UCD GEARY INSTITUTE DISCUSSION PAPER SERIES

Is there a rural-urban divide? Location and Productivity of UK manufacturing

Marian Rizov[1] and Patrick Paul Walsh[2, *]

[1]Middlesex University Business School, UK
and
Wageningen University, The Netherlands

[2]UCD SPIRe and Geary Institute, Ireland

Draft August 2009

Abstract

We compute the productivity gaps in manufacturing industries by urban, rural less sparse and rural sparse locations in the UK. This is done by using firm-specific total factor productivities, which are estimated by a semi-parametric algorithm within 4-digit manufacturing industries using FAME data over the period 1994-2001, by each location. We analyse the productivity differentials across locations by decomposing them into firm differences within the same industry and by differences that are explained by industry composition effects. Our analysis indicates that at the end of twentieth century a rural-urban divide in manufacturing productivity still remains but there is a tendency of convergence between rural and urban location categories. Even though industry productivity is different by location, industry composition effects are positively correlated with industry productivity by location suggesting that locations with high productivity are also characterised by industrial structures with higher productivity.

Key words: Total factor productivity, structural estimation, rural-urban divides, UK manufacturing

JEL classification: D24, R11, R30

* We thank David North and Arie Oskam for discussions on earlier draft and useful comments by anonymous referee. The usual disclaimer applies.

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1 Introduction

Since late 1950s until the end of the century there has been a shift of employment from urban to rural areas and a rise in rural wages which has arguably also been associated with a growth in productivity of all types of rural businesses in the UK (Keeble, 2000; North and Smallbone, 2000; Anderson et al., 2005), in other parts of Europe (Roper, 2001; Terluin, 2003; Terluin et al., 2005), and in the USA (Acs and Malecki, 2003). Authors argue that this trend has slowed down and even reversed recently (e.g., Webber et al., 2008). Therefore the question if differences in aggregate productivity between urban and rural locations still remain and what are the factors affecting rural-urban productivity differentials is of high importance for policies aiming at welfare improvement and economic growth.

Traditional studies commissioned by the Department of the Environment, Food and Rural Affaires (DEFRA) in England and Wales have usually been concerned with productivity differentials at local authority level using aggregate data. However, there are methodological and data problems associated with the *area* approach such as whether to use workplace or residence-based measure and how to incorporate both earnings and profits in the measure of productivity. The alternative is to estimate *business* productivity using micro data at firm or plant level and then aggregate productivity measures to the level of rural and urban location categories. Recently, Webber et al. (2008) estimate labour productivity using plant level data and investigate the presence and causes of differences in productivity across the 2004 DEFRA defined urban, rural less sparse and rural sparse location categories.[1] The main finding is that there is a productivity divide across urban and rural locations - plants in less sparse and sparse rural location categories are 13.5 percent and 21.6 percent less productive than plants in urban locations respectively.[2]

In this paper, similar to Webber et al. (2008), we use micro-data. However, the widely available dataset used in our study - FAME of Bureau van Dijk - is different from the Office for National Statistics (ONS) census data employed by Webber et al. (2008). The advantage of our data over the one used by Webber et al. (2008) is that FAME contains consolidated firm level accounts which avoid problems with identifying plants within multi-plant firms. Furthermore, we apply a structural estimation algorithm to panel data, covering the 1994-2001 period, and extend the analysis of location and performance by estimating total factor productivity (TFP) at firm level which is a more comprehensive direct measure of firm performance compared to the labour productivity estimated for only one year (2004) in the Webber et al. (2008) paper.

Previous studies attempting to link location and productivity apply a two-stage analysis. In the first stage authors estimate firm productivity, and in a second stage they proceed to link productivity to location characteristics. In our view testing for a relationship between location and (unobservable) productivity, *ex-post*, is admitting that there is information that should have been used in the structural model of the unobservable while estimating the production function in the first instance. Therefore, to estimate unbiased and consistent measures of firm productivity, we rely on a behavioural framework which builds on models of industry dynamics (Ericson and Pakes, 1995) and the link between productivity and density of economic activity (Ciccone and Hall, 1996). Following econometric modelling ideas in Ackerberg et al. (2007), the framework underlines our estimation strategy and helps us specify timing and relational assumptions for the firm decisions in a manner similar to Olley and Pakes (1996). In our econometric application we follow Ackerberg et al. (2007) and an extension suggested in Rizov and Walsh (2009). We explicitly allow market structure (factor markets, demand conditions and prices) and investment climate (including institutions) to differ across rural and urban locations. We find that there is indeed a rural -

urban productivity divide, which is due to both differences in industry composition and industry (and firm) productivity as rural industries lag behind their urban counterparts. The aggregate rural - urban productivity differentials are determined mostly by industry productivity differences while differences in industry composition across rural (especially, less sparse) and urban locations are less pronounced.

The paper is organised as follows. In section 2 a brief analysis of relevant literature is undertaken to clarify the link between productivity and density of economic activity and a model of (unobservable) productivity is explicitly formulated. Section 3 introduces the semi-parametric estimation methodology applied in the paper, while section 4 describes the data and variables used in our econometric analysis and reports results of estimating production functions within 4-digit industries. Distributions of productivity estimates by location category are also presented. Section 5 analyses the spatial patterns of aggregate productivity and factors affecting it by the means of decompositions in levels and in changes for each location category. Section 6 concludes.

2 Location, density of economic activity and firm productivity

The origins of the analysis relating location and economic performance of firms can be traced back at least to the work of Marshall (1920) who states that urbanisation and thus, the geographical concentration of economic activities in urban agglomerations can result in a snowball effect, where new entrants tend to agglomerate to benefit from higher diversity and specialization in production processes. There are also benefits to firms from co-locating in close proximity to other firms in the same industry. Both urbanization and localization economies can be considered centripetal forces leading to concentration of economic activities. However, Henderson (1974) building on work by Mills (1967) demonstrates that, in an equilibrium, disamenities from agglomeration may offset the productivity advantages thus acting as centrifugal forces. For example, these include increased costs resulting from higher wages driven by competition among firms for skilled labour, higher rents due to increased demand for housing and commercial land, and negative externalities such as congestion.

A second branch of the literature on agglomeration hypothesises economies of scale internal to firms (Abdel-Rahman, 1988; Fujita, 1988; Rivera-Batiz, 1988). Models with internal increasing returns build on theories of the firm and its market and commonly employ the well known formalisation of monopolistic competition of Spence (1976) and Dixit and Stiglitz (1977) to demonstrate that non-transportable intermediate inputs produced with increasing returns imply agglomeration. In related models, Krugman (1991) demonstrates that agglomeration will result even when transportation costs are small, if most workers are mobile. The essence of all these models is that when local markets are more active, a larger number of producers of the differentiated intermediate inputs break even and the production of final goods is more efficient when a greater variety of intermediate inputs is available.[3]

While previous studies focus on returns to economic mass such as city size, Ciccone and Hall (1996) focus of spatial density and show that density, defined as the intensity of labour, human and physical capital relative to physical space, rather than size is a more accurate determinant of productivity. Density affects productivity in several ways. If technologies have constant returns themselves, but the transportation of products from one stage of production to the next involves costs that rise with distance, then the technology for the production of all goods within a particular geographical area will have increasing returns - the ratio of output to input will rise with density. If there are externalities associated with the physical proximity of production, then density will contribute to productivity for this reason as well. A third source of density effects is the higher degree of beneficial specialization possible in areas of dense activity. A closely related work is by Carlino and Voith (1992) who find that total factor productivity across U.S. states increases with urbanization. More recently, Ciccone (2002) for Europe and Fingleton (2003) for Great Britain report positive association between employment density and productivity. For the case of Great Britain, Rice at al. (2006) explain regional productivity differences by proximity to economic mass. They argue that the detailed modelling of proximity, measured by driving time, to economic mass is more general than the measures of population density in the own or neighbouring regions and that this enables them to derive economically meaningful inferences about the spatial scale over which the productivity effects of agglomeration operate.

In this paper we follow the models of Ciccone and Hall (1996) and Rice et al. (2006) in directly relating productivity to density of economic activity and proximity to economic mass. Given that our strategy is to control for unobservable productivity while estimating production functions, rather than explicitly identifying effects, we use as a proxy a categorical variable based on the DEFRA definition. In 2005 DEFRA brought out both a new classification and a new definition of rural as described in the DEFRA's (2004) strategy paper. The *classification* is based on settlement morphology, while the *definition* is based on the density of the population. In principle, it is possible to have six types of rural locations – town (less sparse); town (sparse); village (less sparse); village (sparse); dispersed (less sparse); dispersed (sparse) (DEFRA, 2005a) – but, in practice, this grouping cannot be readily undertaken for analytical purposes (DEFRA, 2005b) and the combination of the classification and the definition makes little sense for policy analysis. In our study, similar to Weber et al. (2008), the new rural definition is used; a distinction is made between sparse and less sparse locations to allow comparisons to be made between broadly different types of rural location based on the density of population. The sparse and less sparse rural categories are then compared with data for urban locations to examine principal differences in plant productivity between rural sparse, rural less sparse and urban locations.

- Table 1 about here -

Table 1 presents summary statistics of key location characteristics (density of population of working age, business density, etc.) by urban, rural less sparse and rural sparse categories according to the DEFRA definition. There are clear differences across locations with respect to various characteristics of density of economic activity, with urban locations exhibiting the highest density and rural sparse locations being the least dense in economic activity. Our main hypothesis is that productivity is high in locations with high density of economic activity or that have, in some sense, proximity to a large economic mass. We argue that the DEFRA definition of location controls for all these effects and encompasses various agglomeration mechanisms driving productivity.[4] For examples, one mechanism can be technological externalities; firms learn from co-presence with other firms in related activities, so innovating and implementing new technologies efficiently. Another mechanism can be via thick capital and labour markets which work more efficiently, by having lower search costs and generating improved matching of buyers and sellers. A third mechanism can be simply that, in the presence of transport costs, firms gain from having good access both to their customers and to suppliers of intermediate goods and services. We do not seek to identify each of these effects separately, but to merely control for their combined impact by using location-specific information in modelling firm productivity.

Next we explicitly build the productivity and location relationship into a (structural) model of unobservable productivity. We specify productivity of a firm, j, at a point in time, t, following Olley and Pakes (1996) and extensions outlined in Ackerberg et al. (2007) as a function $\omega_{jt} = h\ (i_{jt}, k_{jt}, a_{jt}, l_{jt}, r_t)$ of a firm's capital, k_{jt}, labour, l_{jt}, age, a_{jt}, investment, i_{jt}, and the economic environment that the firm faces at a particular point in time, r_t, and treat the function non-parametrically in our estimation algorithm. Olley and Pakes (1996) derive the function for productivity by inverting the investment demand function of the firm which itself is a solution to the firm's maximization problem.[5] The economic environment control, r_t, could capture characteristics of the input markets, characteristics of the output market, or industry characteristics like the current distribution of the states of firms operating in the industry. Note that Olley-Pakes formulation allows all these factors to change over time, although they are assumed constant across firms in a given period.

In this paper we extend the Olley-Pakes model of (unobservable) productivity in two ways. First, we extend the information content of the economic environment control to vary by type of firm according to the DEFRA definition of rural and denote this by, r_{jt}, where a subscript index j is added. Introducing location-specific market structure in the state space allows some of the competitive richness of the Markov-perfect dynamic oligopoly model of Ericson and Pakes (1995). Note that introducing richer location-specific market structure in the productivity function does minimise the deviations from the original Olley-Pakes scalar unobservable assumption, necessary to invert the investment function, and it may help with the precision of the estimates.

Second, we relax the scalar unobservable assumption all together following modelling ideas in Ackerberg et al. (2007) and an application to firm productivity and trade orientation by Rizov and Walsh (2009). We adjust the model of productivity to allow for exporting status, e_{jt}, to be an additional (endogenous) control variable in the state space that is driven by lagged productivity as in Melitz (2003). This formulation leads to modelling productivity as a second-order Markov process, $p(\omega_{jt} \mid \omega_{jt-1}, \omega_{jt-2})$, where firms operate through time forming expectations of future ω_{jt} s on the basis of information from two preceding periods.[6] The productivity function then becomes

$$\omega_{jt} = h\ (i_{jt}, k_{jt}, a_{jt}, l_{jt}, e_{ji}, r_{jt})\,. \qquad (1)$$

Selection to exporting can reveal better productivity due to higher quality products, know-how, and distribution networks that are needed to overcome sunk cost to get into foreign markets. We specify the propensity to export as a non-parametric function of $i_{jt-1}, k_{jt-1}, a_{jt-1}, l_{jt-1}, r_{jt-1}$ and a vector of other firm-specific characteristics such as type of ownership, corporate governance, and industry groupings. Similarly, location choices may also be endogenous, therefore we specify propensity of firms to locate in urban, rural less sparse or rural sparse areas as a non-parametric function of firm specific $(i_{jt-1}, k_{jt-1}, a_{jt-1}, l_{jt-1}, e_{jt-1})$ and location specific characteristics, listed in Table 1, measuring density of economic activity at ward level. In equation (1), we use the propensity to export, $\hat{e}_{ji}$, estimated from a Probit model, and the propensity to locate in area with higher density of economic activity, $\hat{r}_{ji}$, estimated from an Ordered Probit model, rather than the observed e_{ji} and r_{ji} which allow us to treat the exporting and location decisions as endogenous controls.[7]

3 Econometric framework

To compute unbiased and consistent firm-level (total factor) productivity measure, we need to generate first unbiased and consistent estimates of production function parameters. However, estimating production function parameters is complicated due to the fact that productivity is not observed directly in our data. The first complication arises because unobservable productivity determines input levels which is the classic simultaneity problem analysed by Marshak and Andrews (1944). The second complication arises out of the fact that firms survive based on unobservable productivity type, amongst other factors. If an OLS estimator is used, simultaneity means that estimates for variable inputs such as labour, when considered non-dynamic input, will be upward biased, assuming a positive correlation with unobservable productivity. Exit will depend on productivity type as well as the capital stock representing sunk cost. Thus, the coefficient on capital is likely to be underestimated by OLS as higher capital stocks induce firms to survive at low productivity levels (Olley and Pakes, 1996). Besides the two biases, a potential problem afflicting productivity measure is associated with the spatial dependency of observations within a geo-space. Spatial dependency leads to the spatial autocorrelation problem in statistics since - like temporal autocorrelation - this violates standard statistical techniques that assume independence among observations (Anselin and Kelejian, 1997). Furthermore, spatial dependency is a source of spatial heterogeneity which means that overall parameters estimated for the entire system may not adequately describe the process at any given location.

To deal with the estimation problems outlined above we employ a semi-parametric estimation algorithm in the spirit of Olley and Pakes (1996) following extensions in Ackerberg et al. (2007) and an application by Rizov and Walsh (2009). As in Olley and Pakes (1996) we specify a log-linear production function,

$$y_{jt} = \beta_0 + \beta_k k_{jt} + \beta_a a_{jt} + \beta_l l_{jt} + \omega_{jt} + \eta_{jt}, \qquad (2)$$

where the log of firm, j value added at time, t, y_{jt}, is modelled as a function of the logs of that firm's state variables at t, namely age, a_{jt}, capital, k_{jt}, and labour, l_{jt}. Investment demand, i_{jt} determines the capital stock at the beginning of each period. The law of capital accumulation is given by $k_{jt+1} = (1-\delta)k_{jt} + i_{jt}$, while age evolves as $a_{jt+1} = a_{jt}$,+1· The error structure comprises a stochastic component, η_{jt}, with zero expected mean, and a component that represents unobserved productivity, ω_{jt} as specified in equation (1). Both ω_{jt} and η_{jt} are unobserved, but ω_{jt} is a state variable, and thus affects firm's choice variables – decision to exit and investment demand, while η_{jt} has zero expected mean given current information, and hence does not affect decisions.

Substituting equation (1) into the production function (2) and combining the constant, k_{jt}, a_{jt}, and l_{jt} terms into function $\phi\ (i_{jt}, e_{jt}, k_{jt}, a_{jt}, l_{jt}, r_{jt})$ gives

$$y_{jt} = \phi\ (i_{jt}, e_{jt}, k_{jt}, a_{jt}, l_{jt}, r_{jt}) + \eta_{jt}. \qquad (3)$$

Equation (3) is the first step of our estimation algorithm and can be estimated as in Olley and Pakes (1996) with OLS and applying semi-parametric methods that treat the function ϕ (.) non-parametrically, using a polynomial.[8] Even though the first stage does not directly identify any of the parameters of the production function, it generates estimates of ϕ (.), $\hat{\phi}_{jt}$, needed in the second stage where we can write expected (unobservable) productivity as

$$\hat{\omega}_{jt}(\beta_0, \beta_k, \beta_a, \beta_l) = \hat{\phi}_{jt} - \beta_0 - \beta_k k_{jt} - \beta_a a_{jt} - \beta_l l_{jt} . \tag{4}$$

Next, to clarify timing of production decisions we decompose ω_{jt} into its conditional expectation given the information known by the firm in two prior periods, *t*-2 and *t*-1, and a residual $\omega_{jt} = E[\omega_{jt} \mid \omega_{jt-2}, \omega_{jt-1}] + \xi_{jt} = g(\omega_{jt-2}, \omega_{jt-1}) + \xi_{jt}$. By construction ξ_{jt} is uncorrelated with information in *t*-2 and *t*-1 and thus with k_{jt}, a_{jt}, and l_{jt} which are chosen prior to time, *t*. The specification of the *g*(.) function is determined by the fact that productivity follows a second-order Markov process as discussed in Section 2. Note that the firm's exit decision in period *t* depends directly on ω_{jt} and thus the exit decision will be correlated with ξ_{jt}. This correlation relies on the assumption that firms exit the market quickly, in the same period when the decision is made. If exit is decided in the period before actual exit occurred, then even though there is a selection per-se, exit would be uncorrelated with ξ_{jt}.[9] To account for endogenous selection on productivity we extend the *g*(.) function following Ackerberg et al. (2007) and Rizov and Walsh (2009) as follows:

$$\omega_{jt} = g'(\omega_{jt-2}, \omega_{jt-1}, \hat{P}_{jt}) + \xi_{jt} , \tag{5}$$

where $\hat{P}_{jt}$ is propensity score which controls for the impact of selection on the expectation of ω_{jt}, i.e., firms with lower survival probabilities which do survive to time, *t* likely have higher ω_{jt} s than those with higher survival probabilities. We estimate $\hat{P}_{jt}$ non-parametrically using Probit model with a polynomial approximation. Note that we extend the state variable set with location and trade status information which are important determinants of firm exit decision.

The capital, age, and labour coefficients are identified in the second step of our estimation algorithm. We substitute equations (5) and (4) into equation (2) using expressions for the estimated values, $\hat{\phi}_{jt-1}$, $\hat{\phi}_{jt-2}$ which gives us

$$y_{jt} = b_k k_{jt} + b_a a_{jt} + b_l l_{jt} + g'(\hat{\phi}_{jt-1} - b_k k_{jt-1} - b_a a_{jt-1} - b_l l_{jt-1}, \hat{\phi}_{jt-2} - b_k k_{jt-2} - b_a a_{jt-2} - b_l l_{jt-2}, \widehat{P}_{jt}) + \varepsilon_{jt}, \quad (6)$$

where the two β_0 terms have been encompassed into the non-parametric function, $g'(.)$ and ε_{jt} is a composite error term comprised of η_{jt} and ξ_{jt}. The lagged $\hat{\phi}$ variables are obtained from the first step estimates at t-2 and t-1 periods. Because the conditional expectation of ω_{jt}, given information in t-2 and t-1 periods, depends on ω_{jt-2} and ω_{jt-1}, we need to use estimates of $\hat{\phi}$ from two prior periods. Equation (6) is estimated with non-linear least squares (NLLS) estimator, approximating $g'(.)$ with a polynomial.[10]

Finally, having estimated unbiased and consistent production function coefficients we are able to back out a unbiased and consistent measure (residual) of total factor productivity (TFP) as $TFP_{jt} = y_{jt} - \hat{\beta}_k k_{jt} - \hat{\beta}_l l_{jt}$.[11] In the model of unobservable productivity we have explicitly incorporated spatial and time dependencies by merging spatial interactions with disaggregated modeling of productivity at firm level. In terms of verifying whether variations in location and export status make firms more productive, we have controlled in our model of productivity for market-structure specific shocks (such as demand conditions, factor markets, exit barrier) that are different across locations and export status. We note that these factors remain constant across firms in the same location and export status within a given industry and a time period.

4 Data and productivity estimates

As discussed in Section 2, in our analysis we classify locations as in Webber et al. (2008) into urban, rural less sparse and rural sparse following the 2004 DEFRA definition of rural. We estimate the production functions using the FAME dataset of the Bureau van Dijk. The dataset covers all firms at the Companies House in the UK and includes information on detailed unconsolidated financial statements, ownership structure, location by post code, activity description, and direct exports. The data used in our analysis contains annual records on more than 80,000 manufacturing firms over the period 1994-2001. The coverage of the data compared to the aggregate statistics reported by the UK Office for National Statistics (ONS) is very good as for sales it is 86 per cent and for employment – 92 per cent.[12] The manufacturing sectors are identified on the bases of the current 2003 UK SIC at the 4-digit level and range between 1513 and 3663. All nominal monetary variables are converted into real values by deflating them with the appropriate 4-digit UK SIC industry deflators taken from ONS. We use PPI to deflate sales and cost of materials, and asset price deflators for capital and fixed investment variables.[13]

In this paper, our goal is to estimate unbiased and consistent TFP measures at firm level, within 4-digit industries, and to document the aggregate productivity gaps between urban, rural less sparse, and rural sparse locations. The strategy of our empirical analysis implies that we run regressions within 4-digit industries which leaves us with the 41 largest 4-digit industries, with sufficient number of observations to apply our estimation algorithm. The estimated sample accounts for almost 60 per cent of the manufacturing sales and 56 per cent of the employment in our data. After lags are applied and observations with missing values deleted, there are 23,841 remaining observations for 6,722 firms. The correlations between the ONS aggregate statistics series and the estimated sample series are as follows:

value added (used in the regressions as dependent variable) - 0.94, employment - 0.97 and exports - 0.95.

The descriptive statistics calculated from the estimated FAME sample of manufacturing firms are reported in Table 2. We compare average firm characteristics across urban, rural less sparse and rural sparse locations. Urban firms, compared to their rural counterparts are larger in terms of value added, employment, and capital, and invest more. Urban firms are also more likely to export and to be owned by foreign investors.[14] These characteristics are in accord with the measures of density of economic activity reported in Table 1. Interestingly, industry concentration characterised by market share of the top four 4-digit industries does not show substantial differences across rural and urban areas. However, there are important similarities and differences in the composition of the top four industries dominating each type of location. In the urban and rural less sparse locations dominant are publishing and printing (2222), general mechanical engineering (2852), - miscellaneous electrical equipment (3162), and miscellaneous manufacturing (3663). The rural sparse locations are dominated by meat and dairy production (1513 and 1551), paper and paper production (2112), and miscellaneous plastic production (2524). The finding that the industry composition is very similar in urban and rural less sparse areas is significant and points to the fact that there is indeed a divide but it is across rural areas by their level of sparsity.

- Table 2 about here -

Summary of the aggregated coefficients, over the estimated 41 industry production functions, by location category are reported in Table 3. Coefficient estimates from all 41 industry regressions, number of observations and test statistics are reported in Appendix 1. The aggregated coefficients on labour, capital and age reported in Table 3 are weighted averages using value added as weight. They confirm the differences across urban and rural locations with respect to the shares of capital and labour in output. The coefficient on labour declines systematically across urban and rural areas as its value is 0.71 for urban firms while it is 0.66 for firms in rural sparse areas. The pattern of the capital coefficient is just opposite but differences are quite small – 0.25 for urban firms and 0.26 for firms in rural sparse areas.

- Table 3 about here -

Aggregate productivity measures by location category clearly show that urban firms are the most productive; the TFP of urban firms is 3.75, while it is 3.26 and 3.08 - of firms in rural less sparse and rural sparse areas, respectively. Furthermore, not only the mean but the whole distribution of urban firm TFPs dominates the corresponding distributions of rural firm TFPs. Figure 1 illustrates the distributions of firm TFPs across the three categories of urban and rural locations by the means of kernel density estimates. The Kolmogorov-Smirnov two-sample tests for stochastic dominance are significant at the 5 percent level and confirm the fact that firms in urban locations are most productive.

- Figure 1 about here -

5 Spatial variation in aggregate productivity

The discussion in section 2 and information reported in Tables 1 to 3 as well as Figure 1 suggest that there is a systematic relationship between productivity and the spatial characteristics of rural and urban locations related to density of economic activity. In this section we analyse differences in aggregate productivity across rural and urban locations by applying a decomposition of the spatial variation in levels following Rice et al. (2006). Further, we explore sources of productivity by analysing changes in the decomposition indexes. Spatial variation in aggregate productivity derives from two main sources – differences in the individual firm productivities within each industry, resulting in different average productivities across industries, and differences in the industry composition in each location category.

Let q_r^k be the weighted average, using firm value added as weight, of individual firm productivities (TFPs) in location, r and industry, k.[15] Denote the total value added in location, r by $S_r = \Sigma_k s_r^k$ and the share of industry, k in the total value added in location, r by $\lambda_r^k = s_r^k/S_r$. The average productivity of industry, k for the economy as a whole (i.e., aggregating across all locations, r) is given by $\overline{q}^k = \sum_r s_r^k q_r^k / \sum_r s_r^k$, while $\overline{\lambda}^k = \sum_r s_r^k / \sum_r S_r$ is the share of industry, k in total value added for the economy as a whole. Aggregate productivity, q_r is weighted average of industry productivities in location, r, using industry value added as weight. This aggregate productivity may be decomposed as

$$q_r \equiv \sum_k q_r^k \lambda_r^k = \sum_k q_r^k \overline{\lambda}^k + \sum_k \overline{q}^k \lambda_r^k - \sum_k \overline{q}^k \overline{\lambda}^k + \sum_k (q_r^k - \overline{q}^k)(\lambda_r^k - \overline{\lambda}^k)\,. \qquad (7)$$

The first term on the right-hand side of equation (7) is the average level of productivity in location, r conditional on industry composition being the same as for the economy as a whole; we refer to this as *productivity index*. The second term is the average level of productivity of location, r given its industry composition but assuming that the productivity of each industry equals the economy-wide average for that industry. It is referred to as the *industry composition index*. Remaining terms measure the *residual covariance* between industry productivities and industry shares in location, r. It is important to point out that comparison between productivity and industry composition indexes, while taking into account the residual covariance terms, in equation (7) can provide useful information about the sources of aggregate productivity in various locations.

We compute the productivity index and the industry composition index as specified above for the urban, rural less sparse and rural sparse locations in the UK and report the results by location category, in Table 4, Panel A. Note that values reported are normalised by the term $\sum_k \overline{q}^k \overline{\lambda}^k$ from equation (7). While variation in aggregate productivity by location reflects differences in both productivity and industry composition, the spatial variation observed in the productivity index derives entirely from spatial variation in industry (firm) productivity and is independent of differences in industry composition. A higher value of the productivity index in a given location would suggest that industries in this location are more productive. The spatial variation in the industry composition index derives entirely from differences in the industry composition across locations and is independent of variation in productivity. A higher value of the composition industry index in a given location implies that the more productive industries are represented by larger industry shares in that location. The last covariance term in equation (7) provides information about the link between industry shares and productivity; a positive sign of the term in a given location means that the more productive industries are also larger.

- Table 4 about here -

The results in Panel A are computed as averages for the 1997-2001 period and confirm that urban locations, with the highest density of economic activity, have the highest aggregate productivity. The rural less sparse locations lag behind in aggregate productivity by 13.2 percent, while rural sparse locations are the least productive, with aggregate productivity lower by 18 percent compared to the urban location category. Productivity index and industry composition index also are lower for both rural less sparse and rural sparse categories compared to the urban category as the differentials for the productivity index are 12.7 percent and 23.5 percent, while the differentials for the industry composition index are 10.5 percent and 18.5 percent respectively. The magnitudes of the differentials suggest that rural sparse locations are characterised by both the lowest productivity and the worst industry composition. The covariance term is positive for all location categories but its magnitude is the largest for the rural sparse locations suggesting a substantial unexplained reallocation of industry shares towards more productive industries or increases in productivity of larger industries. From policy view point, efforts to increase firm and industry productivity, through technological innovation and competition, rather than modify industry composition might be more fruitful given the larger scope for improvement in the productivity index compared to the industry composition index.[16]

To explore further the factors affecting aggregate productivity, by location, we analyse changes over time of the decomposition indexes in equation (7). We report results in Table 4 for two periods, in Panel B - for the 1997-1998 pre-Euro period and in Panel C - for the 2000-2001 post-Euro period. The Euro was adopted by the UK's main trading partners in the beginning of 1999 which resulted in a real appreciation of the exchange rate of the Pound against the Euro, over the 2000-2001 period, and led to an increase in competitive pressure on both exporters and non-exporters (through increased import competition). By comparing changes of aggregate productivity in the two periods, with distinct exchange rate regimes and international trade conditions, we are able to derive important results concerning the impact of economic conditions on productivity of various types of location. Specifically, we are able to establish the magnitudes of contributions by both industry productivity and industry composition changes to the aggregate productivity of urban, rural less sparse and rural sparse locations.

The results in Panels B and C show substantial heterogeneity in responses by type of location. Aggregate productivity in urban locations increases with a similar pace in both pre- and post-Euro periods at 2.7 and 2.4 percent respectively. There are dramatic changes in productivity of rural less sparse locations, with a shift from a negative growth of 4.6 percent in the pre-Euro period to a positive growth but close to zero in the post-Euro period. The rural sparse locations are characterised by the highest growth rates in aggregate productivity – 4.7 percent before the Euro implementation and 6.6 percent after that. There is evidence of rural sparse locations catching up with rural less sparse and urban locations in terms of aggregate productivity over the entire period of analysis. It also seems that rural sparse locations are resilient to economic shocks and respond well to increases in competitive pressure, which can be seen, in this case, as a substitute for the impact of density of economic activity.

The sources of aggregate productivity growth vary by type of location. For the urban location category improvements in both productivity and industry composition indexes are evident before and after the implementation of the Euro. There is a relatively substantial decline in the growth of the productivity index in the post-Euro period suggesting that during periods of increased competitive pressure the within industry productivity improvements become less important than the adjustments in industry composition where more productive industries expand. For rural less sparse locations improvement in the productivity index is more important in the pre-Euro period and there is a decline in the effect after the implementation of the Euro, similar to the urban location category. There is also evidence of relative improvement in the industry composition in rural less sparse locations under increased competitive pressure. Despite this, however, the industry composition index remains negative, over the period of analysis, suggesting that the large surviving industries in rural less sparse locations are relatively less productive. The negative residual covariance term in the pre-Euro period also supports the view that the reallocation of industry shares leads to deteriorating industry composition, in the pre-Euro period. However, the residual covariance turns positive in the post-Euro period implying that there is a shift of industry shares in favour of more productive industries under increased competitive pressure. Aggregate productivity in rural sparse locations is positively affected by improvements in productivity index in a manner similar to other location categories but the magnitude is much larger. The impact of the industry composition index is interesting; the change in the composition index shifts from negative in the pre-Euro period to positive in the post-Euro period implying an improvement in the industry composition under increased competitive pressure in the economy. However, the change in the residual covariance term exhibits an opposite pattern by becoming negative in the post-Euro period. We interpret this as evidence that there are in the rural sparse locations less productive industries that manage to survive and even expand.

6 Conclusion

The focus of the paper is on evaluating the productivity gap between rural and urban locations in the UK using micro data. We build a structural model of the unobservable productivity emphasising the link between productivity and spatial density of economic activity and adapt the semi-parametric estimation approach proposed in Olley and Pakes (1996) to estimate the parameters of production functions at firm level, within 4-digit UK manufacturing industries, for the period 1997 - 2001. We allow market structure to differ by endogenous export status and location choices and model productivity as a second-order Markov process which greatly enhances our ability to obtain unbiased and consistent estimates of the production function parameters and thus, back out unbiased and consistent TFP measures at firm level. We aggregate the firm TFPs by location category following the 2004 DEFRA definition of rural and find that aggregate productivity systematically differs across urban, rural less sparse and rural sparse locations as the magnitudes of the differentials are 13.2 percent and 18.0 percent, respectively. Our results are in line with several recent studies, notably Webber et al. (2008), and in broader sense - Rice et al. (2006).

Next, we decompose aggregate productivity into productivity index and industry composition index. The productivity index is the highest in urban locations suggesting that (firm and industry) productivity is strongly influenced by density of economic activity and proximity to economic mass. The industry composition index captures the extend to which manufacturing production in different location categories is allocated to industries that are more or less productive compared to the average for the UK economy. Because industry composition index is positively correlated with productivity index it is evident that locations with high productivity are also characterised by industrial structure enhancing productivity. However, the correlation is not perfect. Even though industry composition (of the top four industries) in urban and rural less sparse locations is very similar, differences in both aggregate productivity and productivity index remain. Further, analysing changes in the decomposition indexes over two periods, before and after implementation of the Euro by the UK main trading partners, reveals substantial heterogeneity in responses across location categories under increased competitive pressure. The main finding is that there is a tendency of rural sparse locations catching up with the urban and rural less sparse location categories in terms of aggregate productivity over the period of analysis.

We also find evidence that increased competitive pressure as a result of changes in trade conditions after implementation of the Euro by the UK's main trading partners has acted as a substitute for the role of density of economic activity in enhancing industry composition, especially in rural sparse locations. From welfare and economic growth policy view point, our ultimate interest is in the ability of various locations to efficiently convert the set of resources available into output, and improvements in the use of resources by reallocating them from less to more productive industries can be just as effective in increasing aggregate output as are the productivity improvements within individual firms and industries. However, in the light of our decomposition results, efforts to increase firm and industry productivity, through technological innovation and within-industry competition, rather than relying on induced changes in industry composition might be more fruitful, given the larger scope for improvement in the productivity index compared to the industry composition index in rural locations.

Notes

[1] The 2004 DEFRA rural-urban definition is extended also to Scotland and Northern Ireland.

[2] Harris and Li (2009) estimate total factor productivity of UK firms and discuss the role of R&D and absorptive capacity at regional level but they do not consider the 2004 DEFRA definition and do not focus on the rural-urban divide.

[3] Fujita and Thisse (2002) and Rosenthal and Strange (2004) offer extensive surveys of the field of economics of agglomeration and implications for productivity.

[4] H. M. Treasury (2001) has defined five generic micro-economic drivers that account for area-based differences in performance: employment and skills; investment; innovation; enterprise; and competition. Courtney et al. (2004) regroup the Treasury's classification in an attempt to accommodate less tangible elements of productivity specifically in rural locations. They also postulate five main drivers. Economic capital embraces infrastructure and innovation and human capital accommodates employment, skills and enterprise. Their other three drivers are social capital (for example, networks and partnerships), cultural capital (political consensus, civic engagement), and environmental capital (quality of living space). Whilst the Treasury drivers apply at the aggregate area level, they are less good at explaining productivity at the firm level.

[5] The invertability of the investment function requires the presence of only one unobservable which Olley and Pakes (1996) refer to as scalar unobservable assumption. This assumption means that there can be no measurement error in the investment function, no unobserved differences in investment prices across firms, and no unobserved separate factors that affect investment but not production.

[6] Note that the fixed effects estimator can be seen as a special case of the Markov process $p(.)$ where productivity, ω_{jt} is set to ω_j and does not change over time.

[7] Results from estimating propensities to export and to locate in areas with high density of economic activity are available from the authors upon request.

[8] Olley and Pakes (1996) show that kernel and polynomial approximations of the unobservable produce very similar results. In our estimations everywhere we use a computationally easier 4th-order polynomial.

[9] Note that the first stage of the estimation algorithm is not affected by selection because by construction, η_{jt}, the residual in equation (2) is not correlated with firm decisions as it is not observed by firm managers.

[10] Woodridge (2009) presents a concise, one-step formulation of the original Olley and Pakes (1996) approach using GMM estimator which is more efficient than the standard Olley-Pakes methodology.

[11] Estimating the age coefficient was only used to separate out cohort from selection effects in determining the impact of firm age on productivity and therefore we do not net out the contribution of age from TFP.

[12] Based on the analysis of Harris and Li (2009), FAME is biased towards larger companies, particularly in the non-exporting populations. Even though we size-weight our aggregations over company productivity this is a caveat of using the data.

[13] Katayama et al. (2003), and related studies, point that production functions should be a mapping of data on inputs and outputs. However, most studies tend to use revenue and expenditure data and use industry level deflators for output, raw material and capital assets to get back the quantity data needed. It is clear that inputs and outputs can be priced differently for exporters and non-exporters within narrowly defined industries. This results in inconsistency discussed by Klette and Griliche (1996) in the case of common scale estimators. We note, however, that allowing for endogenous trade orientation in the unobservable as in Rizov and Walsh (2009) and introducing location information in the state space will control

for persistent exchange rate adjusted pricing gap across locations and between exporters and non-exporters in their use of inputs and their outputs within 4-digit industries. Furthermore, Foster et al. (2005) find that productivity estimates from quantity and deflated revenue data are highly correlated and that the bias vanishes on average and estimated average productivity is unaffected when aggregate deflators are used.

[14] We mark a company as an exporter if we observe in the data exporting by the firm in any year within a 3-year moving window. Rizov and Walsh (2009) also use this data to study productivity and trade orientation and here we follow a similar classification scheme where exporters are defined as firms that consistently export over entire period of analysis. In fact, out of 6,722 firms in the sample, exporters represent between 46 and 56 per cent across the three categories of rural and urban locations.

[15] Note that industry productivity is determined by individual firm productivities and firm market shares, within the industry, as discussed by Olley and Pakes (1996) and Rizov and Walsh (2009), among others. Thus, there could be two sources of industry productivity – within-firm productivity increases and reallocation of market shares towards more productive firms.

[16] There is a large body of literature on international (and regional) specialisation which predicts that general technology (Ricardian) and factor supply (Heckscher-Ohlin) differences jointly determine comparative advantage and thus, specialisation, measured as industry composition. Recent papers, starting with Harrigan (1997), show that the estimated effect of non-neutral technology differences is large and in accord with the theory, suggesting that Ricardian effects are an important source of comparative advantage and determinant of industry composition.

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Table 1
Indicators of density of economic activity by location category, 1997-2001

Indicators	Urban	Rural less sparse	Rural sparse
Density of population of working age (number of residents/km^2)	1778.1 (1454.8)	252.2 (223.8)	37.0 (29.6)
Business density (stock of VAT registrations/km^2)	262.2 (157.5)	12.7 (11.6)	2.5 (2.0)
Job density (number of jobs/resident of working age)	2.6 (1.8)	0.8 (0.7)	0.7 (0.6)
Proportion of knowledge intensive business services in all businesses (%)	16.4 (12.2)	14.9 (11.5)	13.1 (8.4)
Proportion of employees in knowledge intensive business services (%)	14.5 (8.7)	11.4 (7.6)	7.7 (6.1)
Proportion of population with higher education (%)	21.8 (9.4)	19.9 (5.1)	17.5 (2.3)
Capital investment by local authority (GBP/resident)	3425.3 (1352.4)	3190.0 (1401.3)	2812.2 (1331.9)

Note: The summary statistics are aggregated from information at local authority (LAD) level (434 observations in total) and standard deviation (S.D.) is reported in parentheses. Population of working age comprises men, aged 16-64 and women, aged 16-59.
Source: Office for National Statistics (ONS)

Table 2
Descriptive statistics of firm specific variables by location category, 1997-2001

Variable	**Urban, Mean (S.D.)**	**Rural less sparse, Mean (S.D.)**	**Rural sparse, Mean (S.D.)**
Firm characteristics			
Value added (thousands GBP)	17333.3	8606.5	3532.3
	(22381.2)	(4644.5)	(913.6)
Total assets (thousands GBP)	18646.9	12966.2	3030.1
	(48926.1)	(8397.9)	(666.1)
Investment (thousands GBP)	4675.1	4493.9	582.6
	(14716.6)	(4095.9)	(112.9)
Number of full-time equivalent employees	425.3	248.7	137.9
	(261.8)	(68.6)	(24.6)
Share of exporting firms	0.56	0.55	0.46
	(0.50)	(0.50)	(0.50)
Share of foreign owned firms	0.26	0.23	0.11
	(0.44)	(0.42)	(0.31)
Age of the firm	29.0	29.1	36.9
	(22.4)	(22.8)	(33.3)
Industry composition			
List of top four, 4-digit SIC industries, ordered by market share	3663	2852	2112
	2222	3663	1513
	2852	3162	1551
	3162	2222	2524
Market share of top four industries (C4) (%)	37.7	38.0	35.1
Number of observations (Total 23841)	21469	1747	625

Note: Definitions of 4-digit SIC industries are as follow: 1513 – meat and poultry meat products, 1551 – dairy products, 2112 – paper and paper products, 2222 – publishing and printing, 2524 - miscellaneous plastic products, 3663 – miscellaneous manufacturing, 2852 – general mechanical engineering, 3162 - miscellaneous electrical equipment.
Source: FAME, BvD

Table 3

Production function coefficients and productivity estimates aggregated by location category, 1997-2001

Coefficient	Urban	Rural less sparse	Rural sparse
Labour	0.709 (0.057)	0.696 (0.064)	0.665 (0.081)
Capital	0.246 (0.038)	0.250 (0.042)	0.255 (0.050)
Age	0.021 (0.070)	-0.124 (0.090)	-0.126 (0.108)
Aggregate productivity	3.752 (0.971)	3.259(1.021)	3.084 (1.019)

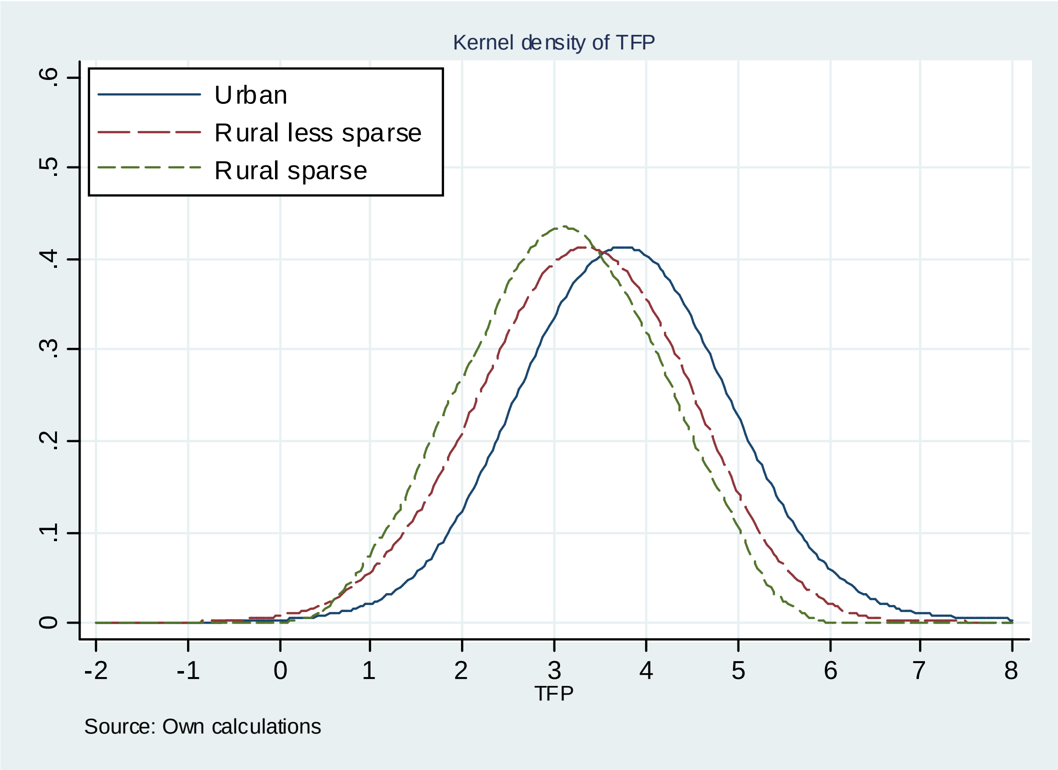
Note: The reported coefficients and aggregate productivity are weighted averages, using value added as weight, from 41 industry regressions on firm level data. The R^2 of all industry regressions are very high, close to 1 (see Appendix 1). Standard errors (standard deviations for productivity) are reported in parentheses.

Table 4
Aggregate productivity decompositions by location category

	$\sum_k q_r^k \lambda_r^k$	$\sum_k q_r^k \overline{\lambda}^k$	$\sum_k \overline{q}^k \lambda_r^k$	$-\sum_k \overline{q}^k \overline{\lambda}^k$	$\sum_k \Delta q_r^k \Delta\lambda_r^k$
Panel A: Levels, average for 1997-2001					
Urban	1.005	1.000	1.004	1.000	0.001
Rural less sparse	0.873	0.873	0.899	1.000	0.101
Rural sparse	0.825	0.765	0.819	1.000	0.241
Panel B: Changes, 1997-1998					
Urban	0.027	0.029	0.024	0.022	-0.004
Rural less sparse	-0.046	0.084	-0.060	0.022	-0.048
Rural sparse	0.047	0.153	-0.230	0.022	0.146
Panel C: Changes, 2000-2001					
Urban	0.024	0.008	0.022	0.013	0.007
Rural less sparse	0.002	0.011	-0.042	0.013	0.046
Rural sparse	0.066	0.078	0.091	0.013	-0.090

Note: For definitions of decomposition components refer to equation (7) in the text.

Figure 1
Firm productivity distributions by location category



Appendix 1: Production function coefficient estimates within 4-digit SIC industries

SIC	Parameters		SIC	Parameters		SIC	Parameters	
(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
1513	***b_l***	***0.55***	***1551***	***b_l***	***0.82***	1584	**b_l**	**0.77**
RS	*s.e.*	*0.06*	***RS***	*s.e.*	*0.08*		s.e.	0.10
	b_k	***0.31***		***b_k***	***0.24***		**b_k**	**0.21**
	s.e.	*0.05*		*s.e.*	*0.08*		s.e.	0.07
	b_a	*0.04*		***b_a***	*-0.03*		**b_a**	-0.04
	s.e.	*0.05*		*s.e.*	*0.10*		s.e.	0.15
	R^2	*0.98*		*R^2*	*0.99*		R^2	0.98
	No	*308*		*No*	*203*		No	162
1589	**b_l**	**0.77**	1591	**b_l**	**0.62**	1598	**b_l**	**0.66**
	s.e.	0.06		s.e.	0.07		s.e.	0.07
	b_k	**0.21**		**b_k**	**0.37**		**b_k**	**0.31**
	s.e.	0.04		s.e.	0.05		s.e.	0.04
	b_a	**0.13**		**b_a**	0.07		**b_a**	**-0.17**
	s.e.	0.06		s.e.	0.09		s.e.	0.06
	R^2	0.98		R^2	0.98		R^2	0.98
	No	416		No	108		No	154
1822	**b_l**	**0.70**	***2112***	***b_l***	***0.67***	2121	**b_l**	**0.56**
	s.e.	0.10	***RS***	*s.e.*	*0.08*		s.e.	0.04
	b_k	**0.21**		***b_k***	***0.28***		**b_k**	**0.33**
	s.e.	0.06		*s.e.*	*0.04*		s.e.	0.03
	b_a	-0.11		***b_a***	*-0.12*		**b_a**	0.09
	s.e.	0.15		*s.e.*	*0.08*		s.e.	0.08
	R^2	0.98		*R^2*	*0.98*		R^2	0.99
	No	502		*No*	*246*		No	459
2125	**b_l**	**0.84**	2211	**b_l**	**0.66**	2212	**b_l**	**0.80**
	s.e.	0.11		s.e.	0.05		s.e.	0.06
	b_k	0.10		**b_k**	**0.18**		**b_k**	**0.23**
	s.e.	0.06		s.e.	0.03		s.e.	0.04
	b_a	**-0.16**		**b_a**	**-0.10**		**b_a**	0.02
	s.e.	0.04		s.e.	0.05		s.e.	0.06
	R^2	0.98		R^2	0.96		R^2	0.99
	No	168		No	723		No	408
2213	**b_l**	**0.83**	2215	**b_l**	**0.68**	***2222***	***b_l***	***0.68***
	s.e.	0.08		s.e.	0.04	***U, RLS***	*s.e.*	*0.03*
	b_k	**0.15**		**b_k**	**0.26**		***b_k***	***0.30***
	s.e.	0.04		s.e.	0.03		*s.e.*	*0.02*
	b_a	-0.07		**b_a**	0.02		***b_a***	***-0.12***
	s.e.	0.10		s.e.	0.04		*s.e.*	*0.03*
	R^2	0.95		R^2	0.97		*R^2*	*0.98*
	No	813		No	259		*No*	*2355*
2320	**b_l**	**0.55**	2413	**b_l**	**0.62**	2416	**b_l**	**0.49**
	s.e.	0.02		s.e.	0.09		s.e.	0.09
	b_k	**0.32**		**b_k**	**0.33**		**b_k**	**0.35**
	s.e.	0.02		s.e.	0.05		s.e.	0.05
	b_a	0.11		**b_a**	-0.15		**b_a**	0.09
	s.e.	0.08		s.e.	0.09		s.e.	0.06
	R^2	0.99		R^2	0.97		R^2	0.98
	No	170		No	480		No	466

Appendix 1 Continued

(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
2430	**b_l**	**0.42**	2441	**b_l**	**0.86**	2442	**b_l**	**0.80**
	s.e.	0.06		s.e.	0.05		s.e.	0.11
	b_k	**0.50**		**b_k**	**0.06**		**b_k**	**0.13**
	s.e.	0.07		s.e.	0.03		s.e.	0.05
	b_a	**-0.12**		**b_a**	0.01		**b_a**	**0.15**
	s.e.	0.04		s.e.	0.04		s.e.	0.07
	R^2	0.98		R^2	0.96		R^2	0.95
	No	226		No	395		No	133
2451	**b_l**	**0.42**	2452	**b_l**	**0.42**	2466	**b_l**	**0.75**
	s.e.	0.07		s.e.	0.06		s.e.	0.08
	b_k	**0.41**		**b_k**	**0.34**		**b_k**	**0.24**
	s.e.	0.08		s.e.	0.08		s.e.	0.04
	b_a	**0.30**		**b_a**	0.20		**b_a**	**-0.25**
	s.e.	0.06		s.e.	0.12		s.e.	0.11
	R^2	0.85		R^2	0.98		R^2	0.98
	No	109		No	257		No	621
2524	***b_l***	***0.66***	2710	**b_l**	**0.70**	2811	**b_l**	**0.55**
RS	*s.e.*	*0.03*		s.e.	0.08		s.e.	0.05
	b_k	***0.29***		**b_k**	**0.22**		**b_k**	**0.32**
	s.e.	*0.02*		s.e.	0.05		s.e.	0.03
	b_a	*0.02*		**b_a**	**-0.24**		**b_a**	**0.18**
	s.e.	*0.04*		s.e.	0.10		s.e.	0.06
	R^2	*0.98*		R^2	0.98		R^2	0.97
	No	*1398*		No	323		No	587
2852	***b_l***	***0.67***	2912	**b_l**	**0.65**	2922	**b_l**	**0.48**
U, RLS	*s.e.*	*0.02*		s.e.	0.04		s.e.	0.06
	b_k	***0.16***		**b_k**	**0.10**		**b_k**	**0.33**
	s.e.	*0.02*		s.e.	0.02		s.e.	0.04
	b_a	***0.06***		**b_a**	-0.05		**b_a**	**0.25**
	s.e.	*0.02*		s.e.	0.04		s.e.	0.06
	R^2	*0.96*		R^2	0.97		R^2	0.98
	No	*2005*		No	460		No	497
2924	**b_l**	**0.73**	2971	**b_l**	**0.44**	3002	**b_l**	**0.77**
	s.e.	0.05		s.e.	0.08		s.e.	0.05
	b_k	**0.18**		**b_k**	**0.52**		**b_k**	**0.25**
	s.e.	0.04		s.e.	0.10		s.e.	0.04
	b_a	-0.05		**b_a**	**-0.36**		**b_a**	**-0.30**
	s.e.	0.06		s.e.	0.14		s.e.	0.10
	R^2	0.98		R^2	0.95		R^2	0.96
	No	466		No	168		No	597
3110	**b_l**	**0.46**	***3162***	***b_l***	***0.62***	3220	**b_l**	**0.62**
	s.e.	0.04	***U, RLS***	*s.e.*	*0.04*		s.e	0.08
	b_k	**0.50**		***b_k***	***0.30***		**b_k**	**0.30**
	s.e.	0.04		*s.e.*	*0.03*		s.e.	0.05
	b_a	**-0.13**		***b_a***	*-0.06*		**b_a**	**-0.26**
	s.e.	0.04		*s.e.*	*0.06*		s.e.	0.08
	R^2	0.97		*R^2*	*0.97*		R^2	0.97
	No	384		*No*	*1669*		No	382

Appendix 1 Continued

(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
3320	**b_l**	**0.74**	3410	**b_l**	**0.52**	3430	**b_l**	**0.74**
	s.e	0.04		s.e	0.08		s.e.	0.10
	b_k	**0.15**		**b_k**	**0.36**		**b_k**	**0.18**
	s.e.	0.02		s.e.	0.05		s.e.	0.06
	b_a	-0.01		**b_a**	**0.16**		**b_a**	-0.36
	s.e.	0.04		s.e.	0.06		s.e.	0.21
	R^2	0.97		R^2	0.98		R^2	0.81
	No	1107		No	241		No	347
3530	**b_l**	**0.73**	***3663***	***b_l***	***0.69***			
	s.e.	0.06	***U, RLS***	*s.e.*	*0.03*			
	b_k	**0.17**		***b_k***	***0.24***			
	s.e.	0.04		*s.e.*	*0.02*			
	b_a	**-0.16**		***b_a***	***-0.11***			
	s.e.	0.06		*s.e.*	*0.05*			
	R^2	0.97		*R^2*	*0.98*			
	No	371		*No*	*2698*			

Note: R^2 statistics and number of observations (No) are from the last step of the estimation algorithm. Coefficients reported in **bold** are significant at 1 percent or better. U denotes urban, RLS – rural less sparse and RS – rural sparse location categories. Industries which U, RLS or RS are reported for are in the top four industries for one or more locations categories.