THE JOURNAL OF ECONOMIC ASYMMETRIES

June, 2012

Volume 9, Number 1

Articles

Optimal Spatial Prediction and the Construction of Regional Indexes

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Abstract

This paper reviews the statistical methods for spatial prediction: the non-parametric "kriging" method and spatial autoregessive models. We discuss the main assumptions involved in each method as well as the advantages and disadvantages in each case. These methods are applied to the FPLI wage index for Florida counties, in order to illustrate a way to select the best econometric model and spatial weights.

1 INTRODUCTION

Regional price indexes are more meaningful than national ones. Wage indexes for cities or counties, for example, require less heroic aggregation assumptions than do those for nations. However, sample sizes for regional indexes are usually much smaller, resulting in large sampling errors. Such errors reduce the credibility of regional indexes, especially if neighboring or similar regions have quite different values. The loss of credibility arise because neighboring goods and labor markets are interrelated. Fortunately, both reliability and credibility can be improved using spatial econometric techniques that take into account spatial patterns of correlation.

Indexes for sub-regions within the scale of spatial variation of the data can be constructed using spatial prediction techniques. Ignoring the spatial dependence results in inefficient estimation and suboptimal prediction. The problem of finding the optimal spatial prediction based on a mean-square error criterion is known as "kriging" [1]. If certain assumptions about the statistical process are used, the spatial correlation structure can be used to construct better estimates. As an example, suppose that we are required to estimate an index for school districts or census tracts, but data is only available at the county level (and a county may contain many districts). Then, estimating the value for the districts would require interpolating the county level data. The

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optimal procedure for doing so is based on kriging. In sum, it implies selecting the optimal neighbor's weights in order to produce an estimate that minimizes the squared error of prediction.

Several explanations can be named for the geographical interrelation in Economics. In terms of the labor supply, the fact that housing decisions made in the past determine an anchor for job search locations and that commuting times generate disutility enlarge the effect of closer job offers and minimize the effect of those far away. Moreover, in terms of the Rosen-Roback model (Rosen, 1979; Roback, 1982, 1987) closer regions may share certain amenities. Therefore, house prices and rent are likely to have a strong spatial dependence (see for instance Dubin, 1998)

From the demand viewpoint, agglomeration economies and natural resources may determine that firms cluster in certain regions and pay similar wages.

We study the spatial prediction properties of a wage index used for allocating school funds among Florida's counties to illustrate the potential gains from such methods. In this paper we focus on predicting under limited information. In particular, we only consider the county's spatial interrelation and location. Two methods are evaluated. First, we use ordinary and universal kriging methods. These are non-parametric methods that fully rely on the spatial location to produce a prediction. Second, we evaluate spatial autoregressive models, which impose a linear regression structure to the spatial model. In this case we consider three different types of spatial weights. The first one corresponds to a weight matrix constructed using a boundary neighbor matrix, that is a 0-1 matrix indicating whether two counties share a boundary or not. The second corresponds to a spatial weights matrix constructed using pairwise inverse distances between county capital cities. The third one uses county-to-county work commuting flows to construct the weights.

2 ORDINARY AND UNIVERSAL KRIGING

In order to state the problem formally, we consider a random process with domain on a surface,

$$\{Z(s) : s \in D\},\ D \subseteq \Re^2$$

where s is a spatial index that varies continuously on a subset of the plane. In particular consider a sample of N counties $\mathbf{Z} = \{Z(s_1), ..., Z(s_N)\}$ with fixed locations on the plane $\mathbf{s} = \{s_1, ..., s_N\}$. Following Cressie (1993) consider the following constant mean spatial process

$$Z(s) = \mu + \delta(s),\ s \in D,\ \mu \in \Re$$

The spatial correlation structure of $Z(.)$ is customarily done in terms of the semi-variogram $\gamma(s_i,s_j) = \frac{1}{2}var(Z(s_i)-Z(s_j))$ or the covariogram function $\sigma(s_i,s_j) = E[(Z(s_i)-\mu)(Z(s_j)-\mu)]$. Under stationarity assumptions $\gamma(s_i,s_j) = \gamma(s_i-s_j)$ and $\sigma(s_i,s_j) = \sigma(s_i-s_j)$, that is the correlations depend only on the distance between two locations, and not on the specific locations of the observations. A random function Z(.) satisfying $E(Z(s)) = \mu$ for all $s \in D$ and $cov(Z(s_1),Z(s_2)) = C(s_1-s_2)$ for all $s_1,s_2 \in D$ is defined to be *second-order stationary*. Furthermore if $\gamma(s_i-s_j)$ and $\sigma(s_i-s_j)$ are functions only of $\|s_i-s_j\|$, that is they do not vary depending on the direction of s_i-s_j, then the random process is called *isotropic*. We will assume that the process analyzed in the paper satisfies both the stationarity and the isotropy assumptions. In our case, the disutility of commuting north, south, west or east can be safely assumed to be the same in any direction.

In the case that $Z(.)$ is second- order stationary, the variogram and the covariogram are related by

$$\gamma(\mathbf{h}) = \sigma(\mathbf{0}) - \sigma(\mathbf{h})$$

In general, much of the spatial correlation analysis is done in terms of the semi-variogram, and we follow this approach. Some definitions are useful regarding variograms. First, if $\gamma(\mathbf{h}) \to c_0$ as $\mathbf{h} \to \mathbf{0}$, then c_0 is defined as the *nugget effect*, which is usually associated with measurement error or micro-scale variation. Second, if $\sigma(\mathbf{h}) \to 0$ as $\|\mathbf{h}\| \to \infty$, then $\gamma(\mathbf{h}) \to \sigma(\mathbf{0})$; $\sigma(\mathbf{0})$ is defined as the *sill* of the semi-variogram. This term denotes the maximum variation that can be extracted from the spatial process. Finally, the smallest $\mathbf{h_0}$ such that $\gamma(\mathbf{h_0}) = \sigma(\mathbf{0})$ is defined as the range of the variogram in the direction of $\mathbf{h_0}/\|\mathbf{h_0}\|$. This term denotes the maximum distance that provides information about the spatial structure. The stationarity assumption requires that as $\|\mathbf{h}\| \to \infty$, $\sigma(\mathbf{h}) \to 0$, that is the process becomes uncorrelated. A violation of this assumption happens when, for instance, some regions imitate others, regardless of the distance between them.

Consider the problem of minimizing the squared prediction error in location s_0

$$\sigma_e^2(s_0) = E\left[Z(s_0) - \ell'\mathbf{Z}\right]^2$$

subject to the condition $\ell'\mathbf{1} = \sum\lambda_i = 1$, which is required for guaranteeing uniform unbiasedness for the predictor. Then, the minimization problem requires imposing an additional constraint which can be expressed in Lagrangian form as

$$E\left[Z(s_0) - \ell'\mathbf{Z}\right]^2 - 2m(\ell'\mathbf{1} - 1)$$

Minimizing over ℓ and m yields the optimal linear combination:

$$\ell_O = \Gamma^{-1}\left(\gamma + \frac{(1-\mathbf{1}'\Gamma^{-1}\gamma)}{\mathbf{1}'\Gamma^{-1}\mathbf{1}}\mathbf{1}\right)$$

$$m_O = -\frac{(1-\mathbf{1}'\Gamma^{-1}\gamma)}{\mathbf{1}'\Gamma^{-1}\mathbf{1}}$$

Here $\gamma = (\gamma(s_0,s_1)...\gamma(s_0,s_N))$ and $\Gamma = (\gamma(s_i,s_j))_{i,j}$. The new information regarding the spatial process is in γ, while the information in the sample is condensed in Γ. Then,

$$\widehat{Z}_O(s_0) = \ell_O'\mathbf{Z} \tag{1}$$

is known as ordinary kriging. Note that the predicted values are weighted averages of the estimated counties' indexes value. As stated in Dubin (1988) the kriging predictor causes a county to contribute more to the prediction the closer (more highly correlated) it is to the point to be estimated. The matrix Γ^{-1} causes counties that are more isolated to be weighted more heavily than counties in certain clusters. Note that if the sample observations were uncorrelated, Γ^{-1} would have produced weights proportional to the inverse of the variance of the observation in each location. Of course, the uniform unbiasedness requirement produces that if s_0 corresponds to a location already in the sample, then $\widehat{Z}_O(s_0) = Z(s_i),\ s_i = s_0$.

The solution to the above minimization problem can also be rewritten in terms of the covariance terms (see Cressie, 1993 p.123):

$$\ell_O = \Sigma^{-1}\left(\sigma + \frac{(1-\mathbf{1}'\Sigma^{-1}\sigma)}{\mathbf{1}'\Sigma^{-1}\mathbf{1}}\mathbf{1}\right)$$

$$m_O = -\frac{(1-\mathbf{1}'\Sigma^{-1}\Sigma)}{\mathbf{1}'\Sigma^{-1}\mathbf{1}}$$

where $\sigma = (\sigma(s_0,s_1)...\sigma(s_0,s_N))$ and $\Sigma = (\sigma(s_i,s_j))_{i,j}$.

The variance of the optimal predictor is:

$$\sigma^2_{e,O}(s_0) = \gamma'\Gamma\gamma - (1-\mathbf{1}'\Gamma^{-1}\gamma)^2/(\mathbf{1}'\Gamma^{-1}\mathbf{1}) \tag{2}$$

The Rosen-Roback model states that local amenities explain a great part of wage differentials. In this context, regions will differ systematically from each other. More generally assume that,

$$Z(s) = X(s)\beta + \delta(s),\ s \in D$$

Here $X(.)$ is a $1\times p$ matrix of covariates and β is a $p\times 1$ vector of unknown coefficients. Define $\mathbf{X}$ as the $N\times p$ matrix of covariates of the N counties, and let $\mathbf{x} = X(s_0)$. Then a necessary and sufficient condition for uniform unbiasedness is that $\ell'\mathbf{X} = \mathbf{x}'$ [2]. The optimal prediction is carried out by considering p different Lagrange multipliers. In this case the optimal predictor satisfies (Cressie, 1993 p.153)

$$\ell_U = \Gamma^{-1}\left(\gamma + \mathbf{X}(\mathbf{X}'\Gamma^{-1}\mathbf{X})^{-1}(\mathbf{x}-\mathbf{X}'\Gamma^{-1}\gamma)\right)$$

$$\mathbf{m}_U = -(\mathbf{X}'\Gamma^{-1}\mathbf{X})^{-1}(\mathbf{x} - \mathbf{X}'\Gamma^{-1}\gamma)$$

Therefore,

$$\widehat{Z}_U(s_0) = X(s_0)\beta + \ell_U'\mathbf{Z} \tag{3}$$

The variance of the optimal predictor is:

$$\sigma^2_{e,U}(s_0) = \gamma'\Gamma\gamma - (\mathbf{x} - \mathbf{X}'\Gamma^{-1}\gamma)(\mathbf{X}'\Gamma^{-1}\mathbf{X})^{-1}(\mathbf{x} - \mathbf{X}'\Gamma^{-1}\gamma) \tag{4}$$

3 SEMI-VARIOGRAM MODELS

Several methods have been proposed for estimating the empirical semi-variogram. Under the constant mean assumption, an intuitive method of moments estimator is based on:

$$2\widehat{\gamma}(\mathbf{h}) = \frac{1}{|N(\mathbf{h})|}\sum_{N(\mathbf{h})}(Z(s_i) - Z(s_j))^2, \mathbf{h} \in \Re^2 \tag{5}$$

where $N(\mathbf{h}) = \{(s_i, s_j) : s_i - s_j = \mathbf{h}; i, j = 1, 2, ...n\}$ and $|N(\mathbf{h})|$ is the number of distinct pairs in $N(\mathbf{h})$. Note that $|N(\mathbf{h})| \leq \frac{n(n-1)}{2}$. This is referred as the *classical* estimator.

Alternative robust variants of the empirical variogram were developed by Cressie and Hawkins (1980):

$$2\overline{\gamma}(\mathbf{h}) = \left(\frac{1}{|N(\mathbf{h})|}\sum_{N(\mathbf{h})}|Z(s_i) - Z(s_j)|^{1/2}\right)^4 / (0.457 + \frac{0.494}{|N(\mathbf{h})|}), \mathbf{h} \in \Re^2 \tag{6}$$

Note that in order to obtain a continuous variogram, some parametric version of the variogram needs to be estimated based on the estimates (5), and (6). The simplest parametric candidate is the ”Gaussian” variogram, which is defined as:

$$2\gamma(\mathbf{h}; \theta) = \theta_1 + \theta_2(1 - e^{-\|\mathbf{h}\|^2/\theta_3^2})$$

Note that in this case the *nugget effect* corresponds to θ_1, while the *sill* is $\theta_1 + \theta_2$. As we show in the next section, this variogram model accommodates the data well.

The parameters are obtained by minimizing the following loss function:

$$LOSS(\theta) = \sum_h |N(\mathbf{h})| \, [\widehat{\gamma}(\mathbf{h}) - \gamma(\|\mathbf{h}\|; \theta)]^2$$

4 SPATIAL AUTOREGRESSIVE MODELS

Alternatively, prediction can be based on a linear regression set-up with spatial autocorrelation, which is broadly the core of spatial econometrics. The spatial structure is usually analyzed in terms of a spatial weights matrix, which specifies the neighbors' correlation on a specific location. Contrary to kriging analysis, this structure is given, and only a few parameters need to be estimated. More formally consider consider a spatial structure with *N* regions/counties (indexed by *i=1,2...N*). Let $W = \{w_{ij}\}, w_{ij} \geq 0, w_{ii} = 0, \sum_{i \neq j} w_{ij} = 1$ denote a matrix of spatial weights, which summarizes the effect of neighboring regions. Note that this matrix need not be symmetric, that is, the effect of a given region on another should not be reciprocal.

Within this framework three different models can be constructed. First a spatial error autoregressive process has the spatial autocorrelation built up in the error structure. This type of structure arises when measurement errors or unobserved characteristics are geographically correlated. This model can be represented as:

$$Z(s) = X(s)\beta + e(s),\ \mathbf{e} = \rho W\mathbf{e} + \mathbf{u},\ |\rho| < 1$$

The parameter ρ provides a measure of the spatial correlation of the error term. The requirement that this parameter is less than one in absolute value plays the same role as in time-series analysis.

Second, a spatial lagged autoregressive process contains a spatial lag of the dependent variable as a control for spatial autocorrelation [3]. This type is the arises when prices in counties are influenced directly by prices in the sourrrunding counties. In this case, the model is:

$$Z(s) = \lambda W\mathbf{Z} + X(s)\beta + u(s),\ |\lambda| < 1$$

Finally, both types can be present in the same model. The latter however has the dissadvantage than if the same weights are used for both the error term and the dependent variable, the model is non-identifiable. Moreover, adding both types is computationally challenging when the sample size is large (see Keleijan and Prucha, 1998). In this paper we will not consider models with both types of spatial structures.

Several testing methods have been proposed to identify the spatial correlation type (see for instance Anselin, Bera and Florax, 1996). In practice, the tests are used to determine the spatial structure that more accurately and parsimoniously describes the spatial process.

5 DATA

The Florida Price Level Index (FPLI) is a cost-of-living index constructed by the Bureau of Business and Economic Research at the Unviersity of Florida using wage data at the Florida's counties level. This index is used to adjust Florida's public school teachers' wages in a way that teachers of the same human capital are indifferent among counties.

Figure 1 maps the FPLI index for the 67 Florida counties in 2003. Notice that in general, the index has higher values in counties along the coastline and also farther south. Overall they show a strong spatial dependence. Its highest values correspond to Monroe county (111.23), followed by Dade (106.64), Broward (106.37) and Palm Beach (105.8 7), neighboring counties in the South Atlantic corner of the state. Other counties with high index values are in the Tampa-St.Petersburg, Jacksonville and Orlando areas. The lowest values correspond to central counties and they show much more similarity among them.

Table 1 presents basic spatial dependence statistics, Moran's I and Geary's C statistics, based on three different spatial correlation structures. The first one corresponds to a weight matrix constructed using a boundary neighbor matrix, that is a 0-1 matrix indicating whether two counties share a boundary or not. The second corresponds to a spatial weights matrix constructed using pairwise inverse distances between county capital cities. The third one uses county-to-county work commuting flows to construct the weights. Both tests emphatically reject the null hypothesis of no spatial correlation, and they show a similar geographical pattern.

We also calculate local Moran I statistics (see Anselin, 1996), which based on each county, compute a local-based Moran I statistic. Estimates for the former appear in table 2. Of the 67 counties sample, 18% in the neighbor weights, 13% in the inverse distance and 16% in the commuting weights are statistically significant. Three clusters stantd out: southern counties, and two northern clusters. As a check of the local instability of the Moran statistics, figure 2 plots of the FPLI and the spatially lagged FPLI for the three weights considered here. Note that the figures reflect the fact that a simple pattern of spatial correlation exists: the existence of a common amenity factor. The figures also identify outliers, identified by the number from table 2, which mostly correspond to southern counties (Broward, Dade, Monroe and Palm Beach).

6 KRIGING ESTIMATES

As mentioned earlier, estimating the variogram is the most important step in the kriging procedure. Figure 3 presents the classical and robust variogram estimators, together with the Gaussian parametric estimates (solid line) and the variance estimate (dotted line). The similarities between the figures determine that there are no serious outliers in the data, as the classical and robust variograms show similar patterns. Moreover, the Gaussian model does a good job for fitting the variograms.

We also consider a model with a non-constant mean based on the coordinates, that is,

$$\mu(s) = \beta_0 + X_s \times \beta_X + Y_s \times \beta_Y + \delta(s) \tag{7}$$

where X and Y are the county coordinates.

We construct a grid that encompass the entire state, and we construct the optimal prediction for each point in the grid based on equations (1) and (3) for ordinary and universal kriging respectively. Estimates for the whole state appear in figure 4, together with the capital cities' location. The figure presents values of the predicted wages by drawing iso-wage contour lines. Note that a North-South pattern dominates the spatial prediction, with a similar for the ordinary and universal kriging models. Overall, counties farther to the South have higher estimated wage indexes. In the North this pattern is less clear, showing some convexity towards the South. Moreover, counties along both coastlines have higher values than central counties. The figure also has the standard errors constructed using (2) and (4) respectively. As expected standard errors are smaller when the prediction is closer to an actual observation (county's capital city). Moreover, the constant mean model has a higher variance than the model that uses the county's coordinates as covariates.

7 SPATIAL AUTOREGRESSIVE ESTIMATES

We now turn to the estimation of the spatial autoregressive models. Table 3 presents OLS estimates of model 7. County's coordinates explain 66% of the variation in Florida's wages, mostly given by the South-North variation. This model should be used as a reference for comparing spatial models. Tables 4 and 5 reports estimates for the spatial error and lagged autoregressive models respectively. In each case we consider both neighbor and commuting flows weights[4]. Spatial autoregressive models reflect a very high spatial dependence (ρ 0.84 to 0.86, λ 0.77 to 0.78) which is consistent with the high values of the Moran's I-statistics reported above.

Finally, in order to select the model that better describes the data we apply Anselin, Bera and Florax (1996) LM tests methodology. Table 6 reports LM tests for the significance of ρ and λ in the spatial error and lag models respectively, as well as the robust tests for each parameter allowing for local misspecification of the other parameter. Individual tests emphatically rejects the null hypothesis of no spatial correlation. However, robusts tests have larger statistics for the error term models. Therefore, in both cases, the spatial error model seems to fit the data more accurately.

A different question is which weights are more appropiate for constructing wage indexes. Provided that the model are non-nested we evaluate the weights performance in terms of the prediction errors. In particular, we map the prediction error for each model. Figure 5 plots the prediction error for the OLS model, circles denoting positive errors and squares negative errors. Figure 6 constructs the prediction errors for the Neighbor and Commuting Flows Weights. It can be observed that the better performance is obtained by using the error model with Commuting Flows.

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Table 1: Spatial dependence tests

Type	Stat	Z	p-value
Neighbor Weights			
Moran's I	0.554	7.735	0.000
Geary's C	0.190	-6.218	0.000
Inverse Distance Weights			
Moran's I	0.692	6.878	0.000
Geary's C	0.204	-7.663	0.000
Commuting Flows Weights			
Moran's I	0.859	8.564	0.000
Geary's C	0.161	-6.012	0.000

Table 2: Local spatial dependence tests

	Neighbor			Distance			Commuting		
County	Stat	Z	p-value	Stat	Z	p-value	Stat	Z	p-value
Alachua	0.064	0.248	0.804	0.019	0.064	0.949	0.012	0.033	0.974
Baker	0.287	0.805	0.421	0.309	0.583	0.56	0.067	0.142	0.887
Bay	0.448	1.120	0.263	0.233	0.393	0.694	0.25	0.314	0.754
Bradford	0.264	0.674	0.500	0.215	0.434	0.664	0.093	0.271	0.786
Brevard	0.058	0.176	0.860	0.040	0.089	0.929	0.062	0.110	0.912
Broward	5.479	11.797	0.000	5.980	8.789	0.000	7.718	12.255	0.000
Calhoun	0.819	2.226	0.026	0.986	1.688	0.091	0.699	1.855	0.064
Charlotte	-0.015	0.000	1.000	-0.003	0.020	0.984	-0.015	0.000	1.000
Citrus	0.460	1.021	0.307	0.411	0.769	0.442	0.410	0.735	0.462
Clay	0.049	0.172	0.863	0.050	0.117	0.907	0.003	0.033	0.974
Collier	3.86	9.369	0.000	2.382	3.608	0.000	2.919	3.477	0.001
Columbia	0.675	1.843	0.065	0.611	1.158	0.247	0.662	1.091	0.275
Dade	8.794	16.264	0.000	7.541	10.739	0.000	8.756	13.938	0.000
DeSoto	0.008	0.063	0.95	0.008	0.039	0.969	0.009	0.042	0.967
Dixie	0.402	0.895	0.371	0.277	0.526	0.599	0.246	0.612	0.540
Duval	-0.048	-0.07	0.944	0.011	0.046	0.963	0.051	0.086	0.931
Escambia	0.299	0.330	0.741	0.209	0.317	0.751	0.224	0.255	0.799
Flagler	-0.001	0.026	0.979	0.001	0.027	0.978	0.015	0.055	0.956
Franklin	0.007	0.041	0.967	0.002	0.027	0.978	0.001	0.022	0.982
Gadsden	0.316	0.711	0.477	0.190	0.341	0.733	-0.051	-0.044	0.965
Gilchrist	0.545	1.493	0.135	0.453	0.869	0.385	0.381	0.858	0.391
Glades	0.025	0.106	0.915	0.061	0.127	0.899	0.152	0.400	0.689
Gulf	0.298	0.672	0.501	0.232	0.397	0.691	0.246	0.451	0.652
Hamilton	0.902	1.693	0.091	0.949	1.669	0.095	0.876	2.038	0.042
Hardee	-0.117	-0.247	0.805	0.135	0.262	0.793	0.049	0.110	0.912
Hendry	0.578	1.583	0.113	0.176	0.311	0.756	0.295	0.492	0.623
Hernando	0.279	0.543	0.587	0.226	0.432	0.665	0.061	0.133	0.894
Highlands	0.002	0.049	0.961	0.115	0.222	0.824	0.157	0.226	0.821
Hillsborough	0.309	0.785	0.433	0.641	1.158	0.247	0.992	1.375	0.169
Holmes	0.978	1.834	0.067	0.872	1.395	0.163	0.784	2.238	0.025
Indian River	0.025	0.086	0.931	0.023	0.061	0.952	0.025	0.049	0.961

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Table 2 – continued from previous page

	Neighbor			Distance			Commuting		
County	Stat	Z	p-value	Stat	Z	p-value	Stat	Z	p-value
Jackson	0.927	2.514	0.012	1.039	1.691	0.091	1.255	1.518	0.129
Jefferson	0.057	0.154	0.877	0.074	0.151	0.88	-0.036	-0.027	0.978
Lafayette	0.626	1.551	0.121	0.742	1.379	0.168	0.672	1.677	0.094
Lake	-0.001	0.042	0.966	0.004	0.036	0.971	-0.014	0.002	0.999
Lee	0.337	0.755	0.45	0.269	0.451	0.652	0.414	0.552	0.581
Leon	-0.086	-0.152	0.879	0.000	0.026	0.979	0.043	0.066	0.947
Levy	0.371	0.933	0.351	0.354	0.669	0.503	0.270	0.558	0.577
Liberty	0.315	0.959	0.338	0.379	0.669	0.503	0.245	0.631	0.528
Madison	0.412	1.033	0.302	0.281	0.510	0.610	0.277	0.743	0.458
Manatee	0.291	0.818	0.414	0.261	0.466	0.641	0.430	0.660	0.509
Marion	0.199	0.571	0.568	0.125	0.255	0.799	0.140	0.211	0.833
Martin	0.713	1.344	0.179	0.436	0.716	0.474	0.875	1.648	0.099
Monroe	9.746	14.611	0.000	13.083	17.258	0.000	13.920	21.244	0.000
Nassau	0.077	0.138	0.890	0.119	0.218	0.828	0.029	0.072	0.943
Okaloosa	0.279	0.440	0.660	0.179	0.288	0.774	0.197	0.293	0.770
Okeechobee	0.014	0.084	0.933	0.015	0.051	0.96	0.029	0.089	0.929
Orange	0.048	0.154	0.878	0.113	0.234	0.815	0.163	0.260	0.795
Osceola	0.008	0.068	0.946	0.031	0.082	0.935	0.069	0.139	0.890
Palm Beach	3.450	6.397	0.000	5.225	7.852	0.000	6.912	8.666	0.000
Pasco	0.008	0.055	0.956	0.001	0.029	0.977	0.022	0.068	0.945
Pinellas	0.815	1.533	0.125	1.443	2.479	0.013	1.919	2.912	0.004
Polk	-0.004	0.039	0.969	0.000	0.027	0.978	-0.011	0.007	0.994
Putnam	0.051	0.192	0.848	0.308	0.578	0.564	0.018	0.085	0.932
Saint Johns	-0.057	-0.089	0.929	0.064	0.135	0.893	0.110	0.199	0.843
Saint Lucie	0.063	0.144	0.886	0.046	0.099	0.921	0.159	0.332	0.74
Santa Rosa	0.285	0.449	0.653	0.346	0.523	0.601	0.302	0.523	0.601
Sarasota	0.197	0.392	0.695	0.659	1.123	0.261	0.800	1.309	0.190
Seminole	0.054	0.149	0.881	0.042	0.103	0.918	0.078	0.140	0.889
Sumter	0.196	0.562	0.574	0.243	0.476	0.634	0.097	0.258	0.796
Suwannee	0.781	1.926	0.054	0.598	1.126	0.260	0.611	1.274	0.203
Taylor	0.165	0.387	0.698	0.082	0.169	0.866	0.032	0.196	0.844
Union	0.501	1.109	0.268	0.612	1.190	0.234	0.355	0.858	0.391

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Table 2 – continued from previous page

	Neighbor			Distance			Commuting		
County	Stat	Z	p-value	Stat	Z	p-value	Stat	Z	p-value
Volusia	-0.009	0.014	0.989	0.038	0.090	0.928	0.073	0.138	0.890
Wakulla	0.041	0.122	0.903	0.057	0.122	0.903	0.003	0.031	0.975
Walton	0.495	1.096	0.273	0.390	0.620	0.535	0.382	0.607	0.544
Washington	0.906	2.228	0.026	0.820	1.355	0.175	0.580	1.087	0.277

Table 3: OLS

Coef.	Estimate	Std.Error	t	p-value
β_0	147.8	15.6	9.49	0.000
β_X	-0.087	0.241	-0.362	0.719
β_Y	-2.056	0.280	-7.35	0.000
σ^2	2.529			
R^2	0.5989	Adj.R^2	0.5862	

Table 4: Spatial error autoregressive

Neighbor Weights				
Coef.	Estimate	Std.Error	Z	p-value
β_0	190.0	40.6	4.68	0.000
β_X	0.173	0.526	0.329	0.742
β_Y	-2.734	0.603	-4.54	0.000
σ^2	2.539			
ρ	0.8416	0.057	14.71	0.000
Commuting Flows Weights				
Coef.	Estimate	Std.Error	Z	p-value
β_0	127.0	28.0	4.55	0.000
β_X	-0.579	0.407	-1.42	0.155
β_Y	-2.848	0.432	-6.59	0.000
σ^2	0.859			
ρ	0.8390	0.039	21.1	0.000

Table 5: Spatial lagged autoregressive

Neighbor Weights				
Coef.	Estimate	Std.Error	Z	p-value
β_0	33.7	15.8	2.13	0.033
β_X	-0.118	0.166	0.329	0.478
β_Y	-0.730	0.267	-2,73	0.006
σ^2	3.0149			
λ	0.7685	0.074	10.81	0.000
Commuting Flows Weights				
Coef.	Estimate	Std.Error	Z	p-value
β_0	29.1	9.85	2.95	0.003
β_X	-0.141	0.107	-1.32	0.187
β_Y	-0.687	0.176	-3.914	0.000
σ^2	1.2134			
λ	0.7758	0.052	14.8	0.000

Table 6: Model selection - LM tests

Neighbor Weights			
ρ	λ	$\rho(\lambda)$	$\lambda(\rho)$
36.1	31.1	7.1	2.0
(0.000)	(0.000)	(0.008)	(0.155)
Commuting Flows Weights			
ρ	λ	$\rho(\lambda)$	$\lambda(\rho)$
319.1	278.1	47.4	6.1
(0.000)	(0.000)	(0.000)	(0.013)

Figure 1: Florida's wage index, FPLI

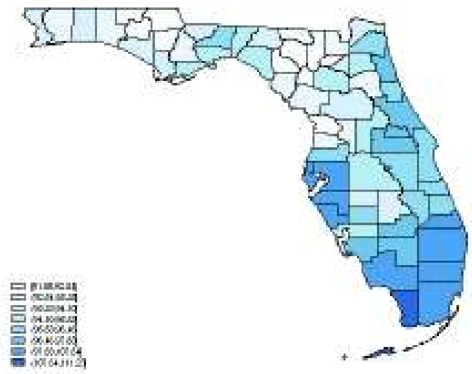


Figure 2: Moran plots

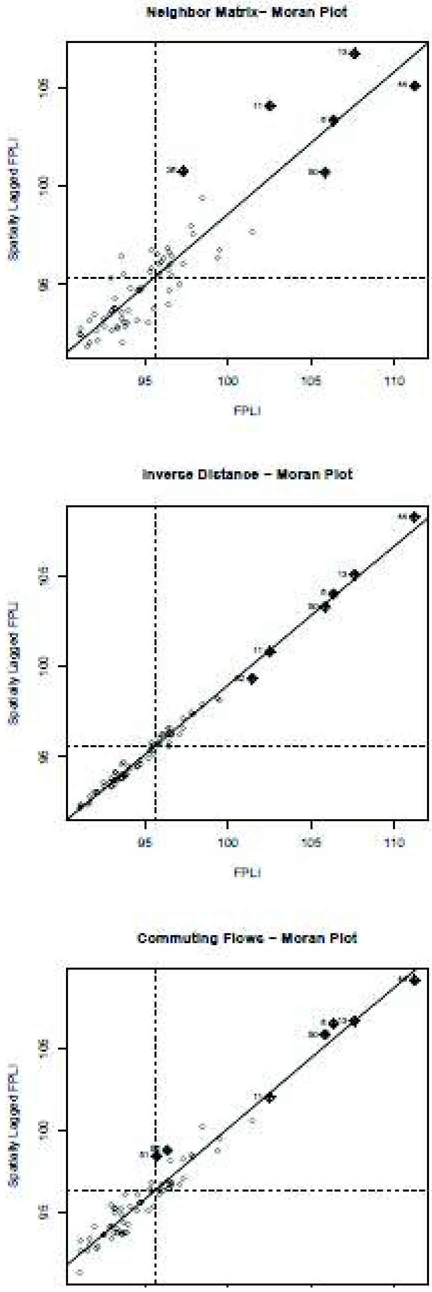


Figure 3: Variogram estimators

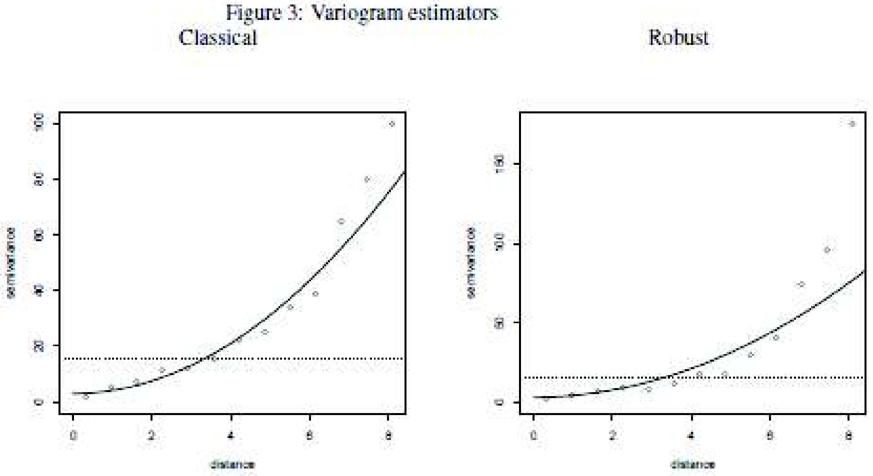
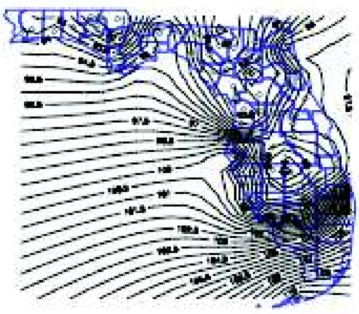
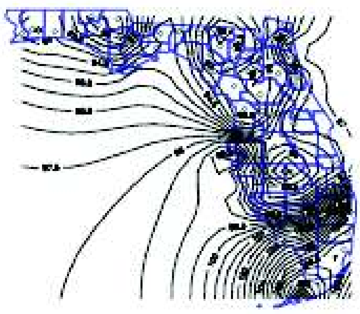


Figure 4: Prediction errors, kriging

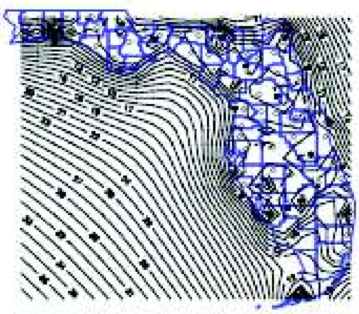
Ordinary kriging (prediction)



Universal kriging (prediction)



Ordinary kriging (std.err.)



Universal kriging (std.err.)

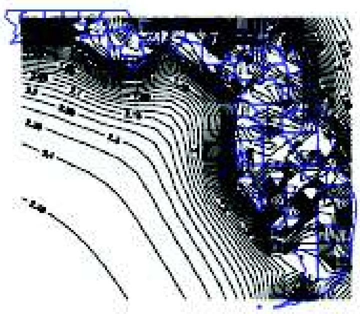


Figure 5: Prediction errors, OLS

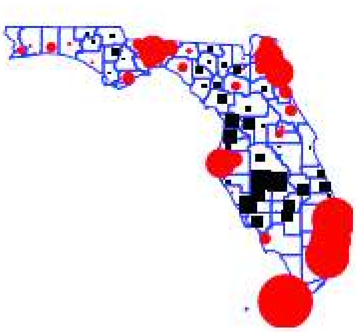


Figure 6: Prediction errors, spatial autoregression