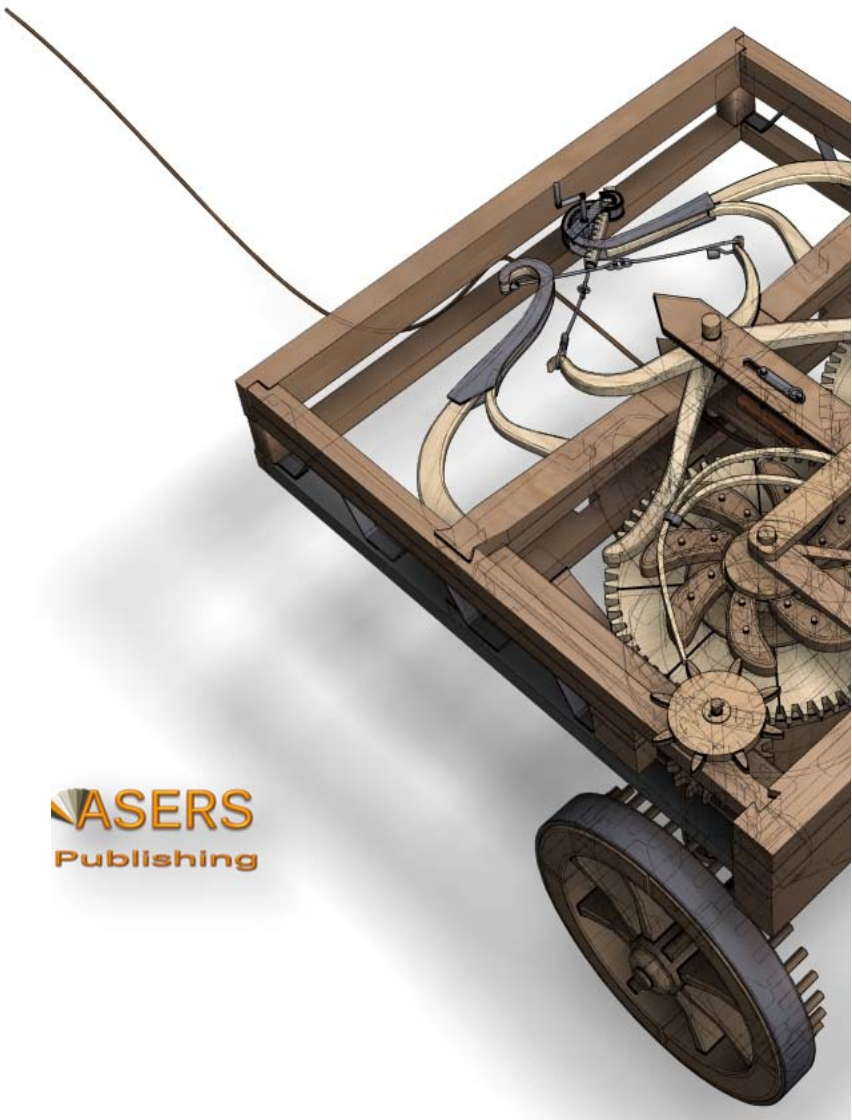
Theoretical and Practical Research inEconomic Fields



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Theoretical and Practical Research in Economic Fields

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SPATIAL ANALYSIS OF POVERTY: THE CASE OF PERU

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Abstract: *The concept of Multidimensional Poverty traditionally was used for comparative analysis across regions or countries. This paper uses the concept of Multidimensional Poverty for each Peruvian region to analyzes spatial patterns, spatial autocorrelation, and identifies spatial spillovers in poverty. We find evidence of statistically significant spatial autocorrelation across regions; in other words, poverty has spatial effects. In more detail, we find that those spatial spillovers are originated in the error terms rather than the endogenous variable. Also, the covariates we use in our regressions are statistically significant and stable across the models.*

Keywords: poverty; spatial econometrics; Peru.

JEL Classification: C21; O10.

Introduction

Poverty is probably the essential concern of countries worldwide, even to be established as the Millennium Development Goals' first goal. Following this goal, the Peruvian government set policies to reduce poverty and extreme poverty. From 2004 to 2015, poverty was reduced from 58 to 22 percent, while extreme poverty fell from 16 to 4 percent. In absolute numbers, nine million Peruvians escaped from poverty.

The concept of poverty is widely investigated in the literature; Sen (1976, 227-230) argues that poverty is not only an income problem. It is composed of different dimensions thatform a more encompassing concept. i.e. a person is not poor only because he does not have enough income to fulfill his needs, but also due to his chances to escape from poverty are reduced due to insufficiency in education, health, and life quality. Nevertheless, we argue that poverty is also a spatial concept. Poverty is typically agglomerated in certain areas, regions with low-quality infrastructure where government policies do not reach the population.

This paper analyzes poverty based on household living conditions by constructing the Multidimensional Poverty Index (MPI, from now on). Therefore, the main objectives of this research are summarized in:

(1) Identify spatial patterns of poverty across the country;
(2) Identify the presence of spatial autocorrelation and clusters of poverty among regions;
(3) Find evidence of spatial spillovers across districts among Peru.

1. Literature Review

One of the first approaches to analyze poverty's spatial component was made by Brunn and Wheeler (1971, 8-15). They do a geographical and factor analysis and identify various poverty faces among US counties. They use the information for socioeconomic status, agricultural productivity, demographic composition, agricultural holdings and investment, and urbanization and manufacturing from the *County and City Data Book of 1967*. They find that these factors have different importance once a county measures its poverty level. Therefore, some counties have similar poverty levels, but the source differs among them. Later on, Bigman and Fofack (2000, 134-139), using a similar methodology, identify five advantages of using geographical data to alleviate poverty. First, it provides clear criteria for determining the target population; second, easy to monitor and administer; third, it influences a household's behavior; fourth, it is possible to improve targeting by combining with other criteria. Finally, in fifth, they can include direct income transfer and other means to increase living standards.

Crandall and Weber (2004, 1279-1281) focus on analyzing the effect of job growth and social capital over the poverty rates. However, they can identify spatial spillovers by using two census tract-level data across the US. From a different perspective, Rupasingha and Goetz (2007, 662-667) investigate the determinants of poverty in the US at county-level data in 1999 by using spatial analysis techniques. They show that social capital, ethnic and income inequality, local political competition, federal grants, foreign-born population, and spatial effects are important determinants to explain poverty levels across the country. Holt (2008, 4-7) uses socioeconomic and health-related data at the county level in the US from the *Community Health Status Indicators* database to describe a spatial analysis of poverty across the country for 2000. The findings reveal significant and stark poverty patterns that the author describes as a "continental poverty divide". The US's poverty levels are concentrated in the south-east counties, while low poverty levels are located in the north-west counties.

Similarly, Grab (2009, 12-18) analyzes the spatial income disparities among households in Burkina Faso using three primary nation-wide household surveys in 1994, 1998, and 2003. He highlights the relevance of the space into the economic analysis of poverty. The author proves that spatial disparities are driven by spatial concentration of households with particular endowments and a large gap in those endowments. i.e. communities are poor because the households' endowment of these communities isinsufficient.

Torres *et al.* (2011, 50-59) use municipal level data to identify Brazil's rural areas' spatial patterns. Using Moran's I indicator, they identify "hot spots" and "cold spots", *i.e.* areas where poverty is agglomerated or dispersed. They find evidence of clusters among municipalities, and the poverty reduction policies must be taken into account when those clusters are identified. Tanaka and Lee (2011, 3-15) combine district-level poverty rates, population census data, income data, and geospatial data in Ghana to investigate the impact of human capital, structural change, infrastructure, and environmental degradation. They find that the working-age population, employment, and the service sector are critical factors for reducing poverty levels.All these findings are correlated with spatial patterns where it is possible to identify "hotspots" or poverty agglomeration. Akinyemi and Bigirimana (2012, 8-9, 12-18) seek for emerging poverty patterns based on household living conditions in Kigali city in Rwanda; also, they look for the contribution of four indicators over the poverty: expenditure, health, education, and services. With data from the *Integrated Living Condition* survey between 2000-2001, they show poverty patterns and the presence of urban-rural dichotomy.

Similarly, for China, Chen *et al.* (2015, 83-89) combine spatial statistical analysis and GIS information to identify patterns and factors of spatial poverty distribution in Xianfeng, China. Thus, they use two key indicators, poverty headcount ratio and the per capita net income of the poverty population. They find evidence of positive spatial autocorrelation and agglomeration of poverty levels across the county.All of the literature presented above shows evidence that poverty has a spatial component that requires research to display more data in favor of this spatial component.

2. Methodology

2.1. Data

Three kinds of data have been used for this research and for building the "Multidimensional Poverty Index" (Odekon 2015, 1075-1076), all belonging to the *National Census 2017* in Peru. These three types of data are the *Housing Characteristics and Services*, *Households' characteristics*, and *Population Characteristics*.

Therefore, the MPI is built by using five dimensions: Education, Childhood and youth, Health, Employment, and Household; they are weighted in the following way:

$$MPI = 0.2(Education) + 0.2(Childhood) + 0.2(Health) + 0.2(Employment) + 0.2(Housing)$$

The *"Education"* dimension is considered a principal factor for households to adapt to social changing conditions. This dimension is composed of two elements:

- *Educational achievements (educ 1)*. Based on the Population Characteristics database, we built a variable for the schooling years for each member of the household since the first grade in elementary school. Then we get the average schooling years for all members older than 15 years old. If the average is less than nine years of schooling, the household is considered deprived;
- *Illiteracy (educ 2)*. We count the number of household members older than 15 years old who cannot read or write. Those households with at least one member falling in this condition, it is considered

deprived.

"Childhood and youth" dimension is considered important since it is a stage where the crucial capabilities and skills are developed to have self-sufficient citizens. During this stage, people have higher probabilities of getting infected with some diseases. On the other hand, for many developing countries, schooling and child labor are risk factors since many households do not have enough income and need young members to leave school and start to work earlier. This dimension is composed of four elements:

- *Educational lag (child 1).* We apply a filter to pick up the member between 7 and 17 years old.We build the educational lag variables by considering the following rule: seven years old and do not have at least one year of schooling; eight years old and do not have at least two years of schooling, nine years old and do not have at least three years of schooling; up to 17 years old and do not have at least 11 years of schooling. Finally, we count the number of household members who fall under this condition; if there is at least one member under this condition, the household is deprived;
- *School absenteeism (child 2).* We count the member between 6 and 16 years old that are currently attending a school. If there is at least one person among these ages that are not attending any school, the household is considered deprived;
- *Childhood Care (child 3).* We count the members younger than five years old who do not have any insurance (public or private) and do not go to any educational institution to get care support. If there is at least one member under this condition, the household is considered deprived;
- *Child labor (child 4).* We count the member younger than 14 years old who are currently working to collaborate with their income. If at least one member is falling under this condition, the household is deprived.

"Health" dimension is crucial since the governments must supply a minimum healthcare level for their citizens to assure people's conditions to follow their objectives. The dimension is composed of:

- *Healthcare insurance (health).* We count the number of members older than five years old that are not affiliated with any health insurance system (public or private). If at least one member is falling under this condition, the household is deprived.

"Employment" dimension is crucial to go over the poverty stage by having a job and not belong to the informal sector. These two conditions help to assure a proper income and have a job with all its benefits. The dimension is composed of the following factors:

- *Employment (employment 1).* We count the members older than 14 years old who currently do not have a job and are looking actively for one. If at least one member is falling under this condition, the household is deprived;
- *Informality (employment 2).* We count the members working in a company with five or fewer employees. If at least one member is falling under this condition, the household is deprived.

"Housing" dimension is important since it creates minimum conditions where families and their members develop their daily-life activities allow them to access essential tools to build their capabilities. This dimension is composed of seven elements:

- *Water access (house 1).* We consider a household is deprived if they do not have access to water service inside the house, inside the building, or from a public sink. Additionally, we consider a household deprived if they do not have access to water less than three days per week;
- *Sewage access (house 2).* We consider a household is deprived if it does not have access to any sewage service inside the house or the building;
- *Floor (house 3).* We consider a household is deprived if the house's floor material is other than parquet, tiles, vinyl, or cement;
- *Walls (house 4).* We consider a household is deprived if the house's wall material is other than bricks, stones, mud bricks, or wood;
- *Roof (house 5).* We consider a household is deprived if the house's roof material is other than concrete, wood, or tiles;
- *Public lighting (house 6).* We consider a household is deprived if the house does not have access to any public lighting;
- *Overcrowding (house 7).* We consider a household is deprived if the house has more than three members per room.

Finally, The MPI is built as follows:

$$MPI = 0.2(Education) + 0.2(Childhood) + 0.2(Health) + 0.2(Employment) + 0.2(Housing),$$

where:

$$
\begin{aligned}
Education &= \frac{1}{2}educ1 + \frac{1}{2}educ2 \\
Childhood &= \frac{1}{4}child1 + \frac{1}{4}child2 + \frac{1}{4}child3 + \frac{1}{4}child4 \\
Health &= health \\
Employment &= \frac{1}{2}employment1 + \frac{1}{2}employment2 \\
Housing &= \frac{1}{7}house1 + \frac{1}{7}house2 + \frac{1}{7}house3 + \frac{1}{7}house4 + \frac{1}{7}house5 + \frac{1}{7}house6 + \frac{1}{7}house7
\end{aligned}
$$

2.2. Spatial Autocorrelation Test

Global spatial autocorrelation analysis is used to identify a situation in which a variable at a specific location correlates with observations on this variable at other locations. In other words, it measures how related are the observations in a particular area respect to its neighbors. One of the most common tests for this analysis is *Global Moran's I*, described as:

$$I = \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})}{\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})^2/2}, \quad \forall i \neq j$$

where n is the number of spatial units of analysis indexed by i and j. x_i are the values of the variable x in the unit of analysis, while the $\bar{x}$ is the mean of the variable x. W_{ij} refers to the weighted matrix $n \times n$ that definesthe influence that an area has over the others. For this research, we use contiguity row standardized weight matrix based on *"Queen"* method, which defines that two regions are neighbors if they share a common border, regardless of how short it is.

$$
\begin{aligned}
W &= \begin{bmatrix} 0 & w_{12} & w_{13} & & w_{1n} \\ w_{21} & 0 & w_{23} & & w_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & w_{n3} & & w_{nn} \end{bmatrix} \\
w_{ij}^{*} &= \frac{w_{ij}}{\sum_{j=1}^{n} w_{ij}}, \\
W &= \begin{cases} 1, & i \text{ neighbor } j, \\ 0, & \text{otherwise.} \end{cases}
\end{aligned}
$$

The *Moran's I* is interpreted as a coefficient of correlation with a range of $[-1,1]$. A positive and significant value of the indicator represents positive autocorrelation among the spatial units, and high values indicateclusters' presence. Similarly, the indicator's negative and significant values show negative autocorrelation and tend to reveal the presence of *"hotspots"*. Finally, values close to zero indicate a random distribution of the variable among the analysis's spatial units.

Local spatial autocorrelation is used to determine the variable's spatial autocorrelation for each spatial unit with respect to its neighbors. Regarding the local indicator's relationship with the global autocorrelation one, local spatial autocorrelation helps us focus more on sublevel when there is no evidence of strong global spatial autocorrelation.Second, local autocorrelation helps explore spatial patterns. Third, local autocorrelation aidsin identifying any inconsistent pattern. The *Local Moran's I* is defined as:

$$I_i = \frac{n(x_i - \bar{x})\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})}{\sum_{j=1}^{n}(x_i - \bar{x})^2}, \quad \forall i \neq j$$

2.3. Spatial Autocorrelation Model

Based on the general form of the spatial autoregressive model with spatial effects proposed by Anselin (1988, 32-40), we can express the model as:

$$
\begin{aligned}
y &= \delta W y + X\beta + WX\gamma + \epsilon, \\
\epsilon &= \lambda W \epsilon + \mu, \\
\mu &\sim N(0, \sigma^2 I_n),
\end{aligned}
$$

where y is the endogenous variable; δ is the coefficient of endogenous variable's spatial lagWy; W is the weighted matrix of spatial neighbors; X is the set of exogenous variables; β is the effect of the exogenous variables represented by $X; \gamma$ is the coefficient to the spatial lag of the exogenous variables WX; λ is the coefficient to the spatial effect into the error terms $W\epsilon$; finally, μ are the uncorrelated disturbances.

By following the general model is the Spatial Autocorrelation Model (LeSage 2008, 21-23), our model is defined as:

$$\begin{aligned} IPM &= W(IPM) + \beta_1 Migration + \beta_2 Language + \beta_3 Female + \epsilon, \\ \epsilon &= \lambda W\epsilon + \mu, \\ \mu &\sim N(0, \sigma^2 I_n), \end{aligned}$$

where IPM is the *"Multidimensional Poverty Index"*. *Migration* is defined as the percentage of households in each district where at least one member migrated during the last five years from another region (i.e. called department for Peru). *Language* is defined as the percentage of households in each district where at least one member speaks another original language than Spanish. *Female* is defined as the percentage of families where the household's head is female. All the parameters are estimated using maxim likelihood methods to obtain robustly estimated coefficients.

Additionally, several diagnostic tests can be applied in the spatial model contexts, *e.g.* Lagrange Multiplier tests contrast the presence of spatial effects (Anselin 2001, 707-708; 2010, 10-11). Therefore, we have the *Lagrange Multiplier Test for Spatial Error* (LM-error):

$$\text{Hypothesis:} \quad H_0: \delta = 0 \quad \text{vs} \quad H_1: \delta \neq 0$$

$$LM\_error = \frac{\left(\frac{e'We}{e'e/n}\right)^2}{tr(W' + W'W)} \quad ,$$

and the Lagrange Multiplier Test for Spatial Lag (LM-lag):

$$\text{Hypothesis:} \quad H_0: \lambda = 0 \quad \text{vs} \quad H_1: \lambda \neq 0$$

$$LM\_error = \frac{\left(\frac{e'Wy}{e'e/n}\right)^2}{D + tr(W' + W'W)} \quad ;$$

$$D = \frac{(WX\beta)'(I - X(X'X)X')^{-1}(WX\beta)}{e'e/n}$$

finally, the Akaike Criterion (AIC) remains a useful indicator to select the best model among all the estimated models.

3. Results

Table 1 displays the descriptive statistics for the primary data we are using in our estimations. These statistics give us a clearer idea of how varied the 1874 districts among Peru are. As we observe in the table, districts are as small as two squared km and as big as 24 049 squared km, but with an average size of 690 square km per district. Furthermore, concerning each dimension, we can identify some evident characteristics. Around 5.3% of the households did not achieve an average of nine years of schooling; similarly, 22.7% of households have at least one member without the skill of reading or writing correctly.

Regarding the *Childhood* dimension, we observe that most households do not fall into the poverty category. Less than 1% of households have at least one member that does not attend any school institution, has no health insurance (public or private), or has a job to contribute to the family income with less than 14 years old. Nevertheless, around 30% of households have at least one-member suffering from schooling lag. The descriptive statistics show that Peru is composed of districts where 18.7% of households have at least one member out of the healthcare system, and 63% of those households have members working in the informal sector. In other words, in a five-member family, one in five does not have any health insurance, and three in five have a job in the informal sector. This description of the households' labor situation complements that 4.7% of households have members without a job.

Concerning living conditions, we identify that 2.2% of the households have no proper access to water services; on the other hand, 38% have no sewage access, and 45% have no adequate electricity access. Also, 45%, 22%, and 16% of the households have poor building conditions on their floor, wall, and roof, respectively.

Finally, 15% of households are considered overcrowded since they have three or more members per room. These previous household conditions bring us a total of 20.1% of households falling into the poverty category under the *"Multidimensional Poverty Index"* concept.

Regarding the covariates we are using in our model, 6.4% of households have at least one member who migrated from another region, 41.6% of them have members who do not speak Spanish, and 31.1% of households have a female as household head.

Table 1. Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
size	1,874	689.61	1922.27	1.99	92.91	500.09	24049.95
Dimensions							
educ1	1,874	0.0530	0.0370	0.0000	0.0300	0.0660	0.3210
educ2	1,874	0.2270	0.1310	0.0060	0.1220	0.3210	0.6890
childhood1	1,874	0.3010	0.0880	0.0430	0.2450	0.3560	0.5870
childhood2	1,874	0.0100	0.0080	0.0000	0.0050	0.0120	0.0910
childhood3	1,874	0.0010	0.0020	0.0000	0.0000	0.0020	0.0130
childhood4	1,874	0.0030	0.0090	0.0000	0.0000	0.0030	0.3150
health1	1,874	0.1870	0.1060	0.0100	0.1000	0.2600	0.6620
Job1	1,874	0.0470	0.0330	0.0000	0.0260	0.0620	0.4990
Job2	1,874	0.6300	0.1320	0.0950	0.5530	0.7210	0.9660
house1	1,874	0.0220	0.0420	0.0000	0.0030	0.0240	0.5480
house2	1,874	0.3810	0.2050	0.0000	0.2210	0.5290	0.9330
house3	1,874	0.4530	0.1920	0.0060	0.3280	0.5890	0.9550
house4	1,874	0.2180	0.2290	0.0000	0.0260	0.3680	0.9420
house5	1,874	0.1550	0.0950	0.0080	0.0900	0.1900	0.7020
house6	1,874	0.4520	0.2220	0.0020	0.2850	0.6210	0.9520
house7	1,874	0.1500	0.1210	0.0000	0.0710	0.1890	0.8650
Endogenous Variable							
IPM	1,874	0.2010	0.0380	0.0810	0.1760	0.2240	0.3600
Exogenous Variables							
migration	1,874	0.0640	0.0530	0.0000	0.0250	0.0920	0.4520
language	1,874	0.4160	0.3980	0.0000	0.0160	0.8860	0.9990
female	1,874	0.3110	0.0760	0.0920	0.2580	0.3680	0.5210

Source: National Census 201 – Instituto Nacional de Estadisticas e Informatica (INEI), Peru.

In Table 2, we observe the spatial autocorrelation for our set of variables that compose the *MPI.* As shown in most cases, except for*childhood 3, childhood 4, job 2*, and *house 1*, the *Moran's I*, which measures the spatial autocorrelation, are higher than 0.4, and in all the cases, it is statistically significant at 1%. These results give a clue to the spatial relationships that multidimensional poverty can have. Most of the variables that characterize poverty on its different faces show positive relational behaviors across space. In other words, poverty expressed in low education levels, insufficient levels of health, work, living conditions, and housing conditions show spatial behavior patterns and positive spatial self-correlation. That is, areas with high poverty levels that influence other places make the latter more likely to be poor.

Figure 1 shows the distribution of the *MPI* throughout the Peruvian districts. The left figure shows the *MPI* values for each district and the *MPI* histogram across them. In this figure, it can be seen that the majority of districts with high levels of multidimensional poverty are located in the central highlands and jungle areas of Peru. In contrast, the coast has low levels of multidimensional poverty.

Table 2. Summary Statistics of Spatial Autocorrelation

Statistic	Moran's I	p-value	Statistic	Moran's I	p-value
educ1	0.6184	0.0000	health1	0.6246	0.0000
educ2	0.6888	0.0000	house1	0.2142	0.0000
childhood1	0.6709	0.0000	house2	0.5146	0.0000
childhood2	0.4348	0.0000	house3	0.5948	0.0000
childhood3	0.2426	0.0000	house4	0.7492	0.0000
childhood4	0.0614	0.0000	house5	0.6140	0.0000
job1	0.4849	0.0000	house6	0.6974	0.0000
job2	0.2725	0.0000	house7	0.4132	0.0000
Endogenous Variable					
MPI	0.5641	0.0000			

Source: National Census 201 – Instituto Nacional de Estadisticas e Informatica (INEI), Peru.

The figure on the right shows *Moran's local* indicator's spatial distribution that measures the *MPI*'s spatial autocorrelation for each district. The figure shows that the communities with high spatial autocorrelation levels are located in Peru's central highlands and jungle. This evidence corresponds with the figure's left side, *i.e.* both maps show that poverty is highly concentrated in the central highlands and parts of the Peruvian jungle.

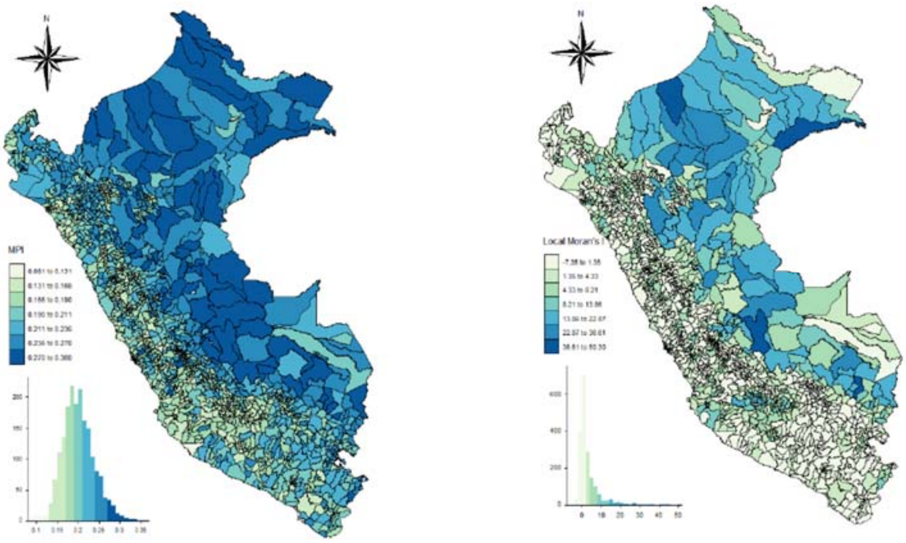

Figure 1. MPI and Local Moran's I per district

Table 3 shows the estimation results. The endogenous variable is the multidimensional poverty indicator, *MPI*, and the control variables were constructed to isolate possible household characteristics that may affect poverty levels within the household. The first control variable, *migrant*, captures the effect of migration between regions, taking the value of 1 when at least one household member has migrated from some other region and 0 otherwise. The second control variable,*language,* measures the second language's effect as a possible cause of poverty in the household. This indicator takes the value of 1 when at least one household member has another language other than Spanish as their mother tongue and 0 otherwise. Finally, the third control variable, *female*, captures the effect of having mothers as household heads. This indicator takes the value of 1 when the household head is female and 0 otherwise. In this table, the columns represent the estimation methods used.

The first column presents the results from an OLS estimation when there are no spatial effects on multidimensional poverty. The second column shows the spatial autoregression model results, where externalities come from the endogenous variable, i.e. the MPI variable of a given district has spatial effects on the surrounding districts. The third column shows the spatial error model results, where the source of spatial autocorrelation is the errors. In other words, the spatial autocorrelation is caused by variables not included in the model or by qualitative sources that could not be adequately captured in the model. Finally, column 4 displays the results of the autoregressive spatial model estimation with spatial errors. In this model, the sources of spatial autocorrelation arethe endogenous variable andthe errors.

Table 3. Estimation Results

Dependent variable: MPI				
	OLS	Spatial Autoregressive	Spatial Error	Spatial Error Autoregressive
migrant	-0.078***	-0.062***	-0.060***	-0.060***
	(0.015)	(0.015)	(0.015)	(0.015)
language	0.008***	0.008***	0.022***	0.023***
	(0.002)	(0.002)	(0.003)	(0.003)
female	-0.221***	-0.209***	-0.188***	-0.188***
	(0.011)	(0.011)	(0.011)	(0.011)
Constant	0.272***	0.249***	0.256***	0.256***
	(0.003)	(0.004)	(0.004)	(0.004)
δ		0.017***		-0.003***
		(0.002)		(0.002)
λ			0.127***	0.128***
			(0.003)	(0.003)
Observations	1,874	1,874	1,874	1,874
R2	0.196			
Adjusted R2	0.194			
Log Likelihood		3,701.63	4,111.52	4,112.32
sigma2		0.001	0.001	0.001
Akaike Inf. Crit.		-7,391	-8,211	-8,211
F-Statistic (df = 3; 1870)	151.596***			
Wald Test (df = 1)		85.818***	1,585.506***	
LR Test (df = 1)		87.192***	906.964***	908.570***
LM Test (df = 1)		1128.8***		

Note: **p <0.1; **p <0.05***; p<0.01*

Source: National Census 201 – Instituto Nacional de Estadisticas e Informatica (INEI), Peru.

The first thing that can be observed from these estimates is that the set of explanatory variables included in the model are statistically significant in all the estimated models. However, the signs appear to be somewhat counter-intuitive. In the variable that captures migration, the results indicate that households with at least one migrant household member from another region are less likely to be in a multidimensional poverty household. This result may be because much of the migratory flow amongPeruvian regions has been from the highlands and jungle areas to the coast and not vice versa. In this sense, migration has likely been from impoverished households to coastal cities searching for better economic and living conditions. Therefore, families with migrant members have possibly left poor households and have been able to escape to some degree from the poverty in which they were in their regions of origin. Under this assumption, the resultant sign of estimation makes sense.

For the variable that captures the second language's effect, it is clear that household members with a mother tongue other than Spanish are more likely to be in a poor household. This result is a consequence of the different social problems and cultural discrimination associated with Peru's mother tongue throughout its territory.The cultural and economic supremacy of those who speak Spanish over those whose mother tongue is one of the native languages such as Quechua, Aymara, Ashaninka, and Aguaruna.

Finally, the variable that captures women's effect as heads of a household has a negative and statistically significant sign in all cases. These results are based on the assumption that families led by women are more likely to plan household spending. Family investment decisions are directed towards developing household members' capacities, such as children. These assumptions are based on other research results for different realities, such as Duflo (2012, 1059-1070), who holds that women tend to have better spending decisions within the household than their male counterparts.

Regarding the estimates of spatial effects, it is observed that both the spatial effects coming from the endogenous variable, as well as the errors, are statistically significant in the three estimated models. In the model where only spatial effects on the endogenous variable are incorporated, a positive and statistically significant coefficient is observed, suggesting that multidimensional poverty in a given district increases multidimensional poverty in a neighboring district. In short, multidimensional poverty shows positive spatial effects. Similarly, when the model only includes spatial effects on errors, the spatial effect is positive and statistically significant, as shown in column 3. Finally, when spatial effects are incorporated in both the endogenous variable and the errors, the coefficients are statistically significant at 1% in both cases; however, the endogenous variable coefficient changes to values close to zero. This result could have two possible explanations. First, the spatial effects coming from the endogenous variable are unstable. When other explanatory variables or other sources of spatial effects are incorporated, the coefficient changes in a large proportion. Second, the interaction between the endogenous variable's spatial effects and the errors produces changes in the coefficient of the spatial effects of the endogenous variable, making it even change its sign, although it is essential to notice that the value is negative but very close to zero. In short, this interaction causes the spatial effects coming from the endogenous variable to lose strength until they are minuscule. It is important to note is that the spatial effects of the errors have remained stable and statistically significant, suggesting that there are factors not incorporated into the model that affect the spatial interaction of the multidimensional poverty indicator. Therefore, an increase of 1 in the *MPI* of a district increases a neighboring district's multidimensional poverty by 0.128.

Furthermore, the *Wald* and *Lagrange Ratio* tests in all cases reject the null hypothesis of no spatial interactions; therefore, there is evidence of spatial effects. Also, the *Lagrange Multipliers* test of column 2 rejects the null hypothesis of no spatial interactions in the error terms; i.e. there is evidence that we must include the coefficient λ in our estimations. To support the LM test, the AIC criterion suggests that we must use the models where the spatial effect on the error terms is included.

Table 4. Spatial Effects

	Spatial Autoregressive			Spatial Error and Autoregressive		
	Direct	Indirect	Total	Direct	Indirect	Total
migrant	-0.0626	-0.0062	-0.0688	-0.0593	0.0009	-0.0584
language	0.0083	0.0008	0.0092	0.0226	-0.0003	0.0222
female	-0.2092	-0.0208	-0.2300	-0.1875	0.0029	-0.1846

Table 4 displays extra information where we include the direct and indirect effects that originated in our set of covariates. The direct effects represent the exogenous variable's effect over the endogenous variable without considering any spatial effects. Under no presence of spatial interactions, the direct effect corresponds to the OLS estimator. On the other hand, the indirect effects represent the exogenous variable's effect over the neighboring districts' endogenous variable. The variable endogenous impact goes back to the endogenous variable in the district of analysis through these effects. Direct and indirect effects can only be calculated when the spatial effects are in the endogenous variable or the explanatory variables but not in the errors. Therefore, the table does not incorporate the externalities generated in the spatial error model.

Direct effects are the explanatory variables' effects on the endogenous variable, similar to the OLS model's coefficients. However, in indirect effects, these capture the exogenous variables' externalities on a neighboring district's endogenous variable. The table shows that in some cases, the effects change sign, more specifically, in the whole set of explanatory variables, the externalities captured by the indirect effects change sign depending on the estimated model. This result is due to the observed instability of the endogenous variable's spatial effect coefficient incorporated in the model, as shown in Table 3.

Conclusions

This research studies multidimensional poverty in Peruvian households at the district level using data from the 2017 census. The study's central hypothesis is that multidimensional poverty also has a spatial dimension that has been little studied in the literature.

Among the main results, we find evidence of spatial correlation of the variables that compose the multidimensional poverty indicator's distant dimensions, *MPI*. A positive and statistically significant *Moran* indicator is observed in all cases. Likewise, it is observed that, in most cases, the value of spatial autocorrelation exceeds the value of 0.5, i.e. there are indications of the spatial dimension of poverty.

In the second part of the study, when spatial regressions are estimated for poverty incorporating some control variables, two significant results are observed. First, the set of explanatory variables are all statistically significant across the estimated models. These results are explained by the social, cultural, and economic changes that Peru has undergone in the last decades. Among these changes, we have a strong migration from the countryside to the city, which not only caused low-income families to seek progress in the big cities, but in many cases, people left their cultural background in search of better opportunities. This fact had some consequences over poverty behavior among districts. Second, there is evidence of spatial effects on the endogenous variable and errors. Moreover, there is evidence that the spatial effects originating in errors have a stable value among the models, while the spatial effects originating in the endogenous variable are unstable.

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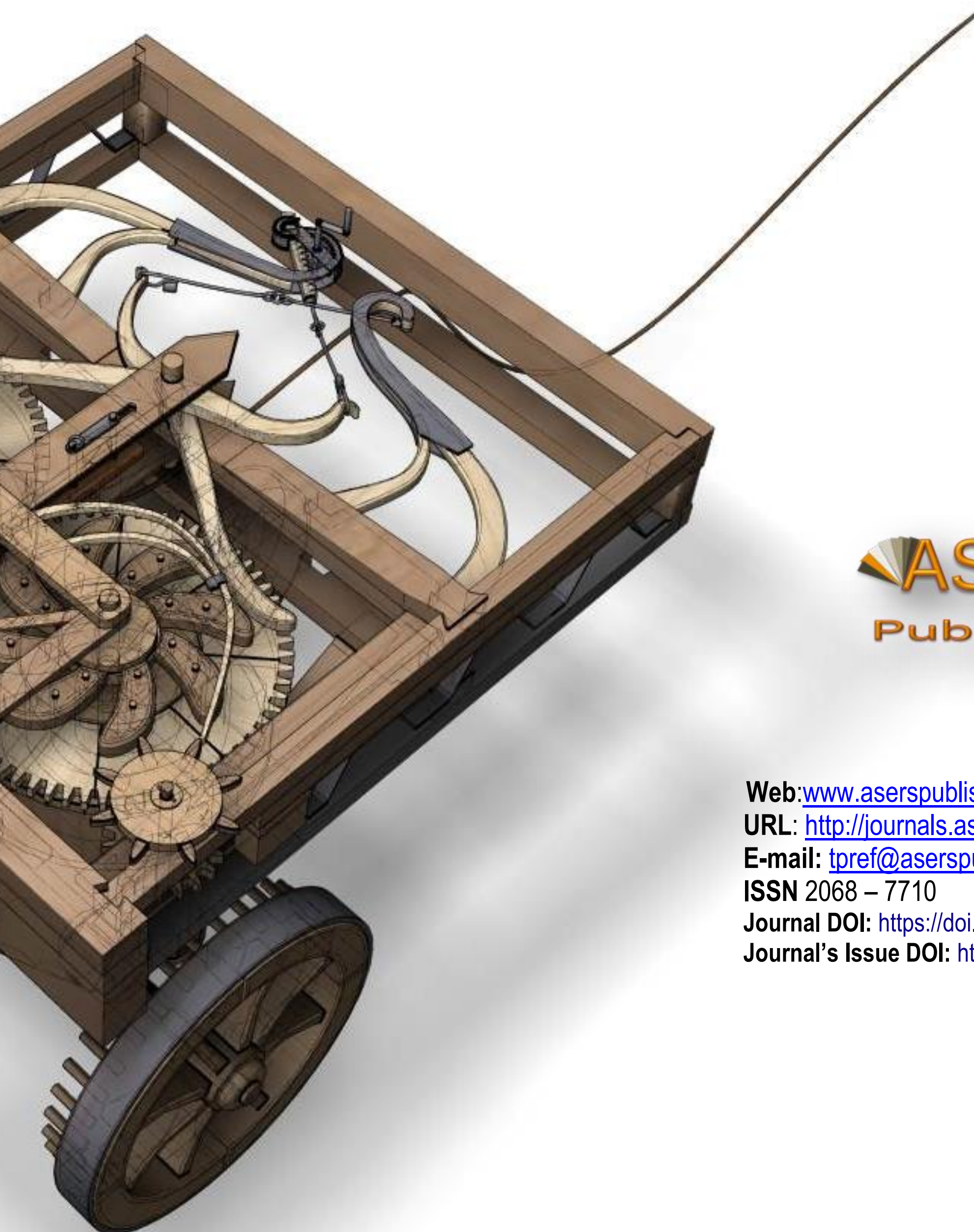

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