New Estimates of Returns to Scale and Spatial Spillovers for EU Regional Manufacturing, 1986-2002

Revised 4th February 2007

Abstract: This paper presents some new estimates of the degree of returns to scale for European regional manufacturing, for the period 1986-2002. To obtain these estimates, the paper makes use of a Verdoorn law framework, estimating both demand- and supply-side versions of the law. Estimation is further embedded within a spatial econometric framework that allows for both "substantive" and "nuisance" sources of spatial autocorrelation. The former arises from cross-regional spillovers in the growth process, whilst the latter is a result of the use of the administrative NUTS1 definition of regions. Whilst the demand-side version of the Verdoorn law yields estimates of substantial increasing returns, the supply-side version is unable to refute the hypothesis of constant returns. It is argued, however, that the demand-side version is to be preferred on *a priori* grounds. The paper also gives consideration to the static-dynamic Verdoorn law paradox and successfully tests a recently proposed explanation of this paradox.

JEL codes: O18, O33, R11

Keywords: increasing returns, Verdoorn law, manufacturing, productivity growth, spatial econometrics.

1. Introduction

There is been a strong tradition in regional economics that has long emphasised the importance of localised increasing returns to explaining regional processes of growth and agglomeration (Kaldor, 1970; Dixon and Thirlwall, 1975; Krugman, 1991; Glaeser *et al*, 1992). However, this tradition has been far from dominant down the years, and, in particular, can be contrasted with a literature that has, instead, routinely assumed constant returns to scale (Borts and Stein, 1964; Barro and Sala-i-Martin, 1991, 1992, 2004). This lack of theoretical consensus has, furthermore, been mirrored in empirical work that, either directly or indirectly, has been concerned with testing for the existence of localised increasing returns. Thus, early studies estimating regional production functions report evidence of either constant or very small increasing returns to scale (Moroney, 1972; Griliches and Ringstad, 1971; Douglas, 1976). Likewise, widespread findings of absolute convergence between regions are normally interpreted within a constant returns to scale framework (Barro and Sala-i-Martin, 1991, 1992, 2004). In contrast, however, recent cross-country evidence suggests that there are significant domestic scale effects, once the degree of international openness is controlled for (Frankel and Romer, 1999, and Alcalá and Ciccone, 2004). Also, importantly, estimation of the so-called Verdoorn law - the relationship between productivity growth and output growth - has consistently provided evidence of substantial localised increasing returns for a wide variety of samples and time-periods (McCombie and de Ridder, 1984; Bernat, 1996; Fingleton and McCombie, 1998; León-Ledesma, 1999; Pons-Novell and Viladecans-Marshal, 1999).

In light of the above, this paper re-examines the question of the degree of localised increasing returns for European regional manufacturing. Using data for the period 1986-2002, it provides some new estimates of the degree of localised returns for a sample of 59 European NUTS1 regions.[1] To obtain these estimates, the paper makes use of a Verdoorn law framework similar to that employed in the literature referred to above. However, in contrast to previous studies using comparable data (Fingleton and McCombie, 1998; Pons-Novell and Viladecans-Marshal, 1999), it estimates not only the usual demand-side version of the law, but also a supply-side version. Whilst the demand-side version sees causation as running from the growth of demand for local products and output to the growth of productivity, the supply-side version sees it as running from the growth of local factor supplies to the growth of productivity (Rowthorn, 1975). As will be seen, the two versions of the law give considerably different estimates of the

[1] The sample was determined by the availability of data for gross investment.

degree of local returns. Furthermore, attempting to control for the endogeneity that might be present in both versions fails to reconcile the divergent estimates. This is because of the different methods of normalisation involved in the process of instrumenting. Given this, we are left with no choice but to fall back on *a priori* theoretical arguments about which version of the law is to be preferred (Maddala, 1992, p. 380). In this context, we argue strongly in favour of the estimates obtained from the demand-side version.

As well as estimating both demand- and supply-side versions of the Verdoorn law, the paper extends previous studies using comparable data in several respects. First, it estimates the law using total factor productivity (TFP) growth, rather than labour productivity growth, as the dependent variable. It, therefore, explicitly controls for labour productivity growth that is attributable to capital accumulation, rather than to the exploitation of localised sources of increasing returns.

Secondly, the paper augments the law to allow for the possibility that both technological diffusion and agglomeration economies act as independent sources of local productivity growth. This is important given the emphasis placed on these factors elsewhere in the regional economics literature (see, *inter alios*, McCombie, 1982a; Baldwin and Martin, 2004).

Thirdly, the estimation of the law is embedded within a spatial econometric framework which, unlike previous studies, allows for both "substantive" and "nuisance" sources of spatial autocorrelation. The former may arise due to the potential for cross-regional spillover effects in the regional growth process. These include, for example, the possibility that fast output growth in one region not only helps to stimulate TFP growth in that region, but, through knowledge spillovers, also in neighbouring regions. Meanwhile, the latter may occur due to the fact that the definition of NUTS regions is based upon administrative boundaries rather than on any set of functional criteria (Roberts and Setterfield, 2006). This makes nuisance spatial autocorrelation in the form of spatial measurement error a likely feature of the data set (Anselin, 2006, p 907). We refer to the spatial econometric framework that we use as the "spatial hybrid model". This model represents an extension of the spatial cross-regressive model to include an error term that follows a first-order spatial autoregressive process.

Finally, the paper revisits the "static-dynamic Verdoorn law paradox" of McCombie (1982b). This paradox arises from the fact that it has typically been found that when the demand-side version of the Verdoorn law is estimated in static (i.e. log-level) form, constant returns to scale are found to exist. This is despite the fact that, for the same dataset, estimation of the corresponding dynamic relationship (i.e. the law in the usual growth rate form) indicates the presence of substantial increasing returns to scale. Since the dynamic law can be derived directly from the static law by differentiating with respect to time, however, both versions of the law should, in principle, give identical estimates of the degree of localised returns to scale. The paper confirms the existence of the static-dynamic paradox for the current dataset and tests a recently proposed explanation for the paradox attributable to McCombie and Roberts (2007).

2. The Verdoorn law - theoretical framework, controversy and the paradox

2.1. The Verdoorn law and its theoretical framework

The origins of the Verdoorn law may be traced back to Verdoorn (1949). Traditionally, the law has been estimated as a linear relationship between labour productivity growth and output growth (see McCombie *et al.*, 2002):

$$p_j = c_1 + b_1 q_j \qquad (1)$$

where p_j and q_j are the growth rates of manufacturing labour productivity and output respectively of region j, usually calculated over periods of about a decade. The coefficient b_1 is the Verdoorn coefficient, and it traditionally takes a value of around 0.5, which has been interpreted as implying substantial increasing returns to scale.[2] If the estimated coefficient of b_1 is not significantly different from zero, this implies constant returns to scale.

Significantly absent from the above specification of the Verdoorn law, however, is the growth of the capital stock (McCombie and de Ridder, 1984). Previous studies of the law pertaining to the European regions (Fingleton and McCombie, 1998; Pons-Novell and Viladecans-Marsal, 1999) do not include this variable. Instead, they rely on Kaldor's (1961) stylised fact that the capital-output ratio is constant. (See footnote 5 below.) Relaxing this assumption, however, suggests an extended version of the law. To see this, note that the Verdoorn law can be derived from a Cobb-Douglas production function of the form:

[2] See, for example, Fingleton and McCombie (1998) and Pons-Novell and Viladecans-Marsal (1999) who obtain estimates of 0.575 and 0.628 respectively for their samples of European regions. For a survey of Verdoorn law studies covering a wide variety of samples see McCombie *et al*. (2002).

$$Q_{jt} = A_0 e^{\lambda t} K_{jt}^{a} L_{jt}^{(1-a)} \qquad (2)$$

where Q, K, and L are the levels of output, capital, and labour respectively. λ is the rate of technological progress. a and $(1-a)$ are production function parameters and, under the usual neoclassical assumptions, they equal the relevant factor shares.[3]

A key assumption of the Verdoorn law is that λ is largely endogenously determined. This can occur, for example, through localised knowledge spillovers emanating from learning-by-doing or induced technological change (Arrow, 1962, Kaldor, 1957). To capture these effects, we specify λ as:

$$\lambda_j = \tilde{\lambda} + \pi[ak_j + (1-a)\ \ell_j] \qquad (3)$$

where the lower case letters k and ℓ denote exponential growth rates of the corresponding upper case variables. $\tilde{\lambda}$ is the rate of exogenous technological progress and π is the elasticity of induced technological progress with respect to the weighted growth of inputs. Both $\tilde{\lambda}$ and π are assumed to be constant across regions.

Substituting equation (3) into equation (2) gives:

$$Q_{jt} = A_0 e^{\tilde{\lambda} t/v} K_{jt}^{\alpha} L_{jt}^{\beta} \qquad (4)$$

where α and β are the observed output elasticities of capital and labour respectively; and $\alpha = (1+\pi)a = va$ and $\beta = (1+\pi)(1-a) = v(1-a)$, where v is the degree of local returns to scale. It should be noted that as a and $(1-a)$ differ between regions and over time, so do α and β, but not their sum, v. This is because $\alpha_j + \beta_j = va_j + v(1-a_j) = v$ (where the regional subscripts, j, have been added for clarity). Note, moreover, that v is more encompassing that the traditional definition of returns to scale. That is to say, it is a composite measure of returns to scale that

[3] In the data, the values of the factor shares differ somewhat both between regions and over time. For expositional purposes, however, we shall treat them here as constant.

also includes the effect of the induced rate of technological change, namely, $\pi[ak_j + (1\text{-}a)\ell_j]$. Consequently, taking logarithms of equation (4), differentiating with respect to time, and rearranging gives:

$$p_j = \frac{\tilde{\lambda}}{\beta v} + \frac{\beta - 1}{\beta} q_j + \frac{\alpha}{\beta} k_j \qquad (5)^4$$

2.2 Augmenting the Verdoorn Law

Recently, data on gross investment has become available for the European regions, thereby allowing for the construction of a measure of k. In this context, OLS estimation of equation (5) seems inappropriate because it is likely that k is endogenous, being largely determined by the growth of output (Kaldor, 1970). To tackle this, equation (5) can be respecified as:

$$tfp_j = \frac{\tilde{\lambda}}{v} + \left(1 - \frac{1}{v}\right) q_j \qquad (6)$$

where $tfp_j = q_j - a\, k_j - (1\text{-}a)\ell_j$ is the growth rate of total factor productivity. Empirically, a is equal to capital's share of total output. In this paper, we calculate this separately for each region as $0.5(a_T + a_0)$, where T and 0 denote the terminal and initial years of the period respectively. Equation (6) has the advantage that the (Verdoorn) coefficient of q is constant unlike in equation (5) where, as we have noted, empirically α and β vary to some extent over time and regions, but v does not. It is for this reason and the endogeneity of k that we prefer to work with equation (6).

However, one problem with equation (6) is that it attributes all of the cross-sectional variation in TFP growth to regional variations in output growth. Yet, part of the variation in tfp_j could equally be due to the diffusion of innovations from high-technology to low-technology regions (McCombie, 1982a; Barro and Sala-i-Martin, 2004, Chapter 8). Likewise, it has been suggested in the regional economics literature that the density of production within a region might be a source of dynamic agglomeration economies and, therefore, increasing returns (Baldwin and

[4] In the absence of data on the growth of capital, if the stylised fact that $k = q$ is invoked, and if $\alpha = \beta$, i.e., the output elasticities of labour and capital are the same in manufacturing, a Verdoorn coefficient of 0.5 implies local returns to scale of 1.33.

Martin, 2004). It therefore follows that cross-regional variations in the density of production might also help to explain the variation in tfp_j.

To capture the above possibilities, the Verdoorn law can be further augmented as follows:

$$tfp_j = \frac{\tilde{\lambda}}{v} + \left(1 - \frac{1}{v}\right) q_j + \theta_1 \ln TFP_{j0} + \zeta_1 \ln D_{j0} \qquad (7)$$

where $lnTFP_{j0}$ is the log of the initial level of TFP for region j and is intended as a proxy for the initial level of technology. According to the diffusion hypothesis, $\theta_1 < 0$ should be expected to hold.[5] lnD_{j0} is the logarithm of region j's output density (D_{j0}), where $D_{j0} = Q_{j0}/H_j$ with H_j being the area of region j in square kilometres. By taking the relevant measure of output density to be the initial output density, expected problems of endogeneity are minimised.[6]

Equation (7) implies that the density of production within region j has an effect on its growth path, and, because it is specified as a relationship between TFP growth and output growth, we term equation (7) the *dynamic Verdoorn law*.[7] An alternative is to specify lnD_{j0} as only having a "level effect" (Ciccone and Hall, 1996; Ciccone, 2002). In this case, lnD_{j0} only affects the *level*, and not the long-run growth rate, of TFP. This does not, however, affect the specification of the Verdoorn law given by equation (6), merely its interpretation. In fact, in this case, it is not possible to directly test for the independent influence of agglomeration economies arising from the density of production. To see this, assume that the functional form underlying the Verdoorn law is now provided by:

$$\frac{Q_{jt}}{H_j} = A_t \left(\frac{K_{jt}}{H_j}\right)^{\alpha} \left(\frac{L_{jt}}{H_j}\right)^{\beta} \qquad (8)$$

[5] Fingleton and McCombie (1998) also attempt to proxy for the initial level of technology. However, given their lack of capital stock estimates, they make use of the initial level of labour productivity. This is less satisfactory than using the initial level of TFP, because variations in labour productivity will also be attributable to variations in the capital-labour ratio.

[6] Using the average density of production over the sample-period, however, made little difference to the results obtained.

[7] Integrating equation (7) with respect to time gives a complex function that is not a Cobb-Douglas involving $\int \ln X dt$, where X is either TFP or D. Consequently, it is not possible to estimate the equivalent static form of equation (7).

where $A_t = A_0 e^{\tilde{\lambda} t / v}$.[8]

In this case, the Verdoorn law in log-level form (i.e. the *static* Verdoorn law) at any time t is given by:

$$lnTFP_{jt} = ln\,A_t + \left(1 - \frac{1}{v}\right) ln\,Q_{jt} - \left(1 - \frac{1}{v}\right) ln\,H_j \quad (9)$$

Hence, under increasing returns to scale $(1 - 1/v) > 0$, the greater the density of production is (i.e., the lower is lnH_j in equation (9) for any given lnQ_j), the higher the *level* of TFP will be. With constant returns to scale, though, the density of production has no effect.

As the area of the region, H_j, is constant over time, the Verdoorn law given by equation (9) is the same as in equation (6), when expressed in growth rate (i.e., dynamic) form. Hence, when the underlying production function is provided by equation (8), estimation of the dynamic Verdoorn law does not allow the separate influence of agglomeration economies to be disentangled from that of increasing returns, interpreted more generally. This may be perhaps more easily understood by substituting $H_j = D_{jt} / Q_{jt}$ into equation (9), which, after some rearrangement, becomes:

$$lnTFP_{jt} = ln\,A_t + \left(1 - \frac{1}{v}\right) ln\,D_{jt} \quad (10)$$

Expressing equation (10) in growth rates also gives equation (6) as $dlnD_{jt}/dt = q_j$.

2.3. Endogeneity and the appropriate specification of the Verdoorn law

The specification of the augmented dynamic Verdoorn law in equation (7) holds true to the origins of the law. Thus, q_j is specified as an exogenous and independent determinant of tfp_j, so that demand growth is seen as the fundamental driving force behind the processes of regional growth and agglomeration (Kaldor, 1970; Dixon and Thirlwall, 1975). However, the traditional neoclassical model of growth (Solow, 1956; Swan, 1956) generally assumes that the growth of

[8] For expositional ease, any possible effect of technological diffusion is ignored.

factors are exogenous, which, in the case of the simple dynamic Verdoorn law given in equation (1), implies that the specification should be $p_j = c_2 + b_2\ell_j$, where ℓ_j is the growth of employment in region j. We shall henceforth term this the "supply-side specification" of the Verdoorn Law in contrast to the "demand-side specification" that we have so far focused on. In terms of our augmented dynamic Verdoorn law, this is equivalent to respecifying equation (7) as:

$$tfp_j = \frac{\tilde{\lambda}}{v} + (v-1)\ tfi_j + \theta_2 \ln TFP_{j0} + \zeta_2 \ln D_{j0} \qquad (11)$$

where $tfi_j = a\, k_j + (1-a)\ell_j$ denotes the weighted growth of total factor inputs in region j.

Early estimations using cross-country data for the advanced countries found that the two simple specifications of the Verdoorn law $p_j = c_1 + b_1 q_j$ and $p_j = c_2 + b_2\ell_j$ gave very different implied estimates of the degree of returns to scale. The demand-side specification found substantial increasing returns to scale with $\hat{b}_1 \approx 0.5$ (Kaldor, 1966, 1975). In contrast, the supply-side specification with ℓ_j as the regressor indicated constant returns to scale, with it not being possible to reject the hypothesis $b_2 = 0$ (Rowthorn, 1975).

The reason for the divergence in the implied estimates of v in the two versions of the law can, however, be easily understood. It occurs because the relationship between the two OLS slope coefficients in the demand- and supply-side specifications of the dynamic Verdoorn law is given by $(1-\hat{b}_1)(1+\hat{b}_2) = R^2$ (see Maddala, 1992, p. 72). Given that most studies have found $\hat{b}_1 = 0.5$ (implying, as we have seen, increasing returns) and that, in cross-sectional data, the R^2 usually presents a reasonably good fit of 0.5, it follows that $(1+\hat{b}_2) \approx 1$ and $\hat{b}_2 = 0$ (implying constant returns to scale) (McCombie *et al.,* 2002).

It should be noted, however, that neither the growth of output nor of factor inputs may be strictly exogenous. To the extent that the Verdoorn law is a production relationship, causation will run from the growth of factor inputs to output growth, i.e., from the supply-side of the economy to the demand-side. By contrast, the demand-side origins of the Verdoorn law suggest the opposite direction of causation. However, even here, it is appropriate to acknowledge that, given that the regional growth and agglomeration processes are circular and cumulative, positive feedback will exist from productivity growth to output growth (Kaldor, 1970; Dixon and Thirlwall, 1975). This being the case, the use of OLS to estimate either equation (7) or equation (11) will be subject to simultaneity bias. Consequently, an appropriate estimator that allows for endogeneity should be used and, ideally, this should help to bring about a convergence of the estimates of v obtained from the two specifications.

2.4. The static-dynamic Verdoorn law paradox

Equations (7) and (9) are what we have referred to as the *dynamic* and *static* Verdoorn laws respectively. In particular, ignoring both the possibility of technological diffusion and agglomeration economies arising from the density of production, the dynamic Verdoorn law can be derived from its static counterpart by differentiating with respect to time. This being the case, it might be expected that the estimation of the following two equations would give identical estimates of v:

$$tfp_j = \frac{\tilde{\lambda}}{v} + \left(1 - \frac{1}{v}\right) q_j \quad (12)$$

$$\ln TFP_{jt} = \ln A_t + \left(1 - \frac{1}{v}\right) \ln Q_{jt} \quad (13)$$

where equation (12) is estimated using cross-regional growth rates and equation (13) is estimated using, say, the same data at the initial and terminal years of the period, with an appropriate year intercept dummy to capture possible exogenous shifts in the relationship over time.

However, previous studies, including those for the European regions (Fingleton and McCombie, 1998) have reported substantially different estimates of v for the two models.[9] In particular, it has been found that whereas dynamic specifications of the Verdoorn law give estimates of v that are significantly greater than unity, static specifications do not. A possible explanation for this "static-dynamic paradox" (McCombie, 1982b) is provided by McCombie and Roberts (2007) in terms of *spatial aggregation bias*. They argue that the ideal spatial unit of observation is not the

[9] Note, however, that Fingleton and McCombie (1998) do not estimate versions of the Verdoorn law that allow for capital accumulation.

administrative region (of which the NUTS1 regions used in this paper are examples), but the "Functional Economic Area" (FEA). The FEA is the area over which substantial agglomeration economies occur and is likely to be determined by various factors, such as journey to work patterns. McCombie and Roberts (2007) suggest that any particular region is likely to consist of a number of FEAs, with larger regions containing more than smaller ones. The spatial aggregation error occurs because the data for each region are the values of output, employment, and capital for each constituent FEA summed *arithmetically*. This potentially biases downwards (the static) estimates of ν obtained from equation (13). However, because growth rates are dimensionless figures, estimation of the dynamic Verdoorn law avoids this bias. Hence, the dynamic Verdoorn law (i.e., equation (12)) is the preferred specification.

Anticipating the econometric results, we find that the static-dynamic Verdoorn law paradox holds for the data set in this paper It is interesting, therefore, to test the spatial aggregation bias explanation of McCombie and Roberts (2007). The paradox, moreover, raises problems concerning the appropriate measure of the level of TFP to use as a proxy for the level of technology in equation (7). Clearly, if there are significant localised increasing returns, then TFP levels could differ because of this factor and so the measure of TFP should be adjusted accordingly. If McCombie and Roberts (2007) are correct then the index of TFP should be adjusted to be:

$$TFP'_{j0} = \sum_f \left(\frac{Q_{fj0}}{K^{\alpha}_{fj0} L^{\beta}_{fj0}} \right) \omega_{fj0} \qquad (14)$$

where f denotes the FEA, j the region and ω_f is an appropriate weight for FEA f.[10] Calculation of this corrected index, however, requires data for the individual FEAs, which is not available. Consequently, the procedure adopted below is to use two alternative proxies for TFP_{j0}. First, the initial level of aggregate TFP was calculated under the assumption of constant returns to scale, namely, $TFP_{j0} = Q_{j0} / K^{a}_{j0} L^{(1-a)}_{j0}$. Secondly, the initial level of TFP was calculated under the assumption that the returns to scale apply to the *whole* of region j's output, namely,

[10] Such as $\omega_{fj0} = Q_{fj0} / \sum_f Q_{fj0}$ or $K^{\alpha}_{fj0} L^{\beta}_{fj0} / \sum_f K^{\alpha}_{fj0} L^{\beta}_{fj0}$.

$TFP^{*}_{j0} = Q_{j0} / K^{\alpha}_{j0} L^{\beta}_{j0}$ where α and β are the estimates implicit in the estimated Verdoorn coefficient. These two measures of TFP provide the limits of the true measure of TFP.

3. Spatial econometric issues

Florax and Folmer (1992) consider the following general functional form for a spatial cross-section regression:

$$y = \boldsymbol{X}\delta + \eta \boldsymbol{W}y + \boldsymbol{WX}\rho + \xi \boldsymbol{W}\varepsilon + \mu \qquad (15)$$

where y is a vector of observations on the dependent variable, $\boldsymbol{X}$ is a matrix of non-stochastic regressors, δ the associated vector of coefficients. $\boldsymbol{W}$ is an *a priori* specified matrix of exogenous weights. η is the spatial autoregressive parameter, ρ is a vector of cross-correlation coefficients, $\boldsymbol{W}\varepsilon$ is the spatially lagged error term and μ is a vector of random errors with E(μ) =0 and E($\mu\mu'$) = $\sigma^2_\mu \boldsymbol{I}$. From this general specification, at least five restricted specifications can be identified.

(i) *Ordinary least squares (OLS)* is appropriate when the constraints $\eta = 0$, $\rho = (0,\ldots.0)'$ and $\xi = 0$ hold, in which case $y = \boldsymbol{X}\delta + \mu$.. This is the correct specification when there is no spatial autocorrelation.

(ii) *The spatial autoregressive or spatial lag model (SAR)* is used when the constraints $\rho = (0,\ldots,0)'$ and $\xi = 0$ hold so that $y = \boldsymbol{X}\delta + \eta\boldsymbol{W}y + \mu$. Thus, the spatial autocorrelation is captured by the spatially lagged dependent variable.

(iii) *The spatial error model (SEM)* results when $\eta = 0$ and $\rho =(0\ldots0)'$ and is given by $y = \boldsymbol{X}\delta + \xi\boldsymbol{W}\varepsilon + \mu$. Here, spatial autocorrelation is assumed to be a nuisance and taken account of by the spatially lagged error term.

The SAR and SEM representations are the most commonly applied in spatial econometric studies (Anselin, 2006, p 904). These specifications have been interpreted as capturing spatial autocorrelation of the "substantive" and "nuisance" variety respectively. Thus, while η in the SAR model has been given the economic interpretation of capturing the strength of cross-regional spillovers (Anselin, 2006, p 905; Pons-Novell and Viladecans-Marsal, 1999, p. 446), ξ in the SEM model has been seen as controlling for measurement errors arising, for example, from non-functional definitions of regional boundaries (Roberts, 2004, p 156) and/or the presence of common regional shocks (Anselin, 2006, p 907). The standard specification search strategy tests-up from the OLS specification to either the SAR or the SEM model through the comparison of two Lagrange Multiplier (LM) tests. These tests are the LM_{SAR} and LM_{SEM} tests. Whilst the former exhibits greater power against the SAR model, the latter demonstrates greater power against the SEM. On the basis of this, the strategy is to choose between the SAR and SEM models on the grounds of which has the largest associated LM statistic. This is unless both test statistics are insignificant, in which case the OLS specification is preferred (Anselin and Rey, 1991; Florax *et al*, 2003). However, given that the SAR and SEM models are both nested within the general model given by equation (15), it follows that this standard strategy is only powerful when either LM_{SAR} *or* LM_{SEM} indicate significant spatial autocorrelation. Furthermore, recent Monte Carlo work suggests that the standard specification search strategy can easily result in misleading inferences being drawn in the presence of both nuisance and substantive forms of spatial autocorrelation (Roberts, 2006).[11]

(v) *The spatial cross-regressive model (SCM)* is used when the restrictions $\eta = 0$ and $\xi = 0$ are imposed so that $y = \boldsymbol{X}\delta + \boldsymbol{WX}\rho + \mu$. Like the SAR model, this model captures substantive spatial autocorrelation. However, it does so through the inclusion of spatial lags of the independent variables, rather than the spatial lag of the dependent variable. In the case of the augmented dynamic Verdoorn law given by equation (7), this is equivalent to the inclusion of $\boldsymbol{W}q$, $\boldsymbol{W}lnTFP_0$ and $\boldsymbol{W}lnD_0$ as additional explanatory variables. These additional variables can be interpreted as capturing cross-regional spillovers to region j occurring and/or being affected by output growth, technology levels and levels of agglomeration in neighbouring regions. This would contrast with estimation of the augmented dynamic Verdoorn law using the SAR model, which would instead see spillovers as occurring *directly* through TFP growth. In this sense, the SCM would seem preferable because it enables the analyst to identify and estimate the *separate*

[11] Sometimes, the standard specification search strategy is replaced by a procedure based upon robust versions of the LM_{SAR} and LM_{SEM} tests attributable to Anselin *et al* (1996). However, this robust version of the strategy can, just like the standard version, result in misleading inferences in the presence of both substantive and nuisance forms of spatial autocorrelation (Roberts, 2006).

contributions of the different independent variables to cross-regional spillovers.[12] This allows, for instance, for testing of the hypothesis that faster TFP growth is more likely to be observed in region j if that region is surrounded by technologically advanced regions.

(v) *The spatial Durbin model.* This model combines the SAR and SCM models by imposing the single restriction $\xi = 0$, so that $y = \boldsymbol{X}\delta + \eta\boldsymbol{W}y + \boldsymbol{WX}\rho + \mu$. Hence, both $\boldsymbol{Wy}$ and $\boldsymbol{WX}$ are included as additional explanatory variables. This specification, however, is likely to suffer from severe multicollinearity between $\boldsymbol{W}y$ and $\boldsymbol{WX}$ and there seems to be a large element of double counting, as $\boldsymbol{W}y$ is hypothesised to be determined by $\boldsymbol{WX}$. If there were a perfect statistical fit, the two would be identical.

Ideally, the appropriate search strategy to select between specifications (i) to (v) would be the Hendry-style one of estimating the general model, equation (15), and "testing down". There are, however, two drawbacks with this strategy. First, if $\boldsymbol{W}y$ and $\boldsymbol{W}\varepsilon$ are highly collinear then the standard errors will be inflated. Secondly, using the same weights matrices in the general model means that the estimated equation is not identified (Anselin, 1988). Yet, it is often difficult to determine on theoretical grounds why the weights matrices should differ between $\boldsymbol{W}y$ and $\boldsymbol{W}\varepsilon$.[13] The upshot of this is that we should be sceptical about distinguishing between the quantitative impact of the two variables and attaching different economic interpretations to them, unless one is statistically insignificant. Thus, we would hesitate to interpret η being statistically significant as capturing a cross-regional spillover effect, unless the estimate of ξ is statistically insignificant.

In addition to specifications (ii) to (v), there is a further spatial model nested within equation (15). Although this model seems to have gone unnoticed in the spatial econometrics literature, it is the one that we prefer on theoretical grounds. It is basically an extension of the SCM to include an error term that obeys a first-order spatial autoregressive process. Essentially, therefore, the model represents a marriage between the SCM and the SEM. By marrying these two models, it is able to capture both substantive and nuisance sources of spatial autocorrelation.

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[12] It should be noted, however, that whereas spillovers as modelled using the SAR model adopt a global character, those modelled using the SCM adopt a local character (Anselin, 2006, p 918; Roberts, 2006, p 22).

[13] Although we are able to do this in one specification of our model (see section 4.2 below).

(vi) *The spatial cross-regressive error model (the spatial hybrid model)(SHM)*

This model involves the single restriction $\eta = 0$ and therefore takes the form $y = \boldsymbol{X}\delta + \boldsymbol{WX}\rho + \xi\boldsymbol{W}\varepsilon + \mu$. As indicated, it presents the advantage of explicitly modelling both the substantive and nuisance components of any possible spatial autocorrelation. In particular, while $\boldsymbol{WX}$ (i.e., $\boldsymbol{W}q$, $\boldsymbol{W}lnTFP_0$ and $\boldsymbol{W}lnD_0$) models the substantive, or economic, component, the nuisance component is captured by $\boldsymbol{W}\varepsilon$.

4. The results for total manufacturing

4.1. Data

The data used in this paper is taken from *Cambridge Econometrics'* Regional Economic Database, supplemented and amended, where necessary, by national sources. Output is gross value added (GVA) in constant 1995 prices and is measured using a purchasing power standard exchange rate, whilst employment is the total number of hours worked. The analysis is confined to the NUTS1 regions, as this is the lowest level of spatial aggregation for which independent gross investment figures are available. Such regions are defined on the basis of country-specific administrative boundaries, which makes nuisance spatial autocorrelation a likely feature of the data. This helps to motivate the use of the SHM as our preferred spatial specification. Overall, complete, reliable information was obtained for 59 regions drawn from 15 European countries.[14] Following, for example, Hall and Jones (1999, p 89, fn 5), the capital stock for region j in the base year of 1986 was calculated using the formula $K_{j,1986} = (I_{j,\ aver.\ 81\text{-}86})/(g_j + \delta)$ where $I_{j,aver.\ 81\text{-}86}$ denotes the average level of gross investment over the period 1981-1986, g the growth rate of gross investment over the same period and δ the rate of capital obsolescence, which was taken to be 5%. Capital stock estimates for subsequent years were then calculated using the perpetual inventory method. Other assumptions for the rate of depreciation were also tried, but the 5% assumption produced the most reasonable cross-regional estimates of capital-GVA ratios.

4.2. Estimation of the demand-side version of the augmented dynamic Verdoorn law

[14] The countries covered are Austria, Belgium, Denmark, Germany, Finland, France, Greece, Italy, Ireland, Netherlands, Portugal, Spain, Sweden, Switzerland, and the UK. A full listing of the regions included in the sample is available on request.

Table 1 presents cross-sectional results for the full-sample period of 1986-2002 for the demand-side version of the augmented dynamic Verdoorn law given in equation (7), using the specifications (i) to (vi) outlined in section 3.[15] In all cases, the measure of initial TFP adopted is the one that makes no correction for increasing returns (see the discussion concerning equation (14)). Likewise, the implied speed of catch-up between regions due to technological diffusion *(ϕ)* that we calculate is based on constant returns to scale.[16] Moran's *I,* as well as the two LM tests, namely, LM_{SAR} and LM_{SEM}, confirm the presence of spatial autocorrelation in the OLS residuals and therefore justify the additional use of spatial econometric methods.

From Table 1, it can be seen that specifications (ii) to (vi) all yielded very similar results, which are close to the OLS estimates. The estimated coefficient on q (i.e. the Verdoorn coefficient) ranged from 0.502 to 0.673, implying that $\hat{v}$ (the estimate of the composite measure of returns to scale) varied from 2.199 to 3.060. These estimates are very similar to those reported in previous Verdoorn law studies and demonstrate the importance of the demand-side in stimulating TFP growth (McCombie *et al.*, 2002).

It is interesting to note that, for all specifications, the implied estimate of $\tilde{\lambda}$ (exogenous rate of technological change) is negative.[17] With the exception of for the SAR model, however, the estimates of the intercept are not statistically significant. The diffusion of innovations from the more to the relatively less advanced regions is also an important source of TFP growth, as indicated by the statistically significant negative coefficient on $lnTFP_{j0}$ with the (conditional) speed of catch-up, ϕ, estimated as being between 1.43% and 2.17% per annum. The output density variable is also significant with a positive coefficient, suggesting the existence of dynamic agglomeration economies as an additional source of localised increasing returns. The estimated coefficient implies that a doubling of the density increases TFP growth by 0.42

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[15] With the exception of specification (i), all specifications were estimated using Maximum Likelihood (ML) techniques. Unless otherwise stated, the spatial weights matrix, ***W***, used in the estimation of the spatial specifications was a simple row-standardised first-order contiguity matrix, with two regions being defined as contiguous if they share a common administrative border.

[16] The estimate of ϕ is given by $\hat{\phi} = -[\ln(1-\hat{\theta}_1 T)]/T$. This excludes the influence of the spatially lagged $lnTFP_{j0}$. The estimates of ϕ that were obtained using TFP^*_{j0}, which are available on request, were lower than those reported in Table 1.

[17] From, for example, equation (7), the estimated rate of exogenous technical change, $\tilde{\lambda}$ can be found by multiplying the constant term by the indirect estimate of ν.

percentage points per annum. Consequently, regional growth cannot be fully explained without taking account of these additional explanatory variables.

It is worth emphasising the virtually identical coefficients and *t*-values associated with ***W****tfp* and $\boldsymbol{W}\varepsilon$ in the spatial autoregressive model (SAR) and the spatial error model (SEM) specifications respectively (i.e., Table 1, equations (ii) and (iii)) This makes it very difficult to discriminate between the two specifications on statistical grounds.

As discussed above, we have good theoretical grounds for preferring what we have termed the "spatial hybrid model", to the SAR and SEM models. Thus, our preferred set of results is given in Table 1 (vi). This is because, as mentioned, the SHM allows for the disaggregation of the substantive components of any spatial autocorrelation, allowing an assessment to be made of the channels through which cross-regional spillovers might occur, while correcting for any nuisance component through $\boldsymbol{W}\varepsilon$. In particular, the different channels are captured by the spatially lagged regressors ***WX*.** In this regard, it shows that a faster growth of output of the surrounding regions has a significant effect on TFP growth of the region under consideration; a 1 percentage point increase in the growth of the surrounding regions increases the growth of TFP in the region by nearly 0.3 percentage points. Thus, the gains from the Verdoorn effect through learning-by-doing and induced technological change are not completely localised to the region in question, but directly spillover into surrounding regions. There is, moreover, evidence of a cross-regional spillover effect from dynamic agglomeration economies as evidenced by the statistically significant positive coefficient of ***W****lnD*. Finally, estimation of the SHM suggests that TFP growth is inversely related to the initial level of the region's TFP. This is consistent with the hypothesis that the more technologically backward a region is, the more it benefits from the spatial diffusion of innovations from the more advanced EU regions and other technologically advanced countries. The estimated coefficient on $\boldsymbol{W}lnTFP_0$ is positive, which might be taken as suggesting that a region benefits from having more, relative to less, technologically advanced neighbours. This might be expected because it increases the propensity to benefit from technological diffusion. Notwithstanding this interpretation, however, the estimated value of the coefficient is statistically insignificant.

We also estimated the models where the level of TFP was adjusted to allow for the presence of increasing returns to scale.[18] For the SHM, this made very little difference to $\hat{\nu}$, which was found to be 3.306 compared to 3.060 in Table 1, equation (vi). The coefficient on *lnTFP* increased from –0.026 to –0.0013 and was still statistically significant. All the other coefficients did not change greatly in magnitude and were statistically significant.

TABLE 1 HERE

A commonly neglected shortcoming of traditional spatial models concerns the weights matrix. In particular, the weights matrices typically used implicitly possess a scale invariance property. Thus, the strength of interaction between region *j* and a neighbouring region is assumed to be independent of the economic sizes of the two regions. This is the case with the weights matrix, ***W***, employed above, so that the inclusion of ***Wq***, for example, implies that the impact on region *j* of a neighbouring region's output growth is independent of the size of that region, which is rather implausible. More plausible is the assumption that scale does matter, so that economically larger neighbours have a greater impact on the growth of *j*. To allow for this, we specify the following weights matrix:

$$W_1 = \begin{bmatrix} w_{1,1} & \cdots & w_{1,N} \\ \vdots & \ddots & \vdots \\ w_{N,1} & \cdots & w_{N,N} \end{bmatrix}$$

where $w_{ij} = \dfrac{Q_i}{Q_j}$ iff i and j share a common administrative border and $i \neq j$, and $w_{ij} = 0$ otherwise. Notice that, in order to preserve the idea that it is the absolute size of regions that matters, this matrix is not row-standardised.[19]

When we used $\boldsymbol{W_1}$ for all the lagged spatial variables, the estimates of the degree of increasing returns did not vary very much. (The full results are not reported here.) Demonstrative of

[18] For reasons of space, the full results are not reported here. They are, however, available on request.
[19] An alternative is to row standardise $\boldsymbol{W_1}$ so that the relative sizes of the surrounding regions, rather than their absolute sizes, are taken into account. This alternative procedure yielded similar results to those reported.

these findings are the following results, which were obtained from estimation of the SHM using the increasing returns correction to $lnTFP_0$ (i.e. $lnTFP_0$*):

$$tfp = -0.025 + 0.491q - 0.003 lnTFP^*_0 + 0.006\, lnD_0 + 0.061 \mathbf{W_1} q + 0.000 \mathbf{W_1} lnTFP^*_0$$
$$(-1.19) \quad (4.25) \quad (-2.41) \qquad (4.29) \qquad (1.06) \qquad (0.068)$$

$$+\ 0.003 \mathbf{W_1} lnD_0 + 0.466 \mathbf{W_1} \varepsilon \qquad pseudo\text{-}\overline{R}^2_{adj} = 0.167;\ \hat{\nu} = 1.963;\ \hat{\phi} = 0.3\%$$
$$(2.77) \qquad (61.09)$$

Thus, the implied estimate of ν is just less than two. Noticeable, however, is that the speed of catch-up due to technological diffusion (0.3% per annum) is slower than that reported in Table 1, equation (vi). This is to be expected, given the correction of TFP for aggregate increasing returns to scale. More importantly, the spatially weighted growth of output is now statistically insignificant.

We also estimated the specifications (i) to (vi) using panel data techniques, allowing for both one–way and two-way fixed effects.[20] In particular, the panel consists of three periods, 1986-1991, 1991-1996, 1996-2002. The results are not reported here, but allowing for the fixed effects did not make any appreciable difference to the results obtained using the cross-sectional data. We have reported the cross-sectional results in preference to the panel data results because of the difficulty of calculating LM_{SAR} and LM_{SEM} using panel data analysis and because of the desirability of using the longest possible time period to minimise cyclical fluctuations (Shioji, 1997; cited in Barro and Sala-i-Martin, 2004, p 496).

4.3. Estimation of the supply-side specification of the dynamic Verdoorn law

It will be recalled, that the supply-side specification of the dynamic Verdoorn law is given by equation (11), where the growth of total factor inputs (*tfi*) replaces output growth (*q*) as a

[20] In doing so, we used the spatial panel estimators of Elhorst (2003), which are ML estimators.

regressor. Here, the causation is hypothesised to run from the growth of inputs to the growth of output and demand rather than *vice versa*. Although a supply-side specification has not previously been estimated for the European regions, when such specifications have been estimated for other samples, they have often been found to suggest constant returns to scale (McCombie and Thirlwall, 1994, Chapter 2).[21] Consequently, we estimated equation (11) for specifications (i) to (vi). The results obtained from estimation of the SHM specification were:

$$\underset{}{tfp} = \underset{(3.11)}{0.016} - \underset{(-1.55)}{0.272 tfi} - \underset{(-3.25)}{0.029 lnTFP_0} + \underset{(1.17)}{0.002 lnD_0} - \underset{(-0.88)}{0.169 \boldsymbol{W} tfi}$$

$$+ \underset{(2.61)}{0.036\, \boldsymbol{W} lnTFP_0} - \underset{(-0.07)}{0.002 \boldsymbol{W} lnD_0} + \underset{(5.03)}{0.526 \boldsymbol{W}\varepsilon} \quad pseudo\text{-}\overline{R}^2_{adj} = 0.506;\ \hat{\nu} = 0.729; \hat{\phi} = 2.20\%\ \text{p.a.}$$

This is the supply-side equivalent to the demand-side specification of the SHM, the results of which were reported in Table 1, equation (vi).

Although the results of the other specifications, i.e., specifications (i) to (v), are not reported for reasons of space, they were, in all cases, also found to suggest either constant (ν = 1) or decreasing returns to scale (ν < 1), despite the corresponding demand-side specifications reported in Table 1 all suggesting increasing returns. If the supply-side specification is correct, the estimate of decreasing returns to scale could be due to a relatively fixed factor of production such as land. It can also be seen that both $lnTFP_0$ and the density variable take on the expected signs but only the former is statistically significant. The spatially lagged level of $lnTFP_0$ also has a significant positive impact on TFP growth, whilst the remaining ***WX*** variables are insignificant. The results obtained using $\boldsymbol{W}_1 tfi$ instead of $\boldsymbol{W} tfi$ and calculating $lnTFP_0$ using the estimated degree of returns to scale were not substantially different – $\hat{\nu}$ invariably showed either constant or decreasing returns to scale. These conclusions also proved robust to the use of panel data techniques.

4.4. FGS2SLS estimation of the dynamic Verdoorn law

[21] The sole exception seems to be provided by McCombie and de Ridder (1984) for the US states, who found increasing returns using both demand- and supply-side specifications of the Verdoorn law.

Given the dramatic differences obtained from the demand- and supply-side specifications of the dynamic Verdoorn law, the assumption of exogeneity is clearly crucial in the estimation of v. Consequently, from either a supply (neoclassical) or a demand-side perspective, both equations (7) and (11) should be estimated by methods that take endogeneity into account and, ideally, the implied estimates of v should converge.

To this end, we make use of a feasible generalised spatial two-stage least squares (FGS2SLS) procedure that has recently been proposed by Fingleton and LeGallo (2006). This approach is designed to control for endogeneity of the explanatory variables in the presence of a first-order spatial autoregressive error process. It is, therefore, ideal for estimation of the SHM. Apart from controlling for endogeneity, the approach, because it is an instrumental variable (IV) approach, has the added advantage of also helping to control for both possible omitted variable bias and the existence of measurement errors in the explanatory variables (Greene, 2003, p 86), which might arise, for example, from the imperfect measurement of distance in the $\boldsymbol{W}$ matrix.[22]

Basically, the FGS2SLS procedure consists of three stages. In the first stage, the equation of interest is estimated using 2SLS; in the second stage, the residuals from the first stage regression are used to obtain a consistent estimate of the spatial error parameter, ξ; and finally, in the third stage, $\hat{\xi}$, is used to filter both the dependent and explanatory variables and 2SLS is re-performed using filtered versions of the first stage instruments. Although any set of appropriate instruments may be used in the first stage, Fingleton and LeGallo (2006) recommend basing them on the three-group method (Barlett, 1949; Kennedy, 2003). According to this method, the instrument of an endogenous variable is taken to be an indicator variable that is coded 1, 0, -1 according to whether an observation on the endogenous variable is in the top third, middle third or bottom third of its distribution. Spatial lags of these indicator variables are also used as instruments.

For the SHM, Table 2 presents the results obtained from re-estimating both the demand- and supply-side versions of the Verdoorn law using the FGS2SLS procedure described above.[23] As

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[22] In contrast to ML estimators, the FGS2SLS estimator also does not rely upon the assumption of a normally distributed error term for its theoretical properties.

[23] The procedure was iterated until the absolute difference between the stage 3 residuals in successive iterations was less than or equal to 0.001. In general, very few iterations were required for convergence.

can be seen, controlling for endogeneity using this procedure made very little difference to the results obtained.[24] In particular, the estimated Verdoorn coefficient in the demand-side version of the dynamic law is 0.633, which is virtually unchanged from when we did not control for endogeneity (see Table 1(iv)).[25] Consequently, despite the instrumentation, localised increasing returns appear just as strong as ever using this specification. Likewise, the supply-side version of the law continues to show non-increasing returns to scale. Hence, instrumentation using Fingleton and LeGallo's (2006) FGS2SLS procedure takes us no closer to a resolution of the controversy over the correct specification for the dynamic Verdoorn law, and, therefore, no closer to a consensus estimate of the degree of localised returns to scale.[26]

TABLE 2 HERE

The problem is due to the fact that two different instruments are being used in the above estimations of the demand- and supply–side specifications. In particular, the groups of observations coded -1, 0, 1 differ according to the direction of normalisation (i.e., whether q or tfi is used as a regressor). These results illustrate the problem of using an IV-based estimation technique when either different instruments are being used or the equation is over-identified. In particular, in this case, the method of normalisation still affects the estimates obtained (Maddala, 1992, pp. 377-381; Greene, 2003, p. 402).

Consequently, use of an IV based estimator does not resolve the problem of the disparities in the estimated degree of local returns to scale, and the method of normalisation has to be determined

[24] This is despite the fact that, from the results of Sargan's test, the instruments appear to be valid. In particular, Table 2 reports two sets of results for Sargan's test. The first set of results is for Sargan's test as applied to the (filtered) instruments used in the third stage of the Fingleton and LeGallo estimation procedure. Meanwhile, the second set of results is for Sargan's test as applied to the (unfiltered) instruments used in the first stage of the procedure.

[25] Durbin's ranking method was also used where the instruments are the ranks of the various regressors. This is a more efficient procedure than the Bartlett three-group method, but Sargan's test suggested some problems with the endogeneity of the instruments which were not present in the case of the latter procedure (see Table 2). Both methods, however, gave almost identical results.

[26] Adopting a slightly different method of instrumentation to that recommended by Fingleton and LeGallo did yield marginally more satisfactory results. Specifically, when, instead of filtering, we recoded the indicator variables used as instruments in stage 3 of the FGS2SLS procedure according to the newly constructed filtered endogenous variables, we found that the supply-side version of the dynamic Verdoorn law gave $\hat{\nu} = 1.04$.

on *a priori* grounds, normally on the basis of economic theory (Maddala, 1992, p.380). In regional economies with capital and labour mobility, the key factor determining the economic performance of a region is its price and non-price competitiveness, including the structure of its production and whether or not it has industries that have a high income elasticity of demand. As Thirlwall (1980, p.420) puts it: "For a region in which capital and labour are highly mobile, in and out, growth must be demand determined. If the demand for a region's output is strong, labour and capital will migrate to the region to the benefit of that region and to the detriment of others. Supply [therefore] adjusts to demand." (See also McCombie and Thirlwall, 1994, Chapter 8; Porter, 1996.)[27] The alternative, namely, that each region faces an infinitely elastic demand curve for its output and can sell as much as it produces, does not seem plausible. Given this, our theoretical preference is to specify output growth as the regressor.

Our argument that the demand-side specification is to be preferred is consistent with findings in other regional samples. For example, in estimating a structural model of city growth determinants for Brazil, da Mata *et al* (2007, p. 16, emphasis in original) find that "The key positive component to growth comes from increases in market potential...; much of what happens to cities is determined by conditions external to them- *demand for their products as driven by what is evolving geographically around them*." It is also consistent with the clear demand linkage that exists in new economic geography models between local labour productivity and market potential (see, for example, Redding and Venables, 2004).[28]

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4.5. Estimation of the static Verdoorn law and resolution of the static-dynamic paradox

Given the variables $lnTFP_0$ and lnD_0, there is no equivalent static specification of the Verdoorn law to our augmented dynamic Verdoorn law that can be estimated. Therefore, for our augmented law, we cannot test for the existence of the static-dynamic Verdoorn law paradox. However, whilst $\ln TFP_0$ and $\ln D_0$ have been found to be statistically significant and give economically meaningful results, their inclusion has not dramatically altered the implied estimates of v obtained. Consequently, using the SHM, we estimated static versions of the demand- and supply-side specifications of the Verdoorn law excluding these variables. That is to say, we estimated:

[27] One of the referees did, however, express a strong preference for the supply-side specification.
[28] We are grateful to Harry Garretson for this observation.

$$lnTFP = c_6 + b_{12}lnQ + b_{13}\mathbf{W}lnQ + b_{14}\mathbf{W}\varepsilon + \mu_1 \qquad (24)$$

and

$$lnTFP = c_7 + b_{15}lnTFI + b_{16}\mathbf{W}lnTFI + b_{17}\mathbf{W}\varepsilon + \mu_2 \qquad (25)$$

The panel data results are reported in Table 3. There are four periods, 1986, 1991, 1996 and 2002. It can be seen that the estimate of v using time effects (which has the effect of allowing for shifts in the production relationship) is, in both cases, consistent with constant returns to scale. This is equivalent to the use of pooled data, with a dummy variable to allow for exogenous technological change. Consequently, for the demand-side specification, the estimates of the static Verdoorn law stand in marked contrast to the dynamic specification. In the case of the supply-side specification, both the static and dynamic estimates are in accord.

As we have seen, McCombie and Roberts (2007) have suggested that the most likely explanation for the static-dynamic paradox is the existence of spatial aggregation bias in the static estimates. According to this hypothesis, the use of a two-way estimator that captures both time and regional fixed effects should give unbiased estimates of ν similar to those obtained from the dynamic Verdoorn law.[29] This is confirmed for the European data set under consideration. As shown in Table 3, once two-way effects are introduced, the static demand-side specification exhibits substantial increasing returns to scale of a magnitude comparable to the estimates from the corresponding dynamic law. We also used an IV approach but given the close statistical fit (i.e., the high OLS R^2), it did not make any significant difference to the estimates, which is consistent with Wold's proximity theorem (Wold and Faxer, 1957).

TABLE 3 HERE

However, interestingly, the static supply-side specification estimated using both one-way and two-way fixed effects gives results consistent only with constant returns to scale. This is not surprising, though. The two-way fixed effects estimator gives an unbiased estimate of ν, by

[29] Using simulation analysis, McCombie and Roberts demonstrate that, using panel data, a one-way fixed-effects (FE) estimation of the static Verdoorn law will lead to a biased estimate of ν, i.e., it will suggest constant returns to scale, by picking up the cross-section variation. However, the two-way FE estimator gives an unbiased estimate, as it also employs the time-series variation in the data that is not subject to the spatial aggregation bias.

capturing the within-region variation of the data, which is not subject to the aggregation problem. In the case here, we know that the within-region variation will approximate to the results using growth rates, and in the case of the supply-side specification, this gives constant or decreasing returns to scale.[30] In the dynamic specifications of both the demand- and supply-side Verdoorn laws, $\ln D_0$ was, with one exception, found to have a significant effect on the growth of TFP, suggesting significant (intra-regional) *dynamic* economies of agglomeration. As we have noted, it is not possible to derive an estimable static specification of this model. However, an alternative hypothesis that we discussed in section 2.1, was that agglomeration economies may be of the *static* variety and hence only have a "level effect" (see, in particular, the discussion of equations (9) and (10)).

Consequently, we estimated both the static demand- and supply-side specifications of the Verdoorn law using output and inputs expressed in per square kilometre terms, (i.e., with these variables divided by H) with panel data and time effects. In both cases, the estimated results did not differ greatly from the "conventional" specification of the static laws using the unadjusted log-levels; in both cases, the hypothesis of constant returns to scale could not be refuted.[31] In retrospect, this is not surprising, as, with constant returns to scale, the results will not be affected if all the variables are divided by H. See, for example, the equivalent specification of the static Verdoorn law as equation (9) when $\nu = 1$ holds. A similar argument holds for the supply-side specification.

Using the density data for both specifications and now also including regional effects, as well as time effects, (so the model is estimated using the two-way estimator) washes out the effect of H, which is due to its inter-regional variation. Consequently, the results obtained are the same as those reported in Table 3 and obtained using the two-way estimator and the log levels of the variables. The demand-side specification exhibits substantial increasing returns to scale and the supply-side specification, decreasing returns to scale. Accordingly, the results using density variables do not shed any further light on whether or not there are increasing returns to scale when levels are used.

[30] It is worth noting, however, that, using postwar data for Spanish regional manufacturing, León-Ledesma (1999) found two-way random effects estimation of the static supply-side specification to give increasing returns.

[31] The results are not reported here but are available on request from the authors.

5. Conclusions

This paper has revisited the question of the extent of localised increasing returns in EU regional manufacturing. This it has done through the spatial econometric estimation of the Verdoorn law. In particular, attention was focused on the estimation of the law using the spatial hybrid model. This is because this model is able to control for both nuisance and substantive sources of spatial autocorrelation, where the former is attributable to measurement error arising from the use of the NUTS classification of regions and the latter reflects the presence of spillover effects between regional economies. Moreover, unlike previous studies for the EU (Fingleton and McCombie, 1998; Pons-Novell and Viladecans-Marsal, 1999), estimates of the capital stock were calculated and used in the specification of the law. Our results with the demand-side specification of the dynamic Verdoorn law with q as a regressor gave estimates of substantial increasing returns to scale, where returns to scale were broadly defined to include the effect of induced technological change. It was also found that the coefficient of the logarithm of the initial level of TFP was negative and statistically significant. This suggests that the diffusion of innovations from the relatively more to the relatively less advanced regions (or from advanced countries outside the EU) was a significant explanatory factor in accounting for disparities in TFP growth. A density variable that was introduced to capture the effect of agglomeration economies on TFP *growth* also proved to be statistically significant, although its quantitative effect was small. These variables, when spatially lagged, often turned out to be significant, suggesting significant cross-regional spillover effects, although, interestingly, the spatially lagged output growth turned out to be not statistically significant when the $\boldsymbol{W}_1$ weights matrix was used.

The alternative supply-side specification, which used the weighted growth of the total factor inputs (*tfi*) as a regressor, always suggested either decreasing or constant returns to scale and the use of a recently proposed FGS2SLS estimation procedure was not able to resolve the discrepancy between the two specifications. This was because estimation of the two specifications using an IV-based method involves the use of different instruments. In these circumstances, we are forced to rely upon *a priori* theoretical arguments to determine the preferred specification. Given this, we argued strongly in favour of the demand-side specification of the Verdoorn law, in which case our results suggest the existence of substantial localised increasing returns, in line with previous studies.

It was also found that the EU regional data gives rise to the static-dynamic Verdoorn law paradox. In particular, estimation of the demand-side specification of the Verdoorn law in static (log-level) form suggests constant returns to scale prevail, whilst estimation in dynamic form suggests substantial increasing returns to scale. The conjecture of McCombie and Roberts (2007) that this is due to spatial aggregation bias is given support by the finding that the two-way fixed effects estimation of the static relationships finds, as predicted, increasing returns in accord with the dynamic estimates. The static supply-side specification still did not refute the hypothesis of either constant or decreasing returns to scale.

Thus, our preferred results provide strong support for the presence of substantial static and dynamic returns to scale at a local level. They, furthermore, indicate the existence of both a significant technological diffusion effect from the rest of the world and the surrounding regions and a significant dynamic agglomeration effect.

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Table 1: The Dynamic Verdoorn Law (Demand-side Specification): Cross-sectional Data, 1986, 1991, 1996 and 2002

$$tfp = c_3 + b_3 q + b_4 lnTFP_0 + b_5 lnD_0 + \{spatially\ lagged\ terms\}$$

	(i) OLS	(ii) SAR	(iii) SEM	(iv) SCM	(v) SDM	(vi) SHM
Constant	-0.001 (-0.47)	-0.005 (-2.37)	-0.001 (-0.38)	-0.003 (-0.94)	-0.003 (-1.05)	-0.003 (-0.73)
q	0.664 (7.95)	0.586 (8.54)	0.502 (6.81)	0.673 (7.96)	0.599 (8.06)	0.673 (8.73)
$lnTFP_0$	-0.016 (-2.61)	-0.016 (-3.17)	-0.022 (-3.34)	-0.026 (-3.40)	-0.027 (-4.20)	-0.026 (-4.55)
lnD_0	0.006 (4.76)	0.005 (5.61)	0.004 (3.44)	0.005 (4.60)	0.005 (4.48)	0.006 (5.60)
$\mathbf{W}q$				0.277 (2.79)	0.046 (0.40)	0.297 (3.40)
$\mathbf{W}lnTFP_0$				0.014 (1.36)	0.018 (2.09)	0.011 (1.11)
$\mathbf{W}lnD$				0.005 (2.93)	0.003 (1.69)	0.006 (3.95)
$\mathbf{W}tfp$		0.406 (4.77)			0.387 (3.16)	
$\mathbf{W}\varepsilon$			0.499 (4.62)			0.499 (4.63)
$\hat{\nu}$	2.975	2.415	2.119	3.058	2.495	3.060
$\hat{\phi}$ *(% p.a.)*	1.43	1.43	1.89	2.16	2.24	2.17
pseudo- $\overline{R}^2$	0.582[a]	0.663	0.675	0.666	0.671	0.757
pseudo- $\overline{R}^2_{adj}$	0.454[a]	0.593	0.552	0.540	0.634	0.666
Moran's I	3.02 [0.003]					
LM_{SAR}	6.29 [0.012]					
LM_{SEM}	14.18 [0.000]					

Notes: [a] $\overline{R}^2$ and $\overline{R}^2_{adj}$ respectively

Figures in parentheses are *t*-ratios and the figures in square brackets probability values.
SAR = spatial autoregressive model, SCM = spatial cross-regressive model, SDM = spatial Durbin model, SEM = spatial error model, and SHM = spatial hybrid model.
LM_{SAR} and LM_{SEM} are Lagrange Multiplier tests for spatial autocorrelation in the form of the spatial autoregressive/spatial lag model and the spatial error model respectively. Both tests are asymptotically distributed as χ^2 with 1 degree of freedom.
$\hat{\nu}$ is the estimated degree of returns to scale, and $\hat{\phi}$ the estimated speed of technological diffusion.

Table 2 The Dynamic Verdoorn Law: FGS2SLS Estimation, Cross-sectional Data, 1986-2002

Demand-side Specification: $tfp = c_4 + b_6 q + b_7 lnTFP_0 + b_8 lnD_0$ + {spatially lagged terms}
Supply-side specification: $tfp = c_5 + b_9 tfi + b_{10} lnTFP_0 + b_{11} lnD_0$ + {spatially lagged terms}

	Demand-side specification	**Supply-side specification**
Constant	-0.001 (-0.41)	0.008 (2.84)
q	0.5789 (5.04)	-
tfi	-	-0.105 (-0.45)
$lnTFP_0$	-0.028 (-4.43)	-0.032 (-3.26)
lnD_0	0.006 (4.96)	0.003 (1.37)
$\boldsymbol{W}q$	0.327 (2.71)	-
$\boldsymbol{W}tfi$	-	-0.372 (-1.44)
$\boldsymbol{W}lnTFP_0$	0.016 (1.43)	0.030 (2.03)
$\boldsymbol{W}lnD_0$	0.006 (2.97)	-0.001 (-0.36)
$\boldsymbol{W}\varepsilon$	0.499 (2.13)	0.470 (1.99)
$\hat{\nu}$	2.37	0.90
$\hat{\phi}$ (% p.a.)	2.32	2.56
Sargan (stage 3)	$\chi^2(2) = 0.1718$ (p = 0.9177)	$\chi^2(2) = 0.5129$ (p = 0.7738)
Sargan (stage 1)	$\chi^2(2) = 0.3842$ (p = 0.8252)	$\chi^2(2) = 2.1498$ (p = 0.3413)

Notes: Instruments used in the estimation procedure

Demand-side: i_q, Wi_q, i_{Wq}, Wi_{Wq} where i_x is an indicator variable coded 1, 0 or - 1 according to whether the observation on variable x is in the top third, middle third or bottom third of its distribution, and Wi_x is the spatial lag of i_x.

Supply-side version: i_{tfi}, Wi_{tfi}, i_{Wtfi}, Wi_{Wtfi} where i_x is an indicator variable coded 1, 0 or - according to whether the observation on variable x is in the top third, middle third or bottom third of its distribution, and Wi_x is the spatial lag of i_x.

Table 3 The Static Verdoorn Law: Panel Data Estimation, 1989,1991, 1996 and2002

Demand-side specification: $lnTFP = c_6 + b_{12}lnQ + \{spatially\ lagged\ terms\}$
Supply-side specification: $lnTFP = c_7 + b_{15}lnTFI + \{spatially\ lagged\ terms\}$

	Demand-side specification		**Supply-side specification**	
	(i) Time Effects	(ii) Time and Regional Effects	(i) Time Effects	(ii) Time and Regional Effects
lnQ	0.034 (1.88)	0.623 (13.66)		
$lnTFI$			-0.040 (-2.23)	-0.380 (-5.21)
$\mathbf{W}lnQ$	0.100 (3.00)	0.038 (0.68)		
$\mathbf{W}lnTFI$			0.038 (1.19)	-0.232 (-2.46)
$\mathbf{W}\varepsilon$	0.651 (15.33)	0.451 (7.91)	0.669 (16.37)	0.361 (5.82)
$\hat{v}$	1.035	2.653	0.960	0.620
$pseudo\text{-}\overline{R}^2$	0.527	0.909	0.548	0.845
$pseudo\text{-}\overline{R}^2_{adj}$	0.950	0.990	0.952	0.983

Notes: - Figures in parentheses are t-ratios and the figures in square brackets probability values.
- $\hat{v}$ is the estimated degree of returns to scale.