Estimating Efficiency Spillovers with State Level Evidence for Manufacturing in the U.S.

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Abstract

Unit specific effects are often used to estimate non-spatial efficiency. We extend such estimators to the case where there is spatial autoregressive dependence and introduce the concept of spillover efficiency. Intuitively, we present an approach to benchmark how successful units are at exporting and importing productive performance to and from other units.

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1. Introduction

The Schmidt & Sickles (1984) (SS) time-invariant efficiency estimator benchmarks the relative performance of the cross-sectional units using the fixed or random effects. The SS estimator was extended to the case of time-variant efficiency by Cornwell et al. (1990) (CSS). We extend the non-spatial CSS estimator to the case where there is spatial autoregressive dependence which involves estimating direct (own), indirect (spillover) and total (direct plus indirect) efficiency. We provide a demonstration of our estimator using a cost frontier model for state manufacturing in the U.S.. In the context of our application, cost efficiency spillovers can be interpreted as benchmarking how successful states are at exporting and importing productive performance to and from other states. For example, firms in different states may effectively export and import efficiency to and from one another via competition.

2. Deterministic Spatial Autoregressive Cost Frontier Model

A deterministic spatial autoregressive cost frontier model for panel data is given in equation (1). We do not discuss spatial panel data models in detail here but for comprehensive and up-to-date surveys see Baltagi (2011, 2013).

$$C_{it} = \kappa + \alpha_i + \tau_t + TL\left(h, q, t\right)_{it} + \lambda \sum_{j=1}^{N} w_{ij} C_{jt} + z_{it}\phi + \varepsilon_{it}, \qquad (1)$$
$$i = 1, \ldots, N; \; t = 1, \ldots, T.$$

N is a cross-section of units; T is the fixed time dimension; C_{it} is the logged normalized cost of the ith unit; α_i is a fixed effect; τ_t is a time period effect; $TL\left(h, q, t\right)_{it}$ represents the technology as the translog approximation of the log of the cost function, where h is a vector of logged normalized input prices, q is a vector of logged outputs and t is a time trend; λ is the spatial autoregressive parameter; w_{ij} is an element of the spatial weights matrix, W; z_{it} is a vector of exogenous characteristics and ϕ is the associated vector of parameters; ε_{it} is an i.i.d. disturbance for i and t with zero mean and variance σ^2.

W is a $(N \times N)$ matrix of known positive constants which describes the spatial arrangement of the cross-sectional units and also the strength of the spatial interaction between the units. All the elements on the main diagonal of W are set to zero. λ is assumed to lie in the interval $(1/r_{min}, 1)$, where r_{min} is the most negative real characteristic root of W and because W is row-normalized 1 is the largest real characteristic root of W.

Equation (1) is estimated using maximum likelihood where the log likelihood function is:

$$\log L = \frac{-NT}{2}\log(2\pi\sigma^2) + T\log|I - \lambda W| - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}(C_{it} - \kappa - \alpha_i - \tau_t - TL(h,q,t)_{it} - \sum_{j=1}^{N} w_{ij} C_{jt} - z_{it}\phi). \quad (2)$$

We ensure that λ lies in its parameter space, account for the endogeneity of the spatial autoregressive variable and the fact that ε_t is not observed by including the scaled logged determinant of the Jacobian transformation of ε_t to C_t (i.e. $T\log|I - \lambda W|$) in the log-likelihood function. We estimate equation (1) by demeaning in the space dimension to circumvent the incidental parameter problem. Lee & Yu (2010), however, show that this leads to a biased estimate of σ^2 when N is large and T is fixed, which we denote σ_B^2, where the bias is of the type identified in Neyman & Scott (1948). Following Lee & Yu (2010) we correct for this bias by replacing σ_B^2 with the bias corrected estimate of σ^2, $\sigma_{BC}^2 = T\sigma_B^2/(T-1)$.

3. Marginal Effects and Direct, Indirect and Total Efficiencies

We can rewrite equation (1) as follows where the i subscripts are dropped to denote successive stacking of cross-sections.

$$C_t = (I - \lambda W)^{-1}\kappa\iota + (I - \lambda W)^{-1}\alpha + (I - \lambda W)^{-1}\tau_t\iota + (I - \lambda W)^{-1}\Gamma_t\beta + (I - \lambda W)^{-1} z_t\phi + (I - \lambda W)^{-1}\varepsilon_t, \quad (3)$$

where ι is an $(N \times 1)$ vector of ones; α is the $(N \times 1)$ vector of fixed effects; Γ_t is an $(N \times K)$ matrix of stacked observations for $TL(h,q,t)_t$; and β is a vector of translog parameters. LeSage & Pace (2009) demonstrate that the coefficients on the explanatory variables in a model with spatial autoregressive dependence cannot be interpreted as elasticities. LeSage & Pace (2009) therefore propose the following approach to calculate direct, indirect and total marginal effects which we present in the context of the kth component of the translog function.

The matrix of direct and indirect elasticities for each unit for the kth component of the translog function are given by:

$$(I - \lambda W)^{-1} \begin{bmatrix} \beta_k & 0 & \cdot & 0 \\ 0 & \beta_k & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & \cdot & \beta_k \end{bmatrix}. \tag{4}$$

Since the product of matrices in equation (4) yields different direct and indirect elasticities for each unit, to facilitate interpretation LeSage & Pace (2009) suggest reporting a mean direct elasticity (average of the diagonal elements in equation (4)) and a mean aggregate indirect elasticity (average row sum of the non-diagonal elements in equation (4)). The mean direct effect is the mean effect on a unit's dependent variable following a change in one of its independent variables. The mean aggregate indirect effect is the mean effect on the dependent variable of one unit following a change in one of the independent variables in all the other units. The mean total effect is the sum of the mean direct and mean aggregate indirect effects. We calculate the t-statistics for the mean effects using the delta method.

Unit specific effects from a deterministic spatial frontier model can be used to calculate time-invariant and time-variant efficiency by applying the non-spatial SS and CSS estimators, respectively, where the efficiencies are comparable to those from a non-spatial deterministic frontier model using the same procedure (see Druska & Horrace (2004) and Glass et al. (2013)). We extend the CSS methodology to the spatial autoregressive case and thus estimate direct, indirect and total efficiencies, which involves recognizing from equation (3) that $(I - \lambda W)^{-1} \alpha = \alpha^{Tot}$, where α^{Tot} is the $(N \times 1)$ vector of total fixed effects. Equivalently using column vector notation:

$$(I - \lambda W)^{-1} \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \cdot \\ \cdot \\ \alpha_N \end{pmatrix} = \begin{pmatrix} \alpha_{11}^{Dir} & + & \alpha_{12}^{Ind} & + & \cdot & \cdot & + & \alpha_{1N}^{Ind} \\ \alpha_{21}^{Ind} & + & \alpha_{22}^{Dir} & + & \cdot & \cdot & + & \alpha_{2N}^{Ind} \\ \cdot & + & \cdot & + & \cdot & \cdot & + & \cdot \\ \cdot & + & \cdot & + & \cdot & \cdot & + & \cdot \\ \alpha_{N1}^{Ind} & + & \alpha_{N2}^{Ind} & + & \cdot & \cdot & + & \alpha_{NN}^{Dir} \end{pmatrix} = \begin{pmatrix} \alpha_1^{Tot} \\ \alpha_2^{Tot} \\ \cdot \\ \cdot \\ \alpha_N^{Tot} \end{pmatrix}, \tag{5}$$

where α_{ij}^{Dir} (i.e. where $i = j$) and α_{ij}^{Ind} (i.e. where $i \neq j$) are direct and indirect fixed effects, respectively. In the same way we obtain direct and indirect residuals, ε_{ijt}^{Dir} and ε_{ijt}^{Ind}, from $(I - \lambda W)^{-1} \varepsilon_t$ in equation (3).

Direct cost efficiency, CE_{it}^{Dir}, aggregate indirect cost efficiency, CE_{it}^{AggInd}, and total cost efficiency, CE_{it}^{Tot}, are calculated as follows.

$$CE_{it}^{Dir} = \exp\left[\min_i \left(\delta_{it}^{Dir}\right) - \delta_{it}^{Dir}\right], \tag{6}$$

$$CE_{it}^{AggInd} = \exp\left[\min_i \left(\delta_{it}^{AggInd}\right) - \delta_{it}^{AggInd}\right], \tag{7}$$

$$CE_{it}^{Tot} = \exp\left[\min_i \left(\delta_{it}^{Dir} + \delta_{it}^{AggInd}\right) - \left(\delta_{it}^{Dir} + \delta_{it}^{AggInd}\right)\right], \tag{8}$$

where $\delta_{it}^{Dir} = \alpha_{ij}^{Dir} + \theta_i^{Dir} t + \rho_i^{Dir} t^2$; $\delta_{it}^{AggInd} = \sum_{j=1}^{N} \alpha_{ij}^{Ind} + \theta_i^{AggInd} t + \rho_i^{AggInd} t^2$; $\delta_{it}^{Tot} = \delta_{it}^{Dir} + \delta_{it}^{AggInd}$. The θ_i^{Dir}, ρ_i^{Dir}, θ_i^{AggInd} and ρ_i^{AggInd} parameters needed to estimate CE_{it}^{Dir} and CE_{it}^{AggInd} can be obtained by regressing in turn ε_{ijt}^{Dir} and $\sum_{j=1}^{N} \varepsilon_{ijt}^{Ind}$ on t and t^2 for each unit.

The aggregate indirect efficiency from equation (7) refers to efficiency spillovers to the ith unit from all the jth units. It is also valid to interpret aggregate indirect efficiency as efficiency spillovers to all the ith units from a particular jth unit. Since $\alpha_{ij}^{Ind} \neq \alpha_{ji}^{Ind}$ and $\varepsilon_{ijt}^{Ind} \neq \varepsilon_{jit}^{Ind}$, the efficiency spillovers to the ith unit from all the jth units will not equal the efficiency spillovers to all the ith units from a jth unit. We only consider efficiency spillovers to the ith unit here.

To calculate direct and aggregate indirect cost inefficiencies, CIE_{it}^{Dir} and CIE_{it}^{AggInd}, as shares of total cost inefficiency, CIE_{it}^{Tot}, where the shares are denoted by $SCIE_{it}^{Dir}$ and $SCIE_{it}^{AggInd}$, CIE_{it}^{Dir}, CIE_{it}^{AggInd} and CIE_{it}^{Tot} must be calculated relative to the same unit, where this unit is the best performing unit in the calculation of CE_{it}^{Tot}. Recognizing that CE_{it}^{Tot} can be disaggregated into its direct and aggregate indirect efficiency components:

$$CE_{it}^{Tot} = \exp\left[\min_i {}_{CE_{it}^{Tot}} \left(\delta_{it}^{Dir}\right) - \delta_{it}^{Dir}\right] \times \exp\left[\min_i {}_{CE_{it}^{Tot}} \left(\delta_{it}^{AggInd}\right) - \delta_{it}^{AggInd}\right]. \tag{9}$$

Taking logs of equation (9) yields an expression for CIE_{it}^{Tot}:

$$CIE_{it}^{Tot} = \left[\min_i {}_{CE_{it}^{Tot}} \left(\delta_{it}^{Dir}\right) - \delta_{it}^{Dir}\right] + \left[\min_i {}_{CE_{it}^{Tot}} \left(\delta_{it}^{AggInd}\right) - \delta_{it}^{AggInd}\right], \tag{10}$$

from which $SCIE_{it}^{Dir}$ is:

$$SCIE_{it}^{Dir} = \left[\min_{i} {}_{CE_{it}^{Tot}} \left(\delta_{it}^{Dir}\right) - \delta_{it}^{Dir} \right] / CIE_{it}^{Tot}. \quad (11)$$

$SCIE_{it}^{AggInd}$ can be calculated in a similar manner.

4. Application

4.1. Data

Our data is for the period 1997-2008 for the contiguous states in the U.S.. We obtained all data from the Annual Survey of Manufactures (ASM) unless otherwise stated and all monetary variables are expressed in 1997 prices using the CPI. The measure of output is value added (q), and the three input prices are the price of capital (h_1), average annual wage of a production worker (h_2) and the price of energy (h_3), where all three input prices and C are normalized by the average annual wage of a non-production worker. The data for C is calculated by summing the annual wage bills for production and non-production workers, expenditure on new and used capital, and expenditure on fuels and electricity. The ASM only contains manufacturing expenditure on fuels and electricity for the U.S. so this expenditure was allocated to the states using annual shares of U.S. industrial sector energy expenditure, where the state shares were calculated using data from the U.S. Energy Administration. The data for h_3 is from the U.S. Energy Administration and is the price paid by the industrial sector per million Btu.

Following Morrison & Schwartz (1996) we assume a harmonized capital market and the price of capital is approximated by $TX_t PK_t (r_t + \gamma)$. TX_t is the corporate tax rate which we obtain for the U.S. from the OECD tax database; PK_t is the PPI for finished capital equipment; r_t is the long-term lending rate for the manufacturing sector approximated by Moody's Baa corporate bond yield; and γ is the depreciation rate, which following Hall (2005) we assume is 10%. The price of capital will not be correlated with the fixed effects because the price of capital varies over time. The price of capital, however, does not vary in the cross section and was therefore found to be correlated with the time period effects so the time period effects were omitted.

We also include a number of z-variables which shift the cost frontier technology. To capture the effect of differences in tax conditions across states we include the ratio of personal current tax payments to personal income (z_1). Since the density of economic activity in a state is not meaningful because parcels of land are often not productive, we follow Ciccone & Hall (1996) and control for agglomeration effects by including average county employment density within a state (z_2). We take account of urban roadway congestion by including urban national highway length shares with a volume-service flow (VSF) ratio: < 0.21; 0.21-0.40; 0.71-0.79; 0.80-0.95; and > 0.95 (z_3-z_7, respectively, where we omit the 0.41-0.70 share). A VSF ratio > 0.80 indicates that congestion has set in. To capture the effect of the sectoral composition of state output we include as shares of state GDP, agriculture, forestry and fishing GDP (z_8), service sector GDP (z_9) and government GDP (z_{10}), all of which we interact with q.[1]

Two states with small manufacturing sectors are highly efficient outliers (Rhode Island and Delaware) and were omitted. We use two specifications of W. The first is a contiguity matrix, W_1. The second is a matrix weighted by inverse distance between all state centroids denoted W_2. W_2 therefore resembles the variable which measures the geographical distance between trading partners in gravity models. With the exception of the data for z_1 and z_3-z_{10}, all the data is logged and mean adjusted. Consequently, the first order coefficients on the time trend, output and input prices can be interpreted as elasticities because at the sample mean the quadratic and cross terms in the translog function are zero.

4.2. Estimation Results

In Table 1 we present the non-spatial Within model (denoted no spatial dependence, No SD) as well as the marginal effects for the W_1 and W_2 models. We get an indication of whether the z-variables are endogenous by using the non-spatial Within model and the Hausman-Taylor with fixed effects model to perform a Hausman-Wu test. The test accepts the null of no endogeneity bias at the 10% level. For both spatial models an LR test rejects the null that the fixed effects are not jointly significant at the 0.1% level.

[1]The tax and income data to calculate z_1, the county employment data to calculate z_2 and the industry level state GDP data to calculate z_8 and z_{10} was obtained from the Regional Economic Accounts. z_3-z_7 were calculated using data from Highway Statistics. z_9 is calculated using data from the Regional Economic Accounts for the industries which constitute the service sector in the Annual and Quarterly Services Report.

Table 1: Fitted deterministic cost frontier models

		No SD	With SD: W_1			With SD: W_2		
Variable		Coef.	Direct Coef.	Indirect Coef.	Total Coef.	Direct Coef.	Indirect Coef.	Total Coef.
$\ln h_1$	β_1	0.408***	0.332***	0.121***	0.453***	0.213***	0.322**	0.535**
		(6.21)	(5.29)	(3.93)	(5.26)	(3.35)	(2.77)	(3.13)
$\ln h_2$	β_2	0.406***	0.481***	0.178***	0.659***	0.556***	0.847***	1.404***
		(5.85)	(7.45)	(4.00)	(6.59)	(8.60)	(3.98)	(5.53)
$\ln h_3$	β_3	0.080**	0.073**	0.027*	0.100**	0.080**	0.121**	0.202**
		(2.77)	(2.74)	(2.45)	(2.73)	(3.10)	(2.59)	(2.90)
$\ln q$	β_4	0.812***	0.798***	0.293***	1.092***	0.778***	1.183***	1.961***
		(8.73)	(9.28)	(4.49)	(8.23)	(9.09)	(4.15)	(5.87)
$(\ln h_1)^2$	β_5	0.185	0.282	0.103	0.386	0.242	0.363	0.605
		(0.60)	(1.04)	(0.99)	(1.03)	(0.81)	(0.79)	(0.81)
$(\ln h_2)^2$	β_6	0.569	0.533	0.196	0.729	0.562	0.856	1.417
		(1.57)	(1.57)	(1.48)	(1.56)	(1.67)	(1.54)	(1.61)
$(\ln h_3)^2$	β_7	-0.123*	-0.099*	-0.036	-0.135*	-0.114*	-0.172*	-0.285*
		(-2.34)	(-1.97)	(-1.85)	(-1.97)	(-2.26)	(-2.01)	(-2.16)
$(\ln q)^2$	β_8	0.005	0.006	0.002	0.008	0.006	0.008	0.014
		(0.53)	(0.75)	(0.73)	(0.75)	(0.70)	(0.67)	(0.69)
$(\ln h_1)\times$	β_9	-0.498	-0.331	-0.119	-0.451	-0.330	-0.499	-0.830
$(\ln h_2)$		(-1.07)	(-0.78)	(-0.75)	(-0.77)	(-0.77)	(-0.76)	(-0.77)
$(\ln h_1)\times$	β_{10}	0.246	0.287	0.105	0.392	0.364*	0.559*	0.923*
$(\ln h_3)$		(1.46)	(1.80)	(1.68)	(1.79)	(2.36)	(2.02)	(2.20)
$(\ln h_2)\times$	β_{11}	0.088	-0.010	-0.004	-0.014	-0.068	-0.108	-0.176
$(\ln h_3)$		(0.48)	(-0.06)	(-0.06)	(-0.06)	(-0.39)	(-0.39)	(-0.39)
$(\ln h_1)\times$	β_{12}	-0.024	0.000	0.000	0.000	-0.009	-0.014	-0.023
$(\ln q)$		(-0.55)	(0.00)	(0.00)	(0.00)	(-0.22)	(-0.22)	(-0.22)
$(\ln h_2)\times$	β_{13}	0.058	0.023	0.008	0.031	0.031	0.047	0.079
$(\ln q)$		(1.14)	(0.50)	(0.47)	(0.49)	(0.67)	(0.64)	(0.66)
$(\ln h_3)\times$	β_{14}	0.005	0.009	0.003	0.012	0.014	0.022	0.035
$(\ln q)$		(0.25)	(0.44)	(0.44)	(0.44)	(0.68)	(0.67)	(0.68)
t	β_{15}	-0.028***	-0.021***	-0.008***	-0.028***	-0.016***	-0.024***	-0.040***
		(-10.04)	(-7.50)	(-5.18)	(-7.94)	(-5.96)	(-4.59)	(-5.85)
t^2	β_{16}	0.001	0.000	0.000	0.000	0.000	0.000	0.000
		(1.82)	(0.73)	(0.69)	(0.73)	(-0.32)	(-0.37)	(-0.36)
$\ln h_1 t$	β_{17}	-0.014	-0.028*	-0.010*	-0.038*	-0.036**	-0.055*	-0.090**
		(-1.21)	(-2.41)	(-2.09)	(-2.36)	(-3.19)	(-2.48)	(-2.83)
$\ln h_2 t$	β_{18}	0.030*	0.034*	0.012*	0.046*	0.038**	0.058*	0.096**
		(2.18)	(2.57)	(2.25)	(2.53)	(2.89)	(2.43)	(2.69)
$\ln h_3 t$	β_{19}	-0.005	-0.005	-0.002	-0.007	-0.002	-0.004	-0.006
		(-0.89)	(-0.86)	(-0.84)	(-0.86)	(-0.42)	(-0.41)	(-0.41)
$\ln qt$	β_{20}	-0.008***	-0.009***	-0.003***	-0.013***	-0.010***	-0.016***	-0.026***
		(-4.49)	(-5.38)	(-3.61)	(-5.08)	(-5.93)	(-3.46)	(-4.44)
z_1	ϕ_1	1.719***	1.360***	0.496**	1.856***	0.934*	1.387*	2.320*
		(4.32)	(3.62)	(3.16)	(3.64)	(2.35)	(2.29)	(2.39)
$\ln z_2$	ϕ_2	0.562***	0.457***	0.167***	0.625***	0.357***	0.539**	0.895**
		(4.98)	(4.47)	(3.49)	(4.41)	(3.34)	(2.84)	(3.17)
z_3	ϕ_3	0.086	0.120*	0.044*	0.164*	0.115*	0.174*	0.288*
		(1.67)	(2.54)	(2.17)	(2.48)	(2.48)	(2.20)	(2.37)
z_4	ϕ_4	0.016	0.054	0.020	0.074	0.052	0.077	0.128
		(0.18)	(0.65)	(0.65)	(0.66)	(0.64)	(0.61)	(0.62)
z_5	ϕ_5	0.222	0.221	0.081	0.301	0.248*	0.377	0.625
		(1.65)	(1.74)	(1.61)	(1.73)	(1.96)	(1.78)	(1.89)
z_6	ϕ_6	0.228	0.235*	0.087	0.322*	0.254*	0.385*	0.638*
		(1.88)	(2.10)	(1.91)	(2.08)	(2.29)	(2.04)	(2.19)
z_7	ϕ_7	0.213*	0.219**	0.081*	0.300**	0.220**	0.333*	0.553**
		(2.53)	(2.86)	(2.43)	(2.81)	(2.86)	(2.45)	(2.70)
z_8	ϕ_8	1.976*	1.884*	0.693	2.577*	1.806	2.735	4.541
		(1.97)	(2.00)	(1.83)	(1.99)	(1.88)	(1.71)	(1.81)
z_9	ϕ_9	1.465***	1.440***	0.529***	1.969***	1.520***	2.316***	3.836***
		(5.40)	(5.57)	(3.79)	(5.34)	(5.96)	(3.57)	(4.58)
z_{10}	ϕ_{10}	-0.482	0.230	0.093	0.323	-0.087	-0.105	-0.192
		(-0.91)	(0.45)	(0.47)	(0.46)	(-0.17)	(-0.13)	(-0.15)
$\ln qz_8$	ϕ_{11}	-1.095	-1.125	-0.414	-1.539	-1.176*	-1.798	-2.974*
		(-1.77)	(-1.95)	(-1.80)	(-1.93)	(-2.08)	(-1.84)	(-1.97)
$\ln qz_9$	ϕ_{12}	-0.700***	-0.564**	-0.207**	-0.771***	-0.529**	-0.803*	-1.332**
		(-3.72)	(-3.33)	(-2.84)	(-3.30)	(-3.07)	(-2.57)	(-2.87)
$\ln qz_{10}$	ϕ_{13}	-1.742***	-2.002***	-0.737***	-2.739***	-1.930***	-2.940***	-4.870***
		(-5.06)	(-6.27)	(-3.81)	(-5.78)	(-5.94)	(-3.57)	(-4.59)
				W_1			W_2	
$\sum_{j=1}^{N} w_{ij} C_{jt}$	λ	–		0.282***			0.609***	
				(7.10)			(11.99)	
Log-likelihood		–		899.03			904.34	

Note: *, **, *** denote statistical significance at the 5%, 1% and 0.1% levels, respectively. SD denotes spatial dependence. $t-$statistics are in parentheses.

The estimates of λ are 0.28 from the W_1 model and 0.61 from the W_2 model, both of which are significant at the 0.1% level. This indicates that there is a lot more spatial dependence when we allow spatial interaction between all states (W_2) compared to when spatial interaction is limited to contiguous states (W_1). This is almost certainly because with W_2 there are more states from which there can be spillovers than there are with W_1. In both models the direct q, h_1, h_2 and h_3 parameters are significant at the 0.1% level. These parameters are also positive which indicates that the monotonicity of the cost function is satisfied at the sample mean. The estimates of direct returns to scale ($1/\beta_4$) from both spatial models are sensible thereby providing support for the model specifications (1.25 from the W_1 model and 1.29 from the W_2 model indicating increasing returns in both cases). For both spatial models, it is clear that the largest indirect input price or output parameter relates to h_2. This indicates that there are larger production wage spillovers than there are output, capital price or energy price spillovers.

We find that the direct z_2, z_6 and z_7 parameters are positive and significant at the 5% level or lower in the spatial models. The implication is that state manufacturing cost will be higher in more urbanized states where employment density and urban roadway congestion are higher. The direct z_3 parameter suggests that state manufacturing cost is higher for the least urbanized states, where low traffic levels on urban highways is a more frequently observed phenomenon.

4.3. Direct, Aggregate Indirect and Total Efficiencies

Efficiencies from the spatial models which are calculated using equations (6)-(8) are denoted by CE_A in Table 2. To calculate the direct and aggregate indirect inefficiency shares, which are denoted by $SCIE$ in Table 2, we use direct, aggregate indirect and total efficiencies which are based on equation (9) and are denoted by CE_B in Table 2. The sample average CE_A from the non-spatial model and the sample average direct CE_A from the W_1 model are in both cases 0.28, which rises to 0.34 for the W_2 model. The average aggregate indirect (total) CE_A is 0.69 (0.25) for the W_1 model and 0.76 (0.32) for the W_2 model. This suggests that direct efficiency is the principal component of total efficiency. Moreover, average total CE_A from the W_1 and W_2 models is below average direct CE_A because there is a sufficient amount of aggregate indirect inefficiency, although as we will see this is not always the case for individual states. We can see from Figure 1 that annual aggregate indirect CE_A is considerably greater than annual direct CE_A over

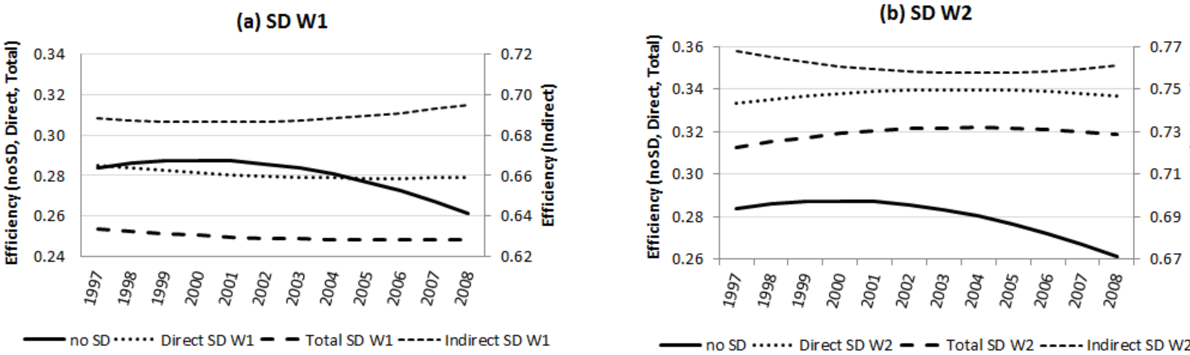

Figure 1: Average efficiency scores

the entire sample for both spatial models. We also observe that annual aggregate indirect CE_A for the W_2 model is always greater than that from the W_1 model.

We can see from Table 2 that we observe states where total CE_A is in between direct and aggregate indirect CE_A because there is an insufficient amount of aggregate indirect inefficiency e.g. New York for W_1 and W_2. Also, Table 2 indicates that, in general, the average direct and average aggregate indirect CE_A rankings are high for several states in the Northeastern region or just outside for both spatial models. The two states with the largest average real GDP and average state manufacturing real GDP over the study period (California and Texas) have the lowest average direct CE_A. In terms of average aggregate indirect CE_A, California and Texas fair much better. A comparison of average direct, average aggregate indirect and average total CE_A for California and Texas indicates that average direct CE_A is the reason for their low average total CE_A.

Some of the estimates of average aggregate indirect CE_B are greater than 1 and when this is the case average aggregate indirect $SCIE$ is negative. This is because New Jersey and Maryland are the best performing states in each period for the calculation of total CE_B for W_1 and W_2, respectively, but this is not the case for the calculation of aggregate indirect CE_B. To illustrate, consider the average estimates of direct and aggregate indirect $SCIE$ of 1.40 and -0.40 for Vermont from the W_2 model. These estimates indicate that Vermont operates below the direct reference level but above the aggregate indirect reference level. We can therefore conclude that Vermont's relative total inefficiency is all due to its relative direct inefficiency as its aggregate indirect efficiency is higher than Maryland's.

Table 2: Selected average cost efficiencies and inefficiency shares

State		No SD	With SD: W_1			With SD: W_2		
			Direct	Agg Indirect	Total	Direct	Agg Indirect	Total
New York	CE_A	1.00(1)	0.75(4)	0.91(4)	0.82(3)	0.63(5)	0.99(2)	0.74(5)
	CE_B		0.75(4)	1.09(4)	0.82(3)	0.63(5)	1.16(2)	0.74(5)
	$SCIE$		1.45	-0.45		1.51	-0.51	
Massachusetts	CE_A	0.97(2)	0.68(5)	0.93(3)	0.76(5)	0.67(4)	0.97(5)	0.77(4)
	CE_B		0.68(5)	1.11(3)	0.76(5)	0.67(4)	1.14(5)	0.77(4)
	$SCIE$		1.39	-0.39		1.51	-0.51	
Maryland	CE_A	0.94(3)	0.86(2)	0.75(9)	0.78(4)	1.00(1)	0.85(11)	1.00(1)
	CE_B		0.86(2)	0.90(9)	0.78(4)	1.00(1)	1.00(11)	1.00(1)
	$SCIE$		0.59	0.41		N/A	N/A	
New Jersey	CE_A	0.93(4)	1.00(1)	0.84(8)	1.00(1)	0.78(3)	0.91(8)	0.84(3)
	CE_B		1.00(1)	1.00(8)	1.00(1)	0.78(3)	1.07(8)	0.84(3)
	$SCIE$		N/A	N/A		1.41	-0.41	
Connecticut	CE_A	0.80(5)	0.81(3)	1.00(1)	0.96(2)	0.78(2)	0.97(4)	0.90(2)
	CE_B		0.81(3)	1.20(1)	0.96(2)	0.78(2)	1.15(4)	0.90(2)
	$SCIE$		6.46	-5.46		2.40	-0.40	
New Hampshire	CE_A	0.51(6)	0.42(8)	0.87(6)	0.44(7)	0.58(6)	0.97(3)	0.67(6)
	CE_B		0.42(8)	1.04(6)	0.44(7)	0.58(6)	1.15(3)	0.67(6)
	$SCIE$		1.05	-0.05		1.35	-0.35	
California	CE_A	0.15(27)	0.11(45)	0.69(13)	0.09(45)	0.11(45)	0.74(14)	0.10(45)
	CE_B		0.11(45)	0.82(13)	0.09(45)	0.11(45)	0.88(14)	0.10(45)
	$SCIE$		0.92	0.08		0.95	0.05	
Vermont	CE_A	0.38(8)	0.44(7)	0.96(2)	0.50(6)	0.56(8)	1.00(1)	0.66(7)
	CE_B		0.44(7)	1.15(2)	0.50(6)	0.56(8)	1.18(1)	0.66(7)
	$SCIE$		1.20	-0.20		1.40	-0.40	
Texas	CE_A	0.05(46)	0.05(46)	0.66(19)	0.04(46)	0.07(46)	0.73(19)	0.06(46)
	CE_B		0.05(46)	0.80(19)		0.07(46)	0.86(19)	0.06(46)
	$SCIE$		0.93	0.07		0.95	0.05	

Note: Rankings are in parentheses where the rankings are in descending order.

5. Concluding Remarks

We have extended the non-spatial CSS efficiency estimator to the case where there is spatial autoregressive dependence. A more detailed empirical application of our estimator covering asymmetric efficiency spillovers would be a worthwhile area for further work.

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