	-0.058	0.160**	-0.059	0.010
West Midlands	-0.026	-0.037	0.170**	-0.044	0.460***	0.140
East Midlands	0.375***	0.101*	0.210***	0.088	0.394***	0.207***
South-West	0.058	0.013	0.172***	0.009	0.591***	0.137***
East	-0.028	-0.095*	0.061	-0.209***	-0.105	-0.042
London	-0.094	0.006	0.118*	-0.057	0.195**	0.058
Scotland	-0.161***	-0.034	-0.075*	-0.051	0.032	0.064
Wales	0.150*	-0.039	0.103**	0.101*	0.309***	0.136***
Unweighted Observations	1,557	1,557	1,557	1,557	1,557	1,557
Unweighted Number of firms	611	611	611	611	611	611
Distinct Number of firms	368	368	368	368	368	368
Wald test	3.460e+07	2.630e+07	1.610e+10	3.377e+06	1.020e+08	7.330e+07
F test	49.92	38.42	97.63	4.581	81.95	12.89
AR(1) z-statistic	-4.008	-2.875	-2.696	-2.850	-3.159	-2.848
AR(1) z-statistic p-value	6.12e-05	0.00405	0.00701	0.00438	0.00159	0.00439
AR(2) z-statistic	0.705	0.460	0.273	0.472	-0.0464	0.602
AR(2) z-statistic p-value	0.481	0.646	0.785	0.637	0.963	0.547
Hansen test	80.42	107.1	102.0	95.70	44.11	93.75
Hansen test p-value	0.144	0.587	0.718	0.849	0.966	0.401

[a] Note all reduced-form parameter estimates have been converted into structural estimates by multiplying through by $\frac{\sigma}{\sigma-1}$. Source: estimation of equation (1)

Table U.1(b): Long-run (weighted) parameter estimates of production function: Electronic Engineering (SIC34) using System-GMM, 1984-2016

Variables	Intra-medium	Intra-low	Intra-high	Inter-medium	Inter-low	Inter-high
ln Intermediate Inputs	0.249***	0.353***	0.445***	0.459***	0.256**	0.612***
ln Employment	0.945***	0.416***	0.291**	0.615***	0.515***	0.188***
ln Capital	0.083*	0.084*	0.125*	0.085*	0.164**	0.165**
Time trend	0.027***	0.018***	0.016***	0.016***	0.022***	0.018***
ln Age	-0.173***	-0.000	-0.065	-0.219***	-0.078	-0.210***
Single-Plant Enterprise	-0.112**	-0.057*	-0.059	-0.039	-0.073**	-0.023
Multi-Region Enterprise	0.115***	0.070**	0.059*	0.104***	0.079***	0.047*
Multi-SIC Enterprise	-0.146***	-0.058**	-0.053*	-0.101***	-0.065**	-0.062**
USA	0.109**	0.010	-0.047	-0.001	0.010	0.115***
EU	0.126***	0.017	0.003	0.043	0.073	0.068*
OFO	0.223***	0.020	-0.028	0.040	0.007	0.124*
ln Distance	-0.396***	-0.231***	-0.042	-0.374***	-0.161	-0.118*
ln Distance × *ln* employment	0.053***	-0.001	-0.001	0.063**	0.038	0.018
Urbanisation	0.091	-0.007	0.015	0.061	-0.004	-0.003
Cities	0.128***	0.062**	0.057	0.153***	0.035	0.079*
ln Herfindahl Index	0.004	0.012	-0.008	-0.006	0.006	-0.024*
$1/\sigma$	-0.056	-0.242***	-0.330***	-0.252***	-0.281***	-0.431***
Mark up $[\sigma/(\sigma-1)]$	0.947	0.805***	0.752***	0.799***	0.781***	0.699***
North-East	-0.215***	-0.110***	-0.108***	-0.146***	-0.126***	-0.080**
Yorkshire-Humberside	-0.176***	-0.078**	-0.047	-0.094***	-0.063**	-0.013
North-West	0.163*	0.063*	0.059	0.138*	0.012	0.051
West Midlands	-0.270***	-0.248***	-0.055	-0.178***	-0.081	-0.033
East Midlands	-0.124***	-0.074**	-0.029	-0.088***	-0.038	-0.024
South-West	-0.399***	-0.372***	-0.070	-0.283***	-0.090	-0.081
East	-0.360***	-0.141**	-0.044	-0.200**	-0.028	-0.052
London	-0.510***	-0.236***	-0.164*	-0.387***	-0.126	-0.175**
Scotland	-0.077*	-0.039	-0.042	-0.075***	-0.041	-0.031
Wales	-0.165***	-0.076*	-0.035	-0.120**	-0.030	-0.016
Unweighted Observations	27,960	27,960	27,960	27,960	27,960	27,960
Unweighted Number of firms	7,311	7,311	7,311	7,311	7,311	7,311
Distinct Number of firms	4430	4430	4430	4430	4430	4430
Wald test	24683	12150	15853	22787	14724	22195
F test	20.97	4.613	1.19	7.96	4.06	3.76
AR(1) z-statistic	-5.946	-2.374	-3.092	-3.673	-2.679	-8.395
AR(1) z-statistic p-value	2.74e-09	0.0176	0.00199	0.000240	0.00738	0
AR(2) z-statistic	-0.235	0.693	0.526	0.813	0.693	-0.0905
AR(2) z-statistic p-value	0.814	0.488	0.599	0.416	0.488	0.928
Hansen test	41.76	26.01	14.12	14.12	18.34	27.98
Hansen test p-value	0.201	0.206	0.516	0.167	0.245	0.141

Table U.1(c): Long-run (weighted) parameter estimates of production function: Motor Vehicles (SIC35) using System-GMM, 1984-2016

Variables	Intra-medium	Intra-low	Intra-high	Inter-medium	Inter-low	Inter-high
ln Intermediate Inputs	0.734***	0.641***	0.361***	0.691***	0.741***	0.386***
ln Employment	0.598***	0.506***	0.742***	0.660***	0.631***	0.716**
ln Capital	0.163***	0.088**	0.270***	0.124***	0.104***	0.283***
Time trend	0.005	0.008**	0.016***	0.008***	0.006	0.015***
ln Age	-0.256***	-0.068	-0.417***	-0.137*	-0.119*	-0.433***
Single-Plant Enterprise	-0.054	-0.030	-0.080**	-0.036	-0.028	-0.068**
Multi-Region Enterprise	0.012	0.040	0.024	0.035	-0.009	0.034
Multi-SIC Enterprise	-0.027	-0.014	-0.058**	-0.026	-0.016	-0.062**
USA	-0.003	0.049	0.132	0.071	-0.014	0.055
EU	0.060	0.018	0.217**	0.062	-0.045	0.108
OFO	-0.041	-0.067	0.057	-0.080	-0.117**	-0.078
ln Distance	-0.300*	0.216	-0.235***	-0.329*	-0.022	-0.329
ln Distance × *ln* employment	0.055**	0.052*	0.047**	0.067	0.230***	0.058
Urbanisation	0.088	-0.109	0.064	0.041	-0.046	0.069
Cities	0.029	-0.012	0.037	0.052	-0.104*	0.055
ln Herfindahl Index	0.040	0.025	0.139***	0.044	0.018	0.092***
$1/\sigma$	0.215***	0.108*	0.080*	0.183***	0.077	0.019
Mark up $[\sigma/(\sigma-1)]$	1.274***	1.121*	1.086*	1.224***	1.083	1.020
North-East	-0.035	-0.209*	-0.114**	-0.053	-0.253**	-0.116*
Yorkshire-Humberside	-0.047	-0.043	-0.084*	-0.063	-0.005	-0.059
North-West	0.100	-0.031	0.143	0.120	-0.091	0.265
West Midlands	-0.063	0.149	-0.036	-0.087	0.380	-0.050
East Midlands	0.005	-0.099**	0.004	-0.016	-0.078*	0.025
South-West	-0.245	0.643	-0.212	-0.142	0.977	-0.131
East	-0.158	0.135	-0.167*	-0.123	0.256	-0.122
London	-0.080	-0.024	-0.062	-0.141	0.265	-0.158
Scotland	0.002	-0.290**	-0.046	-0.050	-0.386**	-0.025
Wales	-0.035	-0.088	-0.030	-0.026	0.007	0.005
Unweighted Observations	11,092	11,092	11,092	11,092	11,092	11,092
Unweighted Number of firms	2,495	2,495	2,495	2,495	2,495	2,495
Distinct Number of firms	1653	1653	1653	1653	1653	1653
Wald test	55903	55220	90708	18650	44583	34519
F test	7.98	3.21	10.27	4.30	7.56	1.27
AR(1) z-statistic	-6.224	-6.962	-2.745	-7.745	-7.017	-4.542
AR(1) z-statistic p-value	4.84e-10	0	0.00605	0	0	5.59e-06
AR(2) z-statistic	2.749	2.817	-1.780	3.344	2.846	0.0367
AR(2) z-statistic p-value	0.00597	0.00484	0.0750	0.000826	0.00442	0.971
Hansen test	15.46	25.14	26.74	15.89	16.97	27.28
Hansen test p-value	0.280	0.121	0.180	0.103	0.200	0.162

Table U.1(d): Long-run (weighted) parameter estimates of production function: Instrumental Engineering (SIC37) using System-GMM, 1984-2016

Variables	Intra-medium	Intra-low	Intra-high	Inter-medium	Inter-low	Inter-high
ln Intermediate Inputs	0.467***	0.295***	0.250***	0.447***	0.450***	0.442***
ln Employment	0.706***	0.703***	0.857***	0.732***	0.666***	0.798***
ln Capital	0.071**	0.157***	0.221***	0.110***	0.104***	0.074***
Time trend	0.009***	0.013***	0.015***	0.009***	0.008***	0.010***
ln Age	-0.115**	-0.170**	-0.261**	-0.147***	-0.154***	-0.091**
Single-Plant Enterprise	0.029	0.100**	0.030	0.065***	0.063***	0.055**
Multi-Region Enterprise	0.082***	0.175***	0.115**	0.116***	0.114***	0.096***
Multi-SIC Enterprise	0.043***	0.048	0.045	0.023**	0.030***	0.025**
USA	0.106***	0.131**	0.173**	0.091***	0.124***	0.094***
EU	0.129***	0.168**	0.197***	0.123***	0.145***	0.096***
OFO	0.157***	0.231***	0.305***	0.157***	0.164***	0.145***
ln Distance	-0.157***	-0.484*	-0.342***	-0.215***	-0.542***	-0.108***
ln Distance × *ln* employment	0.039***	0.028	0.047*	0.059***	0.098***	0.062***
Urbanisation	0.021	0.118	0.207**	0.035	0.010	-0.038
Cities	0.100***	0.099*	0.270**	0.134***	0.106***	0.079**
ln Herfindahl Index	-0.057***	-0.073***	-0.089***	-0.059***	-0.061***	-0.066***
$1/\sigma$	0.022	0.031	0.008	0.006	0.005	-0.008
Mark up $[\sigma/(\sigma-1)]$	1.022	1.032	1.009	1.006	1.005	0.992
North-East	-0.057	-0.069	-0.224*	-0.042	0.012	-0.027
Yorkshire-Humberside	0.002	0.012	-0.067	0.013	0.021	0.034
North-West	0.049	0.066	0.172**	0.051	0.070*	-0.048
West Midlands	-0.183***	-0.609***	-0.374***	-0.191***	-0.391***	-0.088*
East Midlands	-0.095***	-0.171	-0.171	-0.070**	-0.102**	-0.082**
South-West	-0.062	-0.639	-0.342*	-0.009	-0.396***	-0.090**
East	-0.088***	-0.257	-0.293***	-0.086	-0.163**	0.030
London	-0.128***	-0.336**	-0.549***	-0.201**	-0.215***	-0.043
Scotland	-0.009	-0.025	-0.148*	-0.017	0.033	-0.017
Wales	-0.120***	-0.286**	-0.310***	-0.120**	-0.132**	-0.082**
Unweighted Observations	6,939	6,939	6,939	6,939	6,939	6,939
Unweighted Number of firms	2,078	2,078	2,078	2,078	2,078	2,078
Distinct Number of firms	1362	1362	1362	1362	1362	1362
Wald test	24948	19007	10597	21995	18110	22656
F test	49.23	2.86	10.76	37.15	29.74	46.65
AR(1) z-statistic	-1.579	-3.436	-3.435	-1.640	-1.651	-1.805
AR(1) z-statistic p-value	0.114	0.000590	0.000593	0.101	0.0988	0.0711
AR(2) z-statistic	-2.393	1.211	0.883	-2.375	-1.309	-3.026
AR(2) z-statistic p-value	0.0167	0.226	0.377	0.0175	0.191	0.00248
Hansen test	87.95	36.43	35.02	82.45	86.92	90.27
Hansen test p-value	0.146	0.231	0.111	0.128	0.164	0.110

Table U.1(e): Long-run (weighted) parameter estimates of production function: Pharmaceuticals (SIC257) using System-GMM, 1984-2016

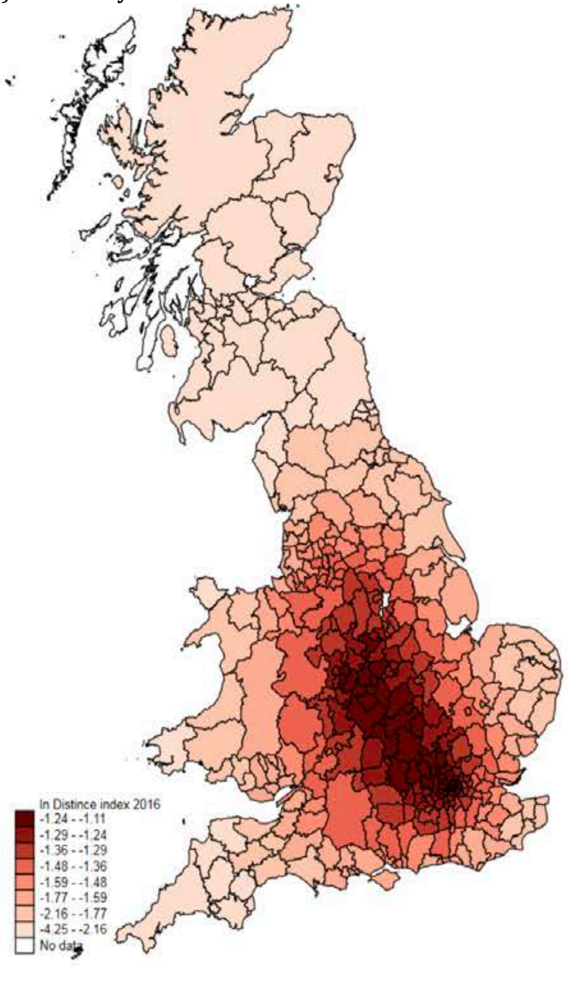
Variables	Intra-medium	Intra-low	Intra-high	Inter-medium	Inter-low	Inter-high
ln Intermediate Inputs	0.641***	0.669***	0.582***	0.649***	0.655***	0.563***
ln Employment	0.464***	0.394***	0.559***	0.562***	0.422***	0.691***
ln Capital	0.126**	0.106***	0.218***	0.141***	0.120***	0.241***
Time trend	0.007**	0.009***	0.006**	0.006***	0.008***	0.005
ln Age	-0.178***	-0.133***	-0.290***	-0.173***	-0.145***	-0.353***
Single-Plant Enterprise	0.044	0.121***	0.028	0.129***	0.126***	0.036
Multi-Region Enterprise	-0.027	0.021	-0.077**	0.016	0.018	-0.062
Multi-SIC Enterprise	0.005	0.035***	0.008	0.031**	0.035**	-0.001
USA	0.084*	0.077***	0.196***	0.110***	0.111***	0.221***
EU	0.108*	0.132***	0.216***	0.114***	0.168***	0.197***
OFO	-0.113	-0.146*	-0.026	-0.033	-0.086	0.113
ln Distance	-0.193	-0.297*	-0.332***	-0.351**	-0.355*	-0.498**
ln Distance × *ln* employment	0.046*	0.084**	0.045***	0.088***	0.086**	0.071*
Urbanisation	0.008	-0.032	0.198***	-0.060	-0.037	0.136
Cities	0.006	0.002	0.081	0.037	0.009	0.127
ln Herfindahl Index	0.087**	0.027	0.083***	0.052***	0.026	0.084**
$1/\sigma$	-0.054	0.012	0.036	0.009	0.050	0.037
Mark up $[\sigma/(\sigma-1)]$	0.949	1.012	1.037	1.009	1.053	1.039
North-East	0.043	0.085**	-0.055	0.032	0.079*	-0.023
Yorkshire-Humberside	0.113**	0.122***	0.188***	0.120***	0.123***	0.190***
North-West	0.149***	0.118***	0.326**	0.140***	0.134***	0.411***
West Midlands	0.106	0.171*	-0.050	0.131**	0.123	0.247**
East Midlands	0.055	0.062	0.055	0.024	0.037	0.201**
South-West	0.193**	0.163	0.041	0.104	0.051	0.051
East	0.039	0.073	-0.142	0.055	0.027	-0.193
London	0.050	0.074	-0.174*	0.033	0.033	-0.135
Scotland	0.094	0.161**	-0.112	0.064	0.125	0.019
Wales	0.072	0.091*	-0.010	0.090**	0.073*	0.128
Unweighted Observations	4,018	4,018	4,018	4,018	4,018	4,018
Unweighted Number of firms	785	785	785	785	785	785
Distinct Number of firms	493	493	493	493	493	493
Wald test	34848	64446	31236	65923	68345	15939
F test	3.48	6.12	13.11	14.96	4.30	4.71
AR(1) z-statistic	-4.827	-4.054	-5.620	-5.058	-3.855	-5.333
AR(1) z-statistic p-value	1.39e-06	5.03e-05	1.91e-08	4.24e-07	0.000116	9.64e-08
AR(2) z-statistic	-0.859	0.524	0.0776	0.0205	0.408	-0.115
AR(2) z-statistic p-value	0.390	0.601	0.938	0.984	0.683	0.909
Hansen test	42.75	110.3	88.07	109.8	107.9	69.20
Hansen test p-value	0.568	0.107	0.144	0.113	0.138	0.276

Table U.1(f): Long-run (weighted) parameter estimates of production function: Aerospace (SIC364) using System-GMM, 1984-2016

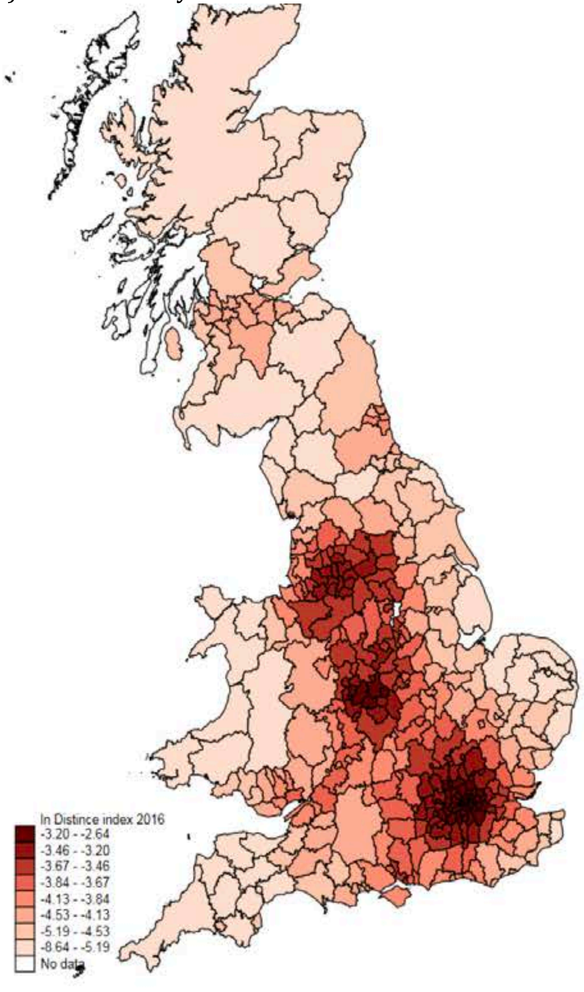
Variables	Intra-medium	Intra-low	Intra-high	Inter-medium	Inter-low	Inter-high
ln Intermediate Inputs	0.645***	0.555***	0.699***	0.535***	0.548***	0.530***
ln Employment	0.294***	0.365***	0.170**	0.408***	0.405***	0.272***
ln Capital	0.089***	0.087***	0.066*	0.119***	0.067**	0.144***
Time trend	0.001	0.004	-0.001	0.005	0.004	0.004
ln Age	-0.018	0.014	0.018	-0.069	0.022	-0.093*
Single-Plant Enterprise	-0.046	-0.060*	-0.041*	-0.058	-0.059*	-0.014
Multi-Region Enterprise	-0.022	-0.003	-0.025	-0.008	-0.027	-0.034
Multi-SIC Enterprise	0.035*	0.019	0.003	0.034	0.047	0.100***
USA	-0.017	0.044	-0.028	0.013	0.043	-0.022
EU	-0.080**	-0.054	-0.115**	-0.094**	-0.041	-0.166***
OFO	-0.069*	-0.066**	-0.094**	-0.071*	-0.047	-0.070
ln Distance	0.151***	0.326***	0.111***	0.206**	0.491***	0.340***
ln Distance × *ln* employment	-0.005	0.013	-0.015	0.015	0.023**	-0.008
Urbanisation	-0.059	-0.091	-0.085	-0.130	-0.122*	-0.297***
Cities	-0.082	-0.139**	-0.053	-0.131*	-0.175***	-0.276***
ln Herfindahl Index	0.042*	0.111***	0.056*	0.100***	0.116***	0.059**
$1/\sigma$	0.090***	0.045	0.075*	0.052	0.053	0.046
Mark up $[\sigma/(\sigma-1)]$	1.099***	1.048	1.081*	1.055	1.056	1.048
North-East	0.031	0.035	0.069	0.160***	0.106***	0.128**
Yorkshire-Humberside	0.089	0.116**	0.089	0.147**	0.129**	0.171**
North-West	0.016	0.033	-0.003	-0.065	0.019	-0.080
West Midlands	0.318**	0.310*	0.209	0.426**	0.552***	0.669***
East Midlands	-0.062	-0.036	-0.038	-0.022	0.111*	-0.001
South-West	0.425***	0.722**	0.228***	0.446***	0.972***	0.483***
East	0.049	0.090**	0.025	0.183***	0.220***	0.155**
London	0.100	0.239***	0.101	0.360***	0.438***	0.444***
Scotland	-0.029	-0.066	-0.001	0.031	0.004	0.029
Wales	0.053	-0.011	0.033	0.194	0.140	0.352***
Unweighted Observations	4,827	4,827	4,827	4,827	4,827	4,827
Unweighted Number of firms	946	946	946	946	946	946
Distinct Number of firms	523	523	523	523	523	523
Wald test	76811	95228	108213	74083	61277	86441
F test	10.20	7.86	21.62	10.83	12.77	45.63
AR(1) z-statistic	-6.379	-4.427	-6.249	-5.001	-4.118	-4.443
AR(1) z-statistic p-value	1.78e-10	9.56e-06	4.14e-10	5.71e-07	3.83e-05	8.87e-06
AR(2) z-statistic	-0.421	1.006	0.257	1.191	0.688	0.00688
AR(2) z-statistic p-value	0.674	0.315	0.797	0.233	0.492	0.995
Hansen test	110.6	49.38	60.44	54.07	50.61	103.4
Hansen test p-value	0.103	0.123	0.319	0.167	0.101	0.217

Figure U.2: Average *ln* Distance based on related industries, by local authority, 2016: 6 sectors in manufacturing

(a) low decay $e^{-0.01(d_{i,j})}$



(b) medium decay $e^{-0.05(d_{i,j})}$



(c) high decay $e^{-0.10(d_{i,j})}$

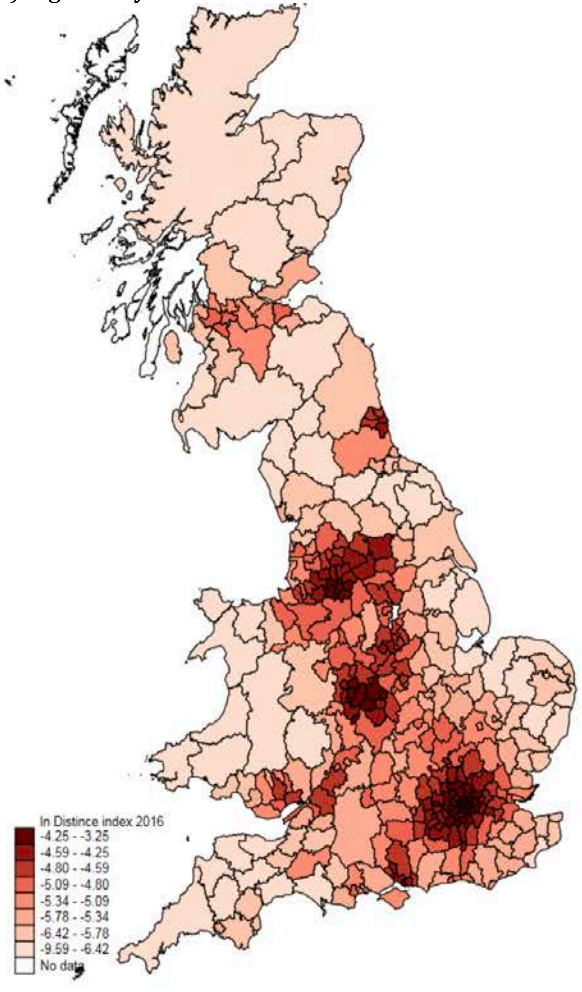
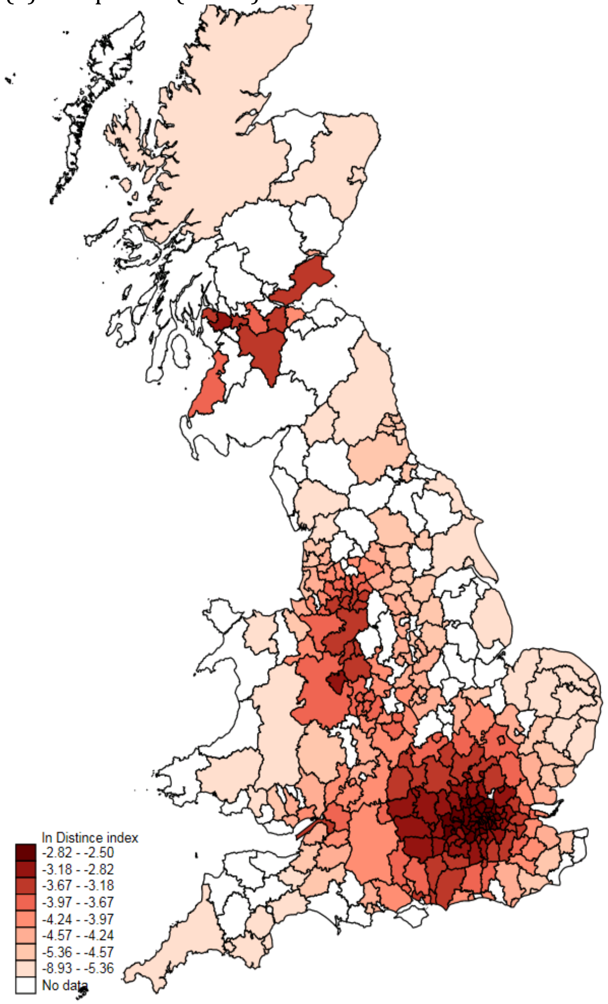
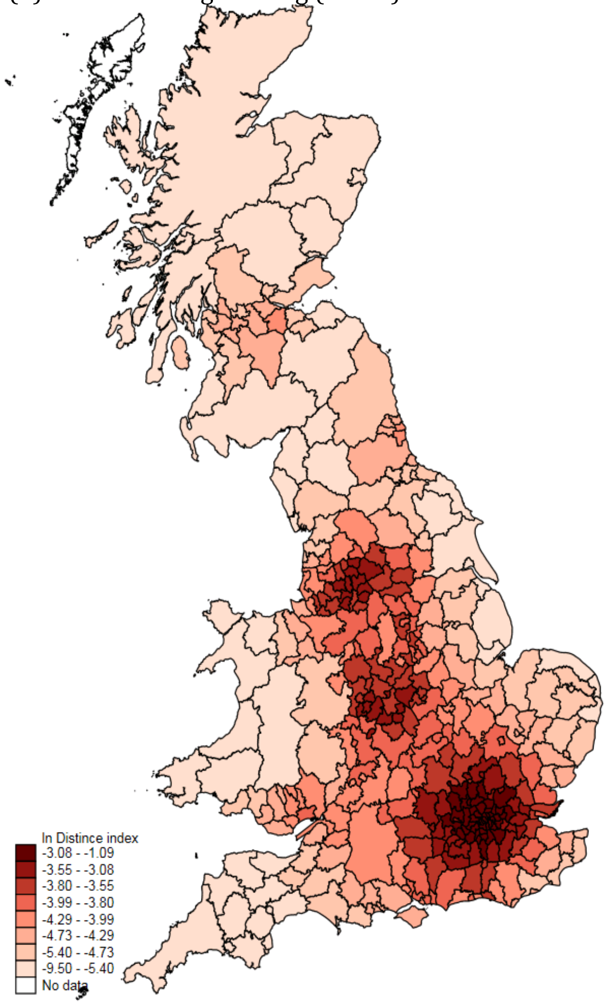


Figure U.3: Average ln Distance by local authority, 2001-16: 6 sectors in manufacturing (all based on medium decay $e^{-0.05(d_{i,j})}$ 4-digit SIC)

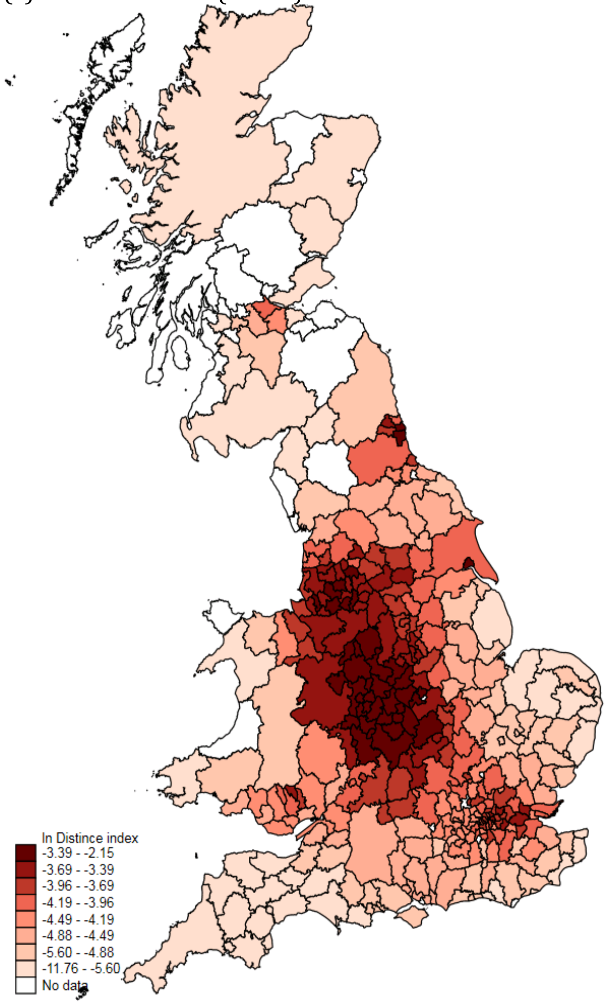
(a) Computers (SIC33)



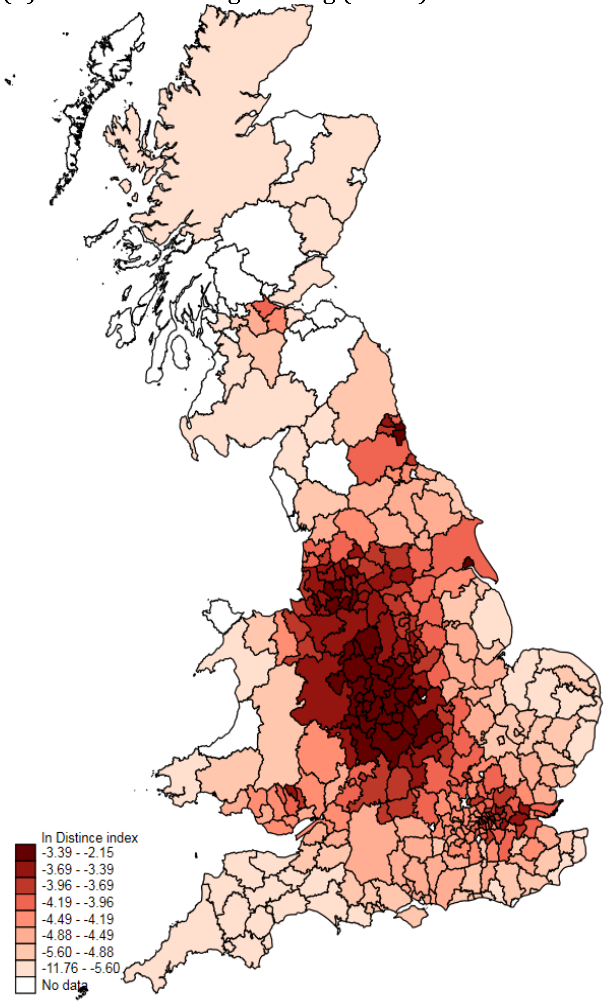
(b) Electronic Engineering (SIC34)



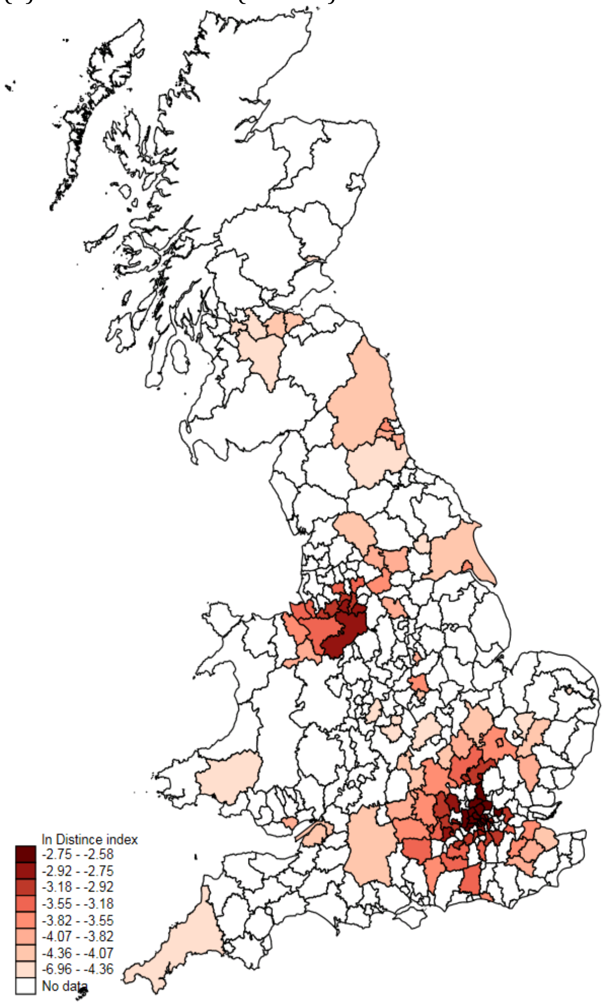
(c) Motor Vehicles (SIC35)



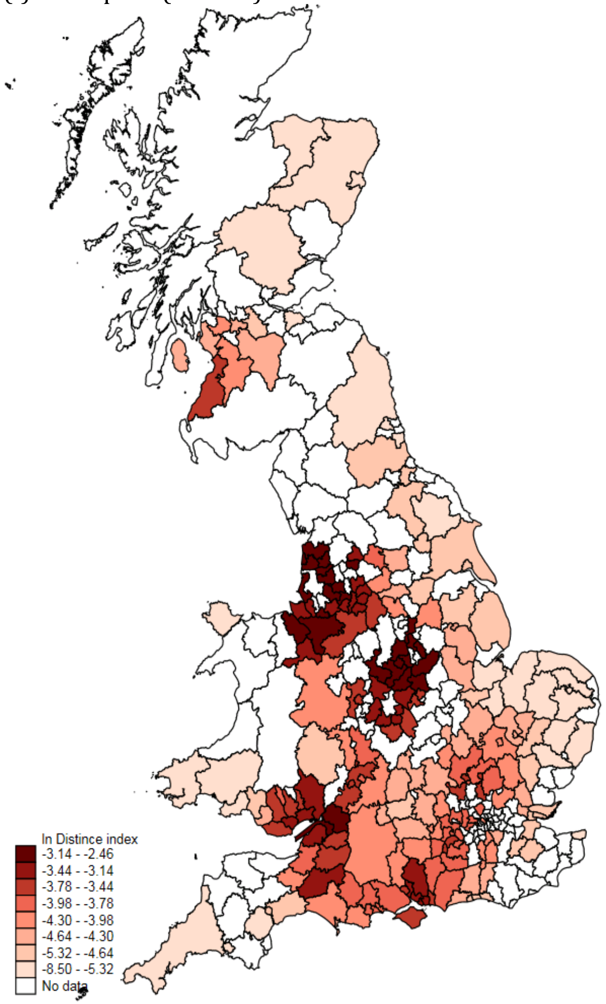
(d) Instrumental Engineering (SIC37)



(e) Pharmaceuticals (SIC257)



(f) Aerospace (SIC364)



Alternative models for the six advanced manufacturing sectors

As explained in the main text, the results presented section 3 were based on the index using distances between plants belonging to the same 4-digit industry with a rate of decay of –0.05. To test the sensitivity of the results to alternative specifications of the distance index, we extend the results presented in Table 3 to include those obtained using different rates of decay and also plants belonging to wider sets of related industries rather than just their own industry. Table U.2 below presents these extended results.

A priori, there is no expectation that one set of results for each industry should be considered 'correct'; firstly, there is little guidance as to the distance over which plants network and interact with other plants, and thus benefit from possible spillovers. Thus, whether a low, medium or high rate of decay should be applied is a matter for empirical investigation.[6] Similarly, whether plants mainly benefit from spillovers from other plants operating in the same industry (where similar products are produced, involving similar technologies and similar human capital requirements), or if spillovers are more likely from plants operating in related industries – which are here defined as a industries sharing input-output linkages, or acquiring similar (knowledge) inputs from the external environment – is again an empirical question. Given for each sector that equation (1) contains the same set of drivers of TFP, with only the specification of the distance index being different, it is possible to be guided by which model provides the 'best fit' both in terms of the overall model and the significance of the coefficients on *ln* Distance and *ln* Distance × *ln* employment. The Wald test reported in Table U.1 tests the null hypothesis that all the parameters in the model equal zero. The F-test is a test that the parameter values for *ln* Distance and *ln* Distance × *ln* employment are jointly zero.

The model with the highest values for both tests provides an indication for which version might be preferred (although the literature on the use of Wald tests when using system-GMM suggests caution should be applied given that two-step GMM estimators are often heavily biased downwards – see Bun and Sarafidis (2013) for a discussion). The 'preferred' set of results based on Wald and F-tests are indicated in Table U.2 with a tick-mark.

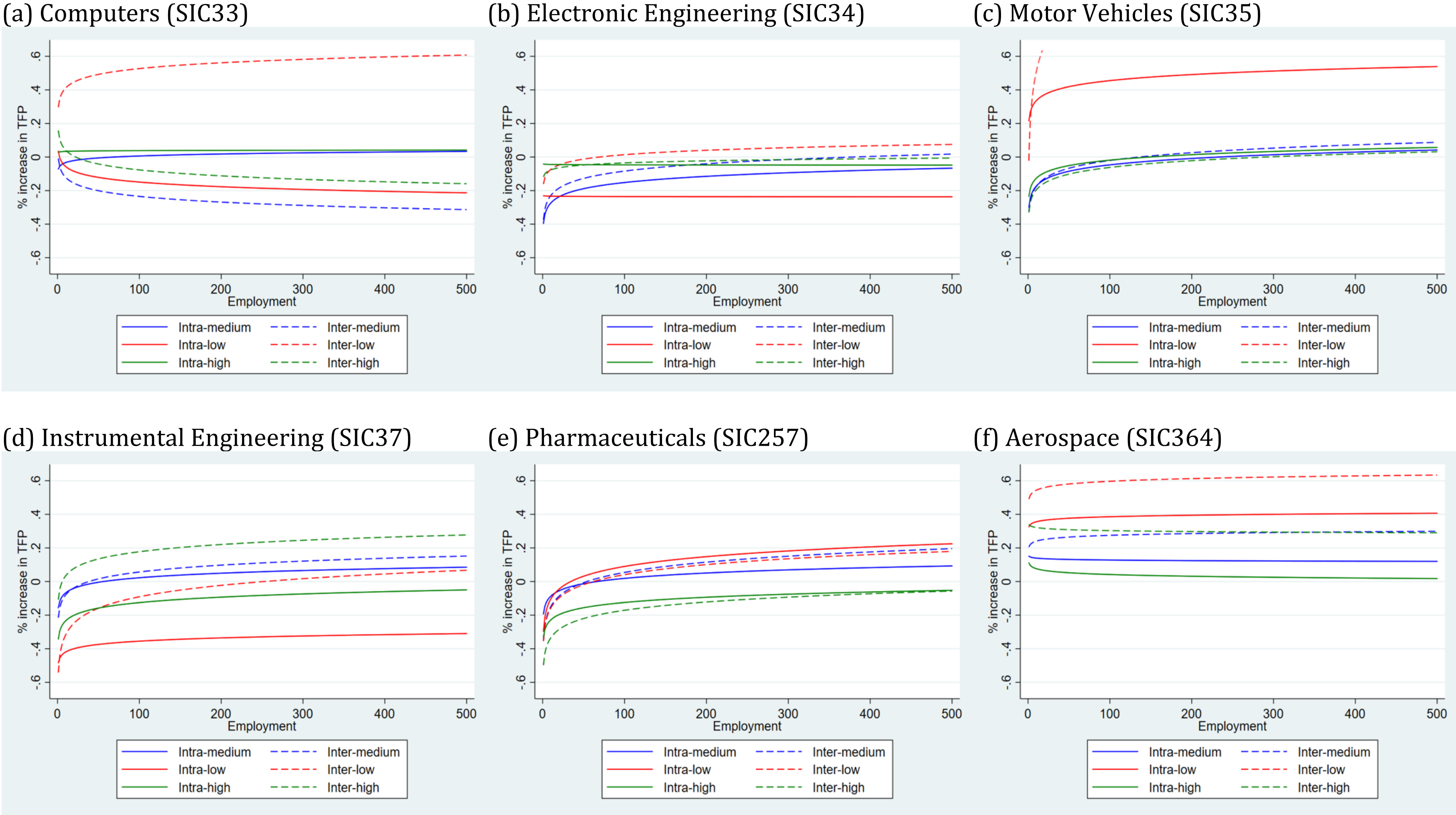
For the computers sector (SIC33), this is the model using an intra-high distance index which suggests that plants in this sector achieve small, but positive and significant advantages from co-location irrespective of size. Figure U.3(a) shows that the results based on intra-medium and intra-high distance indices are broadly very similar. With regard to the other results, based on other distance indices, three suggest spillovers are negative (and increasingly so with size), while those based on groupings of related industries and a low decay rate ('inter-low') suggest strong, positive spillovers exist, especially for larger plants (e.g., TFP is some 0.61% higher due to spillovers for plants employing 500).

[6] Harris *et al.* (2011) make a similar point when discussing the formulation of the 'W' matrix in spatial econometric modelling, where 'W' is based (usually) on different weights being applied to regions located nearby versus further away.

Table U.2: Long-run (weighted) impact of *ln* Distance (different measures) on TFP by size of plant, 1984-2016

		Intra			Inter	
	Low, $e^{-0.01(d_{i,j})}$	Medium, $e^{-0.05(d_{i,j})}$	High, $e^{-0.10(d_{i,j})}$	Low, $e^{-0.01(d_{i,j})}$	Medium, $e^{-0.05(d_{i,j})}$	High, $e^{-0.10(d_{i,j})}$
Computers (SIC33)			✓			
ln Distance	0.035	-0.072**	0.029***	0.297***	-0.009	0.158***
ln Distance × *ln* employment	-0.040***	0.017*	0.002	0.050**	-0.049***	-0.051***
ln Distance × 5	-0.030	-0.044**	0.033***	0.377***	-0.087***	0.076**
ln Distance × 50	-0.121***	-0.005	0.037***	0.493***	-0.199***	-0.041
ln Distance × 500	-0.212***	0.035	0.042***	0.608***	-0.310***	-0.159***
Electronic Engineering (SIC34)		✓				
ln Distance	-0.231***	-0.396***	-0.042	-0.161	-0.374***	-0.118*
ln Distance × *ln* employment	-0.001	0.053***	-0.001	0.038	0.063**	0.018
ln Distance × 5	-0.233**	-0.310***	-0.043	-0.100	-0.273***	-0.089*
ln Distance × 50	-0.236**	-0.188***	-0.046	-0.013	-0.129*	-0.047
ln Distance × 500	-0.238*	-0.065	-0.048	0.075	0.016	-0.006
Motor Vehicles (SIC35)			✓			
ln Distance	0.216	-0.300*	-0.235***	-0.022	-0.329*	-0.329
ln Distance × *ln* employment	0.052*	0.055**	0.047**	0.230***	0.067	0.058
ln Distance × 5	0.300	-0.211*	-0.159**	0.349	-0.221	-0.235
ln Distance × 50	0.420	-0.085	-0.050	0.880**	-0.067	-0.101
ln Distance × 500	0.541*	0.042	0.059	1.410***	0.088	0.033
Instrumental Engineering (SIC37)		✓				
ln Distance	-0.484*	-0.157***	-0.342***	-0.542***	-0.215***	-0.108***
ln Distance × *ln* employment	0.028	0.039***	0.047*	0.098***	0.059***	0.062***
ln Distance × 5	-0.439*	-0.094***	-0.267***	-0.385***	-0.120**	-0.009
ln Distance × 50	-0.375*	-0.004	-0.159***	-0.160	0.016	0.133***
ln Distance × 500	-0.312	0.087***	-0.052	0.064	0.151*	0.275***
Pharmaceuticals (SIC257)					✓	
ln Distance	-0.297*	-0.193	-0.332***	-0.355*	-0.351**	-0.498**
ln Distance × *ln* employment	0.084**	0.046*	0.045***	0.086**	0.088***	0.071*
ln Distance × 5	-0.161	-0.119	-0.260***	-0.218**	-0.209**	-0.384**
ln Distance × 50	0.032	-0.013	-0.155***	-0.020	-0.005	-0.220**
ln Distance × 500	0.226*	0.094	-0.051*	0.177*	0.198***	-0.057
Aerospace (SIC364)			✓			
ln Distance	0.326***	0.151***	0.111***	0.491***	0.206**	0.340***
ln Distance × *ln* employment	0.013	-0.005	-0.015	0.023**	0.015	-0.008
ln Distance × 5	0.347**	0.143***	0.087***	0.528***	0.229**	0.328***
ln Distance × 50	0.376**	0.131***	0.053*	0.581***	0.263***	0.310***
ln Distance × 500	0.406***	0.119***	0.018	0.634***	0.296***	0.292***

Figure U.3: Effect of 1% increase in distance indices on TFP for different sized plants for selected industries, 1984-2016



Source: based on model estimates in Table 1

The results for electronic engineering (SIC34) show that an intra-medium distance index produces the 'preferred' results, and Figure U.3(b) indicates that these are similar to the results based on groupings of related industries and a medium rate of decay, except slightly higher throughout (the inter-medium results were the next preferred model in Table U.2). The results based on other distance indices are generally supportive of the 'preferred' results and confirm that larger plants have higher TFP as a result of co-location. The exception is when an intra-low distance index is used, suggesting a 1% increase in the index leads to a fall of 0.23% in TFP, irrespective of plant size. In motor vehicles (SIC35), the intra-high distance index comes first based on Wald- and F-tests, followed by the intra-medium results. Both suggest (Figure U.3c) smaller plants experience negative spillovers that become positive (but not statistically significant) for larger plants. Two other distance indices produce very similar results but those based on low rates of decay suggest high spillovers, exceptionally so for larger plants (the results for the inter-low distance index are only partially shown on Figure U.3(c) as they are so extreme).

The intra-medium results are confirmed as being 'preferred' in Table U.2 for instrumental engineering (SIC37), with the inter-medium results coming 'second'. Both produce similar profiles (Figure U.3d), and the results based on all the different distance indices confirm that smaller plants generally experienced negative spillovers and larger plants positive outcomes (the exception is when intra-low is used, when spillovers are always negative although for larger plants not statistically significant). In pharmaceuticals (SIC 257), a similar pattern emerges with the inter-medium distance index preferred (inter-low comes next), with both showing that larger plants benefit from spillovers (e.g., those employing 500 by 0.2%), but smaller plants experienced significant, negative impacts (*cet. par.*) on their TFP from co-location with other plants in related industries. Note, for this sector, the previous conclusion based on Table 3 is strengthened, that there is evidence that the effect of higher co-location on smaller (larger) plants is negative (positive).

As shown in the previous section, aerospace (SIC364) is the only sector where there is no evidence that smaller plants experienced negative spillovers. The 'preferred' model is the one using an intra-high distance index, and Table U.2 and Figure U.3(f) show that in this case smaller plants have higher TFP of around 7-8%, but for larger plants there is no significant productivity benefit from co-location. In contrast, the intra-medium results - discussed in the previous section - show a more positive position with all plants experiencing significant, positive impacts on their TFP (albeit a little lower for the largest plants). The results based on other distance indices are even more positive in terms of spillover benefits.

The results presented in this section show that the general conclusion reached in the previous section – which were based on just the intra-medium distance index – is in large part supported (indeed strengthened), especially if the results based on Wald- and F-tests are preferred. Only in two sectors (aerospace and to some extent computing) is there evidence that spillovers are generally beneficial to plants of all sizes; for the others, small plants do not generally experience a positive TFP spillover if they co-locate. There is variability (see especially Figure U.3) depending on which distance index is used; but there is also some evidence that the results based on related industries generate higher estimates of spillovers than those based on within- industry specifications (ranking the six sets of results for each distance index show that generally inter-low achieves top ranking, followed by inter-medium, followed by inter-high; for the 4-digit industry specification there is much more 'noise' in the rankings across the six sectors considered, although weak evidence that they generate lower spillovers and have a similar profile where spillover effects are highest for intra-low, then intra-medium and finally intra-high). This is possibly in line with prior expectations (spillovers are likely higher in larger related industry groupings with low rates of decay and lowest in specific industries with high rates of decay), but the evidence presented here is more tentative in nature, and clearly would benefit from extending the methodology to other (including non-advanced) manufacturing sectors, and indeed services.