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The Drivers of Income Inequality in Cities: A Spatial Bayesian Model Averaging Approach

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Abstract

This study analyzes the drivers of urban income inequality. To that aim, we focus on the case of Spain and derive a novel data set of inequality metrics for a sample of municipalities over the period 2000-2006. Spatial Bayesian Model Averaging techniques are used in order to examine the empirical relevance of a large set of factors taking into account the role of spatial interactions. Our findings suggest that urban inequality is mainly explained by human capital, economic factors and local politics rather than amenities or demography. The results are robust to the use of different spatial functional forms and spatial weight matrices.

Keywords: Income Inequality, Spatial Econometrics, Model Averaging, Spanish Cities.

JEL codes: C11, C15, C21, D31, R10.

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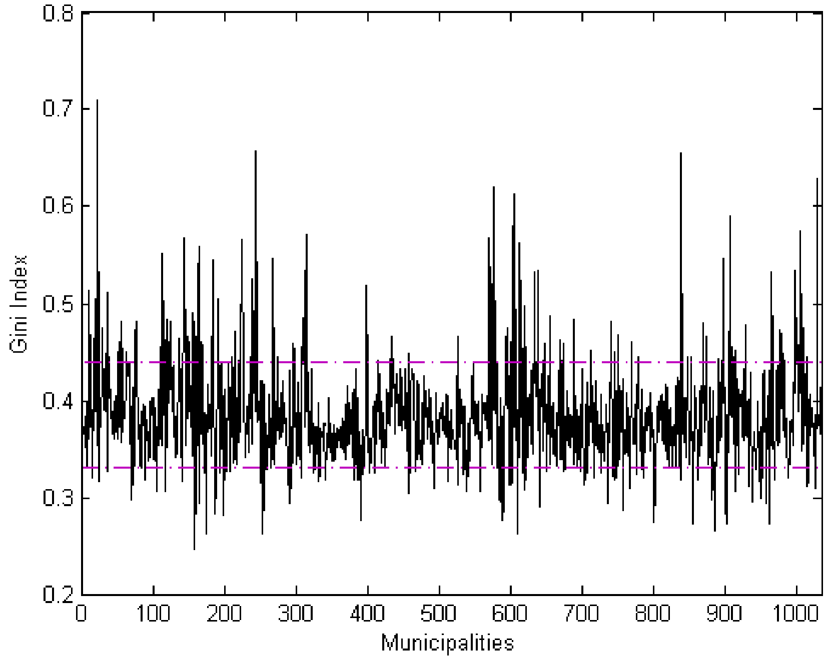
1 Introduction

The study of income inequality is a central issue in economic research and politics, as it is considered to be "one of the biggest social, economic and political challenges of our time" (THE ECONOMIST, 2012). Although it is widely recognized that some degree of inequality in the distribution of income is necessary in order to provide incentives to the most skilled and productive individuals, inequality has a number of negative consequences on the functioning of the society. In their recent study, DABLA-NORRIS *et al.* (2015) assert that inequality: (i) erodes the functioning and quality of the political systems, as it can concentrate political power in the hands of a few elites, resulting in misallocation of resources, corruption and nepotism, (ii) raises the risk of fiscal and financial crises, causing economic instability and reducing growth, (iii) hampers poverty reduction, and (iv) may damage social cohesion and fuel civil and social conflicts, as it lowers intergenerational income mobility and opportunities of the poor. On the other hand, the literature analyzing the drivers of inequality at the country-level has identified various driving forces behind the increase in global inequality levels during the last three decades: (i) technological change and skill premium, (ii) globalization and financiarization, (iii) the decline of some labor market institutions such as trade-union membership, traditionally responsible of the compression in the distribution of wages, and (iv) the progressivity decline of the tax systems in many advanced economies.

To date, however, only a handful of studies have paid attention to the local dimension of income inequality (e.g. GLAESER *et al.*, 2009). The study of income disparities at the city level is particularly relevant given that not only the 54% of the world population lives in cities but also because the widening gap between the bottom- and the upper-tail of the income distribution is leading to important income segregation in many cities worldwide which, in turn, can compromise the social stability and the competitive power of cities as engines of growth (TAMMARU *et al.*, 2015). Moreover, as GLAESER *et al.* (2009) point out, city-level income inequality is likely to be different from national-level income inequality, as it neither responds to the same factors, nor creates the same policy implications. Therefore, the explanatory power of cross-country stylized facts could be compromised at the local level (LEVERNIER *et al.*, 1998).

This being the case, the high cross-sectional variability of local income inequality observed among Spanish cities suggests the need to investigate in depth the causes of income inequality taking into account specific local factors (See Figure 1). A better understanding of the drivers of local income inequality is essential to formulate efficient public policies aimed at curving urban income disparities and to evaluate their effectiveness.

Figure 1: Inequality across Spanish municipalities



To extend our understanding of the patterns and causes of urban inequality, this study draws on a novel data set of local inequality metrics and implements Spatial Bayesian Model Averaging techniques (SBMA, hereinafter) to analyze the drivers of inequality in a sample of Spanish municipalities over the period 2000-2006. The paper makes several novel contributions to the literature.

First, following the methodology described in HORTAS-RICO *et al.* (2014), we derive a novel data set on local income distributions employing Personal Income Tax (PIT) micro-data. With this information in hand, a set of income-related summary measures (including average income, top income shares and inequality measures) are calculated for those municipalities with more than 5,000 inhabitants.

Second, income inequality is analyzed by employing a set of thirty possible explanatory variables that are expected to affect urban inequality patterns. Compared with the limited set of regressors considered in the existing empirical literature, this study rigorously assesses model uncertainty over a larger set of inequality determinants. The set of candidate covariates can be grouped into six categories: (i) economic factors, (ii) demographic characteristics (iii) human capital factors, (iv) fiscal policy, (v) local politics and (vi) local amenities, deemed important for location decisions and population sorting.

Third, building on the theoretical grounds of spatial economics and income inequality theory, we extend previous research on the causes of urban disparities, so as to account for the spatial interaction in the levels of income inequality among Spanish municipalities by means of the Spatial Durbin Error Model (SDEM). It represents, as such, a novel application at the local level, given that previous studies of income inequality at the city level (see, e.g. LEVERNIER *et al.*,1998, GLAESER *et al.*, 2009 or FLORIDA and MELLANDER, 2016) omitted the role of spatial interactions in shaping local inequality patterns.

Finally, and following the previous work by LESAGE and PARENT (2007) and CRESPO-CUARESMA *et al.* (2014), we employ SBMA techniques to perform inference. This methodology is particularly useful to address model uncertainty in the context of spatially interacting municipalities. Contrary to previous studies, where inference is based in single econometric model analysis, the SBMA approach has the advantage of minimizing the likelihood of producing (i) biased estimates and (ii) artificially low confidence intervals (MORAL-BENITO, 2015).

2 Data

2.1 The sample.

In the analysis that follows, municipalities are taken as the geographical unit. The sample data covers almost all the Spanish municipalities with more than 5,000 inhabitants.[1] This is sufficiently representative given that they account for about 85% of the total population. In addition, municipalities above 5,000 inhabitants have the advantage of corresponding to natural political units and they are large enough to provide inequality measures with statistical precision, which makes them suitable for analyzing and discussing public policy.

The analysis covers the 2000-2006 time period. In particular, the income inequality

[1] Ceuta, Melilla, Navarra and the Basque Country together with the Canary and Balearic Islands are dropped from the analysis because of the lack of data.

variable is measured for the year 2006 and most of the explanatory variables are taken in 2001 in order to avoid reverse causality problems. Note that the period of study is particularly relevant to the aim of this paper, since it covers the years of economic growth preceding the financial crisis.

2.2 Income inequality data.

The initial aim is to develop an accurate measure of income inequality so that the driving forces of such phenomenon can be empirically tested. Despite its importance, local income data and, thus, inequality data, remain a key missing element within the official statistics of many developed countries, with Spain being no exception. Household income and expenditure surveys have a territorial representation limited to the regional level, as they do not have a sufficient sampling size to offer a reasonable precision at a smaller level.

To redress this lack of information, a wide range of statistical techniques have been developed over the last two decades aimed at providing reliable estimates of local income. The majority often use micro-data information from surveys, combined with aggregate information about relevant variables for the considered population subgroups. There is, however, a growing body of empirical literature focusing on tax-based research (see, for instance, ATKINSON *et al.*, 2011). PIT samples have emerged as an interesting alternative for overcoming the aforementioned territorial representativeness limitations shown by household surveys when analyzing personal income distributions.

Available micro data on PIT returns from the Spanish Tax Administration Office enable us to derive income distributions at the city level for a representative sample of municipalities. In this study we make use of the 2006 PIT sample, which includes 964,489 records extracted from a population of 17,840,783 personal income tax returns[2]. These micro-level PIT samples are only representative at the provincial level and, therefore, a re-weighting procedure needs to be implemented to derive a representative income sample at the municipal level. As in HORTAS-RICO *et al.* (2014), the methodology employed here relies on a distance function optimization-based approach for survey re-weighting which consists of adjusting the original micro-data

[2]The income variable used is pretax gross income, and it is defined as the sum of salary and wage income, retirement pensions, general unemployment subsidies, some non-exempt welfare payments and some disability pensions, net self-employment income, interest, dividends, royalty income, survivor annuities, net rental and income from other estates including imputed rent for second dwellings homeowners, and realized capital gains (except those from reinvesting in the customary dwelling).

sample weights. Then, local income distributions and selected summary measures can be derived. These data are uniquely qualified to the purposes of the paper; they are the only data containing detailed information on income inequality measures for Spanish municipalities. In particular, we calculate the Gini coefficient at the municipal level as our (pretax) income inequality measure. We use this index as the baseline measure of inequality, mainly because it is the ubiquitous standard in the inequality literature. This index is defined as:

$$G(y) = 1 - 2\int_0^1 L(p;y)\,dp \tag{1}$$

where the Lorenz curve of income $L(p;y)$ at such p-values of ranked relative cumulated-population (so that, $p \in (0,1)$) can be defined mathematically by the expression:

$$p = F(q) \Rightarrow L(p;y) = \int_0^q y f(y) \frac{dy}{d\mu_y} \tag{2}$$

and takes values between 0 (perfect equality) and 1 (complete inequality). [3]

2.3 The determinants of income inequality.

According to the literature, income inequality is driven by a myriad of factors. Human capital is perhaps its most important determinant. Access to education increases the job opportunities and the earning potential of the poor, facilitating their upward mobility. On the other hand, it allows for a more informed participation in the market economy, thus reducing the lobbing ability of the rich (RODRIGUEZ-POSE and TSELIOS, 2009). Educational attainment has an equalizing effect on income distributions and, therefore, educational inequality is expected to be positively correlated to income inequality. FLORIDA (2002) popularized the creative class, an occupational skill concept of a person's capability that reflects accumulated experience, creativity, intelligence, innovativeness and entrepreneurial abilities (FLORIDA, 2008). A greater share of these high-skill workers is expected to be a source of income inequality because of their significantly higher-than-average earnings level, given the existence of positive returns to investment in human capital (MINCER, 1958; CLOUTIER, 1997). In addition, as noted in FLORIDA (2002), income inequality is an unavoidable externality of the rise of the creative class given that a higher proportion of higher-income professionals increases the demand for low-income workers, hence widening the income gap.

[3] Confidence intervals via bootstrap re-sampling methods have been calculated.

On the other hand, an increasing share of low-skilled workers could decrease inequality given the lower dispersion in bottom tail of the income distribution and their compression effect on the overall distribution of income (IZQUIERDO and LACUESTA, 2006). Nonetheless, its effect ultimately depends on the level of minimum wages and the skill distribution across jurisdictions.

Other studies identify the connection between economic factors and income inequality. Even though the a priori effect of average income on inequality is uncertain -depending on whether the increase in income is pro-poor, pro-rich or neutral-, most studies find a positive link between these two variables, reflecting that economic development seems to increase the occupational choices and the earning opportunities of the rich (RODRIGUEZ-POSE and TSELIOS, 2009; FLORIDA and MELLANDER, 2016). The effect of unemployment is also undetermined. A higher unemployment rate decreases the access to wages, which is the main source of income, but its net impact on income inequality would depend on whether unemployment inflows have a larger impact at lower or higher wage segments. In addition, job protection and unemployment benefits are key factors in shaping income distributions, as they can lower inequality through smaller income dispersion (OECD, 2012a). A large literature has documented the industry mix effects on inequality. On the one hand, manufacturing, services and construction sectors have historically allowed low qualified workers to earn relatively high-wages, suggesting that increases in these sectoral shares should lead to more equal income distributions (CLOUTIER, 1997). On the other hand, the agriculture sector is expected to increase income inequality because the strong variation in farm size leads to a greater dispersion of earnings between farmers (LEVERNIER et al., 1995). As concerns female participation, some previous empirical evidence finds a negative effect (LEVERNIER et al., 1998; RODRIGUEZ-POSE and TSELIOS, 2009). However, this result is somewhat unexpected, since its net effect ultimately depends on whether increasing female labor-force participation contributes or not to narrowing the existing gender-wage gap (GONZALES et al., 2015). If female have lower-than-average earnings due to either shorter working hours or wage discrimination in the labor market, then an increase in female participation should have an income inequality-enhancing effect (OECD, 2012a). Other studies have focused their attention on housing values, since increasing housing prices favor landlords and rentiers with respect to renters, thus contributing to an increasing net capital income gap between the two groups (ROGNLIE, 2015). Recent evidence suggests that differences in income have been capitalized into housing prices, reducing returns to living in productive places net of housing costs for unskilled workers, hence forcing them to move out and locate in less productive areas (GANONG and SHOANG, 2014).

In addition, increasing housing prices may exacerbate inequality and block access to opportunities for upward mobility given that as rent consumes an increasing share of a family's budget, educational expenditures decrease, undermining youth prospects and impeding mobility. In the same vein, BONNET et al. (2014) cast some doubt on the impact of homeownership rates on income inequality, since the inter-generational inequality could be balanced by intra-generational equality gains.

Demographic characteristics are also deemed important in shaping income distributions. For instance, the share of immigrants is expected to be a factor in widening inequality, since they tend to earn less than natives (even for similar levels of education) and are likely competing for low-skill jobs, increasing the supply of less-skilled labor and depressing the wages of low-income workers, hence exacerbating existing wage differentials (TOPEL, 1994). Similarly, older populations tend to be characterized by higher income inequality as a result of the accumulation of sequences of transitory shocks that hit households at the lower end of the wage and salary distribution (GUVENEN et al., 2015). On the contrary, increasing household size is expected to produce consumption complementarities and consumption scale economies, reducing the need for high per capita income and thickening the bottom-tail of income distribution (OECD, 2012b). LEVERNIER et al. (1995) and FLORIDA et al. (2008) find that urban populations are expected to increase inequality as existing agglomeration effects disproportionally benefit high-skilled workers given that knowledge tends to diffuse at a faster rate than in rural places, which ultimately reinforces the skill Premium.

Governments have also been active players driving income inequality. As noted in previous studies, income inequality also depends on local policy decisions (GLAESER et al., 1995). As explained in AFONSO et al, (2008), the level of taxation and its progressivity is perhaps the most direct factor reducing income inequality, whereas public spending can affect income distribution directly (e.g., via income transfers and cash payments to poorer individuals) or indirectly (e.g., via spending decisions that improve productivity and job access to the less well off). Similarly, intergovernmental transfers are expected to reduce income inequality, since they provide local governments with an additional source of revenues for public service provision.

Income inequality may also depend on factors related to the political preferences and stability of the local council (TIEBOUT, 1956). Thus, a higher share of votes to left-wing parties is expected to reduce inequality, as parties on the left of the political spectrum tend to promote redistributive policies. The role of government strength and partisan ideological alignment is uncertain, as it depends on the amount of grants received by local governments as well as on the composition of public expenditures. Finally, corruption is expected to be positively associated to income inequality given that it can increase rent-seeking and bribe-taking, thus distorting local governments' efficiency and resource allocation, increasing the operating costs of government and reducing the amount of revenues available for other (welfare/social) services. Similarly, corrupt governments are likely to take biased decisions favoring the well-connected individuals, which are commonly the wealthy elites (GUPTA et al., 2002).

Attempting to explain changes in the income distribution, economists have also considered the impact of local amenities (such as crime rates, urban blight, accessibility or leisure activities, among others). The effect of the amenity covariates is somewhat uncertain and depends on the population shifts they induce and how they affect the population composition in both the origin-destination municipalities. According to the Tieboutś model (TIEBOUT, 1956), individuals are mobile and sort themselves into jurisdictions according to their preferences, so that they create homogeneous communities of like income or race. This mobility hypothesis is particularly relevant among rich people for whom mobility costs are lower. In this setting, certain positive amenities (such as road accessibility) may draw high-income residents to a particular location, whereas certain city problems (such as crime or blight) might encourage their flight from blight.

Definitions, abbreviations, descriptive statistics, data sources and expected effects are presented in Table (1).

Table 1: Definitions, sources and descriptive statistics of the explanatory variables

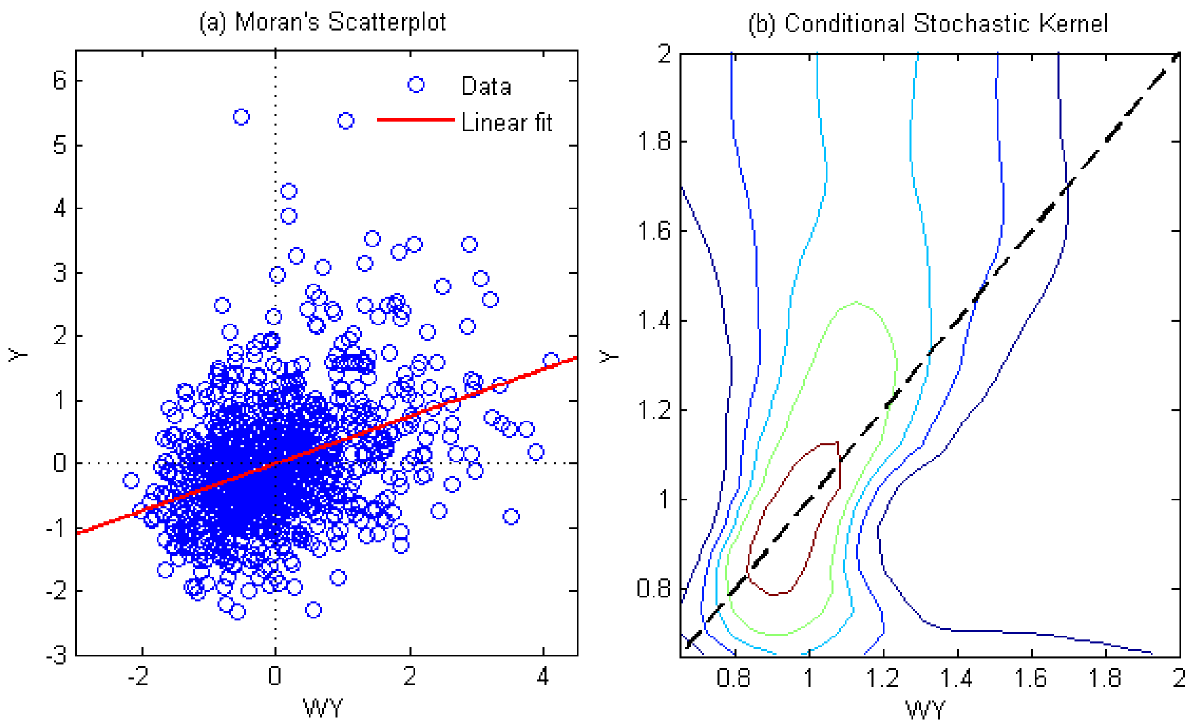
Variable	Definition	Source	Mean	Std	Expected Effect
(i) Human capital					
Creative class (CC) [(1)].	Share of professional and knowledge-work occupations	INE	0.17	0.07	+
Low-skilled workers (LSK)	Share of workforce employed in low-skilled job	INE	0.14	0.08	?
Educational inequality (GED)[(2)]	Gini index of educational attainment	INE	0.41	0.06	+
(ii) Economic factors					
Average income (Y)	Per capita income 2002 (logs)	TAO	9.51	0.26	?
Unemployment rate (U)	Share of the 16 years or older population that is unemployed	INE	0.14	0.07	?
Manufacturing (IND)	Share of workforce employed in manufacturing	INE	0.20	0.12	-
Construction (CON)	Share of workforce employed in construction	INE	0.14	0.06	-
Services (SS)	Share of workforce employed in services	INE	0.33	0.11	-
Agriculture (AG)	Share of workforce employed in agriculture	INE	0.09	0.11	+
Female participation (FEM)	Female share of the labor force	INE	0.42	0.08	?
Housing values (HV)	Average housing value within each municipality (logs)	PAO	12.30	1.19	+
Homeownership rate	Share of houses occupied by owner	INE	0.83	0.06	?
(iii) Demographic factors					
Urban (URB)	Dummy variable, 1 if the municipality belongs to an urban area, 0 otherwise	Boix et al (2012)	0.59	0.49	+
Immigrants (MIG)	Share of immigrants in the resident population	INE	0.04	0.05	+
Old (O)	Share of total resident population that is 65 years or older	INE	0.16	0.04	+
Household size (HS)	Average number of individuals per household (logs)	INE	1.08	0.09	-
(iv) Fiscal policy					
Taxation (TAX)	Per capita regional government revenues from the personal income tax (logs)	SMF	5.54	0.47	-
Public Spending (G)	Per capita regional government total expenditure (logs)	SMF	7.81	0.14	-
Transfers (TSF)	Per capita total local revenues from transfers (logs)	SMF	5.46	0.33	-
(v) Politics					
Left (LFT)[(3)].	Vote share of the left-wing parties in the municipal council.	MHA	0.54	0.18	-
Govt strength (GS)	Share of seats held by the major's party in the municipal council	MHA	0.52	0.11	?
Regional alignment (AR)[(4)]	Dummy variable, 1 if regional and local governments are aligned, 0 otherwise	MHA	0.27	0.44	?
National alignment (AN)[(4)]	Dummy variable, 1 if national and local governments are aligned, 0 otherwise	MHA	0.43	0.49	?
Corruption (CORR)[(5)]	Combined max-min normalized local-regional corruption index	Press reports	0.55	0.43	+
(vi) Local amenities					
Urban blight (HP)[(6)].	Share of total houses with problems	INE	0.23	0.09	?
Crime (CR)	Number of crimes and misdemeanors per 1,000 inhabitants (logs)	INE	0.04	0.02	?
Bars and restaurants (BR)	Number of bars and restaurants per 1,000 inhabitants (logs)	INE	1.77	0.40	?
Road accessibility (RD)[(7)]	Distance from the municipality centroid to the nearest road (logs)	NGI and GIS	8.03	1.22	?
Urban sprawl (US)[(8)].	% of undeveloped land around residential land within the inmediate neighborhood	CLC and GIS	0.63	0.17	?
Distance to coast (CST)	Distance from the municipality centroid to the coast	NGI and GIS	72.35	92.79	?

Notes: Unless specified all control variables are taken at year 2001 and at the level of municipality, except for *taxation* and *total spending* which are measured at the regional level. Distance-based variables have been calculated using Geographical Information Systems (GIS). INE denotes the National Statistics Institute. Most of INE data is comes from the Census of Population and Housing. PAO denotes Property Assesment Office, TAO denotes Tax Adminstration Office, SMF is the Spanish Ministry of Finance, and MHA is the Ministry of Home Affairs. NGI denotes National Geographic Institute and CLC denotes Corine Land Cover data. (1) Includes management occupations, business and financial operations, scientists and intellectuals. (2) Own calculations using the proportion of resident population without studies, with primary, secondary and terciary studies. (3) Parties on the left are: PSOE, PCE, IC, and several left regionalist parties. (4) Regional or national and local governments are aligned if they are controlled by the same party. (5) The index is constructed as: $CI = \left(\frac{C_i - C_{min}}{C_{max} - C_{min}}\right)$ where $C_i = 0.5CC_i + 0.5CR_i$ with CC_i a dummy variable indicating whether there have been corruption scandals in the municipality and CR a continuous variable with the number of corruption scandals in the region. (6) The type of problems considered are noise, dirty, pollution or lack of green space. (7) This variable is constructed by means of GIS. In order to avoid endogeneity problems due to reverse causation, a historical road map (main and secondary roads constructed before the end of the 18th century) has been used as a source of exogenous variation for the definition of the variable. (8) See GÓMEZ-ANTONIO *et al.* (2016) for further details on the definiton of this variable.

3 Econometric Methodology

With the aim of providing a first insight into the spatial pattern of inequality in Spanish municipalities, Figure (1a) displays the Moran's scatter plot. The slope of the regression line is Moran's I statistic and takes a value of 0.22 (p-value 0.00), suggesting that municipalities with high inequality are surrounded by municipalities with high inequality.[4] As a further check on the role played by spatial location of the various cities explaining income inequality outcomes, we estimate a stochastic kernel following the methodology outlined by MAGRINI (2009). Stochastic kernel estimation allows to capture the transitions between the original distribution and the neighbor-relative income inequality distribution. The estimation results shown in Figure (1b) reveal that the probability mass tends to be located parallel to the axis corresponding to the original distribution. Accordingly, spatial effects appear as a relevant factor explaining the observed variability in urban inequality. These findings regarding the role of space suggest that it is necessary to accommodate such interdependence in the modeling process and that an explicit accounting for spatial effects is required by means of spatial econometric models.

Figure 1: Spatial Patterns of Inequality



[4] To compute this statistic we employ a 5 nearest neighbor row-normalized spatial weight matrix.

Econometric studies of LEVERNIER *et al.*, (1998), GLAESER *et al.* (2009) or FLORIDA and MELLANDER (2016) analyze inequality at the urban level but treat the units of analysis as isolated entities, ignoring the spatial characteristics of the data and the potential role of space modulating the economic evolution of inequality at the city level. [5] Nevertheless, insofar every municipality evolves interacting with other municipalities, as suggested by the preliminary evidence in Figure (2), major problems may arise if the spatial characteristics of the data are ignored. The consequences of omitting these interactions from the model specification are potentially important from an econometric perspective, and may cause estimates to become biased, inconsistent and/or inefficient (ANSELIN, 2006; ELHORST, 2014).

As a matter of fact, there could be three different types of interaction effects operating through space that can be distinguished: (i) endogenous interaction effects among the dependent variable, (ii) exogenous interaction effects among the independent variables and (iii) interaction effects among the disturbance terms (ELHORST, 2014). The baseline model used in this study is the Spatial Durbin Error (SDEM) which contains both exogenous and error term interactions. The SDEM reads as:

$$\begin{aligned} y = \alpha\iota_n + X\beta + WX\theta + \epsilon \\ \epsilon = \lambda W\epsilon + \upsilon \end{aligned} \tag{3}$$

where y denotes a $N \times 1$ dimensional vector consisting of observations for the Gini index in the year 2006 for municipality $i = 1, \ldots, N$ and X is an $N \times K$ matrix of exogenous aggregate political, socioeconomic and economic covariates with associated response parameters β contained in a $K \times 1$ vector. α reflects the constant term, ι_n is a $N \times 1$ vector of ones while λ is the spatial diffusion coefficient which captures spatially correlated shocks working through the error term $W\epsilon$. W is a $N \times N$ is a row-standardized matrix of known constants describing the spatial arrangement of the municipalities in the sample. In addition, the model includes the spatial lag of the rest of control variables (exogenous effects), WX, whose impact is reflected by the $K \times 1$ vector of coefficients θ. Finally, $\upsilon = (\upsilon_1, \ldots, \upsilon_N)'$ is a vector of i.i.d disturbances whose elements have zero mean and finite variance σ^2.

Two points are worth mentioning with respect the choice of the SDEM as our benchmark specification. First, it does not require a theoretical model for spatial or social interaction process as common in the case in spatial models including endogenous interactions. Indeed, as explained by GIBBONS and OVERMAN (2012) and

[5] The only exceptions are EZCURRA (2007) and RODRIGUEZ-POSE and TSELIOS (2009) but these analysis are carried out at the regional level.

HALLECK-VEGA and ELHORST (2015), spatial models containing endogenous interactions are generally difficult to justify from a theoretical basis. In the context of income inequality, endogenous interactions would lead to a scenario where changes in one city set in motion a sequence of adjustments in (potentially) all units in the sample such that a new long-run steady state equilibrium of income inequality arises. Second, the SDEM has the advantage of producing local spillovers given by θ, which allows to analyze whether there are important differences in the magnitude of impact associated to a regressor X_j within the city and outside the city WX_j affecting inequality.[6]

As shown in Section 2.3, there are a large number of potential determinants of income inequality at the local level, which results in substantial uncertainty on the true model of inequality. A large literature on Bayesian Model Averaging (BMA hereinafter) over non-spatial regression models containing different variables exists (FERNANDEZ *et al.*, 2001a, b). However, BMA is employed here for spatial econometric models. SBMA allows to consider all possible combinations of regressors and takes a weighted average of the coefficients. Sub-structures of model in Equation (3) are given by subsets of coefficients $\eta^i = \left(\delta^i, \lambda\right)$ with $\delta^i = \left[\alpha^i, \beta^i, \theta^i\right]$ and regressors $Z_i = [X_i, WX_i]$. Assuming that the total number of possible explanatory variables is K, the total number of possible models is 2^K and $i \in \left[0, 2^K\right]$. Inference on the parameters attached to the variables in $Z = [X, WX]$ explicitly takes into account model uncertainty and it is based on probabilistic weighted averages of parameter estimates of individual models:

$$p\left(\eta|y, Z\right) = \sum_{i=1}^{2k} p\left(\eta_i|M_i, y, Z\right) p\left(M_i|y, Z\right) \tag{4}$$

The weights, the posterior model probabilities (PMPs) are given by:

$$p\left(M_i|y, Z\right) = \frac{p\left(y, Z|M_i\right) p\left(M_i\right)}{\sum_{k=1}^{2k} p\left(y, Z|M_k\right) p\left(M_k\right)} \tag{5}$$

Model weights can be obtained using the marginal likelihood of each individual model after eliciting a prior over the model space. The marginal likelihood of model M_i is given by:

$$p\left(y, Z|M_i\right) = \int_0^\infty \int_{-\infty}^\infty \int_{-\infty}^\infty p\left(y, Z|\delta, \lambda, \sigma, M_i\right) \tag{6}$$

[6]Note that this does not necessarily rule out consideration of spillover impacts involving great distances, since this ultimately depends on the functional form of W.

The following priors are used following LESAGE and PARENT (2007):

(i) $\pi_{\delta_i}\left(\delta_i|\sigma^2\right) \sim N\left[0, \sigma^2\left(g_i Z_i' Z_i\right)^{-1}\right]$

(ii) $\pi_s\left(\sigma^2\right) = \frac{\left(v\bar{s}^2/2\right)^{\frac{v}{2}}}{\Gamma(v/2)}\left(\sigma^2\right)^{-\left(\frac{v+2}{2}\right)} exp\left(-v\bar{s}^2/2\sigma^2\right)$

(iii) $\pi_r\left(\lambda\right) \sim \frac{1}{Beta(a_0,a_0)}\frac{(1+\lambda)^{a_0-1}(1-\lambda)^{a_0-1}}{2^{2a_0-1}}$.

Often, Bayesian analysis tries to avoid situations where the conclusions depend heavily on subjective prior information by relying on diffuse or non-informative prior distributions. As parameters governing the prior distributions such as the prior variance increase, the prior distributions become more vague or diffuse. Non-informative priors are obtained in this context by setting $v = 0$, $s =$ and $a_0 = 1.01$. Also note that the g-prior is employed for the model parameters such that the hyper-parameter takes the value of $g_i = 1/max\left\{n, k_{M_i}^2\right\}$ which combines the unit information prior (g-UIP) and the risk inflation criterion prior (g-RIC). This prior scales the variance of the coefficients in δ reflecting the strength of the prior. Lastly, a binomial prior on the model space is employed: $p\left(M_i\right) = \phi^{k_i}\left(1-\phi\right)^{K-k_i}$, where each covariate is included in the model with a probability of success ϕ. We set $\phi = 1/2$ which assigns equal probability $p\left(M_i\right) = 2^{-K}$ to all the models under consideration. The Posterior Mean (PM) of the distribution of η is:

$$E\left(\eta|y,Z\right) = \sum_{i=1}^{2k} E\left(\eta_i|M_i,y,Z\right)p\left(M_i|y,Z\right) \tag{7}$$

while the Posterior Standard Deviation (PSD) reads as:

$$PSD = \sqrt{Var\left(\eta|y,Z\right)} \tag{8}$$

where the $Var\left(\eta|y,Z\right)$ is given by:

$$\begin{aligned} Var\left(\eta|y,Z\right) = & \sum_{i=1}^{2k} Var\left(\eta_i|M_i,y,Z\right)p\left(M_i|y,Z\right) + \\ & \sum_{i=1}^{2k}\left(E\left(\eta_i|M_i,y,Z\right) - E\left(\eta|y,Z\right)\right)^2 p\left(M_i|y,Z\right) \end{aligned} \tag{9}$$

where the first term reflects the variability of estimates across different regression models and the second term captures the weighted variance across different models. Finally, we compute the posterior inclusion probability (PIP) as the sum of probabilities of models including a given variable k, which reflects the probability that a particular regressor j is included in the true model:

$$PIP = p\left(\eta_j \geq 0|y, Z\right) = \sum_{i=1}^{2k} p\left(\eta_{i,j}|M_i, y, Z\right) p\left(M_i|y, Z\right) \tag{10}$$

FELDKIRCHER and ZEUGNER (2011) note that for small number of regressors it is possible to enumerate all combinations of variables. However, given our set of potential explanatory factors it is impossible to evaluate our full model space of size. For this reason, we use the Monte Carlo Markov Chain Model Composition (MC^3) methodology for spatial models developed by LESAGE and PARENT (2007) which builds upon MADIGAN and YORK (1995). The key feature of this econometric procedure is that it eliminates the need to consider all possible models by constructing a sampler that explores relevant parts of the large model space. The algorithm operates in the model space as follows. If we let M denote the current state of the chain, models are proposed using a neighborhood , $nbd(M)$ which consists on the model itself and models containing either one variable more (*birth step*) or one variable less (*death step*) than M. A transition matrix q, is defined by setting $q(M \rightarrow M') = 0$ for all $M' \notin nbd(M)$ and $q(M \rightarrow M')$ constant for all $M' \in nbd(M)$. The proposed model M', is compared with the current model state M using the acceptance probability:

$$P = min\left[1, \frac{p\left(M'|y\right)}{p\left(M|y\right)}\right] \tag{11}$$

The vector of log-marginal values for the current model M and the proposed alternative models M' are scaled and integrated to produce Equation (11). In addition to the birth and death steps, the sampler employed here includes a third strategy to create models which LESAGE and PARENT (2007) label as *move step* consisting on replacing randomly variables in X with variables not included currently in the model which leaves the model proposal M' with the same dimension as M.

4 Main Results

Table (2) reports the results obtained under the SDEM specification when implementing the MC^3 algorithm for the 5,000 top models out of the 60,690 generated by the sampler and a W matrix based on the 5-nearest neighbor's.[7] As usual in

[7]The number of draws to carry out the sampling exercise on the model space was 100,000.

BMA exercises, the concentration of the posterior density in this context is very high. In particular, the top 1% models concentrate the 52.3% of mass, while the top 5% concentrate the 81.6%. We scale the PIPs of the different variables in quartiles to classify evidence of robustness of inequality regressors into four categories so that regressors with PIP $\in [0-25\%]$ are considered as weak determinants, variables with PIP $\in [26-50\%]$ as moderate determinants, with PIP $\in [50-75\%]$ as substantive and with PIP $\in [75-100\%]$ as highly important.

As observed, there is a consistent set of top variables that appears with high frequency in the group of very important determinants. The creative class (100%) is the main driver of local income inequality, followed by a wide range of economic factors, including the share of employment in services (99.9%) or manufacturing (99.9%), housing values (90.1%), average income (84.4%) or the unemployment rate (78.1%). In the group of substantive determinants we find the educational inequality (69.9%), the total spending at the regional level (63.1%) and the level of corruption (55.1%). The local council's ideology (40.3%), the neighbor's local government strength (39.2%) and the neighbor's household size (28.85%) are found within the set of moderate determinants. Finally, weak inequality drivers include demographic factors and local amenities, as well as all other variables reflecting neighbors' characteristics. Overall, our findings suggest, on the one hand, that human capital and economic factors are the key factors shaping local income distributions, even though politics and fiscal policy factors also play a non-negligible role. On the other hand, local income inequality is mainly determined by own city characteristics and, to a lesser extent, by certain neighboring factors, suggesting the need to consider the role of exogenous spatial interaction effects when analyzing income inequality.

We now turn our attention to the model averaged estimates of the SDEM, as they provide the basis for posterior inference regarding the parameters. Model averaged estimates were constructed based on the alternative sets of variables identified by the MC^3 procedure. These results are presented in Table (3) and are based on the 5,000 highest probability models which accounted for 90.35% of the posterior probability mass. As conventional, the model probabilities were normalized to the unity. To conserve space, only the variables that are significantly different from zero are reported.

First, we consider the impact of human capital. As expected, the creative class and the educational inequality are the primary indicators of income inequality. Both variables increase the proportion of higher-than-average income workers, all else equal, widening the income gap. In general, our findings confirm those of previous studies that find evidence of a positive relationship between higher proportions of high-

Table 2: Income Inequality Determinants Posterior Inclusion Probabilities

Variable	PIP	Rank	Variable	PIP	Rank
Creative Class	1.0000	1	W*Urban blight	0.0202	31
Manufactures	1.0000	2	Bars	0.0198	32
Services	1.0000	3	Crime	0.0194	33
Housing Values	0.9000	4	W*Bars	0.0194	34
Average Income	0.8444	5	Taxation	0.0190	35
Unemployment rate	0.7810	6	W*Taxation	0.0186	36
Educational inequality	0.6998	7	W*Crime	0.0184	37
Public Spending	0.6310	8	Construction	0.0166	38
Corruption	0.5514	9	Inmigrants	0.0164	39
Left	0.4032	10	W*Creative	0.0158	40
W*Govt strength	0.3918	11	W*Left	0.0156	41
W*Household Size	0.2846	12	W*Regional Alignment	0.0156	42
W*Trasfers	0.1950	13	Regional Alignment	0.0154	43
Old	0.1760	14	National Alignment	0.0152	44
W*Female participation	0.1702	15	W*Agriculture	0.014	45
W*Unemployment rate	0.0822	16	W*Services	0.0134	46
Distance to coast	0.0732	17	Homeownership rate	0.013	47
Household Size	0.0722	18	Urban blight	0.013	48
W*Corruption	0.0532	19	Agriculture	0.0126	49
W*Distance to coast	0.0530	20	Transfers	0.0125	50
W*Public Spending	0.0510	21	W*Educational inequality	0.0124	51
Female participation	0.0482	22	Govt strength	0.0118	52
Low-skilled workers	0.0424	23	Road Accesibility	0.0118	53
W*Construction	0.0386	24	Urban Sprawl	0.0118	54
W*Housing Values	0.0366	25	W*Road Accesibility	0.0116	55
W*Manufactures	0.0324	26	W*National Alignment	0.0110	56
W*Average Income	0.0302	27	W*Urban sprawl	0.0106	57
W*Low-skilled workers	0.0268	28	W*Urban	0.0102	58
W*Immigrants	0.0222	29	Urban	0.0096	59
W*Old	0.0221	30	W*Homeownership rate	0.0096	60

Table 3: Model Averaged Estimates

Variables	Lower 1% Interval	Posterior Mean	Upper 99% Interval	Posterior Standard Dev
Human Capital Factors				
Creative Class	0.2727	0.3523	0.4807	0.0603
Educational Inequality	0.0847	0.1288	0.1745	0.0441
Economic Factors				
Average Income	0.0358	0.0545	0.0780	0.0161
Unemployment rate	-0.1584	-0.1102	-0.0735	0.0336
Manufactures	-0.1183	-0.0929	-0.0751	0.0196
Services	-0.2624	-0.2163	-0.1671	0.0383
Housing Values	0.0058	0.0071	0.0088	0.0020
W*Unemployment rate	-0.1695	-0.1128	-0.0430	0.0491
W*Construction	-0.1420	-0.1000	-0.0523	0.0567
W*Housing Values	0.0024	0.0054	0.0081	0.0032
Female Participation	0.0203	0.0719	0.1033	0.0322
W*Female Participation	0.0482	0.0826	0.1244	0.0392
Demographic Factors				
Household Size	-0.0571	-0.0423	-0.0095	0.0234
Population $>$ 65	0.0829	0.1570	0.2290	0.0577
W*Household Size	-0.1071	-0.0765	-0.0384	0.0340
Fiscal Policy Factors				
Public Spending	-0.1012	-0.0532	-0.0327	0.0197
W*Transfers	-0.1121	-0.0861	-0.0498	0.0368
Political Factors				
Left	-0.0399	-0.0312	-0.0220	0.0110
Corruption	0.0176	0.0248	0.0323	0.0089
W*Gov Strength	-0.1175	-0.0901	-0.0715	0.0034
W*Corruption	0.0078	0.0260	0.0425	0.0149

skilled workers and higher inequality in educational attainments, both at the regional (FLORIDA *et al*, 2008; FLORIDA and MELLANDER, 2016; RODRIGUEZ-POSE and TSELIOS, 2009) and at the local level (GLAESER*et al.*, 2009).

Similarly, most of the economic controls are statistically significant and have the expected sign. The greater the average income, the higher the income inequality. This result is in line with RODRIGUEZ-POSE and TSELIOS (2009) results, but clashes with those reported in FLORIDA and MELLANDER(2016) and GLAESER *et al.* (2009), where higher levels of income are associated with more equal income distributions. Higher housing values also exert a positive effect on income inequality, as predicted by GANONG and SHOAG (2014). The share of female workforce also has a positive effect, which likely reflects the lower-than-average earnings of this labor group due to either shorter working hours or wage discrimination in the labor market. Evidence supporting this hypothesis has been found in WHEELER (2008). Additionally, we also find that the share of employment in services, manufacturing and (neighboring) construction (sectors associated with relatively high earning for relatively low-skilled workers) correlate negatively with local income inequality, as in RODRIGUEZ-POSE and TSELIOS (2009) or CLOUTIER (1997), among others. Somewhat surprisingly, the local unemployment rate and that of the neighboring jurisdictions help reducing the income gap. Job protection and unemployment benefits could explain this result, as they help equalizing income distributions (OECD, 2012a).

As regards the demographic factors we find that, on the one hand, household size is associated with a decrease in income inequality whereas, on the other hand, the income gap increases with the percentage of individuals older than age 65 in the local population. The fiscal policy factors also affect income inequality. As expected, both public spending and intergovernmental transfers received from upper tiers of governments exert a redistributive role on the local economies and help narrowing income distributions.

Considering the political factors, the empirical results show that income inequalities are lower in those municipalities with a greater vote share of the left-wing parties in the local council. This result is in line with our expectations, since the theoretical role of parties to the left of the political spectrum is to promote an active intervention in the economy and encourage the redistribution of income through public policies. We also find that the greater the government strength, the lesser the income inequality. Finally, we find evidence of the distributional consequences of corruption. In particular, corruption is positively associated local income inequality, as it creates permanent distortions that affect the government role in resource allocation - reducing the level of social services available to the poor - and it is also likely to accrue to the better-connected individuals in society, who belong mostly to the high-income groups (GUPTA *et al.*, 2002).

Finally, in order to verify the results obtained regarding the empirical relevance and the estimated effects of income inequality drivers do not depend on the concrete functional form and spatial weight matrix employed, we perform a robustness analysis taking into account a large number of spatial interaction matrices and different spatial functional forms, which ultimately imply different spatial spillover processes. All in all, the results obtained are quite similar to those reported in the paper (see Appendix).

5 Conclusions and Policy Implications

Income inequality has attracted much attention in economic research. The bulk of this literature is devoted to the analysis of inequality at the national or regional level, whereas only a few studies have focused their attention at the local level. This paper seeks to contribute to the existing empirical literature so as to extend our understanding of the patterns and drivers of urban income inequality. Overall, the present study represents a starting point for spatial income inequality analysis at the local level.

To that aim, we focus on the case of Spain and draw on a novel database of inequality metrics for a sample of Spanish municipalities over the pre-crisis period 2000-2006. According to the literature, however, there are a large number of potential determinants of income inequality at the local level, which results in substantial uncertainty on the true model of inequality. Hence, this paper analyzes the nature of robust determinants of income inequality in Spain using BMA techniques in the presence of model uncertainty. Furthermore, the paper takes into account the spatial dimension of the data and the role of space in modulating the economic evolution of income inequality within cities.

The empirical results show that urban inequality outcomes are mainly determined by (i) human capital, (ii) economic factors (including per capita income and sectoral composition of employment) and, to a lesser extent, (iii) the level of regional spending, and (iv) corruption. The inclusion probabilities for these variables are 0.5 and higher. These results are also robust to the use of different spatial functional forms and spatial weight matrices. Estimates for the variables allow us to examine the magnitude and the direction of impact on local income inequality associated with the variables that exhibit high probabilities of inclusion. Finally, the significance of several neighboring variables reveals the need to account for the spatial dimension of the phenomenon in the modeling process.

Tackling the income distribution issue is an important task of any government's policy. Central and regional governments can modify income distributions via progressive taxes, redistributive public policies or regulations affecting the labor market and favoring the development of specific sectors. Similarly, local policy makers have a handful of tools (such as social services spending, economic development to housing or zoning regulations) they could use for minimizing educational inequality, improving social mobility and sustaining income diversity in cities. In the same vein, local authorities could also help improving performance and local political accountability, since policies that reduce corruption are likely to reduce income inequality as well.

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7 Appendix. Robustness checks

The sensitivity of the main findings presented in the paper can be explored in a number of different ways. First, we examine to what extent the results are contingent on the specific spatial model used to investigate the drivers of inequality. In fact, the analysis performed so far is based on the SDEM with a 5-nearest neighbor's matrix. As discussed in Section 3, there are important reasons to justify the employment of the SDEM as the baseline specification in this particular context. Nevertheless, it is worth mentioning that the SDEM is a local spillover specification. In view of this and in order to complement previous results, alternative spatial spillover specifications are considered. In particular, we estimate the *Spatial Exogenous Lag Model* (SLX) and the *Spatial Durbin Model* (SDM) given by the following equations:

$$y = \alpha\iota_n + X\beta + WX\theta + \upsilon$$

and

$$y = \alpha\iota_n + \rho Wy + X\beta + WX\theta + \upsilon$$

where $\upsilon \sim i.i.d.$. Additionally, we consider the more parsimonious *Spatial Lag Model* (SLM) and *Spatial Error Model* (SEM) specifications which can be obtained imposing the following parameter restrictions on the SDM (converges to SLM if $\theta = 0$ and to the SEM if -$\rho\beta = \theta$) and the SDEM (converges to the SEM if $\theta = 0$).

Figure (A1) reports the PIPs of the different controls for the different specifications. As it can be seen, the main findings remain unaltered. In all the specifications under consideration the variables tend to fall within the same group of relevance. Importantly, the group of important determinants of inequality (creative class, productive structure, housing values, average income and unemployment) is highly robust, being the only exception the relevance of average income in the SLX model, which now falls into the substantive determinants group. Similar results in terms of robustness are obtained for the group of substantive determinants (educational inequality, regional public spending and corruption), as the various spatial models produce PIPs within the 50-75% range. However, in the group of moderate determinants (local council's ideology, neighbor's government strength and neighbor's household size) the PIPs fluctuate more strongly and depend on whether the functional form includes spatial dependence in the error term (higher PIPs) or in the dependent variable (lower PIPs). We find this is also the case in the group of weak drivers, where the share of elderly, distance to coast, neighbor's transfers and female participation are included.

A further consideration is to check whether the sign and averaged impact of the different variables is consistent across spatial models. To that end, Figure (A2) reports the conditional posterior distribution of the parameters of the top ten own-city inequality drivers. As observed, the signs of most of the variables are highly consistent across specifications. Additionally, parameter distribution shapes are close to each other for most of the variables and functional forms, being the SLX model the only exception. This result can be explained by the fact that SLX averaged parameters absorb some spatial dependence that otherwise would be allocated in the spatial error or the spatial lag term.

Finally, we check the robustness of our results with respect to the spatial weights matrix. Given that this is a critical issue in spatial econometric modeling, a broad range of alternative specifications of W are considered. First, we define a set of spatial weights matrices based on the k-nearest neighbors ($k = 10, 15, 20, 25$) computed from the great circle distance between the centroids of the various cities. Second, various inverse distance matrices are constructed with different cut-off values above which spatial interactions are assumed negligible. In particular, we consider matrices with cut-offs at 30, 50, 75 and 100 km of distance. Additionally, exponential distance decay matrices are considered, whose off-diagonal elements are defined by $w_{ij} = exp(-\theta d_{ij})$ for $\theta = 0.01, 0.02$ and 0.03 respectively. Figure (A3) plots the PIPs of the different regressors using the aforementioned spatial weighting schemes and the SDEM specification. As observed, the results for the own-municipality's regressors are quite robust and similar to those presented in the previous section. In particular, within the set of highly-important determinants the PIPs are always above the 90% for all spatial weight matrices. Similar results are obtained for the group of weak determinants, with PIPs below the 10%. However, we find more variability within the PIPs of the moderate and substantive determinants. Both the share of old population and the unemployment rates appear to be more relevant with the k-nearest neighbors spatial weights, whereas their importance decreases when using exponential decay or cut-off matrices. As regards the PIPs for the neighbors' characteristics, we find that most of the variables display probabilities around 20% regardless of the W matrix used, with the urban blight variable being the only exception. This variable turns out to be a highly-important determinant in the context of the k-nearest neighbors matrices. The conditional posterior distributions for the parameters of the main own-city inequality drivers are reported in Figure (A4). Overall, all the variables considered have the expected sign, with magnitudes that fall within similar thresholds to that of the baseline model, regardless of the spatial weight matrix used. The share of employment in services and the per capita income are the only two exceptions, as their posterior conditional probabilities exhibit a more skewed right distribution when the exponential distance decay matrices are considered.

Figure A1: PIPs Across Spatial Models

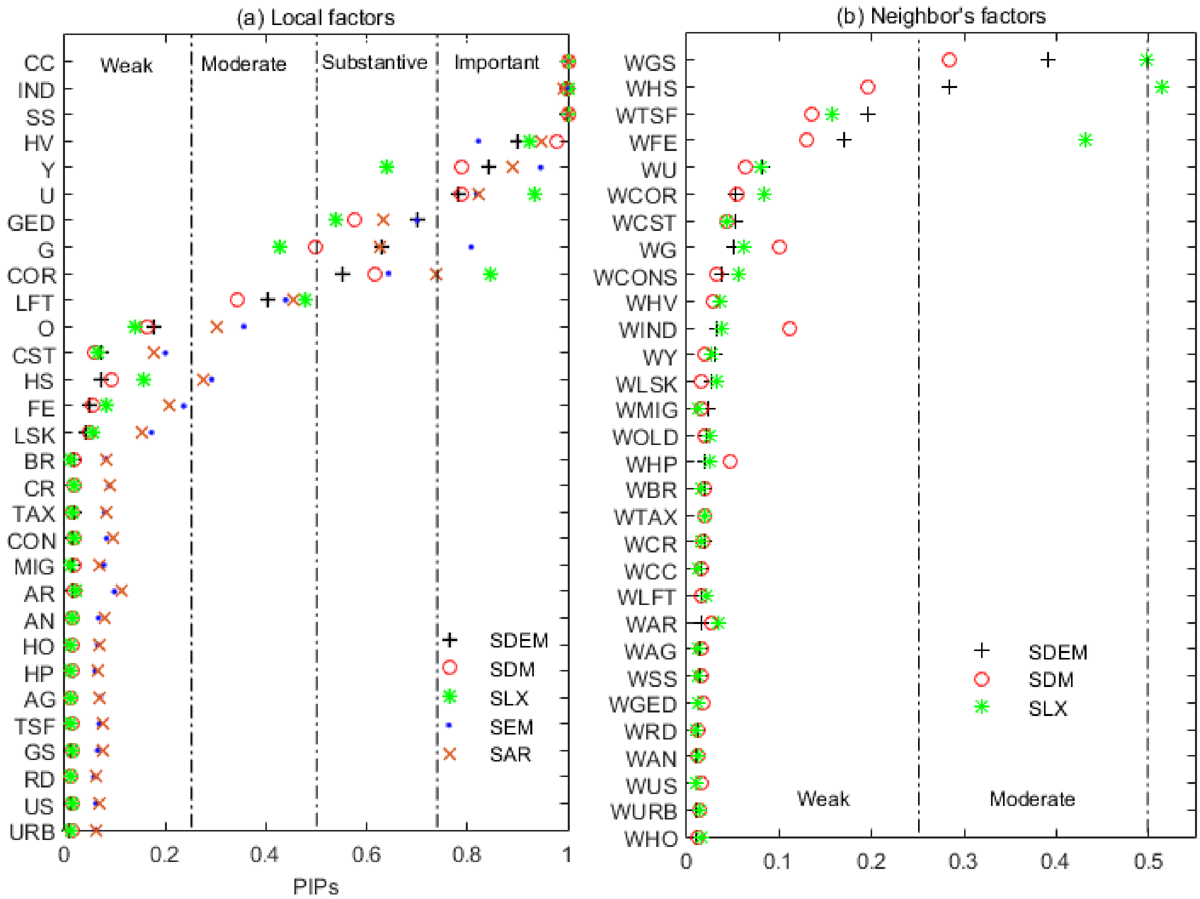
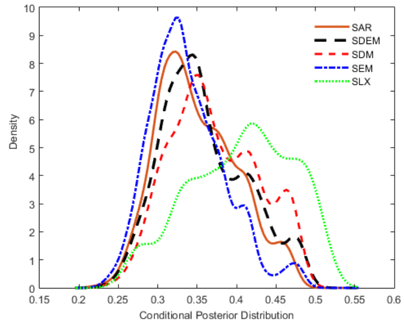
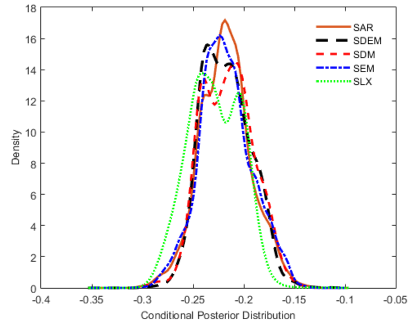


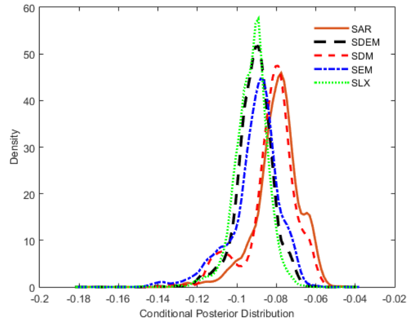
Figure A2: Conditional Posterior Distributions.



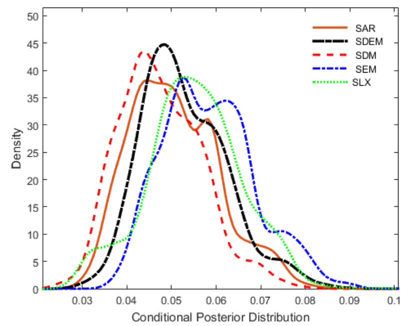
(a) Creative Class



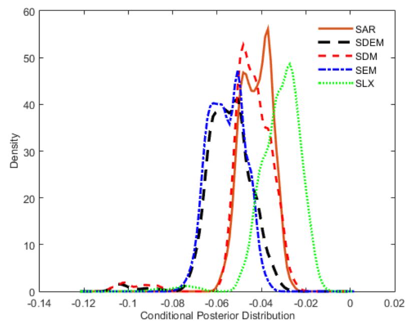
(b) Services



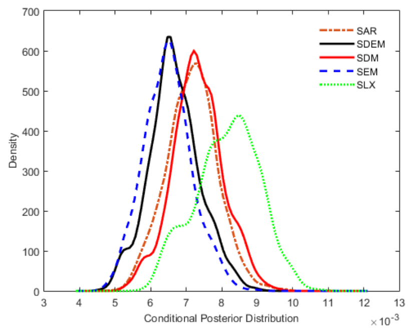
(c) Manufactures



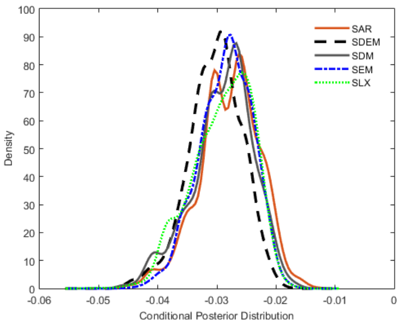
(d) Per capita Income



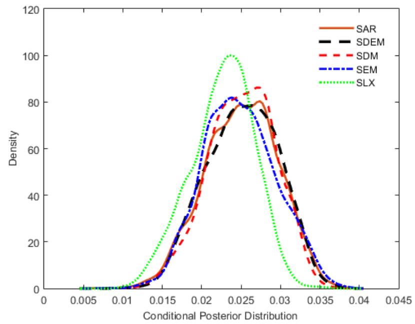
(e) Edudational Inequality



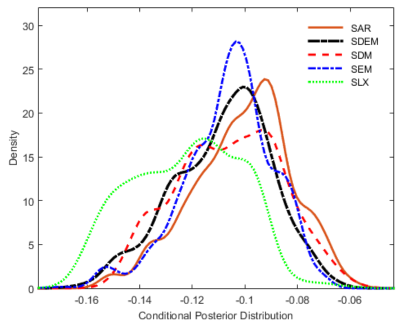
(f) Housing Values



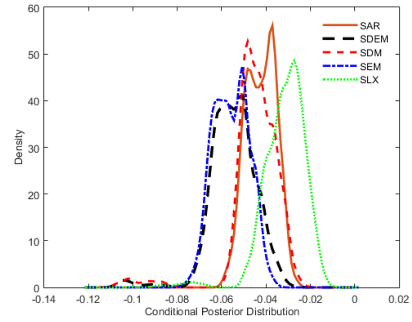
(g) Left



(h) Corruption



(i) Unemployment



(j) Government Spending

Figure A3: SDEM variables PIPs across W's

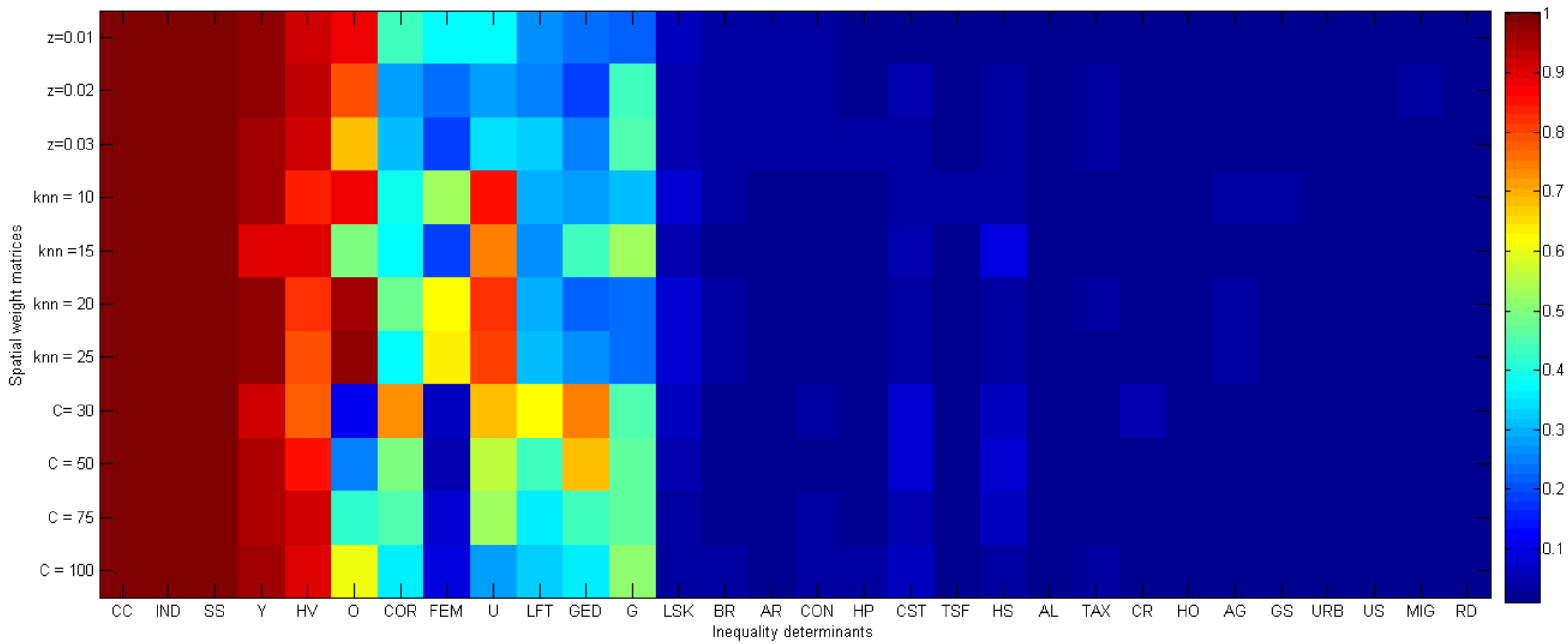
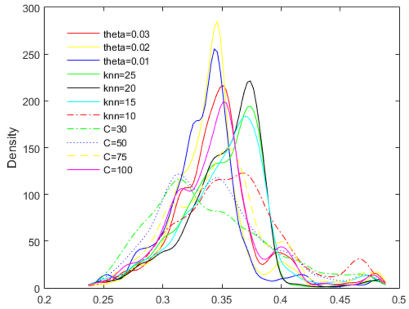
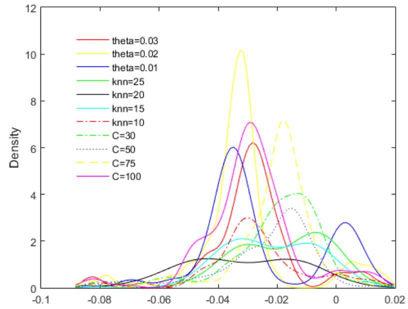


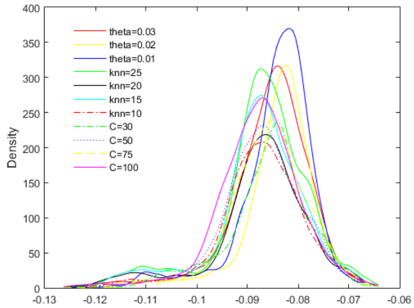
Figure A4: Conditional Posterior Distributions Across Spatial Weight Matrices



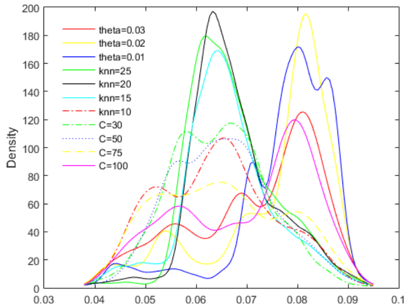
(a) Creative Class



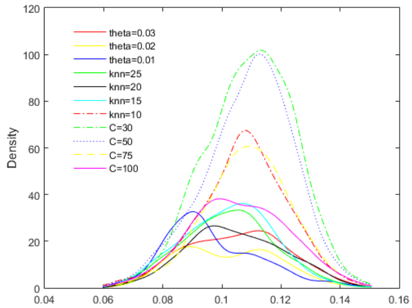
(b) Services



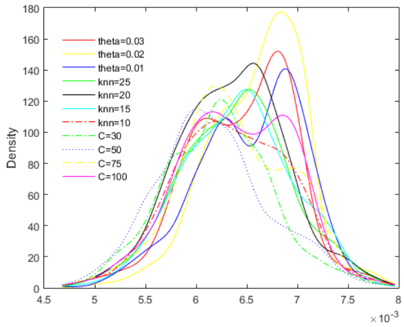
(c) Manufactures



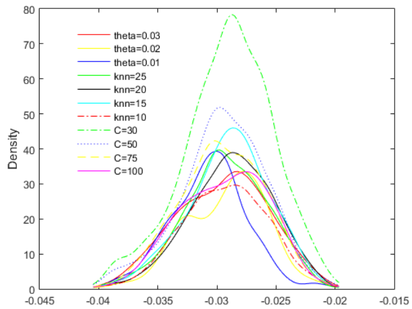
(d) Per capita Income



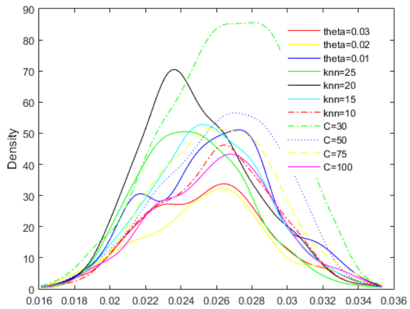
(e) Edudational inequality



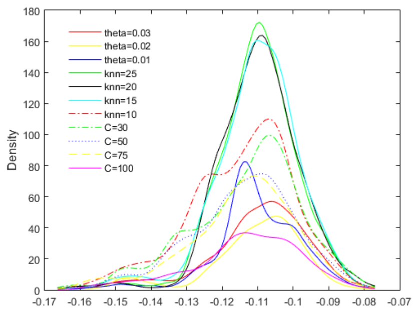
(f) Housing Values



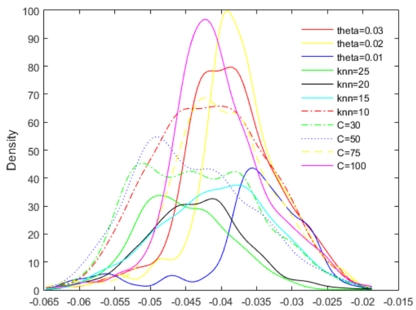
(g) Left



(h) Corruption



(i) Unemployment



(j) Government Spending