LANCASTER UNIVERSITY · THE WORK FOUNDATION PART OF LANCASTER UNIVERSITY · LANCASTER UNIVERSITY Management School

UAB Universitat Autònoma de Barcelona

1. Justification

- Improving educational quality is an important public policy goal.

  Investments in education affect numerous individual behaviors throughout the life course (Hanushek and Kimko, 2000).

- Expanding school choice can improve the efficiency of public schools heightening competition which arises through the geographical location of schools (Hoxby, 2000).

  Understanding the strength of the competitive forces from alternative schools in neighboring areas may shed light on the value added from additional demand (Barrow, 2002).

1. Objectives

- To analyze whether school location has an impact on the relationship between the level of technical quality of public schools (measured by the efficiency score) and the school demand index.
- To test whether or not the type of municipality (rural vs urban) changes the effect of space on the relationship between demand and school efficiency.

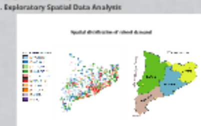
2. Methodology

3. Empirical results

a. Conditional order-m efficiency score

b. Spatial study

1. Exploratory Spatial Data Analysis



4. Conclusions

Summary

Implications

Limitations

Thanks for your attention

Contents

Measuring school demand in the presence of spatial dependence. A conditional approach

Laura López-Torres and Diego Prior

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2. Methodology

1. Efficiency model

- Conditional and robust order-*m* model (Cazals et al. 2002; Daraio and Simar, 2005).

Order-*m* approach creates a partial frontier that envelops only *m* observations from the sample. This procedure is repeated *B* times resulting in multiples efficiency scores from which the final efficiency measure is computed as the simple mean.

Set of inputs $x \in R^p_+$

Set of heterogeneous outputs $y \in R^q_+$

Non-discretionary factors $Z \in \mathbb{R}^r$

Production set (without Z)

$$\Psi_m(x) = \{(x', y) \in \mathbb{R}^{p+q}_+ \mid x' \le x, Y_i \le y, i = 1, \dots, m\}$$

Production set (with Z)

$$\Psi^z_m(x) = \{(x', y) \in \mathbb{R}^{p+q}_+ \mid x' \le x, Y_i \le y, Z = z, i = 1, \dots, m\}$$

- **Conditional order-m efficiency model**

Conditional model works with probabilistic formulation and incorporates the environmental effect, conditioning the characteristics of the non-discretionary factors.

It constructs a boundary representing the reference set in which each unit is compared. For that, smoothing techniques are needed (Badin et al.,2010; De Witte and Kortelainen, 2013).

$$S'_{Y,n}(y \mid x, z) = \frac{\sum_{i-1}^{n} I(x_i \le x, y_i \ge y) K_h(z, z_i)}{\sum_{i-1}^{n} I(x_i \le x) K_h(z, z_i)}$$

Algorithm (following Daraio and Simar, 2005):

1. Compute the equation (*m*=100):

$$\tilde{\theta}^z_m(x, y) - \sup\{\theta \mid (x \mid \theta y) \in \Psi^z_m(x)\} - E\left[\max_{i-1,\dots,m}\{\min_{j-1,\dots,q}(\tfrac{y^j_i}{y^j})\} \mid X \le x, Z = z\right]$$

2. Redo step 1 for b= 1, ..., *B*, where B = 200.

3. Finally, $\hat{\theta}_{m,n}(x, y \mid z) \approx \frac{1}{B}\sum_{b=1}^{B} \tilde{\theta}^{b,z}_m(x, y)$.

2. Spatial model

- UTM coordinates to validate the geographic location of each school.
- High spatial interdependence among schools.
- Application of SE model (Anselin, 1988):

1. OLS regression:

[illegible]

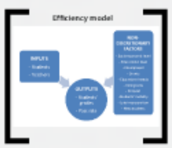
2. Exploratory Spatial Data Analysis (ESDA)
3. Tests for spatial dependence detection.
4. Fix model step 1 to include spatial dependence detected (ML model).

3. Data and Variables

Data from the Catalan Evaluation Council of the Education System.

n = 1,695 public schools.

t = academic year 2009/2010.



2. Spatial model

a) General regression model

$$y = X\beta + u \qquad u \sim N(0, \sigma^2 I)$$

b) Variants of spatial regression models

LAG model

$$y = \rho W y + X\beta + u \qquad W = \begin{bmatrix} 0 & w_{12} & \cdots & w_{1N} \\ w_{21} & 0 & \cdots & w_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1} & w_{N2} & \cdots & 0 \end{bmatrix}$$

ERR model

$$y = X\beta + \varepsilon \qquad \varepsilon = \lambda W \varepsilon + u$$

Mixed structures

$$y = \rho W_1 y + X\beta_1 + W_2 R\beta_2 + \varepsilon$$

2. Spatial model

Tests for spatial dependence detection

Spatial dependence type	Test type	Statistics	Features
Residual	Ad-hoc	**Moran's I (Cliff and Ord, 1972)** $I = \frac{N}{S}\frac{e'We}{e'e}$	e = OLS residuals. N = sample size. S = sum of all w_{ij} W matrix.
	ML	**LM-ERR (Burridge, 1980)** $LM-ERR = \frac{[e'We/s^2]^2}{T_1}$	s^2 = estimation of residual variance. T_1 = tr $(W'W + W^2)$.
		LM-EL (Bera and Yoon, 1992) $LM-EL = \frac{\left[\frac{e'We}{s^2 - T_1(RJ_{\rho-\beta})^{-1}e'Wy/s^2}\right]^2}{[T_1 - T_1^2(RJ_{\rho-\beta})^{-1}]}$	$RJ_{\rho-\beta} = [T_1 + (WX\beta)'M(WX\beta)/s^2]$ $M = I - X(X'X)^{-1}X'$
Substantive	ML	**LM-LAG (Anselin, 1988b)** $LM-LAG = \frac{[e'Wy/s^2]^2}{RJ_{\rho-\beta}}$	All the terms are known.
		LM-LE (Bera and Yoon, 1992) $LM-LE = \frac{\left[\frac{e'Wy}{s^2} - e'We/s^2\right]^2}{RJ_{\rho-\beta} - T_1}$	All the terms are known.
Both	ML	**SARMA Test (Anselin, 1988b)** $SARMA = \frac{\left[\frac{e'Wy}{s^2} - e'We/s^2\right]^2}{RJ_{\rho-\beta} - T_1} + \frac{(\frac{e'We}{s^2})^2}{T_1}$	All the terms are known.

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$$Demand = \gamma + \beta * \tilde{\theta}_m^{b,z} + \varepsilon$$

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		LM-EL (Bera and Yoon, 1992) $LM - EL = \frac{\left[\frac{e'We}{s^2 - T_1(RJ_{\rho-\beta})^{-1}e'Wy/s^2}\right]^2}{\left[T_1 - T_1^2(RJ_{\rho-\beta})^{-1}\right]}$	$RJ_{\rho-\beta} = [T_1 + (WX\beta)'M(WX\beta)/s^2$ $M = I - X(X'X)^{-1}X'$
Substantive	ML	**LM-LAG (Anselin, 1988b)** $LM - LAG = \frac{[e'Wy/s^2]^2}{RJ_{\rho-\beta}}$	All the terms are known.
		LM-LE (Bera and Yoon, 1992) $LM - LE = \frac{\left[\frac{e'Wy}{s^2} - e'We/s^2\right]^2}{RJ_{\rho-\beta} - T_1}$	All the terms are known.
Both	ML	**SARMA Test (Anselin, 1988b)** $SARMA = \frac{\left[\frac{e'Wy}{s^2} - e'We/s^2\right]^2}{RJ_{\rho-\beta} - T_1} + \frac{(\frac{e'We}{s^2})^2}{T_1}$	All the terms are known.

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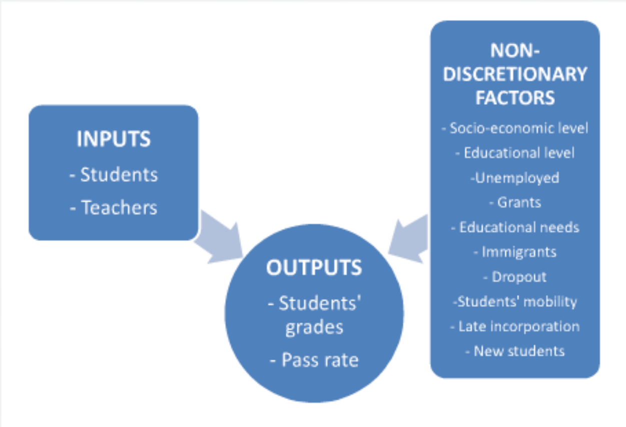
t = academic year 2009/2010.

Efficiency model



Spatial variables

Type	*Variable*		*Description*
Independent	θ_{cond}	Conditional Efficiency score	Efficiency index; reflects the school's performance controlling for environmental variables
	Area	Territorial area	Specific area within the public education network.
Dependent	*Demand*	School demand	Enrollment applications / places offered
Necessary to separate the sample	*Popul*	Population	Number of inhabitants

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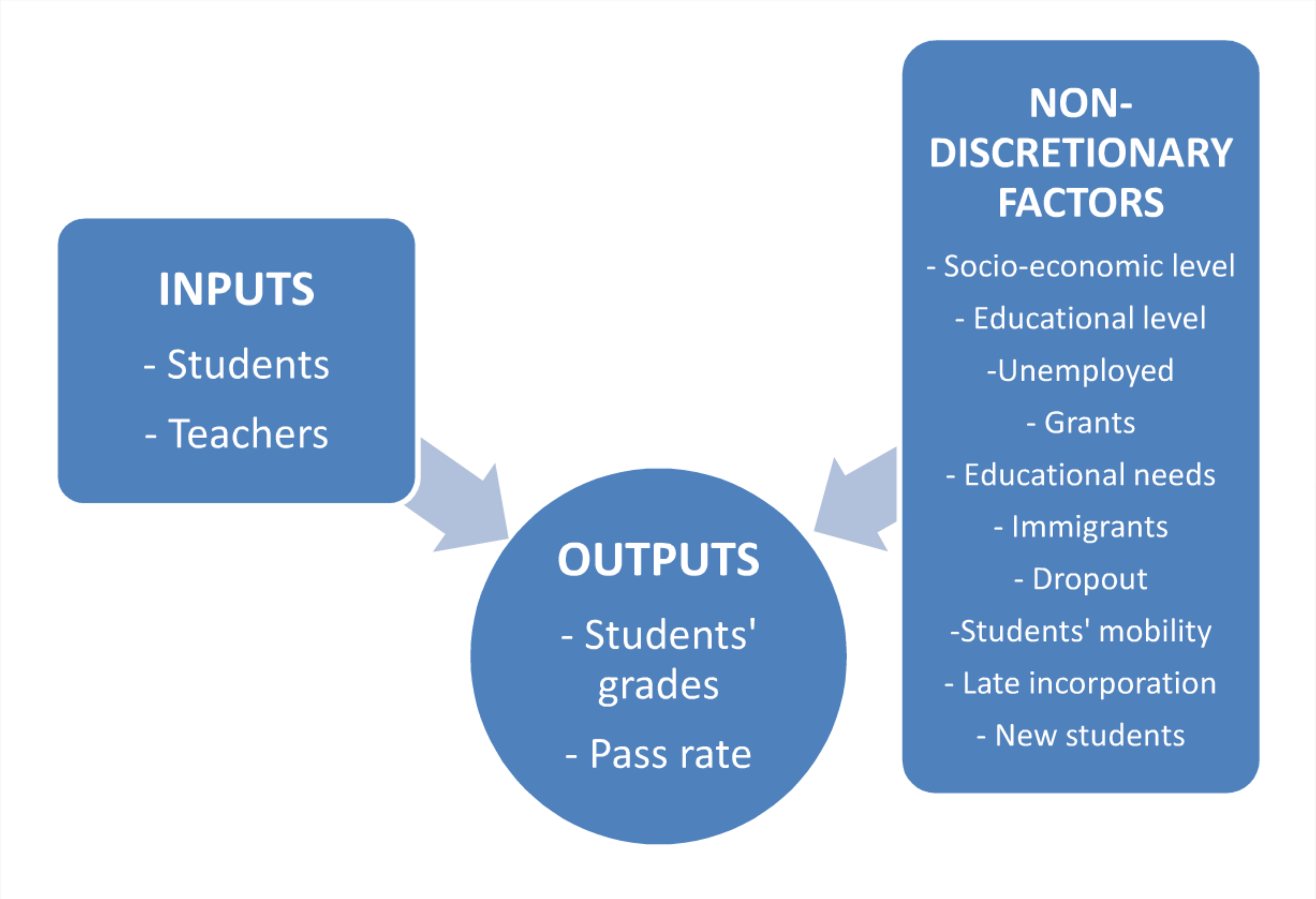

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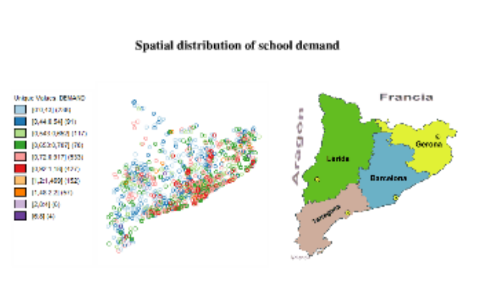
3. Empirical results

a. Conditional order-m efficiency score

Variable	N	Min	Q_{25}	Mean	S.D.	Median	Q_{75}	Max
θ_{cond}	1,695	0.98	1.01	1.20	0.01	1.1	1.21	1.25

b. Spatial study

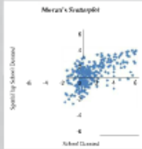
1. Exploratory Spatial Data Analysis



1. Exploratory Spatial Data Analysis

	Moran's I		Getis and Ord's G	
Variable	Statistic	S.D.	Statistic	S.D.
Demand	0.3403***	8.9141	0.5971***	7.3884
NOTE	W=Distance Matrix			

*** = 0.1% significance level



2. Tests for spatial dependence's detection

	Estimated coefficient	p-value
Lagrange multiplier tests		
LM ERR	48.115*	0.04
LM LAG	51.443***	0.000
RLM ERR	0.040	0.841
RLM LAG	3.368**	0.006
SARMA	51.483***	0.000

* = 5% significance level
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3. Spatial regression results

	BASE MODEL	MODEL 1	MODEL 2
		Maximum likelihood approach	
Variable/Model	OLS	LAG	DURBIN
		Estimated coefficients (Std. Error)	
Constant	3.747** (1.174)	3.268** (1.159)	10.787 (5.536)
β	-3.110** (1.171)	-2.622* (1.156)	-2.659* (1.155)
A1	0.071 (0.041)	0.056 (0.041)	0.076 (0.067)
A2	-0.020 (0.046)	-0.197 (0.045)	-0.009 (0.046)
A3	-0.090* (0.045)	-0.074 (0.044)	-0.052 (0.079)
A5	-0.043 (0.041)	-0.034 (0.041)	0.082 (0.116)
A6	-0.270*** (0.042)	-0.191*** (0.049)	-0.239* (0.114)
A7	-0.056 (0.049)	-0.045 (0.042)	-0.010 (0.077)
A8	-0.136*** (0.044)	-0.105*** (0.045)	-0.017 (0.148)
A9	-0.285*** (0.081)	-0.235* (1.156)	-0.138 (0.148)
A10	-0.043 (0.045)	-0.440 (0.045)	-0.054 (0.048)
ρ		0.673*** (0.070)	0.653*** (0.073)
c			-7.523 (5.401)
Lag A1			-0.012 (0.120)
Lag A2			0.455 (0.355)
Lag A3			-0.185 (0.141)
Lag A5			-0.049 (0.150)
Lag A6			0.147 (0.155)
Lag A7			0.009 (0.150)
Lag A8			0.012 (0.182)
Lag A9			-0.085 (0.212)
Lag A10			0.135 (0.161)
LNL	-1,096.067	-1,082.223	1,076.330
AIC	2,214.135	2,188.447	2,216.659

3. Spatial regression results
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School's demand index depends on:

- The efficiency of the school.
- The area where it is operating.
- The neighboring school demand index.

3. Spatial regression results

- Rural vs urban (Eurostat Criterion):
  - Rural < 5,000 inhabitants
  - Urban >= 5,000 inhabitants

	Rural		Urban	
Tests	Statistic	p-value	Statistic	p-value
Moran's I	0.46	0.64	0.044*	0.030
Getis and Ord's G	0.02	0.05	0.091	0.261
LM ERR	0.66	0.41	0.738	0.342
LM LAG	0.55	0.41	1.181*	0.031
RLM ERR	0.15	0.70	0.607	0.560
RLM LAG	0.04	0.85	0.454*	0.040
SARMA	0.69	0.71	1.192*	0.044

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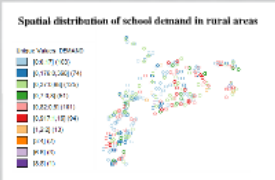

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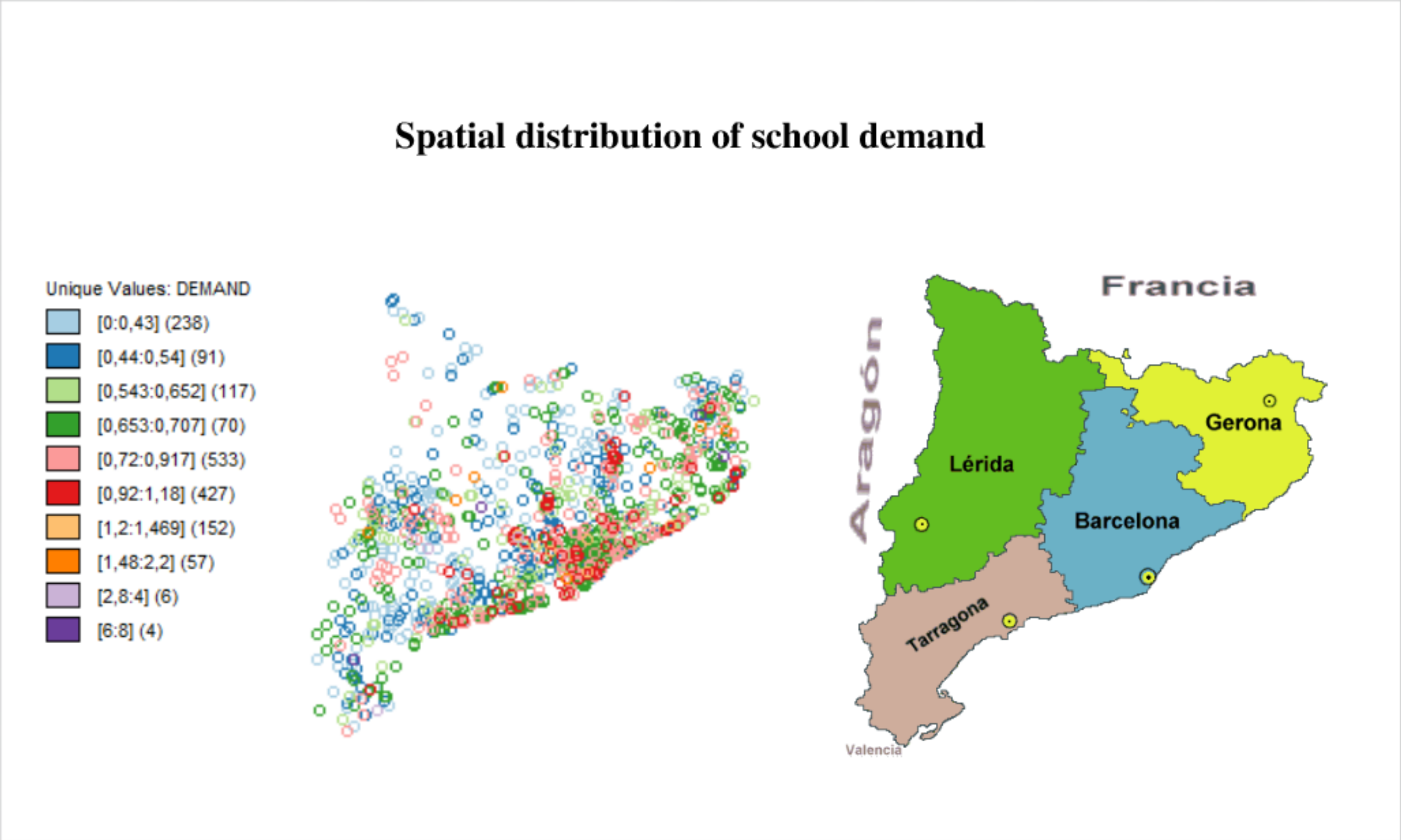

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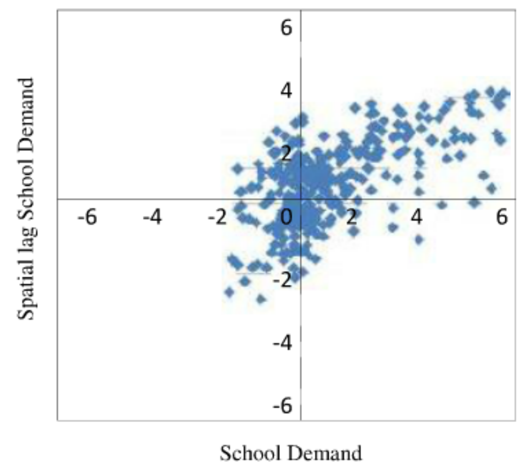
Moran's *Scatterplot*



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A9	-0.295*** (0.061)	-0.235* (1.156)	-0.138 (0.148)
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A6	-0.270*** (0.042)	-0.191*** (0.045)	-0.239* (0.114)
A7	-0.056 (0.043)	-0.045 (0.042)	-0.033 (0.047)
A8	-0.156*** (0.044)	-0.105*** (0.045)	-0.017 (0.143)
A9	-0.295*** (0.061)	-0.235* (1.156)	-0.138 (0.148)
A10	-0.043 (0.045)	-0.448 (0.045)	-0.054 (0.048)
ρ		0.673*** (0.070)	0.683*** (0.073)
α			-7.523 (5.401)
Lag A1			-0.012 (0.135)
Lag A2			0.455 (0.355)
Lag A3			-0.195 (0.141)
Lag A5			-0.049 (0.158)
Lag A6			0.147 (0.155)
Lag A7			0.039 (0.150)
Lag A8			0.012 (0.182)
Lag A9			-0.085 (0.212)
Lag A10			0.135 (0.161)
LN L	-1,096.067	-1,082.223	1,076.330
AIC	2,214.135	2,188.447	2,316.659

3. Spatial regression results

	BASE MODEL	MODEL 1	MODEL 2
		Maximum likelihood approach	
Variable/Model	**OLS**	**LAG**	**DURBIN**
	Estimated coefficients (Std. Error)		
Constant	3.747** (1.174)	3.268** (1.159)	10.787 (5.536)
β	-3.110** (1.171)	-2.622* (1.156)	-2.659* (1.155)
A1	0.071 (0.041)	0.056 (0.041)	0.076 (0.067)
A2	-0.020 (0.046)	-0.197 (0.045)	-0.009 (0.046)
A3	-0.098* (0.045)	-0.074 (0.044)	-0.052 (0.049)
A5	-0.043 (0.041)	-0.034 (0.041)	0.082 (0.116)
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3. Spatial regression results

School’s demand index depends on:

- The efficiency of the school.
- The area where it is operating.
- The neighboring school demand index.

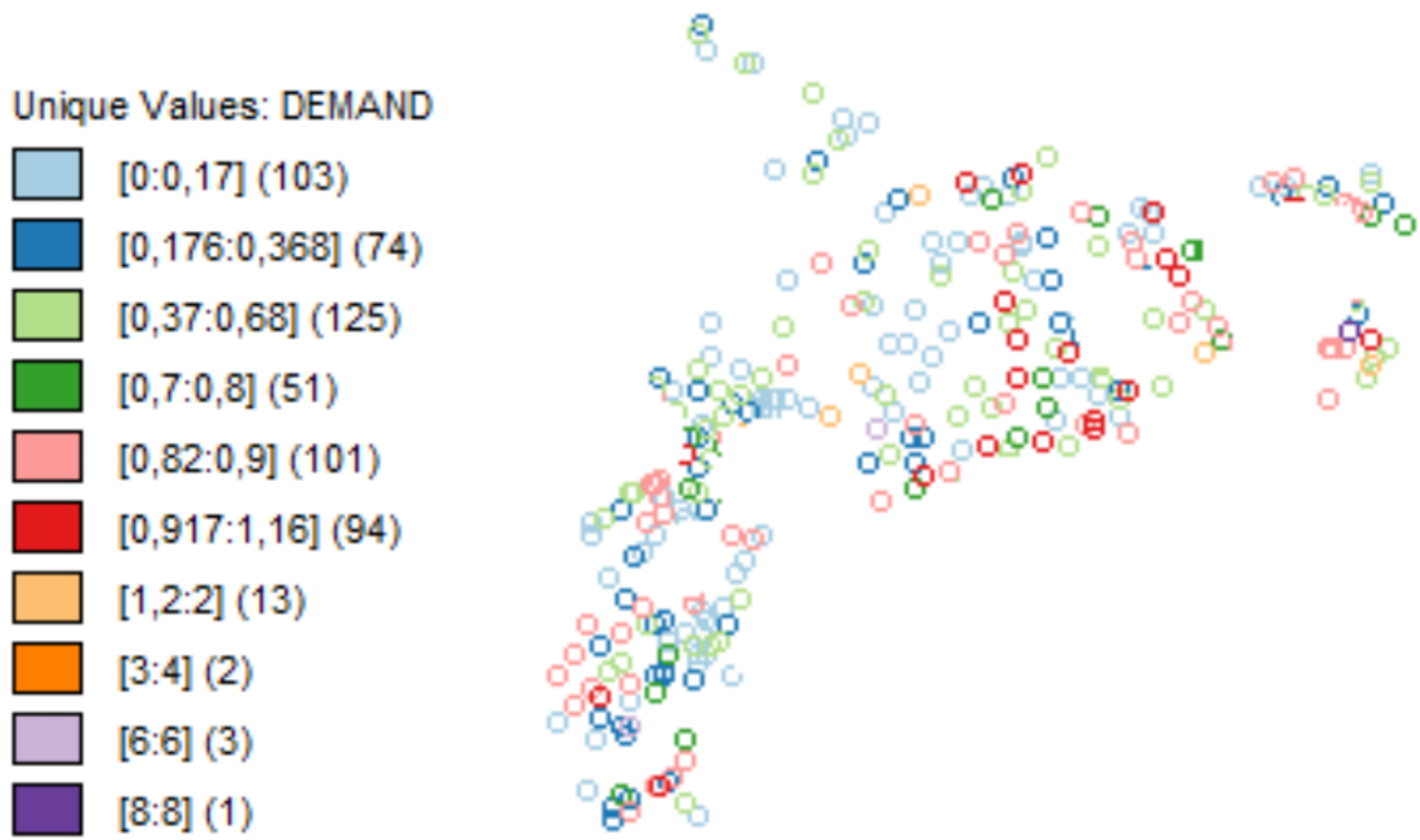
3. Spatial regression results

- **Rural *vs* urban (Eurostat Criterion):**
  - **Rural < 5,000 inhabitants**
  - **Urban >= 5,000 inhabitants**

	Rural		Urban	
Tests	**Statistic**	**p-value**	**Statistic**	**p-value**
Moran's I	0.46	0.64	0.044*	0.030
Getis and Ord's G	0.02	0.05	0.091	0.261
LM ERR	0.66	0.41	0.738	0.342
LM LAG	0.55	0.41	1.181*	0.031
RLM ERR	0.15	0.70	0.607	0.560
RLM LAG	0.04	0.85	0.454*	0.040
SARMA	0.69	0.71	1.192*	0.044

* = 5% significance level

Spatial distribution of school demand in rural areas



4. Conclusions

Summary

- We use a specific approach different from the previous one in two major aspects:
  - First study to offer an analysis of the role of location in explaining the spatial distribution of the school demand in the Spanish context.
  - Use of spatial Econometrics techniques combined with non-parametric and robust efficiency estimations.

Implications

- Provides valuable information to apply improvement programs in less demanded schools.
- Policy makers can introduce additional efforts to reduce the differences among the regions.
  - An active school quality policy might not only affect to one school, but also schools in adjacent zones.

Limitations

- Spatial dependence observed may be partially affected by other neighboring private schools that receive public funds.
- Lack of student level data.
- Availability of information for several years.

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Thanks for attentio

Summary

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Thanks for your attention

Universitat Autònoma de Barcelona

2. Methodology

3. Empirical results

a. Conditional order-m efficiency score

b. Spatial study

1. Exploratory Spatial Data Analysis

1. Objectives

- To analyze whether school location has an impact on the relationship between the level of technical quality of public schools (measured by the efficiency score) and the school demand index.
- To test whether or not the type of municipality (rural vs urban) changes the effect of space on the relationship between demand and school efficiency.

4. Conclusions

Summary

Implications

Limitations

1. Justification

- Improving educational quality is an important public policy goal.

Investments in education affect numerous individual behaviors throughout the life course (Hanushek and Kimko, 2000).

- Expanding school choice can improve the efficiency of public schools heightening competition which arises through the geographical location of schools (Hoxby, 2000).

Understanding the strength of the competitive forces from alternative schools in neighboring areas may shed light on the value added from additional demand (Barrow, 2002).

Contents

Thanks for your attention

Measuring school demand in the presence of spatial dependence. A conditional approach

Laura López-Torres and Diego Prior